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Human Modelling in Assisted Transportation

Models, Tools and Risk Methods

Springer

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Part I
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The Human in Control: Modelling What Goes Right Versus Modelling What Goes Wrong

Erik Hollnagel

1. **Preamble**. The study of human–machine systems or joint cognitive systems has traditionally tried to describe and model what the system—and therefore also the humans—should do. When systems performance differed from design specifications, it was explained as a failure of either the technology or of the humans. While this approach might be reasonable for systems that can be completely specified, it is not reasonable for systems that are underspecified. Since this latter category includes most of the socio-technical systems we have to deal with in today's world, a different approach is required. Instead of looking at joint system performance as either right or wrong, it should recognise that coping with complexity means that performance necessarily must be variable in order to compensate for the underspecification of work and activities. Models and methods must therefore be able account for that.
2. **The engineering approach (Theory W)**. The common (engineering) approaches to human–machine system design views safety as the absence of failures. According to this view, which can be called Theory W, systems work because: (1) systems are well designed and scrupulously maintained, (2) procedures are complete and correct; (3) people behave as they are expected to, and more importantly do what they have been taught or trained to do; and (4) system designers are able to foresee and anticipate every contingency. Theory W thus describes well-tested and well-behaved systems where human performance variability clearly is a liability and where their inability to perform in a reliable manner is a risk.
3. **Bimodality**. We normally assume that things function until they fail. When individual components, such as a light bulb, fail they are discarded and replaced by a new (and identical) component. Composite systems work according to the same principle although failures sometimes may be

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intermittent, especially if complex logic (software) plays a part. Their performance is basically bimodal: either the system works correctly (as designed) or it does not. The principle of bimodality means that the system and/or the system components can be described as being potentially in one of two different modes or states, either functioning or not functioning. Systems are usually designed or engineered to provide a specific function and when that does not happen, for one reason or another, they are said to have failed or malfunctioned.

4. **Engineered systems are tractable**. The engineering approach makes some general assumptions. These are that the description of the system is simple and contains a limited (and manageable) number of details, that the principles of functioning for the system and for its components are known, and that the system is relatively stable so that it does not change before a complete description has been produced. Such systems are completely specified and they are therefore also tractable (easy to comprehend and consequently easy to govern or manage).
5. **Causality**. When something fails or malfunctions, it is assumed that this happens for a reason. More precisely, lack of functioning is an effect that has an identifiable cause. When human factors engineering and the study of man–machine systems began, roughly around the 1950s, systems were tractable. It was therefore generally possible to determine why things failed, to find an effective cause. The causality assumption accordingly made good sense in most cases. But many systems have by now become so complex that it may be practically impossible to unravel the cause-effect relations that we traditionally assume exist.
6. **Underspecified or intractable systems**. Due to the self-reinforcing developments of technologies, services, and societies, a growing number of systems are no longer tractable. For these systems, descriptions are elaborate with (too) many details, the principles of functioning are not completely known, and the dynamics of the systems are such that they change faster than they can be described. Such systems are underspecified and they are therefore also intractable (difficult to comprehend and consequently difficult to govern or manage).
7. **Socio-technical systems**. Today, the conditions for successful organisational performance—and conversely also for unsuccessful performance—are in many cases created by the interaction between social and technical factors, and the systems are therefore called socio-technical systems. The interaction comprises both linear (or trivial) 'cause and effect' relationships and non-linear (or non-trivial) 'emergent' relationships. This has two important consequences: (1) the optimisation of system performance cannot be achieved by the optimisation of the components, social or technical, alone; and (2) safety can be neither analysed nor managed by considering only the system components and their failure probabilities.
8. **'Error mechanisms.'** The bimodality principle and the causality assumption together mean that performance fails when something is not as it should be,

not just in phenomenology but in aetiology. For the human (operator) this has been captured by the concept of a 'human error mechanism,' i.e., a specific way of accounting for—or modelling—how failures (for instance slips, lapses or mistakes) occur.

9. **Human functioning is not bimodal**. It is a fundamental characteristic—and also a fundamental strength—of human performance that it is variable. It is a fundamental characteristic because the 'human as a machine' depends on physiological, psychological, and social processes that are inherently variable. And it is a fundamental strength because it is possible only under exceptional conditions to specify work so well and keep the working conditions so stable that rigid performance is sufficient—or even acceptable.
10. **'Human error.'** Despite these facts, the bimodality principle together with cause effect thinking dominate the ways in which human performance is described and analysed. When human performance does not meet some criterion of acceptability, when something goes wrong, we explain it by invoking the notion of 'human error.' In doing so, we apply both causality and bimodality. Causality justifies a search for the causes of observed effects through either a simple or complex sequence of steps. And bimodality justifies the notion that the cause of the observed performance 'deficiency' is a failure or malfunction, and more precisely a human failure or malfunction.
11. **The determination of 'human error.'** Assuming for a moment that there is a pragmatic value in using the term, it is then necessary to consider how the presence of a 'human error' can be determined. At the very least, there must be a clearly specified standard or criterion against which a particular performance (an event or an action) can be measured, as well as an observed performance shortfall
12. **The Criterion Problem**. In order to state categorically that a 'human error' has occurred, there must be a criterion for acceptable performance. The engineering view argues that human erroneous action should be defined as: "… any member of a set of responses that exceeds some limit of acceptability. It is an out-of-tolerance action where the limits of performance are defined by the system." The psychological (cognitive) view relies on definitions that refer to internalised criteria such as the temporary intentions, purposes and goal structures of the acting individual.
13. **Performance Shortfall**. Most analysts agree that 'human errors' for the most part are negative events where there is some kind of failure to meet a predefined performance standard. There is, however, considerably less consensus on how best to account for the psychological functions that presumably explain 'human errors.' Some adopt a pessimistic interpretation of human performance capabilities, whilst others attempt to account for the occurrence of erroneous action from within a framework of competent human performance.
14. **The pessimistic view on 'human error.'** The pessimistic view is in good agreement with the tenets of information processing psychology and 'human errors' are taken as strong evidence of 'design defects' of the information

processing system. Once these 'design defects' have been identified, it is assumed that guidelines can be developed to determine where the human operator can, and cannot, be trusted to carry out a specific task or activity. It is also possible to design the work situation such that the likelihood of 'human errors' is minimised, for instance by training, by interface design, or by automation, cf., Theory W.

15. **The optimistic view on 'human error.'** The optimistic view emphasises that most 'human errors' have their origin in useful and adaptive processes. Such approaches relate 'error mechanisms' to processes that underpin the human ability to deal with complex ambiguous, and uncertain situations. The view of human performance as basically competent focuses on the correspondence between capabilities and the situation or the demands. Human performance is competent because we can identify the relevant and regular features of a task and use that to optimise resource usage. Since the environment is constantly changing this 'strategy' will sometimes lead to failures—on either a small or a large scale. But the underlying performance adjustments are in themselves correct.
16. **Intractability and coping with complexity**. When the nature of work changes, specifically when we are confronted with underspecified or intractable work situations, it is no longer possible to have a rigid criterion for performance, although it of course still is possible to have a criterion for the acceptability of the outcome. For that very same reason it is meaningless to talk about a performance shortfall, since this requires a standard reference situation. The alternative is to focus on how the joint cognitive systems copes with complexity. Research should therefore look into the reasons for successful coping, rather than the reasons for unsuccessful coping.
17. **Things that go right and things that go wrong**. Despite the focus on 'human error,' it is an undeniable fact that things usually go right and only rarely go wrong. In traffic, for instance, severe and slight injuries are on average expected every 569 and 73 driver years, respectively. It seems that the bias towards the study of performance failures leads to a neglect of normal or 'error-free' performance. If we assume that failures and successes have different origins then there is little to be gained from studying them together. But if we assume that things go right and go wrong for the same reasons, then it makes sense to look at how people cope with complexity, how they adjust their activities to match the conditions—to what has happened, to what happens, and to what may happen. While in some cases the adjustments may lead to adverse outcomes, the same processes that produce successes are the same as the processes that result in errors and malfunctions.
18. **Theory Z**. The view that humans and system performance basically is coping with complexity and that successes and failures happen in the same way can be expressed as a Theory Z. According to Theory Z, systems work because: (1) people learn to identify and overcome design flaws and functional glitches; (2) people can recognise the actual demands and adapt their performance accordingly; (3) people can interpret and apply procedures to match the

conditions; and (4) people can detect and correct when something goes wrong or when it is about to go wrong, hence intervene before the situation becomes seriously worsened. Theory Z proposes that systems work because people are flexible and adaptive, rather than because the systems have been perfectly thought out and designed. Humans are no longer a liability and performance variability is not a risk.

19. **(Successful) coping with complexity**. In modern society, humans are considered the central element of the design process, as well as the major source and contributor to successful performance. Understanding how humans cope with complexity must therefore be implemented into design processes and in safety assessments of innovative technologies to ensure the appropriate consideration of the human factor. Moreover, descriptions—and models—of successful coping can be used to integrate risk-based approaches that make it possible to assess the consequences of human performance variability and to develop ways to monitor and control that.
20. **The bottom line**. Since errors are not intentional, and since we do not need a particular theory of errors, it is meaningless to talk about mechanisms that produce errors. Instead, we must be concerned with the mechanisms that are behind normal action. If we are going to use the term psychological mechanisms at all, we should refer to 'faults' in the functioning of psychological mechanisms rather than 'error producing mechanisms.' We must not forget that in a theory of action, the very same mechanisms must also account for the correct performance, which is the rule rather than the exception. Inventing separate mechanisms for every singe kind of 'human error' may be great fun, but is not very sensible from a scientific point of view.

The Art to Make an Error: The Dilemma Between Prevention, Learning and Mitigation

Klaus Bengler

Abstract

Background Following the established tradition of user centered system design leads to the effect that erroneous behavior of human operator and technical system shall be minimized. As this development goal is in most system constellations to advanced the question on avoidable consequences is more suitable. On the other hand erroneus behavior is a source of information and learning for human operators.

Methods Experiments with user adaptive systems show that adaptiveness includes the risk that system transparency is reduced and the user is not able to handle erroneous situations.

Results The examples show that more information presentation instead of adaptive systems could solve the dilemma and provide learnable environments that keep the user proactive. Additionally it can be shown that there is only limited understanding by the user for technically driven errors in adaptive modules which makes learning difficult at all.

Conclusions Interaction design should take into account that an enabled user is an important part of an error robust system. To ensure these capabilities transparent information presentation is a clear alternative to opaque user adaptive systems. Moreover this approach could help to keep software complexity in a manageable level.

Keywords Error · Adaptivity · Human Machine Interaction · Automation

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Introduction

In a long tradition of user centered system design numerous developers followed the goal to minimize the risk resulting from erroneous behavior of human-machine-systems. Another simultaneous goal is to maximize the efficiency of the whole human machine system (HMS). Whereby—generally spoken—risk minimization can be achieved by minimization of error frequency or error consequences, there is an ongoing tendency to maximize efficiency by automation which results in an increase of monitoring tasks for the human operator. Examples are the layout of pilots' workplaces, vessel operation and increasingly car driving (Fig. 1).

Efficiency by User Adaptive Systems

Therefore it is of increasing importance given a high level of automation to achieve the notorious error free system. The resulting problems evolve from the lack of 100% reliable technical systems and the challenge to draw the line between human erroneous behavior and natural variability in human behavior. Especially in case of efficiency optimization there is a big motivation to reduce human variability. This can be achieved by a priori training, exercise and experience; or by task reduction and increasing process automation which leads in many situations among others to effects of skill reduction and system opaqueness. It should not be overseen that both components (human and machine) get less error robust by this strategy as the interaction is now less sensing and touching and the technical system is more complex and possibly error-prone. The system design is running into a complexity paradox: more safety shall be achieved by more system complexity which causes more weaknesses and less transparency of the machine part of the system for the user. In many cases training efforts are cut and focused to the remaining tasks, weakening the users' general capabilities.

As those effects and discussions are already well known and frequently treated problems it is justified to ask why to discuss them once more.

From the author's perspective the well known effect is amplified by a tremendous emphasize of efficiency and performance requirements. Second, in many

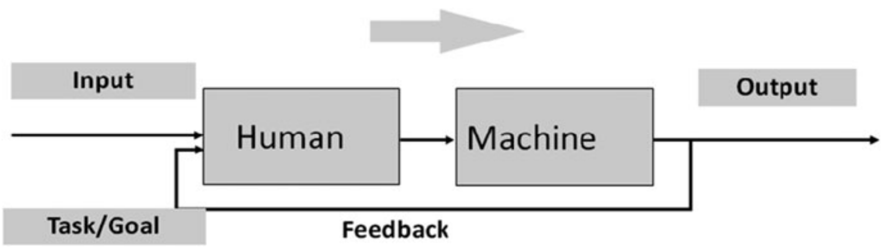

Fig. 1 General model of the human machine system

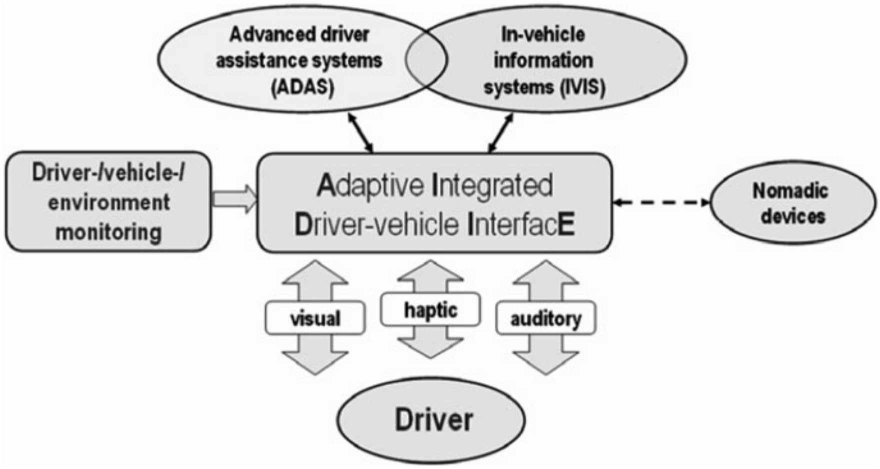

Fig. 2 Illustration of the AIDE concept as an example for a user-adaptive system architecture [1]

cases user modelling and adaptive systems promise to resolve this situation as a panacea (Fig. 2).

Technically spoken the machine is extended by sensation, recognition and interpretation modules that try to build and maintain a user model due to the behavior of the user. This approach is enabled by developments in sensorics, storage und processing. The status of those can be experienced for example in the current DARPA demonstrators which replace the user at all. In everyday life we can experience those systems in dialog system behavior of browsers.

Due to these two facts it seems reasonable to ask whether human operators have learning strategies to interact with imperfect “should-be-intelligent” user adaptive machines implementing a user model and are able to take their decision and error characteristics into account under efficiency pressures. This discussion follows Reason’s argumentation of systems that implement “unfamiliar or unintended feedback loops” [2].

Examples that can be named in this case are again natural spoken dialog systems but also semi-autonomous transport systems. In the case of spoken dialog typical technology driven recognition errors do not meet user expectations based on human–human interaction and lead therefore to curious and non-efficient problem solving behavior by the user e.g. repetition of commands, inefficient trial and error

Currently in many warning systems only a very restricted and simple reaction time based user model tries to resolve the warning dilemma. Given a stable reaction time of the user the system will not warn before and warn or act after a given time-to-collision. Unnecessary warnings and misses shall be avoided using this approach. To some extent this leads to a stable and reliable solution of a technical system.

Adaptive Systems vs. Learning Users

Analysing advanced architectures for future systems unveils in most cases a classical system design including extended user models that assess user state, intention and availability to moderate the system behavior. It is important that these models are based on sensoric input and probabilistic recognition processes of context information which means that their status and influence on system state changes are more or less unlearnable for the user.

Therefore it is of interest whether the existance of an adaptive machine will lead to a change in error qualities and error type distributions (Omission vs. Commission; Active vs. Passive). One result could be that the user is disabled to act as a safety barrier once more. Moreover human variability would again be counterproductive for a stable user model.

This leads to the question whether there is an alternative approach which incorporates human variability into system design and enables the user to build up experience while interacting with the system. The art to make an error cannot mean to increase technical system deficits and make the system more error prone but to make the whole HMS more error robust based context information for an active learning intelligent user. As pointed out in Hollnagel [3] "Errors are useful for learning". On the other hand Reason [2] warns that in all day behavior errors are an important source for learning. In complex systems this has to be avoided: "Whereas in the more forgiving circumstances of everyday life, learning from one's mistakes is usually a beneficial process, in the control room of chemical or nuclear power plants, such educative experiences can have unacceptable consequences." Therefore it has to be investigated whether requirements for learner friendly controllable environments and architectures under efficiency conditions have to be defined for critical environments, too:

- increase of system transparency and feedback to the user
- increase of user involvement and continuos user activity
- decrease of the degree of precise technically automation
- limitation of probabilistic active technical functionality

This seems justified as another group of enabling technologies would also be available in form of advanced display technologies, force feedback actuators, and forward propagation based on ambient information and connectivity to the environment. The goal in this case is to focus on interaction designs based on prospective information presentation instead of monitoring of automated functionality.

It has to be taken into account that the challenge in this case is the limitation of information overflow und successful information integration for the user. Again the target is to establish a learner friendly environment in which the user is able to acquire the necessary skills and routines to optimize overall system efficiency under standard conditions in an anticipative way and limit the consequences of technical errors.

Information Design for Anticipative Driving Behavior

One example is the realization of an anticipation horizon for the car driver using C2X information to provide the driver with information on the further development of the driving situation. The information displayed in the dashboard integrates speed limits, curvatures as well as traffic jams and accidents. It can be shown—although the information is provided in qualitative way—that drivers are motivated to integrate this information into their driving strategy and establish a very anticipative driving style which is fuel efficient and safe as well. In driving simulator experiments the dedicated layout of information presentation especially the incident category which is provided by CarToX connectivity leads to high acceptance and specific behavior. Due to the fact that the CarToX information is incomplete and to some degree unreliable, one has to speak of erroneous technical information in this case. It could be shown in experiments that users are able to use this source of information and transform it into stable error free and efficient driving behavior [4] and without adaptivity on side of the machine.

Summary

This shows that the try to model human error into adaptive system design may not be enough, but moreover counterproductive. It might be reasonable to increase system's stability, transparency and enable the learning user as an anticipative source of safety and efficiency by better visualization. Noted problems to realize this concept like information overflow and increased workload could be solved by innovative technologies that enable integrated presentation of complex data and forward propagation of process states by enhanced system simulations.

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Modeling Differences in Behavior Within and Between Drivers

Andrew M. Liu

Abstract A new generation of driver assistance systems such as advanced collision warning and intelligent brake assist are now available options for the modern automobile. However, the addition of each new system increases the information load on the driver and potentially detracts from their ability to safely operate the vehicle. Over 10 years ago, we [Pentland A, Liu A (1999) A modeling and prediction of human behavior, Neural Comput 11, 229–242] suggested that a car that could infer the current intent of the driver would be able to appropriately manage the suite of systems and provide task relevant information to the driver in a timely fashion. This "smart car" would observe the driver's pattern of behaviour in terms of their control of the vehicle then infer their current driving task using a Markov Dynamic Model. The approach could recognize driver actions from their initial behaviour with high accuracy under simulated driving conditions. Since that time new computational approaches and improved in-vehicle technology (e.g., GPS technology, advanced radar and video/computer vision, etc.) have moved the realization of this concept further along. Yet, one fundamental question still needs to be carefully addressed: Can these driver models, built on statistical descriptions of driver behaviour, accurately model the differences between drivers or changes within an individual driver's behaviour? In this paper, I describe some examples of these differences and discuss their potential impact on a model's ability to consistently recognize behaviour. To ensure the acceptance of the next generation driver assistance systems, these issues will have to be resolved.

Keywords Markov Dynamic Model · Individual differences · Driving style · Driver experience · Fatigue

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Background

Intelligent cruise control and lane departure warning systems have been under development for more than 15 years and have recently reached a level of technical maturity that manufacturers have deemed to be safe and reliable. Most major manufacturers (e.g., Mercedes, Nissan, Ford, BMW, and Toyota) now offer some form of these systems in their luxury automobiles. The driver-system interaction still generally implemented at a "low" level of automation such that ultimate control of the vehicle is still entirely entrusted to the driver, e.g., only visual or audible warnings are presented to the driver to warn of impending collision or lane departure. The intent of the driver, e.g., car following, is established when they activate the system and changes in intent are also initiated by some control activity such as stepping on the brake which disengages the system. The low level of automation prevents the system from interfering with the driver when their intentions change but neglect to deactivate the system. The vehicles are allowed some control authority but only under conditions where the driver may not be able to respond in time to avoid an accident (e.g., activation of brake before collision).

As driver assistance systems are given more control authority under normal driving circumstances, it becomes critical for these partially autonomous driver assistance systems (PADAS) to be aware of the driver's intentions. The proliferation of PADAS in the vehicles means that more warnings or information alerts may be displayed to the driver, potentially resulting in competition for the driver's attention. Thus, driver models that quickly and accurately recognize the current actions or anticipate future actions are needed for PADAS to provide appropriate and timely warnings, information, and/or actions.

Driver Model Development

Our initial work on driver modeling [12, 17] proposed a framework, the Markov dynamic model (MDM), that would be able to recognize a human driver's current action or in the ideal case anticipate the human driver's intended behavior. Figure 1 illustrates an example of a 4-state MDM that exemplifies how human behavior passes through a constrained series of states within the context of a driving action. The MDM can also be structured as a hierarchy of models covering long-time-scale behavior (e.g., at a tactical level such as deciding to pass another vehicle) down to models that describe the finer-grained structure of the behavior in a sub-state (e.g., how the driver prepares to pass another vehicle).

Our initial experiments with MDMs inferred driver behavior based solely on measurements of the driver's vehicle control behaviour which included the heading, velocity, and acceleration control of the vehicle. Experimental tests with our MDMs in a constrained simulated driving scenario showed that we could recognize a driving maneuver in the first 1.5 s with 95% accuracy.

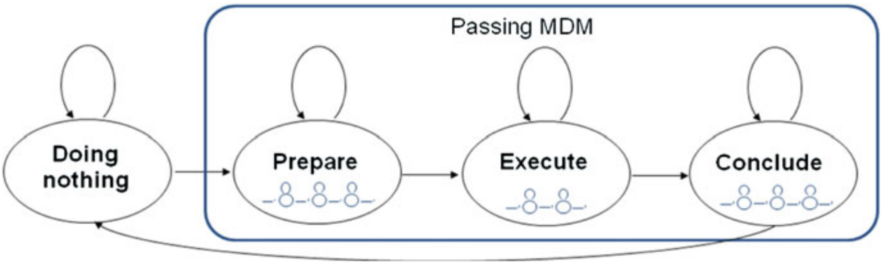

Fig. 1 A Markov dynamic model of driver action (e.g., passing). Finer-grained MDMs could be used to describe driver behavior in the individual sub-states

There are other sources of observable driver behaviors such as driver head movements or eye movements which could be used. The eye movements of drivers have idiosyncratic patterns depending on driving task [8, 9, 11, 15, 23] that could be utilized within the same MDM framework [11] to potentially improve recognition performance [6]. Since drivers tend to preview the road ahead with their eye movements, this information may improve the predictive capability of driver models. The external environment, such as the surrounding traffic, or even path information from a navigation system may further constrain the probable space of driver intentions. Oliver and Pentland [16] used coupled Hidden Markov models (CHMMs) to link the behavior of the surrounding traffic environment with driver control behavior and found that it improved recognition of driver intentions. In the intervening 10 years since our initial work, numerous other techniques have been investigated including stochastic approaches (e.g., Autoregressive HMMs [1]), sparse Baysian learning [14], cognitive architectures [5, 22], support vector machines [13], neural networks [26] and Dempster-Shafer evidence theory [28].

Modeling Differences in Driver Behavior

Most driver models have generally been developed from the behavior of a relatively small population of drivers using a limited number of vehicle types, roadways and traffic conditions. The reported results generally show good recognition performance under these constrained conditions, but it remains an open question whether these models perform equally well when tested across a wider set of drivers, vehicles and under different operating conditions. If a suitable model can be used for many types of drivers, then a generic system could be easily implemented across a fleet of vehicles. However, it seems more likely that the population of drivers will need to be subdivided into subgroups with separate models for each group. In either case, it will be critical that the driver models perform well "out of the box" to ensure the acceptance of and trust in the PADAS.

Differences in Behavior Between Individual Drivers

Based on the body of research, one obvious dimension to group drivers would be their level of experience. Beginning with a study by Mourant and Rockwell [15] that showed how novice drivers tended to focus their gaze across a smaller portion of visual space, many other studies have shown that novice drivers tend to drive at higher speeds, keep a smaller time/distance headway to leading vehicles, and brake later in response to the vehicle or roadway ahead [2]. Typically, experiments to collect data for parameter estimation have used experienced drivers in an attempt to get baseline behavior data. But younger less experienced drivers are disproportionately involved in fatal accidents in the US and might derive greater benefit from driving with a PADAS. Amata et al. [2] compared the performance of multiple regression models estimated from expert, non-expert and mixed population deceleration to recognize deceleration behavior (e.g. releasing the accelerator or using the brake). Model performance was slightly different between the expert and non-expert models, but no conclusions could be drawn since only two expert and two non-expert drivers were used.

Even within the population of experienced drivers, there is likely to be significant variability in behavior due to different "styles" of driving. In this instance, driving style reflects the individual's typical choices of speed, time headway and attentiveness for comparable situations. Unfortunately, there seems to be little agreement about the characterization of driving styles and several different measurement tools exploring many possible dimensions of the driver (e.g., risk aversion, gap acceptance, use of turn signals, etc.) been created to describe driving style. One possible approach to reduce the number of classifications might be multidimensional analysis [27]. Using subjective measurements from a questionnaire assessing driving behaviors, self-esteem, and other typical traits, this analysis showed that drivers could be grouped into eight distinct driving styles. While these types of analyses are far from definitive, they could be a useful tool to test whether their actual driving behavior, measured in a real situation, would lead to similar subject groupings.

The variability between individual drivers might also be lessened with the selection of appropriate parameters for the model. Driver inputs such as the accelerator or brake pedal positions are very noisy signals in the sense that the moment-to-moment position of the pedals probably has a very small impact on actual vehicle speed due to vehicle dynamics. Different drivers would probably exhibit a large variance in distribution of pedal positions for similar velocity or acceleration profiles. Furthermore, deterioration in vehicle sensors, engine performance, or traffic and weather (e.g., dry versus icy roads) conditions could significantly change the pattern of movements for the same intended action. Qiao et al. [20] showed that a change of 4% in the accuracy of their speed sensor, a typical estimate of deterioration by the manufacturers, led to a 5% drop in the recognition accuracy of their models. A better approach is to model variables that drivers are likely to perceive and control, such as time-to-contact. This was an important conceptual difference between our MDM approach and earlier work using classical techniques such as neural nets or fuzzy logic [19, 25]. The MDM was intended to model how a set of dynamic processes (e.g., the driver's set of intended actions) was controlled in order to generate the observed behaviour rather than trying to model the pattern of vehicle parameters directly.

Changes in Behavior Within an Individual Driver

Assuming that a general driver model or a small set of models with reasonable recognition performance could be realized, the models must still account for changes in an individual driver's behavior over both long (e.g., months) and short (e.g., hours or less) time scales. Certainly driver models could be adapted or tuned to a specific driver over time by re-estimating parameters using new behavioral inputs. Figure 2 illustrates how an initial model would segment the driver's real-time behavior into individual actions such as lane changing or passing. Over time, the model would accumulate a number of new examples of a particular behavior, which could be considered a new training set from which to re-estimate the model parameters. For changes that occur slowly over time such as those associated with aging, the model would most likely be able to track the resulting behavioral changes and maintain its recognition performance.

Another obvious cause of change in a driver's behavior is the experience they accumulate over many years of driving. Studies of novice and experienced drivers have typically compared one group to another but have not investigated the pattern of the changes from novice to experienced driver. If the changes evolve slowly

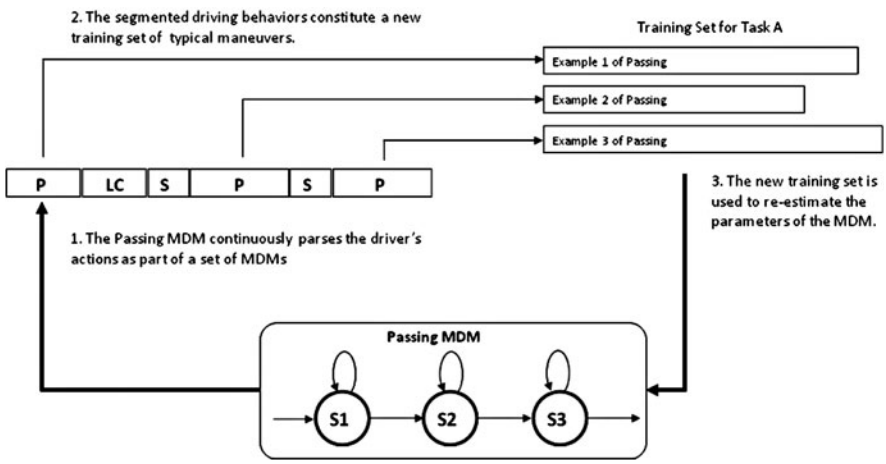

Fig. 2 The parameters of a MDM describing passing could be continuously updated with new examples of the maneuver. The continuous learning could help the model account for changes in vehicle behavior over time

over time (e.g., over a period of months, the driver slowly increases their time headway as they gain experience), then the process of continuously updating model parameters would most likely be able to follow the changes without a loss of performance.

However, learning a complex skill such as driving may not proceed in a smooth and linear fashion, but instead be punctuated by sudden changes in behavior as the driver decides to adopt a drastically different strategy which is more desirable. For example, a novice driver might begin shifting their lateral lane position close to the lane markings when being passed by large trucks after experiencing a near accident from the side. This could result in the driver model occasionally misinterpreting this shift as an intended lane change and activate an unexpected PADAS action or warning. Over time the model might adapt to the new behavior, but time lag would be depend on the magnitude of the change in behaviour and the frequency at which examples of the new behavior. During the period of adaptation, the driver might perceive the PADAS to be less reliable and reduce their trust in its accuracy.

Fatigue, distraction and emotions are other potential causes of episodic and short-term changes in driving behavior. Fatigue in particular can be problematic since people often underestimate their level of tiredness and often assume that they are able to perform at a level higher than what objective measures would suggest [21, 29]. Presently, most approaches for detecting a driver's state of fatigue use machine vision techniques to observe the driver's eyes and calculate the percentage of time of eye lid closure (i.e., PERCLOS) which correlates with fatigue or drowsiness [30]. Thus, these systems are limited to detecting the state when the driver is likely to lapse into micro-sleep episodes. However, the effects of fatigue can affect behavior even before drivers reach than that level of tiredness. Fatigue from prolonged wakefulness or time-on-driving task has been shown to increase the deviations in speed control, steering behavior, and lateral lane position as well as increase reaction time [4, 18, 24]. Sleep restriction studies in which subjects sleep less than 8 hours per night over a period of days have shown that many cognitive processes such as sustained attention, working memory or executive function can be degraded. [3, 10] Degradations in working memory, as an example, might affect the mental workload they are able to sustain. Thus, drivers may monitor important secondary tasks (i.e., monitoring surrounding traffic) less frequently or even not at all. The problem of sleep restriction is particularly worrisome in today's society since a large proportion of people report getting less sleep than generally required [3]. Gunzelmann et al. [7] incorporated mechanisms representing the effects of sleep and circadian rhythms on central cognitive function into a cognitive driver model [22] and generated driver behavior under simulated sleep deprivation conditions. Their generated data showed a pattern of lateral deviation behavior that was very similar to behavior of a human driver under similar conditions [18]. Similar studies using cognitive models will be needed to better understand the relationship of these cognitive functions in the context of performing a complex skill such as driving while fatigued. The knowledge gained from these studies could then be applied to computational driver models for PADAS.

Conclusions

As the next generation of PADAS gain more control authority, they will need to be aware of the driver's current actions or intentions to interact appropriately with the driver. Over the past 10 years, many computational models to recognize driver behavior have been developed with promising results but only for a limited range of drivers. Differences over the larger population of drivers may preclude creating a general driver model. By separating the population into smaller groups along well studied dimensions (e.g., novice versus experienced drivers), the variability in behavior within the group may be reduced, which should improve recognition performance. Driver models must also be able to account for changes in an individual driver's behavior over time. For longer-duration changes, the continuous re-estimation of the model may be sufficient. However, shorter-duration changes due to fatigue and other factors may affect recognition performance and impact the reliability of PADAS. The processes that cause these changes will need to be characterized and incorporated into future driver models.

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Drivers' Information Processing, Decision-Making and the Role of Emotions: Predictions of the Risk Monitor Model

Truls Vaa

Abstract The present paper discusses issues of perception, distraction, unconscious and conscious routes of information processing and decision-making. Three major topics are addressed: Relative risks, risk monitoring, and Intelligent Transport Systems (ITS). A consideration of relative risks is proposed as a fruitful angle to draw up problem statements about accident causation as relative risks allow you to compare risk levels of different road conditions, road user activities, and driver states. A list of 21 relative risks is provided and for each of them an indication of whether there exist an ITS that might mitigate the problem is stated. The relevance of new paradigms provided by evolution and neuroscience is suggested. A model of driver behavior, the Risk Monitor Model (RMM) is elaborated and described. Finally, predictions of the RMM about the outcome of ITS, are stated as seven specific hypotheses.

Keywords ITS · Drivers · Information processing · Decision-making · Relative risk · Damasio · Emotions · Risk monitor model (RMM) · Hypotheses

Introduction

The present paper has three major foci: Relative risks, risk monitoring, and Intelligent Transport Systems (ITS). Relative risks that significantly exceed 1.00 indicate that the risk monitoring associated with certain conditions sometimes fails. The objective is then to explain why it fails and how it can be improved. The application of ITS is one approach, but it is not a straightforward task because

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ITS is a heterogeneous group of systems. Hence, it cannot be treated in a generic way. Doing risk analyses of potential outcomes of ITS system by system, is an option, but tedious and lengthy and you may lose sight of what they might have as common features. The best alternative is possibly to try to understand the interaction between driver and system in theoretical terms, i.e. link ITS to a driver behaviour model, and work out hypotheses of potential outcomes that might apply to ITS in a more generic way. The core of a potential understanding must be to consider the main elements of risk monitoring and discuss aspects of information processing and decision-making. A consideration of relative risks is proposed as a fruitful angle to draw up problem statements about accident causation as relative risks allow you to compare risk levels of different road conditions, road user activities, and driver states. The objective of linking relative risks to Intelligent Transport Systems is then fourfold:

1. To see if ITS address major traffic safety problems
2. Provide an empirical base for discussing effects of ITS theoretically
3. Discuss the role of emotions in drivers' information processing
4. Link relative risks and ITS to predictions based on a model of driver behaviour—which in this context would be the Risk Monitor Model (RMM)

Table 1 ranks some known relative risks. For some of them an existing ITS that might mitigate the risk is proposed. [14, 15]. For some of the activities and states, however, no ITS is known or developed.

Problem Statements Based on Known Relative Risks

The empirical data presented in Table 1 provides options of proposing some problem statements and hypotheses based on known relative risks.

- *Intoxication and illegal drugs:* Drink driving is by far the most dangerous driver state. Blood alcohol concentrations (BACs) above 0.15% show a relative risk of 65, which, together with riding a moped, are the highest relative risks of all [6]. Drink driving is also far more dangerous than using any other intoxicating substance or drug. For example, the relative risks of using benzodiazepines, cannabis and opiates are 1.54, 1.70 and 1.83, respectively [14].
- *Two-wheelers and the representation of danger:* Riding a moped or a motorcycle exhibit relative risks which are comparable with those seen for drink driving [5]. One might hypothesize that a motorcycle, with its motor power, represents a technological extension of the body which might tempt the rider to chose driving speeds and taking risks which he cannot control. This might be a scenario, at least in some cases, but, given the very high relative risk of moped riders, there must be other accident mechanisms involved as the low motor power of mopeds implies a technological restriction of driving behaviour compared to a motorcycle, not the opposite. Then, for accidents involving both a

Table 1 Some known relative risks of driver states, driver activities, road conditions and potential ITS-solution to mitigate the problem (source of relative risk in parentheses)

Driver state/activity/road condition	Relative risk	Potential ITS-solution
Drink driving > 0.15% (sober = 1.00) [6]	65	Alcolock
Riding a moped (car driver = 1.00) [5]	65	No
Drink driving > 0.1 < 0.15% (sober = 1.00) [6]	25	Alcolock
Motorcycle rider (car driver = 1.00) [5]	13.2	No
Drink driving > 0.05 < 0.1% (sober = 1,00) [6]	10	Alcolock
Male drivers age 16–19 (male drivers age 55–64 = 1.0)[5]	9.8	ESC/ISA
Female drivers age 16–19 (male drivers age 55–64 = 1.0)[5]	9.1	ESC/ISA
Female drivers age 75 + (male drivers age 55–64 = 1.0)[5]	4.5	No
Male drivers age 75 + (male drivers age 55–64 = 1.0)[5]	4	No
Drivers with sleep apnea (healthy drivers = 1.00)[15]	3.71	No
Snow or ice covered road (dry road = 1)[5]	2.5	ESC
Mobile telephone use [11]	2.20	No
Driving in darkness—accidents with pedestrians [5]	2.1	Night vision
Driving in 70 km/h (driving in 50 km/h = 1)[3]	1.96	ISA
Immigrated, non-western, male drivers (Norwegian drivers = 1.00) [9]	1.96	No
Immigrated, non-western, female drivers (Norwegian drivers = 1.00) [9]	1.51	No
Road covered with wet snow (dry road = 1)[5]	1.5	ESC
Driving in 60 km/h (driving in 50 km/h = 1)[3]	1.44	ISA
Health impairments—weighted average of 10 main groups listed in Annex III of Council Directive on driving licences [14]	1.33	No
Hearing impairments [14]	1.19	No
Vision impairment [14]	1.09	No

moped/motorcycle and a car, an alternative hypothesis is proposed: Could it be that drivers, in their risk monitoring and looking for dangers, overlook mopeds and motorcycles because they are not recognized as dangers? Could it be that drivers look for other cars because it is cars that represent threats to survival, not motorized two-wheelers [17]? The appropriate concept for this hypothesis would be what Damasio denotes primary emotions, which correspond to the neurobiological apparatus of the newborn infant [2].

- *Age and experience:* The relative risks of young drivers, i.e. 16–19 years of age, have recently been updated [5]. The difference between genders is also less clear as male and female drivers exhibit relative risks of 9.8 and 9.1, respectively. Despite research efforts on the effects of basic driver training for decades it seems inevitable that novice drivers must undergo a period of high accident risk by being exposed to the dangers of real traffic, before the accident risk drops as a function of time and driving experience [5]. Research efforts have not succeeded in identifying those learning mechanisms that effectively reduce the number of accidents. On the contrary, specific driver training aiming at reducing skidding accidents and accidents while driving in darkness have shown the opposite by increasing the number of accidents significantly [4].

- *Evolution:* It is not age as such that causes the accidents, but factors that go along with it, often denoted as "maturation". This concept has recently been actualized by realising the need to understand human behaviour in terms of evolution processes, i.e. both that humans in ancient times probably was more "The Hunted" than "The Hunter" and that the perceptual apparatus of humans was developed in contexts where survival was the main motive and escaping the dangers and threats of predators was a necessity. On the one hand, it is remarkable that the "stone-age monitoring of risks", functions so well in the modern context of road traffic, but, on the other hand it is obvious that the monitoring of risk is not well adapted to the dangers of road traffic, as demonstrated by the distribution of accident risk according to age. It is a necessity for novice drivers "to build their own library of experiences", of schemes, to extract the essence of situations which represent potential threats to survival, to repeat and confirm the experiences and to automate them, a process which Damasio denotes the development and establishment of secondary emotions [2].
- *Neuroscience and paradigm shifts:* Recent developments in neuroscience have added more depth to the concept of maturation, when postulating that the brain is not fully developed in adolescence, it is not until the age of about 25 when the brain is fully developed and "matured". In this process of maturation, the perception of fear is also subject to change, meaning that the adolescent brain may have difficulty in correctly identifying fear until the brain is fully developed.

The perspective of evolution and the achievements of neuroscience represent paradigm shifts in the general understanding of humans in modern society, and it also affects information processing and decision-making of drivers. These paradigm shifts have not been fully acknowledged and accepted in the elaboration of driver behaviour models.

The Risk Monitor Model (RMM)

The RMM is an eclectic model which is based and assembled on several other older, established models and theories [17]. The major contributions to the RMM are:

- Näätänen and Summala's "Zero-Risk Model" [7, 8] and the concept and proposal of a *subjective risk monitor.*
- Taylor who demonstrated that constancy of Galvanic Skin Responses (GSR) seems to be a governing principle in drivers' decision-making and speed-choice [13].
- Damasio's neurobiological model elaborated in his book *"Descartes'Error: Emotion, Reason, and the Human Brain"* [2].
- Wilde's Risk Homeostasis Theory by adopting the idea of a *target*, however revised by substituting the hypothesis of drivers seeking a target *risk* ($\geq$0), by the hypothesis of drivers seeking a target *feeling* [16, 18].

- Bechara et al's demonstration of the role of Skin Conductance Responses (SCR) [1] which confirms Taylor's findings of the role of GSR.
- Learning theory or more formally *operant conditioning*, adopting the scheme

$$\mathbf{S^D \rightarrow R \rightarrow S^R}$$

where S^D denotes the *discriminative stimulus*, R the *response* or *operant*, and S^R the *reinforcing stimulus.* This scheme is especially important in understanding how the target *feeling* in the RMM may operate as reinforcement, for example in explaining speed behaviour.

Even if there is a 20-year time-span between the Näätänen and Summala's "Zero-Risk Model" and Damasio's model, the thinking behind the two is basically the same, although Damasio's perspective is much broader as it considers human evolution, i.e. it does not address drivers in road traffic specifically as done in Näätänen and Summala' model. Central in the "Zero-Risk Model" is the concept *subjective risk monitor*, an idea which is incorporated in the RMM.

In my opinion, Damasio provides a more basic understanding of humans that may serve well as a base for developing a model of driver behavior because of its theoretical foundation on neuropsychology, in which concepts as emotions, feelings and the relationship and interplay between unconscious and conscious process are central. The base for what is labeled "The Risk Monitor Model" is three simple statements, which all are extracted from Damasio [2]:

- *Axiom:* Human's deepest and most fundamental motive is survival.
- *Deductions:* Humans must possess a specialized ability to detect and avoid dangers that threatens his/her survival and an organ which provides the monitoring of potential threats.
- *Assertion:* The body is the organ and the risk monitor.

It follows from the axiom that we must have an instrument, an organ, enabling us to monitor the surroundings and the situations in which we act. This organ is the organism itself, the complete body and its inherent physiology developed by evolution through the history of humans where observation and identification of dangers have been of vital importance. The organism taken as a whole is considered as a monitor, an organ for surveillance whose prime task is to monitor the interior, i.e. the state of the body, and the exterior, i.e. the environment and other actors with which the organism interacts. Damasio postulates a relationship between internal states and external behaviour when the human organism is exposed to certain strain and emotional stress, which forms:

> …. a set of alterations [which] defines a profile of departures from a range of average states corresponding to a **functional balance**, or homeostasis, within which the organism's economy probably operates at its best, with lesser expenditure and simpler and faster adjustments (Damasio [2], pp. 135).

A central concept in the above citation is the *functional balance* which I also will label and define as a *target feeling*. A *target feeling* is a kind of state that drivers are seeking to achieve and/or maintain while driving. The drive to achieve a functional balance is regarded as a central, predominantly unconscious knowledge, which the organism possesses about itself, and which the organism is actively seeking to maintain or to restore. Damasio states his model by saying that something important happens before thinking and reasoning. If, for example, a situation seems to develop into something threatening or dangerous, a feeling of unpleasantness will enter the body, an unpleasant 'gut feeling' may be under way. Because this emotion is knit to the body, Damasio labels it *somatic* ('*soma*' is Greek for 'body') and *marker* because the emotion is marking the scenario. Damasio describes the consequence of this somatic-marker in the following way:

> [A somatic marker]….forces attention on the negative outcome to which a given action may lead, and functions as an automated alarm signal which says: Beware of danger ahead if you chose the option which leads to this outcome….(Damasio [2], pp. 173).

Näätänen and Summala defined *safety margins* as an important mechanism in driver behavioural control, and the obvious relationship to Damasio's somatic marker can be found e.g. in Summala's conclusion [12]:

> Risk perception is basically perceiving a threat to one's physical integrity, a loss of control, or of being suddenly on a collision course. It can be traced back to such environmental dangers as a sudden change in visual stimulation, specifically rapid magnification of textured figure in the field of view which signals that something is moving towards one's body (Summala [12], pp. 56).

However, Damasio goes further by taking into account the roles of emotions and feelings. He separates deliberately and unorthodoxly between emotion and feeling and limits the concept of *emotion* to what goes on in the body of the organism, i.e. the myriads of changes in the state of the body that is induced autonomously in all its parts and organs when the organism is exposed to a given, external event. Damasio limits *feeling* to processes of consciously experiencing, consciously sensing, the changes of the body and the mental states. Damasio distinguishes several levels and defines emotions and feeling as follows [2, 16, 17]:

- *Primary emotions:* Emotions that are innate and unconscious, corresponds to the neurobiological apparatus of the newborn infant.
- *Secondary emotions:* Emotions that are learnt and based on individual experiences, accumulated by the individual. Predominantly unconscious or preconscious.
- *Feelings:* The process of "feeling an emotion", i.e. of "making an emotion conscious", to feel and transform changes in body states into conscious experiences.

Hence, there are two paths of information processing and decision-making, one path predominantly unconscious through primary and secondary emotions, and one predominantly conscious through the path of feelings (Fig. 1). The orienting reflex bridges the connection between emotions and feelings when appropriate stimuli are provided, and always in this direction as there is no such thing as

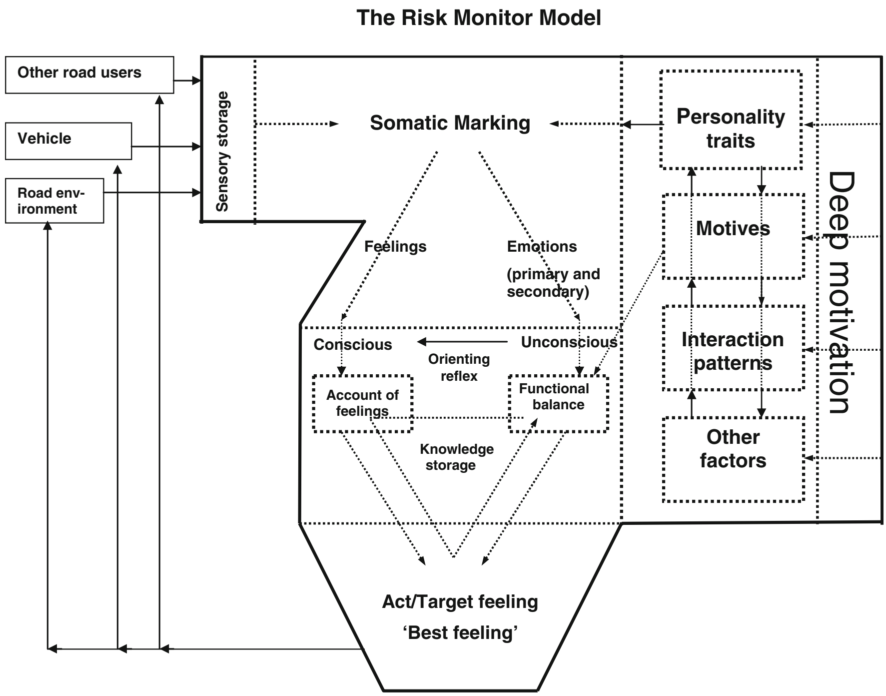

Fig. 1 The Risk Monitor Model (RMM) [18]

"deciding to drive in automated mode"—a "decision" which is done by the organism itself, without any preceding cognitive/conscious appraisals.

While primary emotions are exclusively sub-cortical and directed towards the body, secondary emotions also include activation of numerous prefrontal cortices, which means that these emotions, in addition to the sub-cortical responses of primary emotions, also include cortical, but still unconscious responses activated by external stimuli. It is assumed that the cortical loop in prefrontal cortices which is involved in secondary emotions, may give access to schemes formed and accumulated by the learning history of the individual and that this loop enables the body to react without involving conscious processes. Further, it is this "loop of secondary emotions" that enables the organism to act automatically in behaviours that are over-learnt—as often experienced by drivers in driving tasks. Secondary emotions are then regarded as analogous and identical to what is labeled schemes in Reason's model of information processing [10].

The feelings, i.e. the conscious experience of body states impinged by external stimuli, establish an association between an external object, say a given situation in traffic, and an emotional body state. Hence, by emotions and feelings, the individual is able to evaluate, consider, and chose between alternatives in a situation that demands action. The consciousness needs a continuous update of the "here-and-now", of what the body does and what it experiences. Feelings are then the conscious experience of what the body does—by representations of emotional body states [17]. Or, as Damasio puts it,

> That process of continuous monitoring, that experience of what your body is doing while thoughts about specific contents roll by, is the essence of what I call a feeling (Damasio [2], pp. 145).

A governing principle in the RMM is the one of *target feeling*, i.e. that drivers seek the *bestfeeling* which can be established in any given situation, thus adopting the concept and idea proposed by Wilde [18], but rephrasing it from seeking a target *risk* to seeking a target *feeling*. It should, however, be noted that Taylor, by considering driving as a self-paced task governed by the level of emotional tension or anxiety which the driver wishes to tolerate [13] and Näätänen and Summala's "Zero-Model Model" [7, 8] also propose targets which drivers are seeking. Wilde also proposes a *riskcomparator* in his model, but, as the inherent process of Wilde's comparator only implies cognitive, i.e. conscious activities, it is abandoned in the RMM and replaced by risk monitoring, thus acknowledging Näätänen and Summala's proposal of a *subjective risk monitor*, as risk monitoring is supposed to incorporate both conscious and unconscious activities and thus being more global than Wilde's more limited risk comparator. Considering the dynamics of the RMM one should view driving as encountering ever-changing time-windows where the driver establishes or maintains the best feeling which is obtainable in any given situation. Hence, it is this feeling and the functional balance it represents, which acts as a reinforcing stimulus in a scheme of operant conditioning, for example in chosing driving speeds, irrespective of whether the choices are done consciously or unconsciously.

A main point is the concept of *primary emotions*: The organism is predisposed to look for dangers governed by reflex-like, innate, neurobiological properties that limit perception and information processing, and, as a consequence, also may limit learning of appropriate schemes in certain accident scenarios. It is hypothesized that, in these scenarios, the "looking for dangers" may make drivers less attentive of pedestrians and two-wheelers because these road users are not perceived as threats to survival in the way other vehicles do [17].

Effect of ITS: Predictions of the Risk Monitor Model

In general, a given ITS may represent a feeling of control, a limitation or an enhancement of the "window of opportunities", a source of distraction, or an element which interferes with the process of learning appropriate schemes that govern risk monitoring. More specifically, the following hypotheses of effects of ITS are proposed:

- *Hypothesis 1:* If a car with a given ITS X provides a better feeling of control compared to a car without system X, the assumed accident risk reduction feature of system X might be compensated by a change in driver behaviour, for example by increased driving speeds.

- *Hypothesis 2:* An accident increase is predicted with ITS which enhance the 'window of opportunities', as with ABS for certain accident types.
- *Hypothesis 3:* An accident decrease is predicted for ITS that reduce the 'window of opportunities', as with ESC, ISA, Alcolock,
- *Hypothesis 4:* An accident increase could be expected with IVIS which are dissociated from primary driving tasks, by increasing the frequency of distractions, as with the use of mobile phones and its inherent applications.
- *Hypothesis 5*—Reducing options of implicit learning of risk monitoring: A driver environment filled with too many warning systems may interfere with and deteriorate learning processes of the dangers in real traffic.
- *Hypothesis 6*—Acceptance/Reliance: System X must perform better than the driver. If it fails—it will be abandoned by the driver.
- *Hypothesis 7:* ITS addressing "evolutionary limitations" of risk monitoring may reduce accidents.

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To What Extent May Assistance Systems Correct and Prevent 'Erroneous' Behaviour of the Driver?

Toshiyuki Inagaki

Abstract An error in situational recognition may occur while driving a car, and the error can sometimes result in an 'erroneous' behaviour of the driver. Whether the driver assistance system can cope with such a circumstance depends on to what extent the authority is given to the system. This paper discusses the need of machine-initiated authority trading from the driver to the assistance system for assuring driver safety. A theoretical framework is also given to describe and analyze the driver's overtrust in and overreliance on such a driver assistance system.

Keywords Driver assistance systems · Human-centered automation · Authority and responsibility · Overtrust · Overreliance

Introduction

Main topics of the HMAT Workshop include "methods and tools to prevent erroneous behaviour to mitigate its consequences." Driving a car requires a continuous process of perception, cognition, action selection, and action implementation. An error in situational recognition may occur while driving a car, and the error can sometimes result in an 'erroneous' behaviour of the driver. In order to "prevent erroneous behaviours" of car drivers, it is most fundamental to provide the drivers with assistances for perception and cognition so that the drivers can grasp a situation clearly and correctly. Once the situation is properly understood, it is usually straightforward for the humans to determine what actions need to be done in the situation [5, 13]. Design of human–machine interfaces based on onboard self-sensing technology as well as vehicle-to-vehicle and vehicle-to-infrastructure

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communication technologies play important roles in implementing assistance functions to enhance, augment, and complement driver capabilities for perception and cognition.

What if an error in situational understanding has occurred in spite of such assistances for perception and cognition and if an 'erroneous' behaviour of the driver has been detected? A natural action for the driver assistance system would be to set off warnings to urge the driver to stop or correct the 'erroneous' behaviour. Warnings are expected to assist the driver's action selection.

Suppose the driver did not respond to the warnings. Does the assistance system perform nothing but observe consequence of the driver's 'erroneous' behaviour to occur? Or, may the assistance system take some control action to avoid such a consequence? Answers to the questions are not so simple. When the control action is not directed by the driver but is decided by the assistance system, an issue of authority and responsibility arises, because the driver is assumed to be always in charge and command: The Convention of Road Traffic [3], for instance, states that "Every driver of a vehicle shall in all circumstances have his vehicle under control so as to be able to exercise due and proper care and to be at all times in a position to perform all manoeuvres required of him" (Article 13.1).

This paper investigates the issue of authority and responsibility between the driver and the assistance system, and argues that the assistance system may be allowed to trade authority from the driver to the assistance system based on its decision for assuring safety. When the assistance system is capable to correct and prevent 'erronoues' behaviour of the driver, overtrust in and overreliance on the assistance system become an important issue: Regulatory authorities often express their concerns over the possibility of the drivers' behavioural changes in which they place excessive trust in and reliance on the driver assistance systems [8]. This paper gives a theoretical framework for discussing the driver's overtrust in and overreliance on autonomous assistance systems in a rigorous manner.

Authority and Responsibility

'Erroneous' behaviours may be classified into two types: (1) omission-like behaviour failing to select or implement an action needed in a given situation and (2) commission-like behaviour to select and implement an action inappropriate to a given situation. The former corresponds to case A and the latter to case B in Fig. 1, respectively, under the assumption of technology to sense and interpret traffic conditions and driver behaviours, as well as the three-class categorization of the driver's control action as (a) an action that needs to be done in the given situation, (b) an action that is allowable in the situation, and (c) an action that is inappropriate and thus must not be done in the situation.

Suppose the driver assistance system has determined that the driver's behaviour is 'erroneous.' The assistance system must determine which is more sensible and effective in the circumstance, a warning type support in which a warning is set off

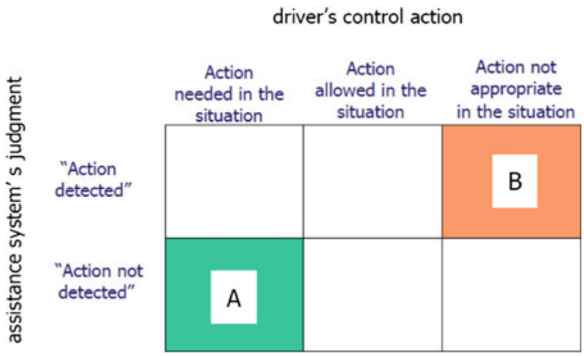

Fig. 1 Control action in a given situation

to urge the driver to react to the situation, or an action type support in which the assistance system executes an autonomous safety control action?

Consider first characteristics of the warning type support. If the 'erroneous' behaviour is of an omission-like type (case A), the warning directs the driver to implement at once a necessary but missing action. If the 'erroneous' behaviour is of a commission-like type (case B), the warning tries to tell the driver to stop doing the inappropriate action. In either case, the driver is maintained as the final authority over the assistance system; it is the driver who decides whether to accept and implement what was meant by the warning. The relation between the driver and the assistance system is fully compatible with the Convention on Road Traffic and the *human-centered automation* principles claiming that the human bears the ultimate responsibility for safety and therefore the human must be in command; see, e.g., [1, 2, 6]. In fact the assistance system's situation understanding can be incorrect because of its limitation. At the same time, the human-centeredness of the warning type support can fail to assure the driver safety: The driver may not be able to cope with the situation, because of a short time allowance or because of internal/external distractions. It can also happen that the driver disregards a given warning based on a 'reasonable' but wrong interpretation of the warning [12].

Consider next characteristics of the action type support. If the 'erroneous' behaviour is of an omission-like type (i.e., case A in Fig. 1), the assistance system executes an action that the driver failed to perform. If the 'erroneous' behaviour is of a commission-like type (i.e., case B in Fig. 1), the assistance system applies control to prohibit the driver to continue doing the inappropriate action. In either case, the authority is traded from the driver to the assistance system, and it is the assistance system that determines and implements the authority trading, which is sometimes called *machine-initiated automation invocation* [10]. Thus the relation between the driver and the assistance system is not fully compatible with either the Convention on Road Traffic or the *human-centered automation* principles. However, as long as the human has limitation, there is a space for the assistance system to execute a control action on behalf of the driver or to correct the driver's 'erroneous' action.

In the design of a mechanism for machine-initiated automation invocation, it is useful to distinguish *hard protection* and *soft protection*. In hard protection, the driver is not allowed to override the assistance system's control action. In soft protection, on the other hand, the driver is given authority to override the control action applied by the assistance system. It is sometimes observed that the drivers prefer soft protection to hard protection, although the soft protection may not be perfect in preventing the driver's 'erroneous' action [11, 12]. The assistance system with a mechanism for machine-initiated automation invocation gives the driver a slight chance to behave as the final authority over the automation, when the design of the assistance system is of soft protection type.

Advanced Safety Vehicle: A Japan's National Project

Advanced Safety Vehicle (ASV) is a car equipped with technology-based driver assistance systems to enhance safety under normal as well as time-critical situations. The ASV project has been conducted since 1991 under the cooperation of industries, academia, and the government. It is assumed there that the driver must be always in charge and that the driver assistance systems are allowed to provide the driver with 'assistance'. Some guidelines for designing driver assist systems are: (1) The system should act in line with intent of the driver. (2) The system should assist the driver to perform safe driving and steady operation. (3) The driver should monitor operations of the assist system when it is in action. (4) The system should not cause over-confidence or overtrust of the driver. (5) The system, when it is in action, should allow the driver's intervention to override its operation. (6) The system's control should be smoothly passed over to the driver when the situation goes beyond the range of the system [7, 16]. The design principles and guidelines for the driver assistance systems were discussed and established in the second 5-year phase of the project (1996–2000) through investigations of negative effects of automation, such as the out-of-the loop performance problem, loss of situational awareness, overtrust, distrust, and automation surprises; see, e.g., [4, 9, 18, 20, 21, 23].

The ASV project has developed various systems that provide the drivers with assistances for perception, cognition, and action selection. However, the Ministry of Land, Infrastructure and Transport (MLIT) as well as National Police Agency of the Government of Japan have been taking a cautious stance on putting systems into practical use when the assistance systems are for action implementation. It is true, of course, that there are such systems. The adaptive cruise control (ACC) and the lane keeping assistance (LKA) are examples of systems for assisting driver's action implementation by *relieving* the driver's load. The electronic stability control (ESC) and the antilock brake system (ABS) are also examples of systems for assisting driver's action implementation by *amplifying* or *extending* the capabilities of the driver.

The arguments become different when it comes to the assistance systems that have capabilities to *back up* or *replace* the driver. Take, as an example, the pre-crash safety (PCS) system that is sometimes called the advanced emergency braking system (AEBS). When the host vehicle is approaching relatively fast to a lead vehicle, the PCS firstly tightens the seat belt and adds a warning to urge the driver to put on the brake. If the PCS determined that the driver is late in braking, then it applies the brake automatically based on its decision. However, the PCS is currently implemented as a *collision damage mitigation system*, in stead of as a *collision avoidance system*. Behind the design decision to 'downgrade' the PCS, there has been concern among the regulatory authorities that "If a driver assistance system would perform every safety control action automatically, the driver may become overly reliant on the assistance system, without paying attention to the traffic situations himself or herself."

Although the above 'concern' seems to be reasonable, there have been some discussions in the ASV project that more precise investigations would be necessary so as not to lose opportunities for the drivers (especially, elder drivers) to be benefited by the assistance system that may back up or replace them when appropriate. The next two sections give a theoretical framework to describe and analyze overtrust in and overreliance on the driver assistance system. Although the two terms 'overtrust' and 'overreliance' are often used as if they are synonyms, this paper differentiates them rigorously.

Overtrust

Overtrust in a driver assistance system is an incorrect diagnostic decision to conclude that the assistance system is trustworthy, when it actually is not. This section gives two axes for discussing overtrust in the assistance system. The first axis is the *dimension of trust* and the second the *chance of observations*.

The first axis is to describe in which way the driver can overrate trust. Lee and Moray [14] distinguished four dimensions of trust: (a) foundation, representing the fundamental assumption of natural and social order, (b) performance, resting on the expectation of consistent, stable, and desirable performance or behavior, (c) process, depending on an understanding of the underlying qualities or characteristics that govern behavior, and (d) purpose, resting on the underlying motives or intents. Three types of overtrust can be distinguished depending on which dimension among (b) through (d) is overrated; the first dimension (a) is usually met in cases of the driver assistance systems.

Overrating of (b) can be seen in a case where a driver thought, "The assistance system has been responding perfectly to all the events that I have encountered so far. Whatever events may occur, the system will take care of them nicely." Improper evaluation of (c) is seen in a case where a driver has been using an assistance system without reading the user's manual at all by thinking, "It would be quite alright even if I do not know the details of the system functions." Overestimation of (d) may be seen in a case where a driver believes that "I do not understand why my assistance system is doing such a thing. However, it must be doing what it thinks it necessary and appropriate."

The second axis for investigating overtrust is to describe how often the driver can see the assistance system functions. The chance of observations affects the ease of constructing a mental model of the assistance system. The possibility of the driver's overtrust can differ depending on whether the assistance system is for use in normal driving or is for use in emergency.

Take the ACC as an example of the assistance system to reduce the driver workload in normal driving. Based on a large number of opportunities to observe the ACC's functioning repeatedly in daily use, it would be easy for the driver to construct a mental model of the ACC. If the driver has been satisfied with 'intelligent' behaviours of the ACC, it may be natural for him or her to place trust in the assistance system. However, the trust can sometimes be overtrust. Suppose the driver encounters a new traffic condition that is seemingly similar to a previous one but is slightly different. If the driver expected that the ACC would be able to cope with the situation without any intervention of the driver, it can be an overestimation of the ACC's functionality.

Take next the PCS as an example of the assistance system activated only in emergency to assure the driver safety. It would be rare for an ordinary driver to see the PCS works, and he or she may not be able to construct a complete mental model of the PCS because of lack of enough number of chances to experience the PCS. The driver might have been told (by a car dealer, for instance) that the PCS shall be activated automatically in emergency. However, the driver may not be fully convinced because of lack of chances to observe himself or herself that the PCS works properly and constantly when necessary.

Overreliance

Overreliance on a driver assistance system is an incorrect action selection decision determining to rely on the assistance system by placing overtrust in it. Regarding overreliance on automated warning systems, there are relevant studies in aviation domain; see, e.g., [15, 17, 19, 22]. Suppose that the automated warning system almost always alerts the human when an undesirable event occurs. Although it is possible for a given alert to be false, the human can be confident that there is no undesirable event as long as no alert is given (A similar situation can happen in automobile domain when the driver is provided with a communication-based alert from the road infrastructure to let the driver know of an approach or existence of cars on a crossing road behind some buildings). Meyer [15] used the term 'reliance' to express such a response of the human. If the human assumed that the automated warning system will always give alerts when an undesirable event occurs, that may be overtrust in the warning system and the resulting reliance on the warning system is overreliance. The definition of overreliance on the driver assistance system, given at the beginning of this section, is a generalization of that of overreliance on the warning system in the previous studies in the sense that the assistance system is not only for setting off warnings but also for executing control actions.

Two axes are given for overreliance in the assistance systems. The first axis is the *benefits expected* and the second the *time allowance for human intervention*.

The first axis is to describe whether the driver can produce some benefits by relying on the assistance system. Suppose the driver assigns the ACC all the tasks for longitudinal control of the vehicle. That may enable the driver to find time to relax muscles and extend legs after stressful maneuvering, or to allocate cognitive resources to finding a right way to the destination in a complicated traffic conditions. In this way, relying on the assistance system sometimes brings extra benefit to the driver, when the system is for use in normal driving.

The discussion can be quite different in case of PCS. The PCS is activated only in emergency, and the time duration for the PCS to fulfill its function is short, say several seconds. It is thus not feasible for the driver to allocate the time and resources, saved by relying on the PCS, to something else to produce extra benefit within the several seconds. A similar argument may apply to other assistance systems designed for emergency.

The second axis, time allowance for human intervention, is to describe whether the driver can intervene into the assistance system’s control when the driver determined that the system performance differs from what he or she expected. In case of ACC, it may not be hard for the driver to intervene to override the ACC when its performance was not satisfactory. However, in case of PCS, it might be unrealistic to assume that the driver can intervene into control by the PCS when he or she decided that the PCS’s performance was not satisfactory, because the whole process of monitoring and evaluation of PCS’s performance as well as decision and implementation of intervention must be done within a few seconds.

Concluding Remarks

It is often useful to provide the driver with multi-layered assistance functions [7]. In the first layer, driver’s perception and situation recognition are enhanced to lead to proper situation diagnostic decisions and associated action selection decisions. In the second layer, the assistance system monitors the driver’s behaviours as well as traffic conditions to evaluate whether his or her intent and behaviours match the traffic conditions. When the assistance system has detected a *deviation from normality*, it gives the driver an alert to make him or her return to normality. In the third layer, the assistance system provides the driver with automatic safety control functions, if the deviation from normality still continues to be observed or if little time is left for the driver to cope with the situation. In such a *situation-adaptive assistance system* (Fig. 2), a mechanism is needed to decide and implement authority trading in a machine-initiated manner, which poses an issue of authority and responsibility [7, 10].

The issue is further linked to that of the driver’s overtrust in and overreliance on the assistance system. Actually, there is a serious concern that the driver may place overreliance on an autonomous and smart driver assistance system. This paper has

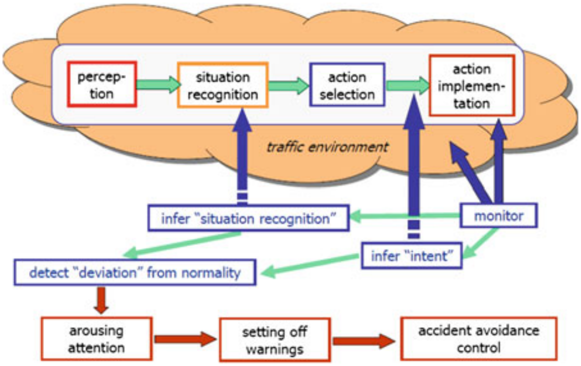

Fig. 2 Driver monitoring and situation-adaptive assistance

given a general framework for describing overtrust in and overreliance on the assistance system, and has argued that whether the driver puts overtrust in or overreliance on the assistance system can vary depending on the characteristics of the assistance system. Based on the framework, the following argument may be possible for PCS, as an example: "Since the PCS is activated only in cases of emergency, it would be very rare for an ordinary driver to see how the system works (i.e., chance-of-observation axis). It is thus hard for the driver to construct a precise mental model of the PCS, and may be hard for him or her to engender a sense of trust in the system (i.e., dimension-of-trust axis). However, it is known that people may place inappropriate trust (i.e., overtrust) without having any concrete evidence proving that the object is trustworthy. Now, let us assume that the driver places overtrust in the assistance system. We have to ask whether the driver may rely on the system excessively (i.e., overreliance). In case of PCS, even if the driver noticed that the system's behavior was not what was expected, no time may be left for the driver to intervene and correct it. In spite of that, does the driver rely on the PCS (i.e., overreliance) and allocate his or her resources to something else at the risk of his or her life? The answer would be negative."

A task force was set up in December 2009 in the ASV project to investigate sharing and trading of authority and responsibility between the driver and the assistance systems, as well as the driver's overtrust in and overreliance on the assistance systems. Multi-disciplinary analyses and discussions, including legal aspects, are planned in the task force. It is expected to draw guidelines for designing driver assistance systems of next generation.

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Man–machine Integration Design and Analysis System (MIDAS) v5: Augmentations, Motivations, and Directions for Aeronautics Applications

Brian F. Gore

Abstract As automation and advanced technologies are introduced into transport systems ranging from the Next Generation Air Transportation System termed NextGen, to the advanced surface vehicle Intelligent Transportations Systems, to future systems designed for space exploration, there is an increased need to validly *predict* how the future systems will be vulnerable to error given the demands imposed by assisted technologies. One formalized method to study the impact of assisted technologies on the human operator in a safe and non-obtrusive manner is through the use of human performance models (HPMs). HPMs play an integral role when complex human–system designs are proposed, developed, and tested. One HPM tool termed the Man–machine Integration Design and Analysis System (MIDAS) is a NASA Ames Research Center HPM software tool that has been applied to predict human–system performance in various domains since 1986. MIDAS is a dynamic, integrated HPM environment that facilitates the design, visualization, and computational evaluation of complex man–machine system concepts in simulated operational environments. A range of aviation specific applications including an approach used to model human error for NASA's Aviation Safety Program, and "what-if" analyses to evaluate flight deck technologies for NextGen operations will be discussed. This chapter will culminate by raising two challenges for the field of predictive HPMs for complex human–system designs that evaluate assisted technologies: that of (1) model transparency and (2) model validation.

Keywords Human error · Human performance modeling · MIDAS v5 · NASA

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Introduction

Human Performance Models (HPMs) have traditionally been used to predict sensory processes, aspects of human cognition, and human motor responses to system tasks. HPM tools are currently undergoing a developmental shift, now being more sensitive to situations that confront a virtual human in systems similar to human-in-the-loop (HITL) situations. HPMs and the human performance modeling process have attempted to integrate operator characteristics (cognitive, attentional, and physical) with environmental characteristics to more accurately represent human–system operations with new, augmented technologies. The growth in HPMs has been to examine human performance in systems including system monitoring (thereby taking information in from the environment) as opposed to the closed-loop view of the human as a mathematical relationship between input and output to a system. These hybrid models that combine closed-loop performance (continuous control), open-loop performance (discrete control) and critical decision-making have been undertaken to represent the "internal models and cognitive function" of the human operator in complex control systems. These hybrid systems involve a critical coupling among humans and machines in a shifting and context sensitive function.

Using Human Performance Models for Technology Development

Modeling can play a role in all phases of new technology development from concept development, through the refinement, and deployment process. HPMs provide a flexible and economical way to manipulate aspects of the operator, automation, and task environment to represent the manner that a human engages with the technology under development. HPMs have arisen as viable research options due to decreases in computer costs, increases in representative results, and increases in model validity. They are especially valuable because the computational predictions can be generated early in the design phase of a product, system or technology to formulate procedures, training requirements, and to identify system vulnerabilities and where potential human–system errors are likely to arise. The model development process allows the designer to formally examine many aspects of human–system performance with new technologies to explore potential risks brought to system performance by the human operator. Often this can be accomplished before the notional technology exists for HITL testing. More comprehensive conclusions can be drawn about technologies being introduced into complex operational environments when used in a cooperative and iterative fashion with HITL simulations. Furthermore, using HPMs in this manner is advantageous because risks to the human operator and costs associated with system experimentation are greatly reduced: no experimenters, no subjects and no testing time. HPMs can be used to conduct system robustness testing to evaluate the system from the standpoint of potential deviations from nominal procedures to determine the performance impact on the human and the system ("what-if" testing).

The Man–machine Integration Design and Analysis System

The Man–machine Integration Design and Analysis System (MIDAS) is a dynamic, integrated human performance modeling environment that facilitates the design, visualization, and computational evaluation of complex man–machine system concepts in simulated operational environments [1]. MIDAS symbolically represents many mechanisms that underlie and cause human behavior. MIDAS combines graphical equipment prototyping, dynamic simulation, and HPMs to reduce design cycle time, support quantitative predictions of human–system effectiveness, and improve the design of crew stations and their associated operating procedures.

History

MIDAS has undergone two paths in its development. The first path termed Air MIDAS focused on specific behaviors in complex human–system interaction and has been applied specifically to aviation operations. This development path was entirely code-based with no visualization capability. The second path, termed the NASA MIDAS and currently MIDAS v.5, focused on cross-domain capability, cognitive behavior model augmentations and has been validly applied to a variety of domains, which include rotorcraft, nuclear power plant, space, and commercial aviation operations [2, 3]. The MIDAS v5 path contains a comprehensive visualization capability associated with the physical and cognitive operations in their respective contexts. MIDAS v5 links a virtual human, comprised of a physical anthropometric character, to a computational cognitive structure that represents human capabilities and limitations. MIDAS can suggest the nature of pilot errors, and highlight precursor conditions to error such as high levels of memory demand, mounting time pressure and workload, attentional tunneling or distraction, and deteriorating situation awareness (SA). MIDAS provides a flexible and economical way to manipulate aspects of the operator, automation, and task environment for analysis.

MIDAS v5 Architecture

Figure 1 illustrates the model's organization and flow of information among the model's components. MIDAS inputs (Fig. 1, left column) include the operational environment (e.g., flight profiles, scenario objects and events, etc.), the operator

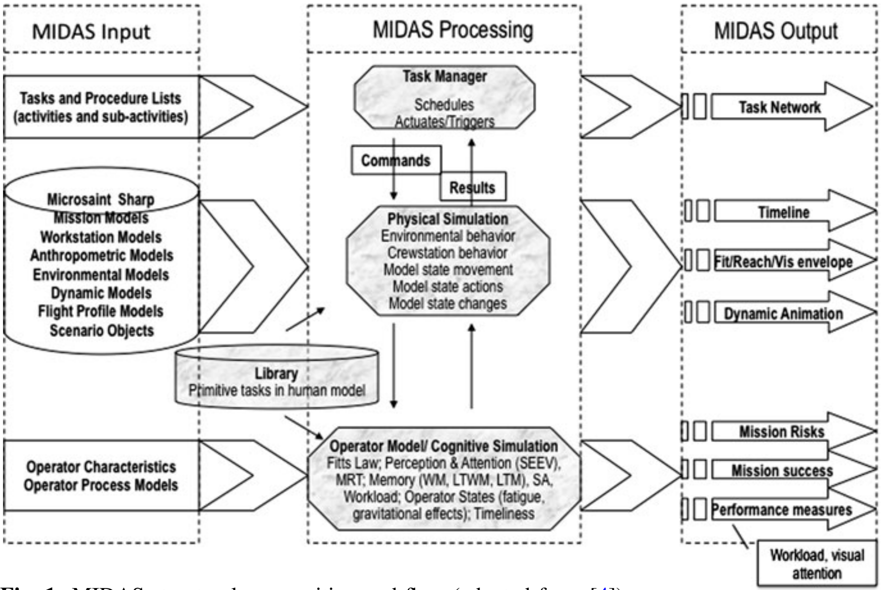

Fig. 1 MIDAS structural composition and flow (adapted from [4])

tasks and operator process models (e.g., algorithms that represent operator characteristics such as expertise). The MIDAS processing model (Fig. 1, middle column) is comprised of a task manager model that schedules tasks to be completed, definitions of the state of models within the physical simulation, a library of "basic" human primitive models that represent behaviors required for all activities such as reach, and cognitive models such as operator perception. The cognitive component is comprised of a perceptual mechanism (visual and auditory), memory (short-term, long-term working, and long-term), a decision maker and a response selection architectural component. The MIDAS output model (Fig. 1, right column) generates a runtime display of the task network, the anthropometry as well as mission performance.

MIDAS Input

Tasks are triggered by information that flows from the environment, through a perception model, to a task network representation of the procedures that then feeds back to the environment. Tasks are characterized by several defining parameters that include conditions under which the task can be performed (e.g., beginning, ending, and wait-for clauses), their priority relative to other tasks, their duration, their interruption specifications, and their required resource to perform the task defined according to the Modified TAWL [5, 6].

MIDAS Processing

MIDAS Perception

MIDAS represents *perception* as a series of stages that information must pass through in order to be processed. The perception model includes visual and auditory information. Visual perception in MIDAS depends on the amount of time the observer dwells on an object and the perceptibility of the observed object. The perception model computes the perceptibility of each object that falls into the operator's field of view based on properties of the observed object, the visual angle of the object and environmental factors. In the current implementation of MIDAS, perception is a three-stage, time-based perception model (undetected, detected, comprehended) for objects inside the workstation (e.g., an aircraft cockpit) and a four-stage, time-based perception model (undetected, detected, recognized, identified) for objects outside the workstation (e.g., taxiway signs on an airport surface). The model computes the upper level of detection (i.e., undetectable, detectable, recognizable, identifiable for external objects) that can be achieved by the average unaided eye if the observer dwells on it for a requisite amount of time. For example, in a low-visibility environment, the presence of an aircraft on the airport surface may be 'detectable' but the aircraft company logo on the tail might not be 'recognizable' or 'identifiable' even if he/she dwells on it for a long time.

MIDAS Memory

Tasks from the MIDAS input process also require knowledge held either in the operator's memory (working, long-term working, and long-term) or available from the environment to be consulted and used to determine subsequent tasks to be completed [2]. Memory is represented as a three stage, time decay model.[1] The stages are working memory (WM), long-term working memory (LT-WM), and long-term memory (LTM). The decay rates cause memory to be above or below a "retrievability" threshold based on the time since the information was last accessed. The retrievability thresholds incorporated into MIDAS are 5 s for WM and 5 min for LT-WM. The WM decay rate is faster than the LT-WM decay rate. Information that falls below the retrievability threshold is forgotten. This causes the perception level to be set to *Undetected* for external visual and auditory information or *Unread* for internal visual information. Newly perceived and recently refreshed attributes will be retained in LT-WM only if a node with newly updated or referenced attributes leaves WM before its attributes have decayed

[1] In contrast to MIDAS v5, memory in Air MIDAS is represented as a two-stage model [7].

below the retrievability threshold. An operator may retain newly perceived information after it leaves WM, at least for a while, until it decays below the LT-WM retrievability threshold. If the information necessary for activity performance is available, and its priority is sufficient to warrant performance, then the schedule within the model operates according to heuristics that can be selected by the analyst. In most cases the heuristic is to perform activities concurrently when that is possible, based on knowledge and resource constraints.

MIDAS Visual Attention

MIDAS' attention-guiding model operates according to the SEEV model [2]. SEEV is an extensively validated model [8] that estimates the probability of attending, P(A), to an area of interest in visual space, as a linear weighted combination of the four components—salience, effort, expectancy, and value. Attention in dynamic environments is driven by the bottom-up capture of *Salient* (*S*) events (e.g., a flashing warning on the instrument panel) and inhibited by the *Effort* (*E*) required to move attention (e.g., a pilot will be less likely to scan an instrument located at an overhead panel, head down, or to the side where head rotation is required, than to an instrument located directly ahead on a head-up display (HUD)) [9]. SEEV also predicts that attention is driven by the *Expectancy* (*EX*) of seeing a *Valuable* (*V*) event at certain locations in the environment. The four SEEV parameters drive the visual attention around an environment such as the dynamic cockpit in a computational version of this model. For example, the simulated eyes following the model will fixate more frequently on areas with a high bandwidth (and hence a high expectancy for change), as well as areas that support high-value tasks, like maintaining stable flight [10].

The integration of the SEEV model into MIDAS v5 allows dynamic scanning behaviors by calculating the probability that the operator's eye will move to a particular AOI given the tasks the operator is engaged in within the multitask context. It also better addresses allocation of attention in dynamic environments such as flight and driving tasks.

MIDAS Output

The MIDAS outputs include the task network, anthropometric, and Computer Aided Design (CAD) model visualizations (using the jack[2] software), timelines of workload and SA, and risk vulnerabilities as inferred from timeline violation of

[2] ™ Siemens PLM Solutions.

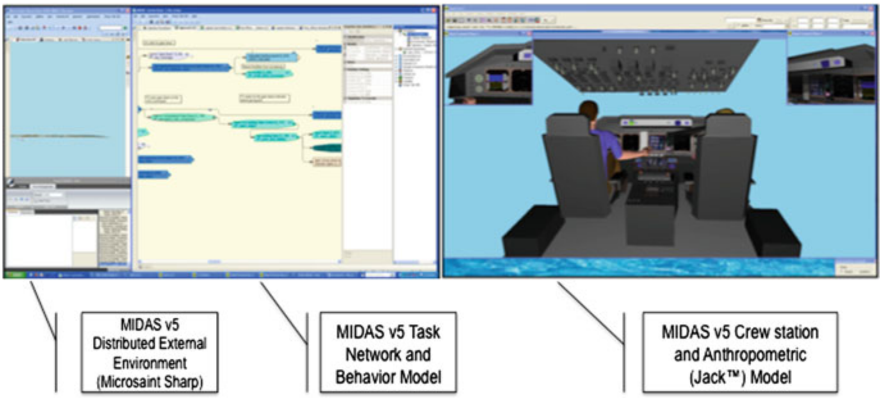

Fig. 2 MIDAS' environment, task, and anthropometric models

optimal response times, workload spikes, or SA violations. MIDAS can suggest the nature of operator errors, and highlight precursor conditions to error such as high levels of memory demand, mounting time pressure and workload, attentional tunneling or distraction, and deteriorating SA. Figure 2 illustrates the integration of the different models in a recent aeronautics model completed with MIDAS v5.

HPM of Next Generation Air Transportation Systems

The current air traffic control (ATC) system in the United States will not be able to manage the predicted two to three times growth in air traffic [11]. The Next Generation Air Transportation System (NextGen) is a future aviation concept that has as its goals to increase the capacity, safety, efficiency, and security of air transportation operations. Two MIDAS HPMs will be highlighted. The first illustrates a human error model of an aviation surface-related application that uses some candidate NextGen concepts as generated by Air MIDAS, and the second illustrates a recent application of NASA's MIDAS in the context of NextGen approach and land operations.

Human Error Modeling

New conceptual designs especially those being developed for complex systems are likely to incorporate technologies that utilize or rely on a human's cognitive capabilities. New conceptual designs often incorporate automation to assist the human operator in their task performance. Automation increases precision and economy of operations but can have the unanticipated effect of increasing a human operator's cognitive, perceptual and attentional workload [12]. The increase in workload often negates some of the benefits afforded to the system from the use of automation. Operators may miss critical events in the environment due to a number of unexpected human-automated systems issues such as unevenly distributed workload, new attentional demands, and new coordination demands among operators. When critical physical events are missed, no response is possible and human errors occur. Model development of the human–system issues underlying human performance and human error is critical for conceptual systems being considered.

Modeling Human Error

An Air MIDAS flight deck model of ramp navigation and gate-approach at the Chicago O'Hare Airport (ORD) was developed to predict human error when technological introductions that took the form of augmented flight deck concept displays [13] were made to current day operations [14]. The control modes in Air MIDAS that had the potential of being sensitive to manipulations include memory errors and their effect on the simulated crew's internal representation. The first error type, declarative memory errors, included errors that occurred when virtual operators forgot the active procedure as a result of having too many procedures of the same type operating at the same time, which invoked the procedure scheduler (dropped tasks = memory loss). The second error type, memory load errors, included errors that occurred as a result of information competing for the capacity-limited WM space. Information was lost if it was not written down to a location from an actively available list from which the operator was able to visually encode the information (for example, a taxi clearance).

Environment triggers (e.g., turns, signs, ATC calls) elicited the human performance. Error rates as measured by missed turns, operator performance times, and workload were output from the HPM. This effort predicted that the model loading factors had an impact on the performance of the forgetting mechanism within Air MIDAS. The computational mechanisms within Air MIDAS replicated the operations of humans when humans forgot a piece of information. When there were a number of items occupying WM, one item in WM was shifted out of the limited capacity store by the subsequent information from the pilot or from the ATC communication. Each type of error emerged based on the environmental requirements and on the loads that were associated with the operator's performance. A prediction for increased auditory and cognitive demands as time in the scenario increased (as the virtual operator approached the second turn) was also found. The Air MIDAS model provided useful information about the risk factors that increase the probability of error and was useful for providing insight into mitigation strategies when errors occur.

"What-If" NextGen Approach and Landing Application

MIDAS v5 has been applied to examine a NextGen approach to land concept termed the very closely spaced parallel approach/operations (VCSPA/O). Based on Raytheon's Terminal Area Capacity Enhancement (TACEC) parallel approach procedures, VCSPA/O requires that runway spacing be reduced [15]. This reduction in distance between the runways increases the likelihood of wake vortex incursion during independent simultaneous operations. VCSPA/O requires that a safe and proper breakout maneuver be calculated and presented via new displays to the cockpit crew [15]. In order to evaluate the VCSPA/O concept, two MIDAS v5 models were generated. The first was a Simultaneous Offset Instrument Approach (SOIA) model that contained the current-day procedures, and the second was a NextGen VCSPA/O model that contained advance displays of traffic and wake information in the cockpit and a modification to the roles and responsibilities of the flight crew and ATC modeled operators. The advanced technology in the "NextGen" VCSPA/O condition enabled closer separation in low visibility, lower landing minima, autoland capability, and enhanced wake and traffic data. The MIDAS model involved over 500 tasks and culminated in a verifiable model of approach and land operations (vetted during the model building process by Subject Matter Experts; SMEs). Performance profiles along the variables of operator workload, visual attention, and cockpit alert detection times for both the captain and first officer during the descent, approach, and land phases of flight were collected. Both conditions were run in Instrument Meteorological Conditions (IMC) with no out the window (OTW) visibility 100 times. The SOIA flight crew broke out of the clouds at 2100' and maintained separation from traffic and monitored runway alignment OTW. The VCSPA modeled flight crew monitored traffic separation and wake information on the ND throughout the approach and broke out of the clouds at 100'. This model effort illustrated the "what-if" capability within MIDAS. The "what-if" approach was completed when MIDAS was exercised with one set of displays and procedure sets designed to represent current day operations and roles followed by a second model with an alternate set of displays and procedures encoded to represent the NextGen operations and roles.

Important insights regarding the impact of NextGen VCSPA/O operations on pilot workload, visual attention, and alert detection times were revealed through this research. The MIDAS model predicted increased workload during descent and initial approach due to increased information available (traffic, weather, wake) on the flight deck but reduced workload during final approach and land due to automated landing procedures and ease of information retrieval (traffic and runway alignment) in the NextGen condition. Technologies that shift the workload demands away from the visual modality using auditory and haptic displays should be pursued as NextGen operations may tax the visual and cognitive-spatial channels to a greater extent than current day operations during specific phases of flight. Furthermore, the NextGen condition suggested a *more balanced workload* across the descent, approach, and land phases of flight than current day operations.

In terms of visual attention, NextGen condition may draw visual attention to the ND, which suggest that the pilots will more likely be heads-down during the critical minutes before touchdown (TD). Increased head-down time within the cockpit due to the presence of additional, more salient, information, may draw pilots' attention into the cockpit at inopportune times leaving pilots vulnerable to external hazards (other aircraft or obstacles on the runway, terrain). It is important to remember that other instantiations of the VCSPA/O concept (with different operational requirements) may reveal different human–system vulnerabilities.

This MIDAS v5 effort led to a greater awareness of potential parameters such as the change in roles and responsibilities in the NextGen that should be included in system designs and enabled the research program to visualize the interactions that are likely in future NextGen operations. It is anticipated that additional validation approaches will be developed and applied to the VCSPA/O model and that additional "what-if" scenarios including alternative pilot roles and responsibilities, and information requirements will be implemented.

Conclusion

Automation often changes the nature of the human's role in the system. Therefore, as automation and technologies are developed, it becomes increasingly important to predict how the human operator perceives and responds to the automation. MIDAS has proven useful to identify general human–system vulnerabilities and cross-domain error classes and to recommend mitigation strategies and system re-designs to account for the vulnerable areas, or risks, in system design [4]. Fundamental design issues can therefore be identified early in the design lifecycle, often before hardware simulators and HITL experiments can be conducted. HPMs are most useful when used cooperatively with HITL simulations to supplement the HITL research. HPMs like MIDAS provide an easy to use and cost effective means to conduct experiments that explore "what-if" questions about concepts of operation in specific domains of interest.

A number of significant challenges exist for the state of the art in HPMs, two of which will now be highlighted.

Transparency

Model transparency refers to the ability to comprehend the performance of the models, the relationships that exist among the models being used, which models are triggering in the model architecture, and whether the model is behaving as the model developer would expect. Transparency in integrated HPMs is needed to support model verification, validation, and credibility. However, model transparency can be difficult to attain because of the complex interactions that can exist among the cognitive, physical, environment and crew station models, and because the cognitive models embedded within integrated HPMs produce behaviors that are not directly observable. Three types of transparency that the MIDAS researchers have found useful to understand, interpret, and increase the confidence in the complex models' output include transparency of the input, transparency of the integrated architecture, and transparency of the output [16].

Validation

Validation remains a very large challenge for the HPMs community because statistical validation is oftentimes seen as the Holy Grail for determining whether a model is suitable but when models are deemed statistically valid, they generalize less, and are less re-usable for applications in new contexts. This places the field of modeling into the conundrum of making models that are statistically valid (i.e. a high correlation between predicted and actual data) but that lack the ability to generalize to other tasks or scenarios. When the generalizability of the model is limited, then its value as a cost-effective approach to predict complex human–system interactions is reduced.

Validation is further challenged when modeling future technology concepts where no or little HITL data exists upon which to statistically validate a model (as in the NextGen aviation systems or concepts being designed for the Space program). It is argued that the definition of model validation must be expanded beyond that of statistical results validation to be more representative of a 'model develop—model verify—model manipulate—model validate' iterative process, a process that is currently underway in MIDAS' FAA modeling of NextGen operations. The *model develop* phase of an HPM effort is one that is comprised primarily of model verification, where the inputs parameters such as the SEEV weights and workload primitives, are built from and operate as expected given the model's context. *Model verification* is the process of determining whether a model and its associated data behave as intended by the model developer/analyst. The model manipulate phase is where the model's conceptual parameters are manipulated to bring the overall model performance closer to expectations. The *model validation* phase determines the degree to which a model and its associated predictions are an accurate representation of the real world, from the perspective of the intended users of the model. Formalized 'develop-validate' iteration cycles are an important step toward increasing the credibility of HPMs particularly as the complexity of human–system operations increases.

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Operational Modeling and Data Integration for Management and Design

Nick McDonald, Rabea Morrison, Maria Chiara Leva, Brian Atkinson, Fabio Mattei and Joan Cahill

Abstract
Background Increasing focus on managing the performance of systems is driven by the relentless need to improve efficiency and save cost, by new safety management regulation and by growing interest from manufacturers in design for operability. Both the design of operational systems and the management of those systems depend on having a model of how such systems work. Such a model should be supported by operational data.
Methods A new framework for modeling operational systems in aviation links operational models to smarter data integration in a framework of reports that support better management of risk in the operation, organizational change and improvement, and better design capabilities.
Conclusions A common framework of modeling and analysis can address the convergent needs of research, system design, management and regulation to have an integrated, rich, evidence-driven understanding of complex operational systems.

Keywords Operational performance · Aviation · Data integration · Process analysis · Risk · Design

The Demand

Commercial Competition

Commercial competition, driven partly by the 'low-cost' business model, is driving aviation organizations to change the way in which they do business, cutting costs and developing a leaner enterprise. The low-cost carriers, relatively

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new entrants to the business, grew their companies around this business model. The low cost model cuts margins to the minimum, therefore these operators need to understand and monitor risk in the operation very stringently. Older organizations cannot build their organization from scratch. Therefore they have to change an established system with its strong cultural and institutional supports, without compromising core operational goals.

New Regulation

New safety management regulations originating in ICAO (International Civil Aviation Organisation) require organisations to be proactive and strategic, anticipating risks and ensuring that safety evidence becomes an effective driver of change. Formal compliance is no longer an option: it generates cost that does not deliver value and provides no assurance that risk is being actively managed. However, the complex basis of system safety in an 'ultra-safe' system like aviation cannot be done with one organisation's data. It requires the integration of more and more data across the sector. The problem, though, is not just the aggregation of data, but how to analyse it and use it productively.

Design

The old way of aeronautics R&D, in which manufacturers invest in new technologies for future products, is gradually being replaced by a new approach in which manufacturers engage with customers (system operators) to design integrated system capabilities which deliver technology-enabled cost-effective services. This is design for operability. Operability is delivered by the operational sector (airlines, maintenance companies, air navigation service providers, airports). Realising the benefits of new technologies requires, in turn, innovation in new operational concepts and new management systems in an integrated system design capability.

Convergence

Overall, therefore, there is increasing convergence between the fundamental capabilities involved in the design, operation, maintenance and regulation of large integrated operational systems. Consider the following. Design for operability allows manufacturers to deliver services to meet customer business needs; designers therefore have to understand the business processes of their customers. Smart integrated operational systems (like the SESAR and NextGen future air traffic management systems) cross organisational boundaries using new information technologies; both designers and operators need to understand multi-organisational operational systems. Information-rich capabilities transform maintenance processes and reduce the maintenance burden on operations; this enables smarter integration between maintenance and operations, even when done by separate companies. Integration of diverse operational information enables new performance management, risk management and organisational change capabilities; this explosion of information also enables new management capabilities between organisations and across the industrial lifecycle (design to operations). Regulation draws on organisational capabilities to manage and reduce risk, providing a smarter, more cost effective and more global service; there are thus new opportunities to ensure that integrated operational systems are developed and operated to meet society's goals.

These trends demand a new level of understanding of the internal logic of operational systems that can offer credible ways to transform and improve the system. Core capabilities that need to be supported by that new understanding include: integrated, evidence-based risk assessment that encompasses safety, quality, operational and commercial risks; effective support both for organizational change and system redesign; and transparent, smart regulation of operational reality accountable to operational requirements, business needs and regulatory authorities.

The Gap

Organisational Integration

Despite these trends, organisations find it difficult to integrate their different functional units in a common programme of change. Organisational boundaries define 'silos'; the transverse processes that are necessary to manage performance, assess risk and manage improvement have to find effective ways to cross the 'grey areas' between these silos. Symptoms of this organisational deficit include the following: there is no consensus about what it means to be 'proactive' in the management of safety; there is no integrated framework for managing in an integrated way all the human related functions in an operational system; influential change programmes (like lean enterprise and six sigma) lack systemic methodologies for managing human and social functions; no coherent management framework links change to achieve diverse goals across the areas of safety, lean, security, environmental impact. The boundaries between organisations are obviously stronger than internal boundaries. Integration of these management process across the system-of-systems of aviation (flight operations, maintenance, air traffic management, airport gound operations) is therefore more difficult. Furthermore, although there are well established processes for managing technical problems, the cultural gulf between design and manufacturing organisations, on the one hand and operational organisations on the other is large. Thus design for operability of new complex systems remains highly problematic.

The problem is compounded by the fact that the methods, tools and databases that are used to help manage these processes in the various organisations have separate non-integrated functions. Thus there is often no shortage of data but it lacks integration. Consequently, judgment and decision-making are not supported by good evidence, and furthermore, attempts to proactively manage the work process tend to be ad hoc, informal and not planned strategically. Evidence-based evaluation of system improvement and change is rare. System designers lack relevant operational data to support design requirements and to evaluate prototypes. Thus, aspirations to be proactive & systemic are not generally matched by the capability to do so.

The Challenge

These problems of management and design can be seen as knowledge management problems: having the right knowledge, and being able to manage it by sharing or exchanging it, transforming it, and applying it in action. Defining the problem in this way enables the development of knowledge-based solutions—integrated software systems, training and organisational development programmes. The capability that needs to be fostered includes both to be able to understand the system as well as to be able to change it. Three types of knowledge give the power to influence system performance.

Knowing how the system works comes from modeling operational activity and analysing the mechanisms of its operation. We have targetted our modelling activity at the level of the operational process. Drawing initially from business process mapping, a new approach has been developed that maps the process activity itself, the resources in, the mode of control of the process and other sources of influence on it. These models seek to give and account of how and how well the process achieves its outcomes.

Knowing what the system is doing comes from monitoring and analysing various kinds of operational data: for example, resource inputs, process outcomes, operational reports, audits and investigations. There is a large range and vast volume of data. Choosing the right data and making sense of it cannot effectively be done without having a working model of the operation to organise the assembly and analysis of the data in a productive way. This is why the model has to address the operational system, its inputs, activity and outputs, and not variables at other levels of analysis, like cognitive states, which are not easily measurable in an operational situation and do not give leverage over system change.

Knowing how to change the system comes from a management process which guides management action from analysis into recommendations (or requirements), into implementation of change or redesign and evaluation of that change. Knowing what is wrong is not the same as knowing what needs to be done to put it right;

Fig. 1 Process activity window

knowing what needs to be done is not the same as knowing how to do it; and knowing how to do it is not the same as being able to implement the change. Each stage in the 'quality cycle' of improvement and change is more difficult than the last. This is why there is so little literature on implemented and evaluated change. A considerable effort within the HILAS project[1] went towards the definition of a set of organisational processes for managing performance, risk and change at operational, tactical and strategic levels. Rethinking organisational processes as knowledge transformation and management processes made it possible to redefine the HILAS processes as a series of reports which manage operational data, data that is analysed and transformed with the help of the modelling framework.

Putting these three types of knowledge together makes up the following crude but powerful knowledge management 'equation':

- How it works + what it is doing + how to change = power to influence future system performance

Modeling How the Operational System Works

A high level overview of components of a model of the operational process is illustrated above in Fig. 1. This process activity window provides a way of understanding the logic and dynamics of the process. The conceptual framework is summarized as follows.

At the centre of the diagram, 'What Happens' defines & maps the functional logic of the process and its tasks (why they happen in the order and sequence that they do),

[1] HILAS—Human Integration in the Lifecycle of Aviation Systems. Contract 516181 under EU 6th Framework program.

Table 1 Process mechanisms and systemic constraint

Process activity perspective	Function of perspective	Systemic constraint
Process activity sequence	Functional logic of transformation of inputs to outputs	Resonance defines opportunities to damp or amplify variance
Hierarchical process system	Relationships between business processes, operational processes & tasks	Emergence defines extraneous influences at different process levels
Process states and dependencies	Defines resources & preconditions for movement through process. Basic parameters for risk analysis	System constraints balancing resources to demands and sequential dependencies
Team system	Network and co-ordination of local and global team	Social cohesion—team integration, competence and trust
Information system	Links people, technology and process	Information integration across process space defines opportunity for process transformation

together with its links and dependencies on resource inputs & other processes. This represents the process as it normally happens, typically capturing a lot of tacit knowledge not normally represented in procedures or official process maps. Processes can be represented in a hierarchy from business process to individual task or activity.

The resources necessary to enable the process to function are delivered through the ‘links to the wider process system’, which is mapped in the previous module. Resources include people (both the immediate process and task teams as well as the ‘global team’ involved in all support functions); information; and tools, technologies and material resources. Resources define one form of dependency that limits the movement from one process state to another.

‘What controls the process’ describes how the process is controlled and managed, where that functional control is through people rather than technology. Control over the process can be through the management of the competence and knowledge of process agents, through the specification of standard procedures, or through mutual adjustment (interpersonal interaction) or leadership or supervision.

Those factors that influence process functioning, but are not defined in the rest of the process functional model, can include a wide range of personal, organizational and environmental phenomena. Typically (though not always) these are beyond the direct control of process management.

The outcomes of the process activity can be immediate functional results and further consequences. Influencing these through manipulating other parts of the model defines the goals or objectives of change.

The analysis of each of these elements proceeds with progressive depth and moves through stages of description, evaluation and requirements (or recommendations). The analysis and representation of the process system in terms of these mechanisms and outcomes also permits analysis of a set of high-level systemic constraints on process functioning. A number of these have been explored and are briefly summarized in Table 1.

What Is the System Doing—Data

If a model of the operation tells us how the system works, then data from the operation tells what the system is doing.

Linking outcomes to antecedents in conditional probabilities is fundamental to analysing risk. The antecedent is often the hidden term in risk assessment. Risk is commonly defined as the probability times the severity of the consequence, but the consequence of what? In flight operations, for example, it can be argued that the risk is largely built into the operation before the aircraft departs. This implies the necessity to link data recording those pre-flight inputs to data recording process outputs. It is therefore essential to link data from different stages and parts of the process together. Despite the existence of extensive silos of data from different parts of the process, this has proved unexpectedly difficult to do, for a range of largely organizational reasons. However, a system model is a key resource to make sense of how to pull together meaningful data sets from disparate data sources. Once one moves from a simple conditional probability matrix to a more complex network of probabilities, a model becomes essential.

There is (fortunately) an inverse relationship between probability and severity—more severe outcomes are less frequent than minor variations in outcome. Therefore it is essential to try to get a composite picture that exploits the strengths and weaknesses of knowledge about different types of outcome. The distribution of minor variations may indicate vulnerabilities of the system to major breakdown. The investigation of major breakdown will rely on analyzing the normal mechanisms of the operation, trying to establish what causal influences came from normal system variation, what came from exceptional events. Again it is the function of a model to guide the analysis of major and minor variations in the system, ensuring that the inferences about the underlying mechanisms of system functioning are justifiable.

System Change as a Management Process

Process Knowledge

Knowledge about the reality of operational processes is captured in process models that map the activity, represent dependencies that link to performance indicators, and identify hazards and safeguards. This knowledge gives leverage over process change and the redesign of functional, social and information structures.

Operational Status

Ongoing information about the process is represented in operational data, integrated from a variety of organizational data sources, and displayed as trends against preset boundaries. Operational reports and audit reports provide information on problems, issues and events in the operation.

Assessing Risk

Each report or data anomaly receives an initial risk assessment to prioritise its status in the following processes. One or more reports or data sets may then be combined to form 'projects' which represent a common problem space. Three complementary types of risk analysis can then follow

- Investigation & other qualitative analyses
- Analysing probabilities of 'cause and effect' in multiple reports
- Analysing probabilities of 'cause and effect' in operational data

All analysed risks are then represented in an integrated risk register which prioritises the areas in which the organization has to take action to improve its systems and processes.

Managing Change and Redesign

Recommendations are derived using the process knowledge resource in the mapping tool to map the future process, conduct a future risk assessment and set evaluation metrics. Recommended actions are defined in terms of their scope—local or systemic, technical or organizational.

The decision to implement change or redesign actions provides a new opportunity to form an implementation project from overlapping requirements (and this can generate fresh risk assessments). The trajectory of implementation will depend on the scope of the action, which is tracked through various stages.

Evaluation

Evaluation reconciles the projected benefits (and costs) derived from the recommendation phase with the actual benefits (risk reduction) and costs achieved in the implementation phase, taking into account the quality of the implementation.

This evaluation can be complemented by the deployment of a set of diagnostic tools designed to measure and assess the organisation's culture (readiness for change, safety), leadership capabilities and gap analysis to meet regulatory standards. This enables the design and evaluation of a planned programme of organizational change, starting with an initial diagnosis and following up with periodic assessments of the transformation of organizational systems, capabilities and culture.

Business Needs

Business performance outcomes are linked down to operational performance indicators in an organised framework for managing operational data.

Applying the same data-driven logic to the HILAS process itself provides a powerful framework to risk-manage the change management process itself. This provides an assessment of the resilient adaptability and capacity to change of the operation and its support functions. This is the essence of effective self-regulation and can be used to provide accountability to external stakeholders.

Conclusions

The HILAS system represents a new attempt to resolve the contradictions between theory and practice. The capability to assemble real operational data in a meaningful way provides the key both to new ways of doing grounded, systemic longitudinal research in socio-technical systems, as well as giving to designers and management much greater leverage over the systems they are designing and managing. It brings to the foreground the ability to manage that change.

It requires a 'joined-up' organization to realize the capabilities that can deliver a step change in operational functioning. More so, it opens up new ways of managing the system-of-systems (as in aviation), through the joint management of shared risks, as well as providing a focus for collaboration, benchmarking and learning.

If these capabilities can be realized then new possibilities are opened up across the Industry Lifecycle. Design for operations, particularly for complex transformative systems like SESAR and NextGen can be radically enhanced by having a strong empirically-based operational model to design into. It opens up new possibilities for regulation that is smart and transparent because it is incisive and in-depth.

Acknowledgement The research leading to these results has received funding from the European Commission Framework Program, under the TATEM, HILAS and ALICIA projects, and from Enterprise Ireland under the C+program.

The ISi-PADAS Project—Human Modelling and Simulation to support Human Error Risk Analysis of Partially Autonomous Driver Assistance Systems

P. Carlo Cacciabue and Mark Vollrath

Abstract
Background The objective of this paper is to discuss the goals and scope of the EU project ISi-PADAS, its theoretical backgrounds and assumptions and the principal results achieved to date. Models of driver behaviour and of Joint Driver-Vehicle-Environments (JDVE) systems, as well as "classical" reliability analysis methods, represent the starting points of the proposed research plan.
Methods The main aim of this Project is to support the design and safety assessment of new generations of assistance systems. In particular, the development of autonomous actions is proposed, based on driver models able to predict performances and reaction time, so as to anticipate potential incidental conditions. To achieve this objective two main integrated lines of development are proposed: (1) an improved risk based design approach, able to account for a variety of human inadequate performances at different levels of cognition, and (2) the development of a set of models for predicting correct and inadequate behaviour.
Discussion This paper shows that different kinds of JDVE models and evolutionary risk analysis approaches are required to achieve the goals of the Project. Possible solutions are presented and discussed. In addition, a methodological framework is introduced that is capable to accommodate different types of models and methods while maintaining the same safety and risk assessment objectives.

Keywords Driver modelling · Driver Assistance Systems · Risk Based Design · Human Reliability Assessment · Cognitive modelling

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Introduction

In the domain of automotive transport, Advanced Driver Assistance Systems (ADAS) allow human drivers to permanently remain in full control of the vehicle. With this directive the means to correct errors of the driver by assistance systems are limited, as certain accidents cannot be prevented. Partially Autonomous Driver Assistance Systems (PADAS), i.e., systems that take over full control of the vehicle in specific cases, are needed. To this aim, a design methodology must be applied that can prove the effectiveness of such systems and, at the same time, the increase of safe driving.

The ISi-PADAS (Integrated Human Modelling and Simulation to support Human Error Risk Analysis of Partially Autonomous Driver Assistance Systems)[1] project focuses on a time saving driver-model-based evaluation of the effect of PADAS with the aim to prove that the actions of such systems may actually prevent driver mishaps without introducing new ones.

In the current industrial development process, including recent research projects, the effects of assistance systems are investigated empirically by performing expensive and time consuming tests in driving simulators or with prototypes on test tracks. Further effects are examined after market introduction based on field operational tests and accident reports. The ISi-PADAS project develops an innovative methodology to support design and safety assessment of PADAS using an integrated Driver-Vehicle-Environment modelling approach. This enables to reduce enormously the cost of field studies and analysis, while offering the user, i.e., the designer and the safety analyst, the instruments for performing at a low price an enormous amount of studies and evaluations.

This goal can be achieved if two main instruments are developed and integrated in an appropriate methodological frame. These are, namely: the development of a set of models for predicting correct and inadequate driver behaviour; and an improved risk based design approach, able to account for a variety of inadequate performances at different levels of cognition.

Modelling human behaviour has been an extensive area of research in many domains, such as nuclear and energy production, transport systems, etc. The approaches based on linear models and control theoretical approaches of the 1970s (e.g. [13]) have been gradually replaced by non-linear models, based upon Artificial Intelligence (AI) principles (e.g. [1, 17]), and, more recently, on Neural and Bayesian Networks or Genetic Algorithms (e.g., [7, 10, 20]). This becomes even more complicated if we consider complex behavioural tasks such as vehicle driving in situations that are contextually dynamic and depend on changing environmental and traffic conditions [4, 12, 16].

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Modelling driver behaviour cannot be done without imbedding it within the traffic system as a whole. This comprises of three interactive parts: Drivers, Vehicles, and the Environment (DVE) [14]. Any traffic situation is the result of the interaction between these three systems. Naturally, the driver is a critical component of the traffic system. Attempts have been made for many years to estimate the importance of the driver as an accident cause (e.g. [6]). It has been estimated that road user factors are sole or contributory factors in a great majority of road crashes. There is no generally accepted model of the complete driving task. There are detailed descriptions focusing on perception and handling aspects, and reporting what drivers really do in every possible ("normal") situation from the beginning to the end of a journey (e.g. [11]). There are also more analytical approaches focusing on driver behaviour in relation to task demands, with the purpose of trying to explain and understand the psychological mechanisms underlying human behaviour [2, 8, 19].

An improved methodology for risk based design is the natural configuration where to exploit driving modelling and simulation approaches, predicting critical or error-prone situations. The interaction of the driver models with the simulated vehicle in the simulated environment can be examined in accelerated time for behavioural changes, errors of the (virtual) driver and critical situations up to accidents. As for the case of driver modelling, "classical" approaches to risk analysis, such as for example the definition of Safety Integrity Levels (SIL) [9] or the human error risk assessment techniques (e.g. [18]) are not sufficient to accommodate for the variety of diversification and time dependent situations that can be generated and evaluated by means of predicting simulations. Consequently, a specific effort has to be dedicated to this development.

In this paper, these two issues will be discussed and the state of development in the context of the ISi-PADAS Project will be reported with respect to the advances reached in both lines of development after almost two years of work within the team.

Modelling Driver Behaviour

Aims and Procedure of the Modelling

The Driver-Vehicle-Environment (DVE) modelling approach will be an effective and working simulation of driver behaviour, based on modelling driver cognitive processes. Driver models are a means to make psychological knowledge about driver behaviour readily available to system designers. When driver models are integrated with models of the vehicle and the traffic environment they can be used as computerised simulations in early development stages to predict driver behaviour including driver errors. In this way they can support decisions between design alternatives and can be applied for testing the need for specialized assistance systems.

Moreover, such a driver-model-based simulation of traffic scenarios can streamline the amount of simulator tests with human subjects by highlighting those scenarios that require more detailed investigation due to predicted potential hazards. This also enables to avoid the bias of professional test drivers to unconsciously avoid scenarios with highest possible risk. Both improvements will save effort and time during the development of safe driver assistance systems.

The general plan of this project is to develop a model of driver behaviour based on a cognitive approach and to transform it into a software simulation integrated in a general platform (Joint Driver-Vehicle-Environment Simulation Platform JDVE) that simulates DVE models in an effective and consolidated way. This platform will allow rapid simulation of a vast number of traffic scenarios to predict the probability and risk of driver errors for different PADAS design alternatives. In this way the platform will be used as a technical basis for a new methodology to support Human Error Risk Analysis during a risk based design process.

This JDVE is developed by a close interaction between empirical investigations and modelling. Empirical investigations of driver behaviour without PADAS are conducted with the aim to better understand causes of driver errors in specific driving situations. The results of the experiments with regard to the psychological processes involved in these errors are used for the modelling. These models enable to predict under which circumstances driver will conduct errors. This understanding of the psychological mechanisms is also used in the development of PADAS target systems which should be able to support the driver in a way that counteracts these errors. In phase II of the project, empirical investigations will be conducted with these PADAS target systems using traffic scenarios where driver errors (without PADAS) are highly probable. It will be examined to which extent the PADAS are able to improve safety by preventing these errors. The results of these experiments will again be used for driver modelling. However, this time the models include the interaction with the PADAS.

Types of Models within ISi-PADAS

The models which have been developed may be classified in three different categories, which are (1) predictive models, (2) simulation models of the driver and (3) models for analysis of the driving activity. The *predictive models* are per nature focused on the probabilities of occurrences of behaviours, decision-making or accident risks, without necessary explaining the reason why these effects or these consequences will occur. Indeed, predictive models are really not models of the driver. They are dedicated to performance predictions and/or a risk assessment, in relation with a driving task in given conditions. Within ISi-PADAS, a predictive model is being developed which accounts for two modules: the first one is the Decision Model, which receives input from Vehicle and Environment [4]. The second one is the Control Model, whose purpose is to determine the final output of the driver in terms of actions and possible errors of performance, such as Steering Angle and Acceleration/Breaking pedal position.

The *simulation models* are virtual models of the human driver, able to drive a virtual car into virtual environments. In other words, the objective of this modelling approach is to dynamically generate and then virtually emulate the actual human driver's activity on a computer. According to theses dynamic simulations, it becomes possible to provide predictions of human performances. However, and by contrast with the predictive models, *simulation models* are in this case not limited to predict the probability of occurrence of a particular driving performance in a given context. They can also be used for understanding the origin of this performance and in order to explain why such consequence occurs. Within ISi-PADAS, two of these simulation models are developed.

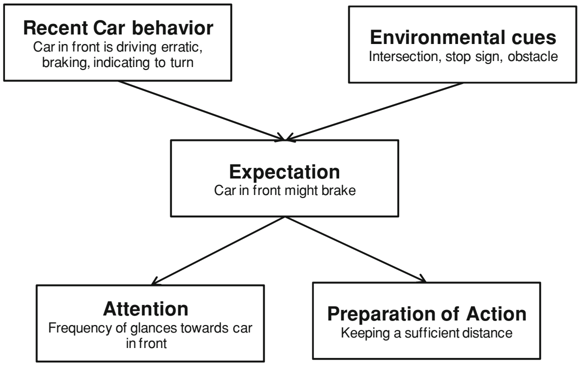
The last driving modelling approach relevant in the ISi-PADAS project concerns *models for analysis* of the driving activity. In this framework, the aim is not to virtually generate a driving performance, but to dynamically analyse driving performances as implemented by human drivers, from and external observer point of view. Synthetically, the aim is to provide on-line or off-line diagnosis concerning the driver status (e.g. level of distraction, drowsiness), for example, or the quality of the observed driving performance (e.g. is the observed behaviour adequate, or not, according to the traffic conditions or the current driving task requirements). These kinds of models can be used to assess the current driver state and adapt the PADAS in a way to support the driver adequately and fitting to his or her current state.

These three kinds of models play different roles in the development of PADAS. The first type of model, the predictive model is especially relevant for the development of PADAS in order to examine how a PADAS changes the probability of critical situations. This approach will be described in more detail in the second part of the paper. The third type of model, the models for analyses are integrated directly into the PADAS and are thus especially relevant for the development of the PADAS target system itself. The last type of model, the simulation models are used in the JDVE for the development of PADAS as described above. Driver behaviour without PADAS is modelled in order to better understand causes of errors. Driver behaviour with PADAS is modelled in order to examine how drivers react to PADAS and to which driving safety can be enhanced by the interaction of driver and PADAS. This last approach will be demonstrated by giving some results from the first phase of the project.

Relationship between Empirical Investigations and Driver Modelling

The project is currently finishing phase I and starting with phase II with the preparation of empirical studies with PADAS. In this section the connection between the empirical investigations and the modelling is demonstrated. Selected results of an

Fig. 1 Summary of hypotheses about expectations of the driver



experiment from the Technische Universität Braunschweig are presented and it will be discussed how these can be integrated in the simulation models.

Driver Expectations and Driver Behaviour

Based on an in-depth analysis of accidents [3, 15] the hypothesis was generated that driver expectations play a major role in causing these accidents. If a driver does not expect that the car in front to brake, it is possible that he/she may neglect paying attention and thus noticing too late if stopping is necessary. Moreover, he/she may follow so closely the leading vehicle that it becomes impossible to brake in time even when attention is paid. These expectations are probably generated from two main sources, the recent car behaviour and environmental cues (see Fig. 1). On the one hand, the recent car behaviour (e.g., driving erratic, braking, indicating a turn) may lead to the expectation that this car will brake again, soon. On the other hand, environmental cues like intersections, stop signs or obstacles may give rise to the expectation that the driver will soon stop. This expectation should influence the amount of attention focused on the car in front and whether or not the driver is preparing for the possible event that the car in front might stop, e.g., by keeping a larger distance. These ideas were tested in a simulator study focusing on the recent car behaviour.

This was varied by a lead car which either did not brake (no expectation), brake once or twice quite hard or four times more softly. After having shown this behaviour, this car drove at a constant speed for about 300 m and the driver had to follow that car. Then an intersection appeared and the car in front either used the indicator, became slower and turned or did not signal but braked hard at the last moment and turned afterwards. Gaze and driving behaviour were examined. In accordance to the hypothesis, drivers gazed more frequently at the car in front when it had braked beforehand as compared to when it hadn't braked. However, drivers did not adapt their speed or distance in the car-following situation. When the driver turned, the minimum time-to-collision (TTC) was measured indicating

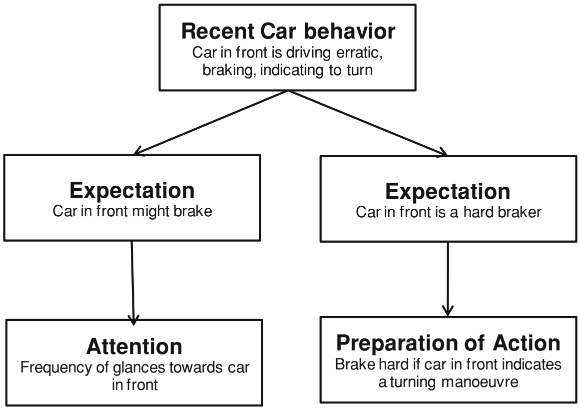


Fig. 2 Modified model of the driver expectations

how well the drivers reacted to the braking manoeuvre of the car in front. When it had signalled beforehand, these TTCs were much larger than without signalling. Additionally, an effect of the recent car behaviour could be demonstrated if the car in front signalled its manoeuvre. In this case, drivers kept a much larger TTC if the car in front had braked hard twice.

Thus, this experiment yielded three results for the driver modelling:

1. The recent car behaviour is important for the attention allocation and preparation of action.
2. If the car in front has braked one or more times, drivers gaze more often at this car.
3. Drivers do not adapt their distance, but are more ready to react if the car in front indicates that it will become slower.

It seems that the drivers create two expectations regarding the behaviour of the car in front. The first is something like “that car might brake suddenly”. This expectation influences gaze behaviour, but drivers do not adapt their speed or distance. The second is an expectation like “this is a car that might brake strongly”. This one is only activated if there is some indication that the car in front will stop. In our experiment this happened when the car in front used the indicator. The drivers can then react faster and thus keep larger distances.

These results can be summarized as shown in Fig. 2. The recent car behaviour influences expectations which change the attention allocation and other expectations which are used to react in certain situations. The next step is to include these findings in the driver model. With regard to causes of driver errors it follows that drivers will not pay attention to cars as much as required if these drive very smoothly and fail to show signs indicating that they will stop. When the car in front has displayed a soft braking behaviour, they will not expect a sudden, hard braking by this driver. Thus, this model should point to some situations where drivers will probably have difficulties to react if the car in front suddenly stops. These situations can then be used with PADAS to examine whether these systems can really support the driver and increase safety. Appropriate experiments will be conducted in the second phase of the project.

Risk Based Design Methodology for Dynamic Interactions

Aims and Procedure of the Risk Based Design Methodology

The aim of the Risk Based Design (RBD) methodology under development is to improve the current design process of driver assistance systems, such as PADAS, by effectively introducing a methodology for the evaluation of hazards associated to inadequate driver behaviour, based on the driver models and the Joint DVE Simulation discussed above.

In a modern safety design perspective, standard methods of risk based approaches have to assess the consequences of erroneous behaviour in order to develop the appropriate countermeasures in terms of different levels of safety management. An approach of this nature enables to evaluate dynamic human–machine (in this case JDVE) interaction processes, once types and modes of erroneous behaviours are defined at different levels of cognition, as discussed above. Its implementation in a risk analysis presents a number of problems for the definition of the probability of error occurrence, as well as recovery, and relative uncertainty distributions. A second difficulty derives from the complexity of the situations that are generated every time an error prone context is identified. The simulation associated to the JDVE model must be able to account for many different dynamic interactions, possible behaviours and system responses. When the combination of erroneous behaviours and events becomes particularly complicated, it is very likely that this exceeds the modelling and simulation capabilities [5].

It becomes therefore essential to take a further step of simplifying the error modelling architecture, by selecting fixed intervals of observation of the JDVE interaction, so as to maintain a certain level of dynamic stepwise processes, and, secondly, by reducing the variety of erroneous behaviours that are accounted for. In terms of safety and risk analysis, three steps can be implemented in order to enable the inclusion of these aspects in a safety assessment approach:

Requirement 1. Identification of intervals of observation of the JDVE interaction, at which possible alternative human performances can be evaluated for assessing consequences.

Requirement 2. Definition and selection of types and modes of human performance, according to taxonomies that are compatible with the overall objective of the analysis.

Requirement 3. Evaluation of the consequences of procedures and/or tasks, in risk assessment terms, i.e., by combining the probability of success/failure of the various branches and sequences composing a procedure.

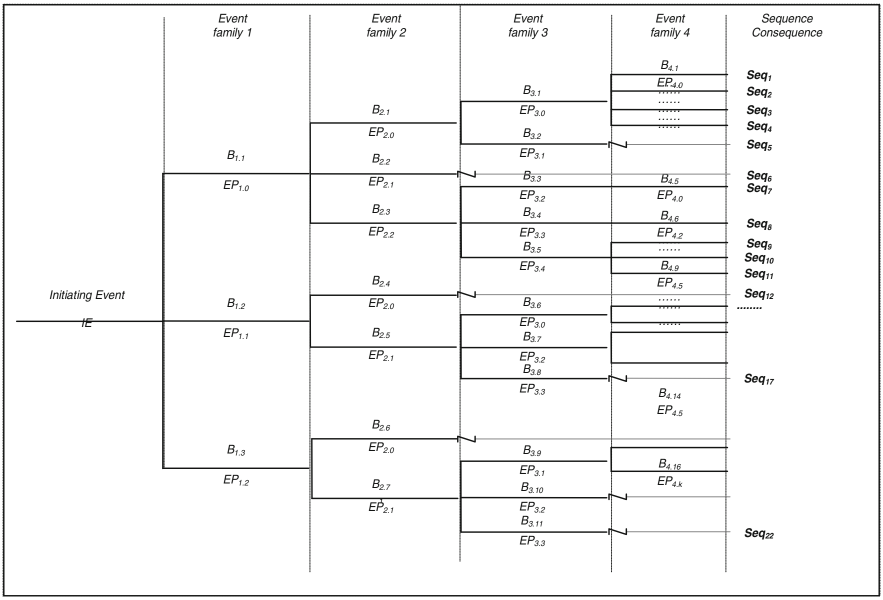


Fig. 3 Expanded Human Performance Event Tree

This approach could be defined as "quasi-static", in the sense that specific time intervals are identified for assessing the JDVE process, and thus preserving some time dependence in the safety analysis. Moreover, in this case, contrary to the usual binary alternatives of classical "human error event trees", different human responses are considered at each node of the "quasi-static" JDVE tree. Therefore, it is no longer possible to differentiate between success or failure of the procedure, but it is necessary to evaluate each sequence in terms of its consequences.

The implementation of these requirements leads to what may be called Expanded Human Performance Event Tree (EHPET).

The Expanded Human Performance Event Tree

The proposed approach considers an alternative method to the simple binary possibility success vs. failure, by enabling the possibility of analysing two or more modes of behaviour (branches) at each node of the Human Performance Event Tree. Figure 3 shows the structure of an EHPET, where a variety of possible sequences/consequences are generated, following an Initiating Event (*IE*).

Each branch of the tree is associated to an Expected Performance (*EP*), numbered according to the Event family under consideration. An Event family is represented by the possible alternative types and modes of behaviour defined during the first step of analysis (*Requirement 1*). According to the usual formalism of event tree approach, the alternative at the top of each branch represents the most commonly expected performance, in relation to the event sequence. As an example, $EP_{2.0}$ represents the *EP* of Event family 2 which is most likely to occur at the specific time interval of observation, whereas $EP_{2.2}$ is the third mode of possible performance, defined a priori during the in the initial steps of the method (*Requirement 2*). In this way, it is possible to identify the logical relationship between different events of JDVE.

The branches are numbered in sequence and in relation to the Event family to which they are associated, e.g., $B_{1.2}$ is the second branch of Event family 1.

The sequences (*Seq*) are numbered in succession and are built by combining the *IE* and the subsequent *EPs* of each branch. The overall probability of a sequence is calculated by combining the probability of the *IE* and the probabilities of the *EPs* that occur in that sequence. The assessment of the consequences associated to each sequence requires the deterministic evaluation of the actual outcome the sequence of events in terms of damage to humans, environment and involved technical system (*Requirement 3*).

JDVE Model in the EHPET

The integration of driver models and JDVE Simulation Platform in the RBD methodology is a very important step. The final objective is to utilise the driver models and the simulation platform in order to simulate and analyse a vast number of scenarios with a very reduced time consumption.

From a theoretical point of view, three possible contributions from JDVE can be envisaged:

1. Driver models can be utilised for the identification of events associated to driver inadequate performances. This implies that:
   - They can provide support for the development of a taxonomy focused on human errors.
   - They can be used for the verification of the Expanded Human Performance Event Trees. In this case, by simulating a specific situation with driver models, it is possible either:
     1. to validate the considered events and to understand if the sequences are consistent or not with the overall scenario and initiating event; or
     2. to identify new and different possible branches of the EHPET that were not originally imagined by the analyst.
2. Driver models can be used for the evaluation of probabilities of driver events. In this sense, they give a very important support to classical safety analysis and human error risk analysis techniques.

3. Driver models can be used for the evaluation of consequences of specific sequences of the EHPET. In this way, they support the evaluation of the severity of a certain branch and therefore they are of fundamental importance for the assessment of the risk.

For the validation of EHPETs, the driver model should be able to support the verification of the consistence of the existing events with respect to the overall scenario and initiating event. Moreover it should allow the identification of new possible branches of the tree that were not originally imagined by the safety analyst. For these purposes, therefore, the JDVE models defined as *models for analysis* are best appropriate.

For the assessment of probabilities of alternative driver behaviours, the driver model should be able to provide numerical evaluations of different possible performances. Therefore, the JDVE type models defined as *predictive models* are most adequate for use in these cases.

For the prediction of consequences for sequences of the tree, the driver model should have the possibility to be forced to go along specific branches of the Expanded Human Performance Event Tree. This can be done by enforcing, in the simulation, certain human performances, without taking into account the detailed aspects of mental processes. In other words, when reaching a certain node in the tree, where a human action/task is considered, the simulation is carried on following the driver actions that need to be assessed (either correct or inappropriate) independently of any modelling considerations. In this case, either *predictive models* or *simulation models* are suitable to sustain the RDB methodology.

Conclusions

The positive impact of current Advanced Driver Assistance Systems (ADAS) with regard to traffic safety is limited by the large time and effort required in the development process for ensuring their safety. This becomes even more essential when ADAS develop into PADAS–systems which may partially intervene autonomously. It has to be ensured that these systems are really beneficial and that the driver will not produce new errors in the interaction with these systems. Within ISi-PADAS it is examined how driver models may improve and accelerate this design process. It has become clear, that different kinds of models are required to achieve this aim. One important part of the results of the project will be to show the benefits but also problems of these different kinds of models. This will enable to include these models in a new risk-based design methodology. The second part of the results is the driver models themselves. The simulation models will enable to better understand how and why driver errors occur. They are based on experiments like the one described in this paper. This knowledge can be used to design PADAS which should counteract these errors. These are supplemented by predictive models which identify critical situations without necessarily understanding all cognitive processes of the driver involved in the error. However, they support the development of efficient PADAS by focusing on the relevant scenarios. Finally, models for analysis of the driving activity may be embedded as integral parts of the PADAS in order to assure that the PADAS are fine-tuned in accordance with the driver's current state. The second phase of the ISi-PADAS project concentrates on the interaction between driver and PADAS to demonstrate the potential of these different classes of driver models.

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The HUMAN Project: Model-Based Analysis of Human Errors During Aircraft Cockpit System Design

Andreas Lüdtke, Denis Javaux and the HUMAN Consortium

Abstract The objective of the HUMAN project is to develop a methodology with techniques and prototypical tools supporting the prediction of human errors in ways that are usable and practical for human-centred design of systems operating in complex cockpit environments. The current approach of analysing systems is error prone as well as costly and time-consuming (based on engineering judgement, operational feedback from similar aircraft, and simulator-based experiments). The HUMAN methodology allows to detect potential pilot errors more accurately and earlier (in the design) and with reduced effort. The detection of errors is achieved by developing and validating a cognitive model of crew behaviour. Cognitive models are a means to make knowledge about characteristic human capabilities and limitations readily available to designers in an executable form. They have the potential to automate parts of the analysis of human errors because they offer the opportunity to simulate the interaction with cockpit systems under various conditions and to predict cognitive processes like the assessment of situations and the resulting choice of actions including erroneous actions. In this way they can be used as a partial "substitute" for human pilots in early development stages when design changes are still feasible and affordable. Model- and simulation-based approaches are already well-established for many aspects of the study, design and manufacture of a modern airliner (e.g., aerodynamics, aircraft systems, engines), for the very same objective of detecting potential problems earlier and reducing the amount of testing required at a later stage. HUMAN extends the modelling approach to the interaction of flight crews with cockpit systems.

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Keywords Human Error Analysis · Cognitive Modelling · Aircraft Cockpits · Pilot-Cockpit Interaction

Introduction

The objective of the HUMAN project is to develop a methodology with techniques and prototypical tools supporting the prediction of human errors in ways that are usable and practical for human-centred design of systems operating in complex cockpit environments.

The current approach of analysing systems is error prone as well as costly and time-consuming (based on engineering judgement, operational feedback from similar aircraft, and simulator-based experiments). The HUMAN methodology allows to detect potential pilot errors more accurately and earlier (in the design) and with reduced effort.

The HUMAN project is funded under the 7th Framework Programme of the EU. It started in March, 2008 with a duration of 3 years. The project is coordinated by OFFIS and involves six partners from four countries: Airbus (France), Alenia Aeronautica (Italy), University of Louvain (Belgium), German Aerospace Institute (DLR, Germany), TNO (Netherlands) and OFFIS (Germany). Next Step Solutions (Belgium) is a subcontractor to Airbus.

Related Work

There is a growing consensus that design support systems can be created by using accurate models of cognitive behaviour. However, the question of how such models can be developed for system design has received limited attention. Few researchers have attempted to apply a theory-based or empirical approach to cognitive processing activities that take place when decisions and actions (including potential errors) are carried out in the cockpit [1]. Current cockpit system design evaluation schemes therefore rely heavily on qualitative judgments by aviation experts and on expensive and logistically difficult simulator-based experiments with live subjects. This may be reduced by using a new methodology in which the error probability (and more extensively the subsequent error detection and management strategies) is predicted based on cognitive models of human behaviour interacting with an interactive target cockpit system prototype or design (a formal simulation of this system if no physical prototype exists, as is typically the case at the initial stages of design).

Cognitive models are intended to describe mental processes of human beings. An overview of extant cognitive computational models is provided, e.g., in [2, 3]. In the HUMAN project the term cognitive model refers to computational models that allow execution. Only these models have the potential to simulate human behaviour to predict pilot–cockpit interaction (including errors) as required for the purpose of HUMAN. With regard to system design the goal is to *understand* and *predict* mental processes in such a way that the system design can be adapted to the capabilities and limitations of the pilots.

Cognitive models usually consist of two parts: a *cognitive architecture*, which integrates task independent cognitive processes (like generic human decision making strategies, memory and learning processes) and an *activity model*: a formal model of task specific know-how (e.g., pilot activities like SOPs and rules for good airmanship). Advanced cognitive models can also incorporate a *knowledge model*: a formal model of general or specific knowledge relevant to the tasks to perform. In order to simulate behaviour the activity and knowledge models have to be "uploaded" to the architecture. Thus, a cognitive architecture can be understood as a generic interpreter that executes such formalised models of activities and knowledge in a psychological plausible way. The architecture imposes stringent constraints on the format of the activity and knowledge models. In most cases "if–then"-rule formats are used for the activity model. Semantic networks are typically used for the knowledge model.

Cognitive architectures were established in the early 1980s as research tools to unify psychological models of particular cognitive processes [4]. These early models only dealt with laboratory tasks in non-dynamic environments. Furthermore, they neglected processes such as multitasking, perception and motor control that are essential for predicting human interaction with complex systems in highly dynamic environments like the air traffic environment addressed in HUMAN with the AFMS (Advanced Flight Management System) target system. Models such as ACT-R [5] and SOAR [6] have been extended in this direction but still have their main focus on processes suitable for static, non-interruptive environments. Other cognitive models like MIDAS [7], APEX [8] and COGNET [9] were explicitly motivated by the needs of human–machine interaction and thus focused for example on multitasking right from the beginning.

The recently finished Human Performance Modeling (HPM) element within the System-Wide Accident Prevention project of the NASA Aviation Safety Program performed a comparison of error prediction capabilities of five architectures [10]: ACT-R, Air-MIDAS, D-OMAR, IMPRINT/ACT-R and A-SA. It has been demonstrated that these architectures are able to predict pilot errors due to several error production mechanisms: situation awareness degradation, memory degradation and interference, pilot expectation and habit, distraction, and workload.

HUMAN advances cognitive modeling by developing a model which allows to predict errors due to cognitive processes that lead to deviations from normative pilot activities, e.g., due to Learned Carelessness and Cognitive Lockup.

Approach

The prediction of probable human errors is achieved in HUMAN by developing and validating a cognitive model of crew behaviour. Cognitive models are a means to make knowledge about characteristic human capabilities and limitations readily available to designers in an executable form. They have the potential to automate parts of the analysis of human errors because they offer the opportunity to simulate the interaction with cockpit systems under various conditions and to predict cognitive processes like the assessment of situations and the resulting choice of actions including erroneous actions. In this way they can be used as a partial "substitute" for human pilots in early development stages when design changes are still feasible and affordable.

Model- and simulation-based approaches are already well-established for many aspects of the study, design and manufacture of a modern airliner (e.g., aerodynamics, aircraft systems, engines), for the very same objective of detecting potential problems earlier and reducing the amount of testing required at a later stage. HUMAN will extend the modelling approach to the interaction of flight crews with cockpit systems. To realize this target the main research and development work in HUMAN has been to produce key innovations on three complementary research dimensions:

- *Cognitive modelling*: to develop an integrated cognitive crew model able to predict human error categories with regard to deviations from normative activities (Standard Operating Procedure (SOP) and rules of good airmanship).
- *Virtual simulation platform*: to develop a high-fidelity virtual simulation platform to execute the cognitive crew model in realistic flight scenarios in order to analyse the dependencies (including the safety effect of likely pilot errors) between the pilots, a target system in the cockpit, the aircraft and its environment.
- *Physical simulation platform*: to thoroughly investigate pilot behaviour on a physical simulation platform (comprising a full-scale flight simulator) to produce behavioural and cognitive data as a basis for (1) building a detailed knowledge base about cognitive processes leading to deviations from normative activities in the complex dynamic environment of modern aircraft cockpits and for (2) validating and improving the predictions of the cognitive model generated on the virtual simulation platform.

The general idea of the virtual and physical platform is to use the same core system for both in order to ensure the *functional equivalence* between the two platforms (Fig. 1). This equivalence is a fundamental precondition for validating the cognitive model by producing one the one hand, data sets for predicted crew activities (on the virtual platform) and on the other hand, data sets for actual crew activities (on the physical platform). Predicted and actual crew activities will be compared to assess the quality of the model predictions and to derive requirements for model improvements.

The core system is the generic cockpit (GECO), a full scale simulator provided by the DLR, one of HUMAN's partners. In HUMAN it incorporates a target system, the Advanced Flight Management System (AFMS) with flight management functions and crew interface functionality compatible with 4D flight planning and guidance and trajectory negotiation by means of a data link connection. In the project the system is extended towards issues pertaining to the future Air Traffic Management context, like trajectory negotiation.

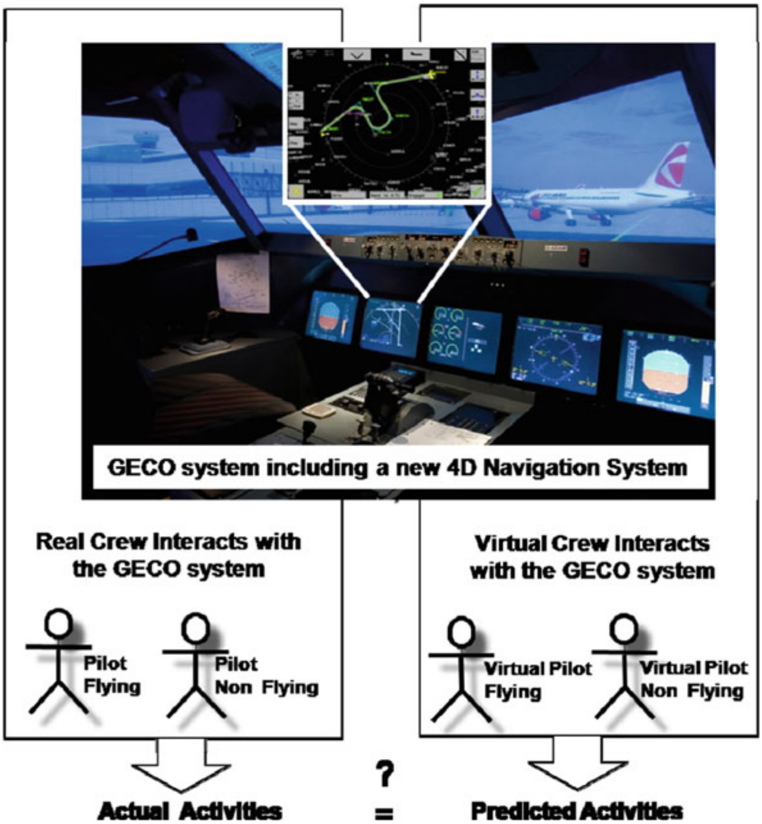

Fig. 1 Physical and virtual simulation platforms sharing the same core system

After the preparation of the platforms they are used in two experimental cycles to generate a knowledge base on pilot behaviour and to validate and improve the cognitive crew model.

Target System

Today, the flight management system, which controls the lateral and vertical movement of an aircraft, is operated by a multi-purpose control display unit (MCDU). The MCDU consists of a small monitor and an alphanumerical keyboard, by which the pilots type in the desired flight plan changes. Flight plans consist of a certain number of waypoints, identified by a three or five letter code, which is entered into the MCDU. The airplane's autoflight system can be coupled to the flight plan, which then follows the plan automatically. However, clearance requests and reception for the different sections of the flight plan are mandatory,

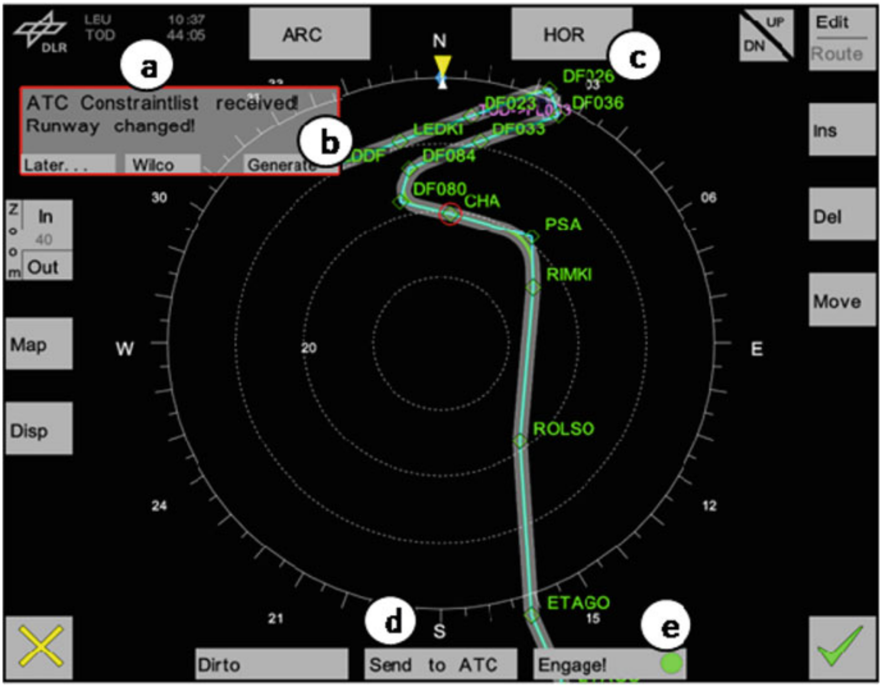

Fig. 2 AHMI of the flight management target system

and are today performed via voice communication with the ATC. Problems with this are that communicating route changes via voice is a lengthy and error-prone process [11], and that the interaction with the MCDU is cumbersome and inefficient (e.g., [12]). As described in the introduction, future flight management systems and their user interfaces try to tackle these problems. For our study we use an advanced flight management system and its AHMI, which have been developed by the German Aerospace Institute (DLR, Braunschweig, Germany). Both systems are used as demonstration settings for the current research, without their design playing a role in the validity of the current research.

The AHMI represents flight plans on a map with their status being graphically augmented by different colours and shapes, e.g., if a new trajectory is generated after the flight plan has been changed, it is displayed as a dotted line, while the active trajectory is solid of another colour (cf. Fig. 2). Still, pilots can insert, move or delete waypoints, but also handle a lot of different events, e.g., display weather radar information, allowing graphical re-planning to avoid a thunderstorm. However, the insertions do not necessarily make use of keyboards such as the MCDU—manipulation is done directly on the map by trackball cursor-control. Any trajectory created by the pilot is generated as a data-link, ready to be sent to ATC for negotiation.

The advanced flight management system and its AHMI is used in HUMAN as a target system to demonstrate the predictive capabilities of the cognitive flight crew model by simulating the interaction between system and crew in different re-planning scenarios according to a set of normative activities.

Re-planning means modifying the current flight plan via the AHMI by changing the lateral or vertical profile. Changes to the route can be initiated either by the pilots or by the controllers. In the first case the pilots introduce the changes into the route and send it down to ATC (downlink). In the latter case ATC sends a modified route up to the aircraft (uplink). Uplinks are indicated to the pilots via a message box (Fig. 2a). In order to handle the message the Pilot Flying (PF) has to first generate the trajectory for the modified plan by clicking on the “Generate” button in the message box (Fig. 2b). As a result the new trajectory is shown as a dotted line. Afterwards s/he has to check the changes on the horizontal view and then on the vertical view in order to see if they are acceptable. In order to access the vertical view the View-button has to be pressed (Fig. 2c). If the changes are acceptable s/he clicks the “Send to ATC” button (Fig. 2d) to acknowledge the uplink. After feedback from ATC is received s/he has to press the “Engage” button (Fig. 2e) to activate the new trajectory.

Cognitive Model

Executable cognitive models are intended to describe mental processes of human beings like assessing situations and choosing actions resulting in time-stamped action traces. These cognitive models usually consist of two or three parts: a cognitive architecture, which integrates task independent cognitive processes, and a formal model of task specific know-how (e.g., flight procedures). A formal model of general or specific knowledge appropriate for the task can also be incorporated. In order to simulate behavior the task and possibly knowledge models have to be “uploaded” to the architecture. Thus, a cognitive architecture can be understood as a generic interpreter that executes task related knowledge in a psychological plausible way.

CASCaS

CASCaS is the cognitive architecture developed by OFFIS and TNO in the framework of HUMAN as well as in other projects. A key concept underlying CASCaS is the theory of behavior levels [13] which distinguishes tasks with regard to their demands on attentional control dependent on the prior experience: autonomous behavior (acting without thinking in daily operations), associative behavior (selecting stored plans in familiar situations), cognitive behavior (coming up with new plans in unfamiliar situations). Figure 3 shows the modular structure of CASCaS. The knowledge processing component encompasses one layer for each behavior level. On the layer for autonomous behavior we model manual

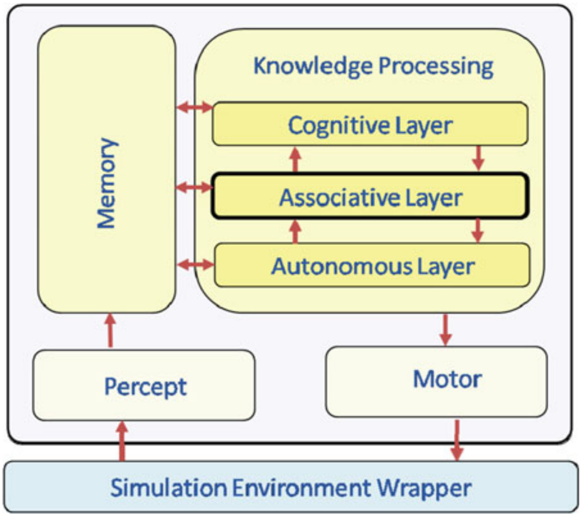

Fig. 3 Cognitive architecture CASCaS

control of tasks like steering and braking using modeling techniques like control theoretic formulas. This layer is not used for the pilot model in HUMAN but for modeling car driver behavior [14] in other projects, such as ISi-PADAS. The layer for cognitive behavior is currently developed by researchers of TNO Human Factors and has been described in [15].

Percept and Motor Components

The percept and motor component interact with a simulated environment by reading and manipulating external variables. The Simulation Environment Wrapper provides data for the percept and motor component by connecting CASCaS to different simulation backends. In HUMAN we connected CASCaS to the flight simulator software used by the DLR for experiments with human pilots. In this way the model can be executed and data can be recorded in the very same environment in which human subject pilots also interact (cf. the functional equivalence principle mentioned above). This allows validation of the model by comparing model data with human data. Throughout the paper we use the term *virtual flight* meaning that the pilot model interacts with the simulated aircraft in a simulated dynamic environment.

Memory

The memory component of CASCaS stores declarative knowledge and procedural knowledge. Declarative knowledge is knowledge about facts (“`knowing what`”) like the function and purpose of the different cockpit instruments of a particular aircraft type. Such declarative knowledge about aircraft is typically learned by human pilots in the Aircraft Type Rating Training. Furthermore, this knowledge also includes knowledge about the current situation/context which is acquired, e.g., by reading actual values from the instruments during the flight. Procedural knowledge is knowledge about how to do things ("knowing how"). Procedural knowledge most relevant for the aviation domain is knowledge about how to perform flight procedures.

We represented declarative knowledge about the aircraft and cockpit state using simple variable-value pairs: $I \times V$, where I is a set of interaction elements like cockpit instruments and V is a set of data types. A pair (i, v_{mem}) denotes that the model believes that element i (e.g., the altimeter or a message box) shows value v_{mem}. These pairs represent assumptions about the current state of the aircraft and airspace under the simplification that all relevant flight parameters are indicated on associated interactive cockpit elements. At every point in time during a virtual flight, the model has either correct, incorrect or no information about the various instruments: for every $i \in I$ either $v_{\mathrm{mem}} = v_{\mathrm{env}}$ or $v_{\mathrm{mem}} \neq v_{\mathrm{env}}$, or $v_{\mathrm{mem}} = \mathrm{nil}$, with v_{env} being the actual value of i and *nil* a constant representing lack of information.

The model perceives information from the environment via percept actions (performed by the percept component) represented as operators with two parameters: *percept*(i, v_{mem}). The operator reads the actual value v_{env} from interaction element i and assigns this value to v_{mem}. Values can be retrieved from memory via memory-read operators: *memory-read*(i, v). The operator retrieves the memorized value v_{mem} of interaction element i and assigns this value to v.

Associative Layer

In CASCaS procedural knowledge in the associative layer is modeled in the form of "if–then" rules. In HUMAN, the rules formally describe a mental representation of flight procedures. The format of our procedure rules is a Goal-State-Means (GSM) format (Fig. 4). All rules consist of a left-hand side (IF) and a right-hand side (THEN). The left-hand side consists of a goal in the Goal-Part and a State-Part specifying Boolean conditions on the current (memorized) state of the environment. Apart from the condition the State-Part contains memory-read operators to specify that in order to evaluate the condition the associated values v_j of interaction elements i_j have to be retrieved from memory. The right-hand side consists of a Means-Part containing motor and percept operators (writing values and reading values in the simulated environment), memory-store operators as well as a set of partial ordered sub-goals.

The model foresees two special rule types: *reactive rules* are used for immediate behavior (as opposed to goal-based behavior) in order to instantly react to events in the environment—these rules contain no Goal-Part; *percept rules* are

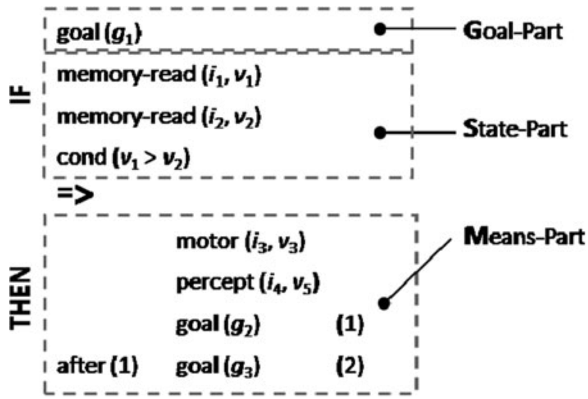

Fig. 4 Format of CASCaS rules

used to store perceived values into the memory—these rules have exactly one percept operator on the left-hand side and a corresponding memory-store operator on the right-hand side.

On a sub-symbolic level each rule r has got a strength parameter, which is computed by $P-C$, where P is the expected probability that the current goal g will be reached when r is selected and C represents the expected cost for reaching g with r. C is the average time that is needed until g is achieved. C is normalized by referring to a maximum time needed for g.

Rules are selected and applied in a so called cognitive cycle which consists of four phases. In phase 1 a goal g is selected from the set of active goals. In phase 2 all rules containing g in their Goal-Part are collected and a memory retrieval of all state variables in the Boolean conditions of the collected rules is performed. Phase 3 starts after all variables have been retrieved. Then, one of the collected rules is selected by evaluating the conditions. Finally, in phase 4, the selected rule is fired, which means that the motor, percept and memory-store operators are sent to the motor, percept and memory component respectively and the sub-goals are added to the set of active goals. The cognitive cycle is iterated until no more rules are applicable. The default cycle time is 50 ms like in ACT-R. This time may be prolonged depending on the memory retrieval in phase 2.

Cognitive Layer

The *cognitive layer* reasons about the current situation and makes decisions based on this reasoning. Consequently, we differentiate between a decision-making module, a module for task execution and a module for interpreting perceived knowledge (sign-symbol translator).

The *decision-making module* determines which goal is executed. Goals have priorities, which depend on several factors: first, goals have a static priority value that is set by a domain expert. Second, priorities of goals increase over time if not executed. Implicitly, temporal deadlines are modelled in this way. If, while executing a goal, another goal has a clearly higher priority than the current one, the execution of the current goal is stopped and the new goal is attended to.

The *task-execution module* executes the goals that have been chosen by the decision-making module. (Sub-)tasks might be passed to the associative layer if rules exist in long-term memory.

The *sign-symbol translator* is based on Rasmussen's differentiation between signs and symbols [16]. This module raises the level of abstraction of the signs perceived by the percept component and stored in short-term memory by identifying and interpreting the situation, and thereby adding extra knowledge to the sign. In addition, background knowledge is applied to judge and evaluate the current situation.

Interaction Between Layers

The associative and cognitive layers interact in the following ways: first, the cognitive layer can start (and thus delegate), monitor, temporally halt, resume and stop activities on the associative layer by manipulating the associative layer's goal agenda. Monitoring of the associative layer is realized through determining whether the appropriate goals are placed in the goal agenda.

The associative layer can inform the cognitive layer about the status of rule execution, e.g., current execution is stuck because for the chosen goal no rules are available in long-term memory or execution of a perceived event cannot be started for the very same reason. In these cases the cognitive layer starts to perform the goal or event. Furthermore, the cognitive layer can take over control at any time. Currently this is initiated by setting the parameter "Consciousness". If the value is "associative" then every event will first be processed if possible and the cognitive layer becomes only active if no rules are available. If the value is "cognitive" then the cognitive layer processes each event independent of the availability of rules.

Experiments

The approach to performing the experiments is a cyclical process of producing working hypotheses, deriving experimental scenarios to test them, producing and comparing actual activities (on the physical simulation platform) and predicted activities (on the virtual simulation platform) activities, in order to derive and implement necessary adjustments of the cognitive crew model. This cycle will be performed twice in HUMAN.

The design of validation scenarios, to be used on both the physical and virtual platforms, was guided by defining high level conditions and low level conditions for provoking events or phenomena (e.g., errors) we were interested in.

For example, we show here the high level test condition for the error production mechanism Learned Carelessness:

1. T is a task which is triggered by an event E.
2. T involves performing a check C of flight parameter P which can either be true or false. If false nothing has to be done, if true pilots have to start a sub-task Tsub.
3. A sequence of scenarios is flown in which E occurs n times and T (including the check C) has to be performed. The result of check C in all these task repetitions is that the corresponding flight parameter P is false which means that Tsub does not have to be performed.
4. During the n + 1 repetition of T flight parameter P is manipulated in a way that it is true and normatively Tsub has to be performed.

For this high level condition we had the hypothesis that pilots will omit check *C* after a certain number m ($m < n$) of repetitions of *T* because they assume (based on their experience during the first $m-1$ repetitions of *T*) that the checked flight parameter *P* will not be true for the remaining scenarios. Thus, they trade off benefit against the effort of checking *P*.

In a next step, we instantiated the variables of the high level condition to produce the low level condition. Due to the nature of the target system we decided that *T* is a re-planning procedure with a modified flight plan uplinked by ATC to the pilots. As described above the normative re-planning procedure involves checking the vertical part of the trajectory on the vertical view of the AHMI. For example, the pilots have to check if the cruise flight level (CFL) has been changed and if this change violates current altitude constraints. In order to access the vertical view they have to press the View-button on the AHMI. If an altitude violation is detected the CFL has to be adjusted accordingly. The low level hypothesis was: because the check of the vertical view costs effort, in terms of time needed for goal selection, percept and motor actions, and because altitude changes by ATC appear very seldom in our scenarios, we assume that the check will be omitted due to Learned Carelessness after *m* repetitions of the re-planning procedure.

Eight concrete scenarios (A–H) have been defined which included 24 ATC uplinks. Scenario B and G were the only scenarios that included altitude violations. G was conducted at the beginning (first scenario) of each experimental session to prove that the subjects were in principle able to detect and handle such violations. B was conducted at the end (cf. high level condition 4, above) to investigate if Carelessness has been learned. Scenario B starts during cruising at flight level 250 (25,000 feet) on a flight inbound to FRA (Frankfurt, Germany—the associated flight trajectory is shown in Fig. 2). Passing waypoint ETAGO (approx. 130NM inbound to Frankfurt), a system non-normal message pops up advising the crew of a fuel-pump malfunction. The normative procedure requires the crew to initiate a descent to maximum flight level 100 in order to assure adequate pressure for continuous fuel feed to the respective engine (approx. 60NM earlier than planned). This has to be done by a cruise-level alteration in the current flight route via the

AHMI followed by a trajectory generation, negotiation and activation according to the normative re-planning procedure as described above. During descent, in the vicinity of waypoint ROLSO, the crew receives a shortcut uplink which clears the flight to proceed directly to waypoint CHA. The scenario foresees that the uplink contains the standard flight level for the current arrival segment which is flight level 110, 1000 feet higher than the previous clearance and off the operational envelope regarding the system malfunction. This is to be recognized by the pilots while checking the vertical profile of the uplink. The altitude should be corrected and then re-negotiated with ATC. If the incorrect altitude was engaged by the crew then the aircraft would re-climb to flight level 110.

The experiment flight trials for the first cycle of experiments have been performed in 2009, starting in August up to December. Fifteen airline pilots participated as responsible subject pilots (Pilot Flying, PF). The Pilot Non-Flying was a DLR pilot who acted according to scripted guidelines that were part of the experimental set-up. According to the schedule each subject pilot had to fly all eight scenarios in the same particular order. Each session lasted 2 days. Data recordings included flight parameters, pilot motor actions, gaze-data, video and audio recording. In the model-based experiments the cognitive pilot model flew each of the eight scenarios 12 times. Data recordings included flight parameters, model motor and percept actions. After each flight, the pilot performed a debriefing, with an experimenter and the Pilot-Non-Flying. The aim of the debriefing was to gather interesting data on things that happened at specific points during the flight (the so-called "points of analysis", specified prior to the flight for some of them, or produced during the flight or the debriefing itself, in reaction to interesting events). To standardize the debriefing procedure, a decision-tree has been built, to be used by the experimenter to conduct the debriefing session, and determine in the most objective way information such as if an error has occurred (at the point of analysis), if yes, of what type (e.g., error of omission) and what could be the underlying error production mechanism (e.g., learned carelessness). The debriefing also attempted to evaluate the pilot's goals at the points of analysis.

In parallel of the experiments on the physical simulation platform, experiments, on the very same experimental scenarios, were conducted on the virtual simulation platform, with the CASCaS cognitive model, and similar data were recorded.

Data analysis was then conducted, in order to produce requirements for improving CASCaS. Two main sources of data were used:

- Debriefing data, for the experiments on the physical platform. They were used to determine if errors on the physical platform (real pilots) occurred in the same conditions than on the virtual platform (virtual pilots), and if the error types and error production mechanisms corresponded.
- Data logged on the physical and virtual simulation platforms during the experiments. They were used to test a series of hypotheses (n = 13), related to pilot behavior (e.g., the distribution of pilot's gaze in the cockpit depends on the flight phase). The validity of the hypotheses was evaluated, on the physical and virtual simulation platform (i.e., if an hypothesis is true on the physical

platform, is it also true on the virtual platform), and then associated behaviours and performance were compared between the two platforms (e.g., distribution of gaze on various Areas Of Interest in the cockpit), in order to improve the cognitive model.

The result of data analysis allowed to produce a series of requirements for improving the cognitive model. They will be used to tune the model or implement new features, to be tested in cycle 2. Among the requirements obtained:

- The NAV (navigation) display should be included in the virtual pilot's scanning patterns. The experiments clearly show that real pilots also scan this display, aside the PFD and AHMI displays. This also applies to the cockpit windows (outside view).
- If a value can be found on two displays (e.g., PFD and NAV) the model should be able to decide which one to perceive, based on the associated effort.
- In the same line of thought, the general visual scanning of the cognitive model has to be improved, using the data obtained with the pilots during cycle 1 as a reference. For example, the areas of interest (AOI) attended by the virtual and real pilots at different flight levels or flight phases show too many differences.
- Task switching should be improved and better mimic human strategies (in some ways the model performs better than humans).
- The uplink procedure has to be implemented more realistically, notably in terms of task completion times.
- New error production mechanisms will have to be implemented in the model for cycle 2, including loss of information in working memory and working memory limitations, selective attention and possibly inadequate multi-tasking.

With regard to the Learned Carelessness hypothesis an in depth investigation of behavioral data of one pilot shows that this pilot started to omit the check of the vertical view (in line with the hypothesis), but after a while he began to perform this check again (not in line with the hypothesis). Surprisingly, though he consulted the instrument in question again, he did not recognize the incorrect altitude of the uplinked flight plan in scenario B. In order to explain this behavior the memory component of the cognitive architecture has to be improved to model (1) that Learned Carelessness may be neutralized by contextual information, (2) that the same instrument may provide several information, and (3) that carelessness may be learned selectively for a subset of this information only. The data analysis with regard to Learned Carelessness is still ongoing.

Beside the mere analysis of experimental data, whose aim is to improve the cognitive model, we also learned a series of lessons from the execution of cycle 1, which will help improving the experimental procedure for cycle 2:

- the experimental scenarios will have to be better tuned to the hypotheses we want to test, some hypotheses could not be tested in cycle 1 because the scenarios did not allow the production of relevant data;
- obviously, the scenarios will also have to address the new error production mechanisms to be investigated in cycle 2;

- the performance, and in particular reliability, of the eye tracking system will need to be improved, we have got too many datasets of poor quality for some pilots;
- in order to provoke Learned Carelessness the procedure has to be easy to learn: we will define a measure for the procedure complexity based on the number of associations needed to model the corresponding declarative knowledge.

Methodology for the Analysis of Human Error

One of the main endeavors of HUMAN, beside the development, testing and tuning of a pilot and crew model, is to make the tools and methodologies developed within the project, including the cognitive model, available to the industry. To do this, we have modeled with our industrial partners the system design process for cockpit systems such as the ones we believe our tools and methodologies could be useful to.

The process followed is similar in its successive steps to that indicated in the ARP 5056 Flight Crew Interface Considerations in the Flight Deck Design Process for Part 25 Aircraft. It however goes beyond ARP 5056, by paying *more explicitly* attention and effort to Man–Machine System (MMS) and Man–Machine Interactions (MMI) design. It also follows elements of ARP 4754 Certifications considerations for Highly Integrated or Complex Aircraft Systems.

It involves five main, possibly iterative, steps (Fig. 5).

We are presently (May 2010) in the process of determining where and how in those steps the main tools developed in HUMAN, such as the cognitive model, the virtual simulation platform, a procedure editor and an editor for scenarios can be used. One possibility is certainly to use the cognitive model and the virtual

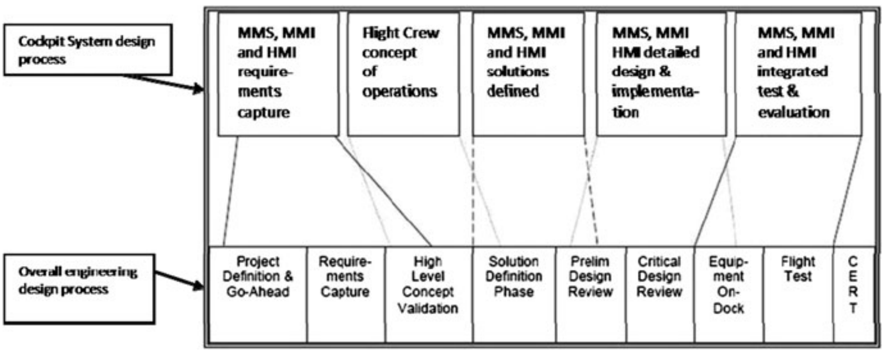

Fig. 5 Basic cockpit system design process shown in relation to overall engineering design process

simulation platform to support system development at a very early design stage. The trend in modern aviation is to rely more and more on models of all aircraft systems and structure, and basically, the only missing "system" is the Human element. We believe that a model such as CASCaS can play this role and therefore allow the complete virtual simulation of an aircraft and its crew. This should allow to test alternative cockpit system designs, including their Human Machine Interfaces (HMI) but also related aspects such as the operational procedures foreseen for the systems.

Further Developments

The developments and effort made during HUMAN on the cognitive model, the various tools and methodologies will be continued, notably in the framework of other projects. We envision addressing the following aspects:

- Improve the modeling of the memory component: the memory component currently used in CASCaS is too simple. It for example does not clearly make distinctions between short-term and long-term memory
- Better ground the model in contemporary neuroscience. Short-term and long-term memory declarative knowledge for example are stored in completely different brain structure, as is also the case for procedural knowledge
- Additional error production mechanisms and error types
- Modeling of aspects of cooperation between several agents working on the same task.

Summary

We have described the HUMAN project, an EC funded project whose main goal is to develop a cognitive model of a crew on a modern airliner, and then make it available to the industry, with a suite of associated tools. To develop the cognitive model, we are relying on a series of experiments, on a physical platform (with real pilots) and on a virtual platform (with virtual pilots, i.e., the cognitive model), where the goal is to compare real and virtual performances, in particular in the domain of error production. We believe that our tool will be of interest for the industry to perform early evaluation of system design alternatives (or other operational aspects), at a very preliminary stage of the design process.

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The ITERATE Project—Overview, Theoretical Framework and Validation

Magnus Hjälmdahl, David Shinar, Oliver Carsten and Björn Peters

Abstract
Background In recent years, a variety of driver support and information management systems have been designed and implemented with the objective of improving safety as well as the performance of vehicles. While the crucial issues at a technical level have been mostly solved their consequences on driver activity remains open and needs to be fully explained. Of particular importance are their effects on driver behaviour and strategies, and their impact on the operation and safety of the traffic system. The aim of ITERATE (IT for Error Remediation And Trapping Emergencies) is to develop and validate a unified model of driver behaviour to be used in various applications concerning driver interaction with innovative technologies in emergency situations.
Method This model will be applicable to and validated for all the surface transport modes (road, rail and water). A unified model of driver behaviour will be of great use when designing innovative technologies since it will allow for assessment and tuning of the systems in a safe and controllable environment. Such a model will be experimentally tested in large and small scale simulators and then validated for other modes transport and experimental platforms.

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Results The unified model of driver behaviour developed was used to design and set up a series of car and train driving experiments in five countries. However, experimental results are pending.
Conclusions At the concept stage, the model could guide designers in identifying potential problem areas whist at the prototype stage, the model could inform on the scenarios to be used in system evaluation. In this way the systems will be better adapted to the drivers before being available on the market and will provide better support to the driver in emergency situations. Along the same lines, the model could be of use for authorities as a guide in assessing and approving innovative technologies without performing extensive simulator experiments or large scale field trials.

Keywords Behavioural modeling · Simulator · Surface transportation · Maritime transportation · ITS · DAS · Support systems · Emergency situations

Overview of the Project

The ITERATE project started in January 2009 and will end in December 2011. The objective of ITERATE is to develop and validate a unified model of driver behaviour (UMD) in interaction with assistant systems applicable to and validated for the road, rail and water transport modes. Drivers' age, gender, experience, personality and culture (whether regional or company/organisational) are factors that are considered together with influences from the environment and the vehicle. Furthermore, driver state in terms of workload and fatigue will also be considered when developing and validating the UMD.

ITERATE is based on the assumption that the underlying factors influencing human behaviour such as age, gender, experience, life style, attitudes and culture etc. are constant among transport modes. This assumption allows for a unified model of driver behaviour, applicable to all surface transport modes, to be developed. This will be done within ITERATE and the model can be used to improve design and safety assessment of innovative technologies and make it possible to adapt these technologies to the abilities, needs, driving style and capacity of the individual driver.

The project consortium includes seven partners from five countries:

StatensvägochTransportforskningsinstitut (VTI) Sweden; University of Leeds (UNIVLEEDS) UK; University of Valenciennes (UNIVAL) France; Kite Solutions s.n.c.(Kite) Italy; Ben Gurion University (BGU) Israel; Chalmers University (Chalmers) Sweden; MTO Psykologi (MTOP) Sweden (since February 2010 MTO Säkerhet).

The ITERATE project consists of 9 work packages (WP) including Management (WP0) and Dissemination (WP8). The relationship among WPs 1 through 7 are shown the PERT (Program Evaluation and Review Technique) diagram (Fig. 1). WPs 1 and 2 have set the framework of the project in terms of model

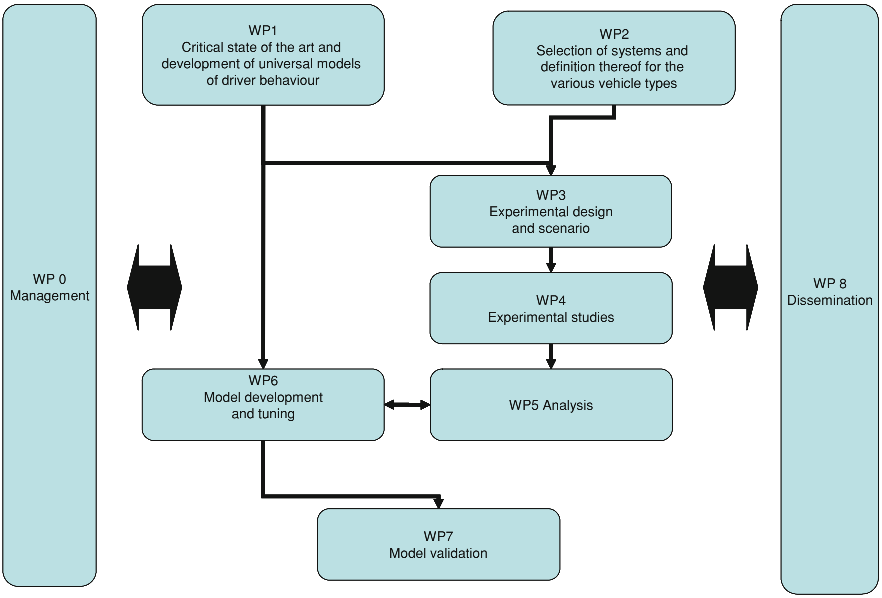

Fig. 1 Flowchart and relationship among the nine work packages

design and systems included in the study. Work packages 3, 4 and 5 are building on this framework to carry out the experiments needed. These experiments are being conducted in two standard road and rail driving simulators which are travelling among the partners, to allow data collection in the five countries represented in ITERATE. WP 6 is running in parallel, based on the theoretical models determined in WP1, to develop the software needed for the UMD evaluation. When the first set of experiments in WP4 have been completed, WP5 and WP6 will work together to feed the model with the parameters produced from the experiments. Finally, WP 7 will critically review the model and compare the simulated UMD with data obtained from real drivers of cars and trains and navigators of ships while operating their vehicles in a set of "driving" simulators.

The first three WPs have been completed and currently the main effort is devoted to experimental studies. WP1 included a critical review of existing models of driving behaviour and finally proposed a UMD to be tested in the further work (see below). Two public deliverables have been produced within WP1 [6, 7]. A review was also conducted in WP2 in order to identify driver support systems for critical situations: This was followed by a selection process aiming to determine feasible systems across modes of transport which could be used in the simulator experiments in WP4. Two deliverables were produced in WP2 [2, 5]. The objective of WP3 was to prepare for the experiments which included development of scenarios, selection criteria for participants, formulating hypothesis, and specifying dependent and independent variables for the experiments. This is all described in [3]. Furthermore, two identical and portable PC based simulators were built by LEEDS and

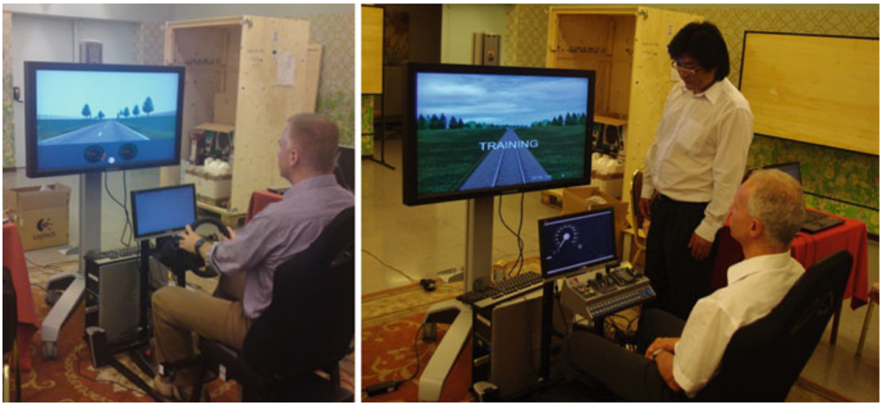

Fig. 2 The mobile car and train simulators developed in ITERATE

Table 1 The number of subjects planned for each experiment in ITERATE

	WP4 PC car Sim	WP4 PC train sim	WP4 Full scale car sim	WP4 Full scale train sim	WP7 Full scale car sim	WP7 Full scale train sim	WP7 Full mission bridge sim	Total
VTI	32	32		32	32			128
LEEDS	32	32	32					96
VAL	32	32				32		96
KITE	32	32						64
BGU	32	32						64
CHAM							20	20
Total	160	160	32	32	32	32	20	468

VTI. Substantial effort was spent to ensure that all hardware was identical. LEEDS developed a passenger car simulator software and VTI a train simulator (see Fig. 2). WP4 will deliver data to WP5 for analysis and WP6 will develop a mathematical model of the UMD based on the analysis in WP5 (see also [10]).

The two simulators will be circulated among the five partners in the five different countries. According to the plan 300 subjects will participate in the experiments with the PC based simulator (see Table 1). Currently, one is stationed in the UK and one in Italy where it was demonstrated during the HMAT (Human Modelling in Assisted Transportation) workshop in July 2010. A web-based questionnaire (SPSS Dimensions) was developed for the experiments and all data are collected at one site. A hazard perception test developed in Norway is used at all sites [8]. Furthermore, simulators can be remotely accessed for direct updates and support from the developers if needed.

ITERATE will not just make use of simple simulators. In addition to the PC-based simulators, the project will also use full-scale passenger car, train and ship simulators. Two full-scale simulators for road and rail will be used in WP4 and finally, the UMD will be validated in WP7 using full-scale simulators for road, rail and ship (see also [4]).

Towards a Unified Model of Driving Behaviour

The first work package in ITERATE (WP1) contains a critical review and synthesis of existing models of human behaviour for drivers of road vehicles, trains and ships. Based on this review a reference model of Driver–Vehicle–Environment was developed and described. The first step involved a critical review of Driver-Vehicle-Environment (DVE) models and identification of the most important parameters that are implemented in such models; in different surface transport modes and in different safety-critical situations. The next step was to develop a Unified Model of Driver behaviour (UMD) and to define key parameters for specific applications. The proposed UMD will be used to support the design and safety assessment of innovative technologies, and make it possible to adapt these technologies to the abilities, needs, driving styles, and capabilities of individual drivers. The following is a very brief description of the driver, vehicle, and environmental factors that were identified as critical in the literature review, and subsequently included in the model. For a more elaborated discussion see also [6, 7, 9].

Driver Factors

Culture—The rules of the road, the social environments (e.g. values, beliefs), and the norms of behaviour, represented by Country/Culture may vary significantly from country to country and can influence the attitudes and behaviours of drivers.

Attitudes/Personality—A complex mental state involving beliefs, feelings, values and dispositions to act in certain ways, represented in this study by Sensation Seeking—Some personality traits may have negative effects on driving performance, and some aspects of risky driving such as the effect of "sensation seeking".

Experience—A factor whose value changes over time but is fixed for a given trip, represented by various skills such as hazard perception that develop over time. These skills distinguish experienced drivers from novice drivers, and have been shown to correlate with crash risk with experience decreasing risk.

Driver state—A driver's physical and mental ability to drive, represented in our model by fatigue. To have greater control over the level of fatigue, and to reduce the costs of the experiments, within the ITERATE project we will use task-induced fatigue—that results from a monotonous task or time-on-task, further compounded by time of day—in the model validation studies. Monotony of the road environment has an adverse effect on driver performance, and fatigue caused by prolonged driving in a complex road had the greatest impact on driving behaviour.

Task demands—This is defined as a function of a number of factors. There is the roadway baseline requirement, the density of traffic on the roadway, the need to make a manoeuvre such as a lane change and the proximity to the navigation choice point also called Manoeuvre Proximity. In addition task demand can be imposed by in-vehicle systems and by perhaps inappropriate secondary tasks. In our study it will be measured by subjective workload. Workload (strain) and performance are important mediators between the driving task demands and traffic safety. Very high task demand creates the potential for driver overload and hence risk. It is also linked to fatigue. Very low workload can also be problematic because of monotony.

Other driver variables—Gender and Age.

Environmental Factors

A significant demand placed on the driver is to continuously adjust to the changing and often degraded environment. In our driver-centred model, the environmental parameters will consider driving behaviour and performance from the perspective of the driver's perception, attention and choice behaviour. The model will try to predict the effects of the environmental changes on errors, and reaction time. Particular attention will be paid to the effects of safety–critical situations that may require emergency actions such as obstacle avoidance or speed adjustments in response to unexpected situational demands. Factors identified in previous research that will be incorporated here include:

Roadway features—road type (e.g. number of lanes, lane width, shoulders, divided highway, and locality) and alignment; i.e., curvature.

Traffic—density (Vehicles per mile or km) and mix (Cars, motorcycles, Large/Heavy Goods Vehicles).

Visibility—Weather (rain, snow, fog), and light conditions

Vehicle Factors

Vehicle factors include acceleration and deceleration capability as well as vehicle handling and the potential for loss of control. These aspects are handled through a vehicle dynamics model.

In terms of the dependent variables, the theoretical model has the objective of predicting error propensity; i.e., the potential for slips, lapses, mistakes and violations, as they changes with time. Thus fatigue increases the probability of committing an error, as does high momentary task demand. Error propensity can be further broken down into the probability of slips and lapses, mistakes and violations. In the case of a warning system, the overall system is intended to reduce errors that might otherwise occur; i.e., reduce error propensity. But secondary errors can also arise in the interaction with a warning system. Drivers can miss a warning (lapse) because of fatigue or overload, and they can deliberately ignore warnings (violation). The experiment to test the model is focussing on how the interaction with assistance systems varies both between and within operators.

Testing and Validating the Model

A very large experiment, perhaps even the biggest common simulator experiment, in a European project, has been planned as a means of testing the ITERATE theoretical model, and, should the effects predicted by the model be confirmed, also as a means of providing parameter values to the software version of the model.

There has been a structured process to move from the theoretical model through the identification of systems with commonalities across the models, then through the creation of hypotheses and scenarios, to the definition of an experimental design (see [1]). The outcome of that process is an experiment across five countries (Sweden, the UK, France, Italy and Israel) and two modes (road and rail). The analyses will be carried out separately for the two modes, but the expectation is that the influence of the same factors will be confirmed for each mode.

In order to eliminate one source of variation, the experiment will be conducted with identical simulators. Two modest "travelling" simulators have been specified with the same hardware and software. Each can be set up with either a train or a car interface, and the switch from one interface to the other takes only a few minutes. One simulator will be used in three countries; the other in two.

The driver assistance systems being used in these experiments have been chosen because they have large commonalities in operation across the two modes. Because rail vehicles are only controlled longitudinally, and because intervening driver aids differ radically between the modes, it was decided to use warning systems affecting longitudinal control. For both rail and road, a speed warning system has been specified. For rail this is a version of the warning functionality of ERTMS. For car driving, it is a warning version of Intelligent Speed Adaptation (also sometimes called Speed Alert). The system used here warns about exceeding the speed limit, about driving too fast on the approach to a lower speed limit, and about driving too fast on the approach to sharp horizontal curves. The road environment is a two-lane rural road that passes through some villages. The rail system also warns about inappropriate speed, and the hypotheses being tested are, at a high level, identical across the two modes.

For car driving only, it is important to look at both major aspects of longitudinal control, i.e. speed and headway. Therefore the experiment also includes a stretch of motorway driving with an active Forward Collision Warning system. There is no counterpart to this system in rail, because headway is not directly controlled by the driver.

The planned number of participants is 32 car drivers and 32 train drivers in each of the five countries, i.e. 320 participants in total. The experimental design has the following main factors:

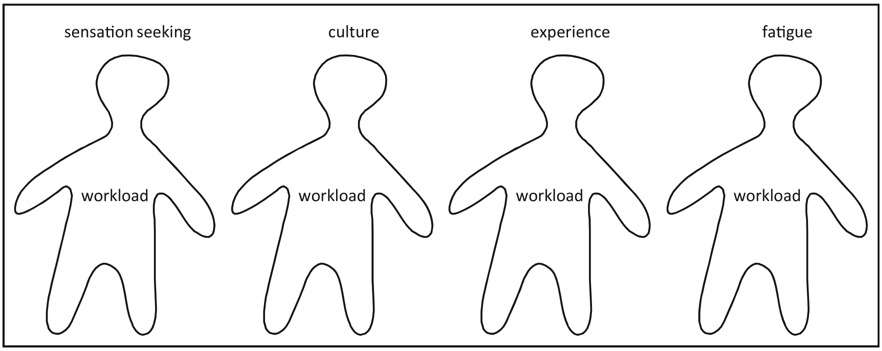

Fig. 3 Overall experimental design

- Culture, represented by the countries, with five levels
- Personality in terms of individual scores on a sensation-seeking questionnaire
- Experience, in terms of years holding a car driving or train operating licence with two levels for each mode. For car drivers, inexperienced is defined as holding a valid license for less than one year and experienced is defined as being licensed for more than five years and driving over 10,000 km a year (6,000 miles in the UK). For train drivers, inexperienced is defined as driving post-qualification for less than 2 years and experienced as driving for more than 4 years.
- Fatigue with two levels: the non-fatigued group attend the experiments in the morning after a normal night's sleep, while the fatigued group attend in the afternoon after lunch. The fatigued group is requested to refrain from consuming drinks containing caffeine with their lunch and are also subjected to observing a 30 min fully automated motorway drive.
- Task demand, with three levels of workload. The levels are manipulated by means of a serial subtraction task in which the participants have to count backwards in sevens (the most demanding level), in ones (the medium level) and not at all (the low level).

In addition, questionnaires are being collected on traffic culture and driver attitudes. The overall experimental design is illustrated in Fig. 3, where the within operator factor is shown inside the figures and between operator factors are shown outside. The experimental design allows the investigation of all the factors in the ITERATE theoretical model as well as, in theory, the statistical interactions among those factors.

A comparison of results between high-end and low-end simulators is also planned; at both VTI for rail and at Leeds for car driving, and 32 additional participants will undergo the experiment in a sophisticated simulator. This will allow an analysis of whether there is any "contamination" of any of the results from the lack of a motion system, the comparatively simple user interface, and the small field of view in the ITERATE travelling simulators. The major check will on the overall validity of the findings using the less sophisticated simulator rather than on the precise values in the data. If the general direction and size of the effects are confirmed, then the results can be considered "valid".

Software Model Validation

This initial set of experiments is intended to confirm the overall relationships that are proposed in the project's theoretical model, identify some important interactions among the factors and provide numerical values for the relationships that can then be applied in the software version of the model. That software model will be further validated in a second set of experiments where the outputs from a set of simulations using the model will be compared against a set of human-in-the-loop laboratory experiments. Those experiments will be conducted in three modes—car, train and marine—using high-end simulators. The plan is for 32 participants in each mode, but the scenarios for this set of experiments are yet to be defined.

Future and Expected Outcome

The final software version of the model is intended to be a first step in ITERATE's aim of predicting how both behavioural and cognitive factors interact with driver assistance systems. Once the proposed model is validated within the limited scope of ITERATE, further work and applications can assume a number of directions, some related to research and development and some related to application:

1. Further improvements on the model to provide a better fit between the independent driver, vehicle, and environmental variables studied and the performance outcome measures.
2. Expansion of the model to additional variables that were considered in the literature review but not included in the model and in the experimental validation process. This could include the effects of driver personality measures such as locus of control, type of license (regular versus professional license), and various medical conditions and temporary driver impairments such as alcohol and drugs. Environmental variables could include weather and road service level and vehicle variables could include vehicle type, field of view, etc.
3. Consideration of any mode-specific factors.
4. Evaluation of the relative benefits of different crash warning and crash avoidance technologies for implementation in vehicles and future standards.
5. Consideration of whether the model can be developed into a real-time supervisor and manager of driver interaction with the vehicle and the environment and with driver support systems.

Project deliverables can be downloaded from the ITERATE web site (http://www.iterate-project.eu).

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Part II
Human Models in Transportation

From Theoretical Model to Experimental Data: A Structured Approach to Design Experiments to Seed a Model of Vehicle Operation with New Systems

Yvonne Barnard, Oliver Carsten and Frank Lai

Abstract In this paper we will discuss a methodology developed and applied in the European ITERATE project with the objective of designing experiments that will provide data to seed the ITERATE theoretical model of operator behaviour in different surface transport modes: road vehicles, rail transport and ships. A structured approach was taken involving seven steps: (1) Selection of operator support systems to be studied; (2) formulation of hypotheses on the effects of the operator parameters from the model on the interaction with the systems; (3) final system selection; (4) operationalisation of operator parameters and identification of ways to measure them; (5) development of scenarios; (6) development of experimental set-ups; and (7) specification of simulators and experiments.

Keywords Automotive environment · Driver modelling · Field studies · Experiemtal design

Introduction

In this paper we describe the methodology developed and applied in the European ITERATE project (IT for Error Remediation and Trapping Emergencies). This methodology has as its objective to design experiments that will provide data to validate the ITERATE theoretical model of driver behaviour. The objective of

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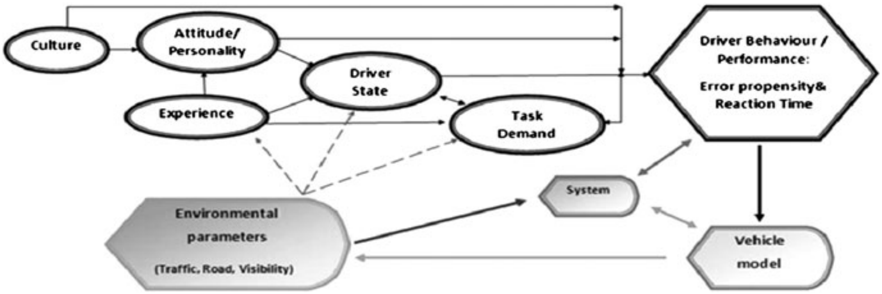

Fig. 1 The ITERATE unified model of driver behaviour

ITERATE is to develop and validate a unified model of driver behaviour (UMD) and driver interaction with innovative technologies in emergency situations. This model will be applicable to and validated for different surface transport modes: road vehicles, rail transport and ships. In all transport modes, new technologies supporting operators in their driving task are being developed and deployed. These systems have the potential to enhance safety. Examples are systems that control and limit the speed of a vehicle or that warn for obstacles, helping to avoid collisions. These driver assistance systems may, however, also cause new problems such as overreliance and increased risk taking.

Although different transport modes have different requirements on the kind of support that is needed and on the way in which it is provided, factors playing a role in how humans deal with support systems may show commonalities. For example, sleepiness is a dangerous condition that poses problems for car, train and ship operators, operator monitoring systems may provide support in all modes. However, some operators may over-rely on such a system, continuing driving while sleepy and relying on the system to warn them in time before they run into problems. Different human characteristics, such as personality and experience, may cause operators to behave differently.

To study the behaviour of operators of different transport modes, the ITERATE project has adopted the following three-stage approach:

1. Development of a high level theoretical model of driver behaviour (see Fig. 1), specifying the factors that play a role in potentially dangerous or risky behaviour of drivers in different environmental conditions;
2. Validation of the model by experiments and study of how the different factors interact;
3. Construction of an executable simulation model with which it is possible to predict the effects of support systems on driver behaviour. Such a model could guide designers and evaluators of new systems.

This model shows driver-related parameters that influence directly or indirectly driver behaviour and the probability to encounter a dangerous situation, in other words to augment or diminish the propensity to make errors and/or the operator's reaction time. The behaviour is further influenced by the environment, driver assistance systems, and the vehicle operated. The driver parameters considered in this model are culture, attitude and personality, experience, the driver state (such as fatigue) and the demand of the task. These parameters may interact with each other. To study these relations, experiments needed to be designed in which 384 car and train drivers in five countries drive with a driving simulator. In a later phase of the project also ship navigators will be studied.

Structured Design Approach

A major challenge we faced was how to determine what experiments would provide scientifically sound information needed to feed the simulation of the ITERATE model in the next stage, and are at the same time feasible from a practical point of view. A scientific approach is based on the testing of hypotheses, but designing and especially selecting hypotheses is a difficult task. The number of possible hypotheses may easily become very large. Designing experiments to test hypotheses poses similar problems; many different experimental scenarios may be used.

Design processes may be seen as problem solving in an open space. Where problem solving in closed domains, such as mathematics, leads to a unique and correct solution, in open domains many correct solutions can be generated, and it is hard to determine which solutions are the best. This is the case for design of all kinds of products, both physical products, such as buildings and cars, and more abstract products, such as training courses and software specifications.

For some products it is possible to test whether they function correctly, for example software, but other products can only be tested after they have been used by users, for example looking at the exam results of the trainees who took the designed course. Design can be evaluated against the specifications for the product. Designing experiments is in principle not different from other design processes. The specifications for the ITERATE experiments state that they should test the variables in the theoretical model, and that they should provide useful input for the simulation model. However, many different experiments will meet these criteria. And whether the outcomes of the experiments will provide sufficient and useful knowledge to feed the simulation model can only be judged after the experiments have been performed. There is another similarity with most design processes: time and resources are limited. Deciding which hypotheses and experiments to pursue and which ones to leave aside is a crucial step in the procedure. Ideally one would like to perform some experiments and subsequently iterate the whole process if the outcomes are not satisfactory. However, this is not possible within the means of the project.

The solution that is widely adopted in design processes is to use a structured approach. Goel and Pirolli [1] defined generic features of design tasks such as the need for problem structuring, distinct phases in the problem solving process, the use of problem decomposition and incremental design, the application of a limited commitment mode control strategy and the combination of top-down and bottom-up strategies. So a structured approach may be characterised by a decomposition of the design process into well-defined and distinct steps, where at the end of each step choices are narrowed down and justifications provided for the decisions made.

Verstegen et al. [2] developed a structured approach for designing complex instructional products (such as simulators). For the ITERATE design process, these principles were applied as follows:

1. Design was done in a systematic way.
2. Design was based on the theoretical model, keeping the simulation model in mind.
3. Design was an iterative process, but iteration was mainly to be limited to iteration within each step, due to constraints in time and budget.
4. Assumptions were made explicit, and justifications provided for all decisions.
5. Every step and choice was documented in both internal documents and in public deliverables.
6. Work was performed in interaction with all relevant partners using workshops as well as e-mail, phone and web-based discussions to reach consensus.

Using these principles, we developed a structured approach, partly based on the FESTA methodology for designing tests for performing field operational tests, aimed at testing the effects of in-vehicle systems [3, 4]. In this methodology, the design of tests starts with determining which functions of in-vehicle systems should be evaluated. Research questions are defined as well as hypotheses. These form the basis for developing the tests and determining the performance indicators. The final stage involves defining how these indicators can be measured and what sensors to use for measurement. After all these specifications, the real test can start. The ITERATE structured approach follows these steps in its general aspects.

The ITERATE Methodology

The ITERATE methodology consisted of seven steps (for more detailed descriptions, see ITERATE [5–8]).

Step 1: Selection of Systems to be Studied

A review of existing technologies supporting car drivers, vessel pilots and drivers of trains, trams and subways was carried out, using a standardised description. The template described the level of the operation task the system supports (strategic, manoeuvre, control), the level of automation (information, advice, assistance, intervention, automation), the time frame to an event that would occur between detection by the system and an action by either operator or system, and the time for the operator to make a decision when alerted by the system. In total 21 systems were reviewed. The standardised description made it easy to identify commonalities and differences between the technologically very different systems.

Step 2: Formulation of Hypotheses

Hypotheses were formulated on the effects of the operator parameters by applying the theoretical model on user interaction with the systems. For each system and for each parameter, several hypotheses were formulated, in total more than 200. We used a standardised description:

- *Input*: one of the model parameters selected (for example, experience);
- *Pathway*: describing the mechanism by which the input influences the outcome (for example, sensation seekers have a higher tolerance for risk and thus ignore warnings);
- *Effect on operator's interaction with the system*: describing what the operator would do when interacting with the system (for example, a sensation seeker would respond later to a warning);
- *Effect on the system functionality*: describing how the system would behave given the operator's behaviour (for example, if more warnings are ignored, the system would intervene);
- *Risk potential*: describing whether it is hypothesised that the risk for safety would increase or decrease;
- *Example scenario*: describing a typical situation in which the operator would behave in the hypothesised way and the system as expected.
- Next we examined the commonalities between the hypotheses for the proposed systems and formulated 10 general hypotheses addressing a common effect for operators of all three modes. An example hypothesis: "Operators will receive more warnings when fatigued than when alert."

Step 3: Final System Selection

Based on commonalities between the systems and hypotheses identified in step 2, a final selection was made of six systems, three systems with a collision avoidance function and three systems with a speed management function.

Step 4: Operationalisation of Operator Parameters and Identification of Ways to Measure Them

For the five operator parameters (sensation seeking, fatigue, experience, workload and culture), an inventory was made on how to define and to measure these.

The different measurement methods, such as questionnaires, tests, and psycho-physiological measures, were summarised and advantages and disadvantages were discussed.

Step 5: Development of Scenarios for the Selected Hypotheses

For all car and train hypotheses, scenarios were developed that could be used in a first set of experiments (ships will be addressed later, in the second set). In total, 71 scenarios were developed. The template for scenario description contains the following elements:

- Situation in which the system would be active (e.g. change in speed limit);
- *The characteristics and state of the participants* (the operators) (e.g. experienced drivers, or drivers with high workload induced by means of a secondary task);
- *The trigger*: the event that would trigger an action from the system (e.g. a speed limit sign);
- *The expected reaction from the operator to the trigger and to the system's warning* (e.g. the driver does not pay attention to the sign and only reduces speed after the warning);
- *Environmental conditions*, such as traffic, weather and light conditions, and type of road or track (e.g. low traffic density, night time, rural road);
- *Measures to be taken before, during and after the experiment*, to determine the effect of the scenario or to establish the level of one of the parameters. The measures may be driving related, measured automatically by the simulator, measured by the experimenter, or the participant may give a subjective opinion (e.g. number of warnings received, amount of deceleration, reaction time, questionnaire on sensation seeking, subjective workload rating on a scale).

Step 6: Development of Experimental Set-Ups

The 71 scenarios were analysed and reviewed for common features. Scenarios sharing the same types of road or track and/or environment were identified. Furthermore, scenarios that are familiar for all countries and that do not require too many resources for implementation were selected. They formed the basis for developing an experimental set-up in which several scenarios could play sequentially, addressing most of the ten general hypotheses defined in step 2.

In the experiments 192 train drivers and 192 car drivers will drive for some 90 min along a road or track, encountering different scenarios in which they have to change their speed (to test driving with a speed management system) and to act to avoid a collision (to test driving with a collision avoidance system). The group of participants will be split up in experienced and inexperienced operators. Half of the participants will be somewhat fatigued before starting the experimental drive. All participants will drive under conditions of medium, high and low workload. Culture will be studied by looking at differences in results from the experiments in the five different countries. Sensation seekers will be identified by means of a questionnaire. In this way we are able to investigate the influence of the different operator parameters as well as the interactions between them.

Step 7: Specification of Simulators and Experiments

The experimental set-up formed the basis of a detailed specification of the experiments and the simulations. The hardware of the portable simulators will consist of a workstation with a powerful graphics card. A 40 inch wide-screen 1920×1080 monitor to display the main driver view, a 15 inch wide-screen 1366×768 monitor to display the instrumentation for the dashboard or train cabin, including the support systems, a steering wheel and pedals for the car and controls for the train, and a seat. In addition, the full motion car simulator of the University of Leeds and the train simulator of VTI will be used. The experimental roads and tracks to be implemented in the simulators were specified in detail. The details of the experiments were specified as well as the questionnaires to be administered.

Conclusions

A systematic design process to proceed from the initial operator model to a detailed specification of the experiments was performed step-by-step. There were several iterations of some of the steps, and the results of each step were discussed until a consensus was reached. Many of the steps were first initiated at a workshop in which all partners of the ITERATE project participated, during which we regularly worked in small groups. Between workshops and consortium meetings, discussion took place by email, telephone and on-line conferences. Developing hypotheses and scenarios is a creative process, which cannot be undertaken by a single individual in isolation; discussing, critiquing and iterating are essential parts of such a process. The structured approach was valued by the consortium partners as a fruitful one and boosted the collaboration and exchange of ideas. This was especially of importance because the partners come from different disciplines and study different transport modes. Although some system descriptions, hypotheses and scenarios were developed that will not be used in the first set of experiments, we do not regard them as a loss of effort. They will potentially be used for the next set of experiments aiming to validate the simulation of the model to be developed, and they will also be useful for further research in this area.

We are confident that with these experiments we will be able to provide new insights into the behaviour of operators driving with support systems. We have had extensive discussion of alternative experimental designs and investigated many options on what variables to include in the experiments and how to study these variables. A major decision was to include all the five parameters that influence driving behaviour according to the model: personality/attitude, experience, driver state, task demand, and culture. In all five countries precisely the same experimental procedures will be followed. This means that we will have sufficient numbers of participants for each set of parameters, and that we will be able to investigate differences between countries as well. What is even more important is that we succeeded to design experiments in which the interactions between parameters can be studied. As a literature study showed (see ITERATE [5]), most previous research has been focussed on the behaviour of operators driving with support systems with respect to a single variable. For example, insights exist on how fatigue influences driver behaviour, but less is known about the differences in behaviour between experienced and novice drivers who are fatigued and who drive with a speed warning system.

Not only does the interaction between model parameters provide a new research focus, but also the differences and commonalities between the different transport modes form an area about which little is known. The experiments have been designed with the aim of ensuring comparability between the train and the car experiments on issues such as experimental set-up, the systems and the support they bring, the events that will happen, and the characteristics and experimental manipulation of the participants. The experiments are not completely identical, and nor can they be due to task and environmental differences and differences in the driver populations. We do expect that the train drivers will exhibit a lesser degree of sensation seeking and that it will be hard to recruit a sufficient number of female train drivers. However, both types of driver will drive with a speed management and a collision avoidance system, they will encounter situations in which they have to adapt their speed or stop the vehicle, and they will get warnings from the systems if they do not do so in time. The way in which their fatigue and workload is to be manipulated in the experiments is exactly the same. Knowledge about the differences and commonalities between the behaviour of train and car drivers will give valuable insight into how task and driver characteristics affect the interaction with systems.

Future Work

The next step in the ITERATE project is performing the actual experiments in the car and train simulators in five countries: France, Israel, Italy, Sweden and the UK. The data from the experiments will be analysed and transferred to the work package in which the simulation model will be developed. The theoretical architecture of the unified model of driver behaviour will be implemented in a numerical simulation and software platform tool. The results from the experiments will be used for the tuning (calibration) of the model. Finally, the software tool will be adapted for exploitation in design processes and safety studies. Furthermore, an additional set of validation experiments will be performed, where the ship domain will also be investigated, leading to further adaptation of the model.

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Learning Optimal Control Strategies from Interactions with a PADAS

Fabio Tango, Raghav Aras and Olivier Pietquin

Abstract This paper addresses the problem to find an optimal warning and intervention strategy for a partially autonomous driver's assistance system. Here, an optimal strategy is regarded as the one minimizing the risk of collision with an obstacle ahead, while keeping the number of warnings and interventions as low as possible, in order to support the driver and avoid distraction or annoyance. A novel approach to this problem is proposed, based on the solution of a sequential decision making problem.

Keywords Automotive environment · Optimal warning and intervention strategy · Partially Autonomous Driver Assistance System · Markovian Decision Processes

Introduction

The FP7 EU project ISi-PADAS (*Integrated Human Modelling and Simulation to support Human Error Risk Analysis of Partially Autonomous Driver Assistance Systems*) aims at conceiving an intelligent system called PADAS (Partially Autonomous Driver Assistance System) in order to aid human users to drive safely, by providing them with pertinent and accurate information in real time about the external situation and by acting as a co-pilot in emergency conditions. The system interacts with the driver through a Human-Machine Interface (HMI)

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installed on the vehicle using an adequate Warning and Intervention Strategy (WIS). Such a system constitutes an innovation in the field of PADAS, since it intervenes continuously from warning up to automatic braking in the whole longitudinal control of the vehicle [1]. This paper addresses the problem of finding an optimal WIS for a PADAS. The strategy is a set of decision rules that determine, as a function of the vehicle's situation, the sequence in which signals are sent and the sequence in which the vehicle is decelerated. The MDP model has been a cornerstone of much research in Operations Research and in Machine Learning (specifically, Reinforcement Learning) since the past five decades and more [2]. Efficient algorithms (based on dynamic programming and linear programming) for problems of sequential decision making under uncertainty, such as the one we confront in this paper, modelled as MDPs, have been conceived [3, 4].

Description of PADAS Concept

In this context of ISI-PADAS project, a specific *Partially Autonomous Driver Assistance System* (PADAS in short) has been developed and implemented in the simulator, including the interfaces between the driver and the system (tactile, visual and acoustic) in order to provide the right information in the right way at the right time. This includes both the intervention of the assistance system and the warnings to the drivers.

In the project, an analysis of the in-depth accident study has been conducted to derive hypotheses about causes of driver's errors responsible for rear-end crashes [5]. For this aim, the dataset comprising 4256 accidents from Braunschweig 2002 has been used [6]. Additionally, a sample from the German National Accident Database (Statistisches Bundesamt) from 2002 was used including 185004 accidents [7]. All rear-end crashes take part for 73.3% of analysed accidents and in particular 22.81% of the severe accidents (with major damage of more than 6000 Euro, injuries or fatalities). Following a vehicle too closely represents the most important cause of accident in 85, 61% of all the cases analyzed. Moreover 75, 98% of the rear-end crashes occur in undisturbed/flow traffic (where the expectation of an event is probably low).

In this context, many studies have shown the benefits of FCW in reducing the number and severity of front-to-back collisions or shunts [8] and of ACC in conditions where drivers have to cope with car following tasks in limited traffic flows or heavy–but not congested–traffic (see http://www.prevent-ip.org for several field test performed by Dutch Ministry of Transport or see [9]).

Therefore, the project has developed a target system, which is focused on the assistance to the user in longitudinal driving task and it is thereby called *Longitudinal Support System* (or LOSS, in short). In particular, it can prevent a collision with a leading vehicle by providing warnings to the driver, up to bringing the vehicle to a halt independently of driver's action, through the support for an assisted braking action. The system has two mechanisms at its disposal in order to realize this collision-avoidance capability: (1) it can provide warning signals to the

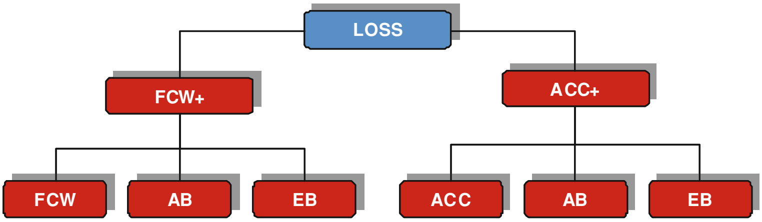

Fig. 1 Functional architecture of the LOSS application, showing the two modalities and the constituting functions

driver and (2) it can decelerate the vehicle. The Fig. 1 illustrates the functional scheme of PADAS application:

Two types (or modes) of LOSS have been considered: the Advanced Forward Collision Warning (FCW+, in short) and the Advanced Adaptive Cruise Control (ACC+, in short) which are both constituted by 3 functions:

- Forward Collision Warning (FCW) or Adaptive Cruise Control (ACC)
- Assisted Braking (AB)
- Emergency Braking (EB)

FCW is the "traditional" FCW system, if the driver travels too close (too short headway) or too fast with respect to the vehicle ahead on the same trajectory of the host-vehicle. Alternatively, the first function can be the "traditional" ACC, in which not only the speed is kept at the specific value, but also the distance is kept within pre-defined threshold of headway. The AB function provides the proper assistance to the driver: if the driver acts on the brake pedal, thus indicating the will to brake, then the system is able to modulate the braking action automatically. Finally, if the driver ignored warning and AB did not intervene (i.e. driver did not apply on the brakes) EB acts in order to avoid accidents or minimising the effects in case this is not avoidable anymore.

The MDP Model

A problem model as an MDP contemplates a decision maker who must take a decision in each of T decision epochs or *periods*. T may be finite or it may be infinite. In each period, the problem occupies one of N possible states and the decision maker chooses one of K alternatives or actions available to him. The probability that the problem occupies a given state in a period is only conditional on the state occupied by the process in the previous period and the action chosen by the decision maker in the previous period. This property is called the *Markov property*.

In any period t, if the problem occupies the ith state, $1 \leq i \leq N$ and the decision maker chooses the kth action, $1 \leq k \leq K$ the probability that the problem occupies the *j*th state, $1 \leq j \leq N$ in period $t + 1$ is denoted P_{ij}^{k}. The sequence of states s_1, s_2, s_3,…, s_t occupied by the problem till any period t forms a Markov chain. To control this Markov chain, we impose *costs*. That is, the decision maker incurs a cost in every period which is a function of the state occupied by the problem in that period and the alternative chosen by him in that period. In any period t, the cost incurred by the decision maker if the process occupies the *i*th state, $1 \leq i \leq N$ and the decision maker chooses the *k*th alternative is denoted C_{ik}.

Optimality Criteria

The number of periods T is called the *horizon* of the problem. If it is finite, the problem is said to be with a *finite horizon*, and the objective of the decision maker is to minimize the expected sum of costs $E\left\{\sum_{t=1}^{t=T} c_t\right\}$ incurred over T periods. Problems which terminate in a fixed number of steps can be modelled as finite horizon problems. Many practical problems of sequential decision making however either do not terminate in a fixed number of steps or do not terminate at all (machine maintenance problems are a typical example). For such problems, when modelled as MDPs, no assumption is made about the horizon T. Consequently, T is considered to be infinite, and the problem is said to be with an infinite horizon. The objective of the decision maker is to minimize the expected sum of *discounted* costs over the infinite horizon $E\left\{\sum_{t=1}^{t=T} \beta^t c_t\right\}$where $\beta \in (0, 1)$. The discount fact signifies that the decision maker, when making a decision, places more importance on immediate decisions than later decisions.

The problem of collision avoidance does not have a fixed duration, and hence it must be treated as an infinite horizon problem.

Optimal Strategy

For infinite horizon MDPs a *policy*, also called a *strategy*, describes the manner in which the decision maker takes decisions in each period. Formally, a strategy is a function p which assigns each state $i = 1,..., N$ and an action $p(i)$, $1 \leq p(i) \leq K$. In following p, the decision maker chooses the $p(i)$th action if the problem is in the ith state *in any period* (i.e., the strategy is independent of the period). An *optimal* strategy is one which achieves the optimality criterion, that is, one which has the smallest expected sum of discounted costs.

For every MDP there exists an N-vector (V_1, V_2,…, V_N) of reals such that for $i = 1, 2, \ldots, N$, the following equation is satisfied,

$$V_i = \min_{k=1}^{k=K}\left(C_{ik} + \beta \sum_{j=1}^{j=N} P_{ij}^{k} V_j\right) \tag{1}$$

The number represents the expected sum of discounted costs incurred by the decision maker over the infinite horizon if the problem starts in the ith state. This set of equations is called the set of *Bellman's equations*. This vector can be determined through dynamic programming (examples of algorithms include *value iteration* and *policy iteration*) or through linear programming. An optimal policy p^* can be then derived from the vector (V_1, V_2,..., V_N) as follows: for $i = 1, 2, \ldots, N$,

$$p_i^* = \arg\min_{k=1}^{k=K}\left(C_{ik} + \beta\sum_{j=1}^{j=N} P_{ij}^k V_j\right) \tag{2}$$

The following Section describe the collision avoidance problem as an MDP.

The Collision Avoidance Problem MDP

The collision avoidance problem consists of devising a method of using the system's resources (capability to send warning signals to the driver and to decelerate the vehicle) such that the probability of a collision is minimized. A set of audio-visual-haptic signals constitutes the set of warning signals available to the system. The capability of decelerate the vehicle is manifest in the following manner: at any time t, the system can choose a number $b \in [0, 1]$ and apply braking pressure equal to b times the maximum braking pressure of the vehicle.

We consider that at any time t, a collision of the host vehicle with the leading vehicle occurs if the *time to collision* at time t drops below ε. The time to collision at time t is defined as the ratio $d_t/(v_t - v_t')$ where v_t and v_t' are respectively the velocities of the two vehicles at time t and d_t is the distance between them at time t.

Let x denote a small duration. Let θ_t denote the time to collision at time t. In the absence of a PADAS (i.e., when the system does not send any signals or decelerate the vehicle), we assume that the probability that the time to collision θ_{t+x} at time $t + x$ assumes a given value θ' is dependent on the value θ of the time to collision θ_t at time t,

$$\text{prob.}(\theta_{t+x} = \theta') = \text{prob.}(\theta_{t+x} = \theta' | \theta_t = \theta)$$

However, we assume that the value of θ_t is the only quantity on which it is conditional. In other words, we assume that it is independent of the time to collision at times $t-x$, $t-2x$, $t-3x$, etc. as well as of any other factors. That is,

$$\begin{aligned}&\text{prob.}(\theta_{t+x} = \theta' | \theta_t = \theta) = \\ &\text{prob.}(\theta_{t+x} = \theta' | \theta_t = \theta, \theta_{t-x}, = w_{t-x},\ \theta_{t-2x}, = w_{t-2x}, , \ldots, \theta_1 = w_1)\end{aligned}$$

On the other hand, in the presence of PADAS, we assume that the probability that the time to collision θ_{t+x} at time $t + x$ assumes a given value θ' is dependent not only on the value θ of the time to collision θ_t at time t but also on the signal sent h_t by the system at time t and the fractional brake pressure b_t applied by the system at time t,

$$\text{prob.}(\theta_{t+x} = \theta') = \text{prob.}(\theta_{t+x} = \theta' | \theta_t = \theta,\ h_t = h,\ b_t = b) \tag{3}$$

Again, we assume that this probability is independent of the past history of time to collisions, signals sent and decelerations of the vehicle.

So, if we follow the evolution of the vehicle in the presence of PADAS (operating with a certain strategy), with a view to monitor the collision of the vehicle, we can use the time to collision as a variable of interest, and we obtain a sequence consisting of the time to collision, the signals sent by the system and the decelerations caused by the system: (θ_1, h_1, b_1, θ_2, h_2, b_2, …, θ_T, h_T, b_T,). This sequence in fact defines a Markov chain because of the assumption behind Eq. 3.

We can thereby model the collision avoidance problem in the presence of PADAS as an MDP. The MDP unfolds over discrete time steps each of duration 300 ms.

A state in this MDP is a time to collision. The minimum value of the time to collision is 0 s and the maximum value can be considered to be 50 s (as far as collision avoidance is concerned, any value above 50 s can be considered equivalent to 50 s). So, a state in the MDP is a number in the interval [0, 50]. This is an infinite set, and in order to render it finite, we exhaust the interval into disjoint partitions of unequal sizes. As an example: [0, 0.5), [0.5, 1), [1, 1.5), [1.5, 2), [2, 3), [3, 5 s), [5, 7), [7, 10), [10, 15), [15, 50]. These partitions represent the states of the (finite) MDP. The portioning just described gives 10 states. So, if the time to collision is say 0.73 s, the MDP is in the 2nd state, if it is 2.15 s, the MDP is in 5th state and so on.

An action in this MDP is a pair consisting of a signal and a fraction of the maximum braking pressure representing intended deceleration. The signal comes from a finite set. The deceleration is from the interval [0, 1]. The set of actions is therefore also an infinite set. In order to render the set of actions finite, we consider only a subset of points from the interval [0, 1]. To be precise, we consider the set {0, 0.05, 0.1 ,…, 0.85, 0.9, 0.95, 1}.

As for control costs, we impose costs for three features: a cost for the time to collision (the higher the time to collision the lower the cost; we impose negative costs on very high time to collisions), a cost for braking (again, the larger the braking, the larger is the cost) and finally a cost for sending signal (with each signal is associated a level of urgency; the more urgent the signal, the larger is the cost). So, a state-action pair in this MDP incurs a combined cost depending on the state (i.e., the time to collision) and the action (i.e., the signal sent and the braking applied).

A strategy for this MDP is a function that maps each time to collision partition to a pair of the type (h, b).

Computing the Optimal Strategy

As described in Description of PADAS Concept, an optimal strategy can be obtained by applying Eq. 2, which in turn requires the computation of the discounted-cost vector (V_1, V_2, …, V_N) by solving the set of equations (1). These equations can be solved using dynamic programming. The particular algorithm is called *value iteration* [1]. In order to employ this algorithm, we need to know the state transition probabilities P of the MDP. To be precise, we want to answer the following question for each pair of partitions i, j and for each possible action *(h, b)*: if the time to collision at time t falls in the ith partition and the system takes the action *(h, b)*, what is the probability that at time $t + 300$ ms, the time to collision will fall in the jth partition?

The answer to this question will depend on the human driver who's driving the car since he is part of the environment, whether the time to collision falls or rises or stays the same upon receiving a signal and a possible deceleration depends in part on him. Now, since one human driver may not react in the same manner as another, we have to consider an "average" human driver. The behaviour of an average human driver is understood from data collected during simulation trials.

The simulation trials data is organized in the form of a set of *episodes*. Each episode is sequence of state action pairs of the MDP model of the collision avoidance problem described in the last section. Thus, by running through all the episodes, the probabilityP_{ij}^k can be determined as $P_{ij}^k = B_{ij}^k / \sum_{j'=1}^{N} B_{ij'}^k$ where B_{ij}^k is the number of times the transition (i, k, j) was observed in the data. If $\sum_{j'=1}^{N} B_{ij'}^k$ equals 0, the probability is defined as $1/N$.

The value iteration algorithm is as follows: 1) Initialize each element of a vector (V_1, V_2, …, V_N) to 0; 2) Initialize each element of a vector (B_1, B_2, …, B_N) to 0; 3) compute $V_i \leftarrow \min_{k=1}^{k=K} \left(C_{ik} + \beta \sum_{j=1}^{j=N} P_{ij}^k B_j \right)$ for $i = 1, 2 ,.. ,N$; 4) $B_i \leftarrow V_i$ for $i = 1, 2, .., N$.

If $|V_i - B_i| \geq 0.001$ for even a single i, go to step 3, otherwise stop.

Data Analysis and Results

The experiments were divided into three phases: data collection, optimal strategy construction and testing. In the data collection phase, a car simulator was equipped with a PADAS that used a preliminary MDP strategy *p0* and about trials of about 600 min involving different human drivers driving the simulator were conducted. The data collection phase was required to understand human driver behaviour or reaction with reference to PADAS, that is, to determine the probability P_{ij}^k for each pair of states i, j) and each action k of the MDP. *p0* was a stochastic strategy. It has been tried out different actions in a state according to a probability distribution.

In the second construction phase, an optimal strategy was obtained through value iteration. Data collected was used to create the probability matrices P^1, P^2, …, P^K which are needed in value iteration. In fact, two optimal strategies were constructed based on two different partitions of the set of possible time to collisions. We refer to the two policies as $p1$ and $p2$. For the sake of demonstration, we describe $p1$ below:

TTC interval	Action to take
[0, 0.5)	Send emergency signal, apply maximum brake
[0.5, 0.5)	Send danger signal, apply 80% brake
[1, 2)	Send danger signal, apply 40% brake
[2, 3)	Send danger signal, apply 20% brake
[3, 10)	Send collision warning signal, don't apply any brake
[10, 50]	Send normal signal, don't apply any brake

In the testing phase, $p1$, $p2$ and a *hand-coded* strategy which we shall call $p3$ were tested by using each of them in turn as the PADAS strategy in simulation trials involving different human drivers. Note that the hand-coded policy was based just on common sense

Two variables were monitored: the time to collision and the distance between the vehicles. A collision was said to have occurred if the time to collision dropped to less than 1.5 s or if the distance dropped to less than 1 meter. The following table gives the result of the three policies. The following table lists the percentage of samples in which a collision occurred according to the two definitions given above. These results show that the strategies derived using the MDP approach render the driving experience safer by reducing the number of collisions and near collisions.

Policy	Time to collision (%)	Distance (%)
$p1$	2.1	1.5
$p2$	1.5	2.4
$p3$	3.8	4.3

Discussions and Conclusions

This paper has presented the approach followed by ISI-PADAS project, for the design and optimization of the warning and intervention strategies of the PADAS, called LOSS, modeling the problem as a Markovian Decision Process. We used data collected from simulation trials to learn the unknown parts of this MDP (i.e., the state transition probabilities). We then solved the MDP using value iteration, and obtained an optimal strategy. Our approach can be said to be a sort of *model-based reinforcement learning* [10, 11].

Preliminary results indicate that there is some real benefit in adopting this approach: the percentage of collisions or near collisions drops down by a non-negligible amount. The other advantage of our approach is that the optimal strategy is constructed directly from the data; no hypothesis is made about driver behaviour. Indeed, we can say that the MDP approach provides us the right framework to allow us, as a by-product, to construct a driver behaviour model embodied in the state transition probabilities of the MDP.

Our work opens up interesting possibilities for conceiving intelligent systems for vehicles. The entire range of algorithms for solving MDPs, including those from the domain of reinforcement learning such as LSPI [12] can be directed to constructing sequential decision making strategies for intelligent systems that are based entirely on observed data, and not on complex hypothesis.

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Selecting Human Error Types for Cognitive Modelling and Simulation

Tina Mioch, Jan-Patrick Osterloh and Denis Javaux

Abstract This paper presents a method that has enabled us to make a selection of error types and error production mechanisms relevant to the HUMAN European project, and discusses the reasons underlying those choices. We claim that this method has the advantage that it is very exhaustive in determining the relevant error types and error production mechanisms, and that the final objects are selected according to explicit requirements, without missing relevant error types and error production mechanisms.

Keywords Human error · Error types · Error production mechanism · Cognitive modelling

Introduction

It is a well known fact that human errors are the main contributing factor in aviation incidents and accidents (according to a Boeing study in 2004, human errors are involved in 62% of the accidents [1]). The main objective of the European project HUMAN is to build a methodology for human error prediction that is applicable in early phases of the design of a new system. The method foresees to simulate the interaction with the system by means of a dynamic

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cognitive model. By having a model of the crew, human behaviour is predicted, including specific types of errors considered as relevant by the manufacturers, cf. [5]. To achieve this objective, we rely on two functionally equivalent simulation platforms, a physical simulation platform, comprising a full scale simulator usable for human-in-the-loop experimental simulations, and a virtual simulation platform. The virtual simulation platform will be used to produce predicted crew activities (with a special focus on human errors) on a series of dedicated experimental flight scenarios also used on the physical platform. The behaviour of the pilots in the experiments on the physical simulation platform is then compared with the behaviour of the cognitive model on the virtual simulation platform, to validate and improve the cognitive model.

A major input for the development of the cognitive model is the selection of the errors on which the HUMAN project will focus. The cognitive model should be able to predict errors that can occur during interaction with a target system, which in HUMAN is a cockpit system known as the Advanced Flight Management System (AFMS), which user interface is the Advanced Human Machine Interface (AHMI). We also need to determine the cognitive mechanisms that cause the selected error types. In this paper, we therefore differentiate between the concepts of error type (ET) and error production mechanism (EPM). ETs are the observable behaviour (phenotypes), while EPMs are the mechanisms by which error types occur (genotypes). This paper will describe the process by which the ETs and EPMs for HUMAN have been selected.

Method

To select ETs (Error Types) and EPMs (Error Production Mechanisms) appropriate for HUMAN we decided to apply the following strategy, based on 6 steps:

1. Definition of requirements for error taxonomies. As we use existing taxonomies as a source for the ETs and EPMs, and some in domains very remote from human factors (e.g., insurance companies), we need to make a selection, and therefore define requirements our source taxonomies have to comply with.
2. Literature review.
3. Selection of relevant taxonomies. A subset of the candidate taxonomies found in step 2 are selected, based on the requirements defined in step 1. These are our source taxonomies that are particularly relevant for our target domain and the framework of the HUMAN project.
4. Definition of requirements for ETs and EPMs. The source taxonomies contain plenty of ETs and EPMs, with only a subset of them useful for HUMAN. A selection therefore has to be made based on requirements specified for ETs and EPMs.
5. Documentation of ETs and EPMs in the selected taxonomies. To perform the selection of the final ETs and EPMs (step 6), each ET and EPM first has to be

described along a series of dimensions, relevant to the requirements specified in step 4.

6. Selection of final ETs and EPMs. The ETs and EPMs found in the source taxonomies (step 4) and documented in step 5 are evaluated according to the requirements, ratings are provided, and the final selection is made.

Several general principles guided us during the performance of these six steps. First of all, the goal was to be as exhaustive as possible. For that reason, we first produce candidate taxonomies, and then candidate ETs and EPMs. Also, the selection processes should be as rational and explicit as possible. This is why we specify explicit requirements, for taxonomies as well as for ETs and EPMs. Last, the selection processes should be as 'democratic' and efficient as possible, making use of all resources available to us. Every potential contributor in the project is be required to provide inputs.

Step 1: Definition of Requirements for Error Taxonomies

The selection of a scope in which to investigate human error taxonomies, error types and error production mechanisms is particularly important. The ETs and EPMs selected will become the central focus of HUMAN. The scope we selected for error taxonomies is 'The modern cockpit in a future ATM environment', since it relates to the overall scope of HUMAN itself. Aiming at something larger (e.g., other vehicle types than aircraft) would be too ambitious and yield selected ETs and EPMs which, despite being very interesting, are beyond the modelling and investigation capabilities of HUMAN.

Having determined the scope, we identified requirements for selecting the taxonomies actually relevant for HUMAN: beside that the taxonomies have to be relevant within the defined scope, they should cover the most relevant ETs within the defined scope, and should include either observable error characteristics (phenotypes) for each ET, or the taxonomies should focus on understanding the cognitive process involved in the production of human error (genotypes) and the associated EPMs. In addition to this, the taxonomies should refer to ETs and EPMs that have either a significant frequency of occurrence, or whose occurrence is particularly safety threatening. In order to easier defer the EPMs, taxonomies with strong theoretical or methodological foundations should also be preferred, and they should be well-established and well-tested.

Step 2: Literature Review

The first step was collecting papers on human error taxonomies and human errors in general, to get a better acquaintance on existing taxonomies. In this initial research, we did not limit our search to aviation, but also included other safety critical domains. In addition, we collected also literature about the relevancy of errors to the aviation. Listing this literature in this paper would exceed its scope. A very interesting and exhaustive error taxonomy literature survey can be found in [4]. The authors of this document categorized the taxonomies by their different foundations:

- *Task-based taxonomies* mostly describe lists of 'external error modes', which refer to the structure and elements of the external human task and classify the overt characteristics of the error. An examples for these taxonomies is [11].
- *Communication system models and taxonomies* mostly deal with mass communication, and are not primarily models of cognition. However, some of the models can be used to model communication within HUMAN, e.g. [10].
- *Information processing models and taxonomies* examine human performance by attempting to trace the information flow through several processing stages from information input to response output, e.g. [12].
- *Symbolic processing models and taxonomies* regard humans and computers as general purpose symbol manipulating systems, and are closely related to the information processing tradition, and related to artificial intelligence and cognitive science, e.g. [6, 8, 9].
- *Other models and taxonomies* bundle other taxonomies, not fitting in the above schema, e.g. the situation awareness error taxonomy of [2].

We used this categorization, but added also other interesting taxonomies that were not described in [4], e.g. [7, 3]. For each paper on our list of potential error taxonomies, we wrote small summaries, to make it accessible for all partners involved in the selection process. This list has then been used to select these taxonomies, fitting to our requirements and are of particular interest for HUMAN.

Step 3: Selection of Relevant Taxonomies

Each partner involved in this task identified, independently of each other, the most relevant human error taxonomies, in accordance with the requirements. By doing this independently, we attempted to ensure that the selection process was exhaustive, as objective as possible, and that no interesting candidate was missed. Noticeably, most of the taxonomies finally selected were selected by all partners. We discussed the proposed taxonomies and their associated papers or reports extensively, taking the requirements explicitly into account. At the end, we decided to add to the commonly chosen taxonomies some of the taxonomies chosen by only a single partner, as this was in line with the requirement of being able to cover most of the relevant Error Types. After these discussions, we all agreed on the following 'source' error taxonomies:

- *The Phenotype* oriented taxonomies of [11]: very relevant within the defined scope, and including observable error characteristics.

- *The Genotype* oriented taxonomies of [2, 6, 7, 8, 9]: very relevant within the defined scope, and focusing on understanding the cognitive processes involved in human error production.

The lists above not only cover most of the categories of taxonomies in [4], but also additional ones, mentioned in separate literature. The only category we decided to leave out is the communication models and taxonomies, since we had no communication model for HUMAN. To reduce the risk of ignoring or even rejecting important ETs and EPMs, it was decided to ask the other HUMAN experts, namely human factor experts and pilots, to comment on the completeness of the selection and whether the error types in the source taxonomies occurred frequently in the cockpit. The experts approved the selection and did not propose any additional taxonomy or error types. In addition, we also performed cross checks with the FAA error list (FDAI Database).

Step 4: Definition of Requirements for ETs and EPMs

In order to select ETs and EPM for HUMAN in a very systematic way, with explicit procedures and decision criteria, we derived the following requirements for ETs and EPMs: 1) The ET/EPM should be frequent in modern flight cockpits. 2) They must be relevant for the HUMAN target system (AFMS and AHMI). It must be possible to 3) detect the associated error types (ETs) in the data that we will gather in experiments with human pilots (PSP), and 4) the error production mechanisms (EPMs) behind the ET must be understandable (i.e., it must be possible to derive them from the observations on the PSP). Last but not least, 5) the effort for predicting the EPMs with the cognitive model must be compatible with the resources of HUMAN.

Step 5: Documentation of ETs and EPMs in the Selected Taxonomies

With the list of selected taxonomies from step 3, we have a list of potential ETs and EPMs. We documented the potential error types on different dimensions, according to the requirements derived in step 4. Seven human factor experts and pilots evaluated the frequency and relevance of the ETs, and three cognitive modelling experts evaluated the possibility to detect the ETs and evaluated the EPMs on understandability and effort for predicting them.

Figure 1 shows an example of documentation for one of the ETs, namely Entire task omitted. This error type belongs to the phenotypical, task-based taxonomy [11]. For each identified EPM, the two dimensions *predictability* and *understanding* are evaluated, for example for learned carelessness, see Fig. 2.

Documentation of ET: *Entire task omitted*		
Description		
Occurs when the entire task to be achieved is omitted		
Example		
The crew do not execute the after takeoff checklist		
Theoretical affiliation(s), if any		
None		
References		
Swain (1982), Swain & Guttman (1983)		
Error production mechanism(s)		
- inadequate planning - loss of information in working memory - routine capture	- learned carelessness - ineffective prospective memory	
Cognitive process(es) affected by the error type		
Plan execution, procedure execution		
Plausible frequency of occurrence with AHMI (in GECO)		Relevance for cockpit crew in ATM environment
Expert 1	rare 1 2 3 4 5 frequent	Not relevant 1 2 3 4 5 relevant
Expert 2	rare 1 2 3 4 5 frequent	Not relevant 1 2 3 4 5 relevant
Expert 3	rare 1 2 3 4 5 frequent	Not relevant 1 2 3 4 5 relevant
Expert 4	rare 1 2 3 4 5 frequent	Not relevant 1 2 3 4 5 relevant
Expert 5	rare 1 2 3 4 5 frequent	Not relevant 1 2 3 4 5 relevant
Expert 6	rare 1 2 3 4 5 frequent	Not relevant 1 2 3 4 5 relevant
Expert 7	rare 1 2 3 4 5 frequent	Not relevant 1 2 3 4 5 relevant
Comments (optional)		
The relevance is derived from the fact that there are some tasks like transitional checklists that cover items that had been performed in the past. Such as the gear retraction during take-off. The associated after take-off checklist is read considerably later. As tasks like gear retraction are so obvious, any checklist containing mostly items of similar obviousness bears the risk of omission.		
Possibility to detect the error types		
Expert 8	easy 1 2 3 4 5 hard	
	It obviously very easy: the whole task is missing (e.g. no take-off briefing)	
Expert 9	easy 1 2 3 4 5 hard	
	Based on behaviour data, Eye movements (as part of behaviour data), Comparison with normative behaviour	
Expert 10	easy 1 2 3 4 5 hard	
	Seems to be easy to detect	

Fig. 1 Example of documentation of the different dimensions for the ET *Entire task omitted*

After the ratings have been collected, the mean values of all ratings constituted inputs for the selection process in step 6. Discussions were held when very conflicting ratings were provided by the experts.

Step 6: Selection of Final ETs and EPMs

The final selection is based on the documentation of the ETs and EPMs described above. The results of the documentation are aggregated into a single table, for each candidate ET and EPM, to help with the selection process. This allows us to derive associated cost (in terms of development effort), and the difficulty and risk (of failure) for the project for all ETs and EPMs. We used a series of formulas in the table to calculate the 'interestingness' of the ETs and EPMs in a formal, explicit, and as objective as possible way. An ET will be considered interesting if it is frequent, relevant for HUMAN and easy to detect on the physical simulation platform. A formula computes a value based on these three ratings and considers the ET as 'interesting' if the value obtained is above a threshold I_{ET}. An EPM will be considered interesting if it is easy to understand and to predict. Another formula computes a value based on the two respective ratings and considers the EPM as 'interesting' if the value obtained is above threshold I_{EPM}.

Another formula is used to calculate a recommendation for selecting ETs, i.e. an ET is recommended for selection, if it is above I_{ET}, and it has at least one contributing EPM with a calculated value above I_{EPM}.

Even though these formulas provided a first set of candidate ETs, we developed two further formulas for the final selection by the experts: the first formula

Documentation of EPM: ***Learned Carelessness***						
Predictability with the cognitive model:						
	SUM	4	MEAN	2	FINAL RATING	2
Expert 9	easy 1 2 3 4 5 hard					
Expert 10	easy 1 2 3 4 5 hard					
Observability understanding						
	SUM	13	MEAN	4,3	FINAL RATING	4,3
Expert 8	easy 1 2 3 4 5 hard					
	It's hard (4), if not very hard (5) to prove that a simplified action pattern observed in the simulator is the by production of learned carelessness. This can only be done with some confidence when the predictive capabilities we have regarding these implicit learning phenomena exactly predict the simplified pattern observed. In this case we may have good reasons to believe they are at play.					
Expert 9	easy 1 2 3 4 5 hard					
	- video based post-interviews - eye movements				- based on behaviour data (including historical data over several episodes) - rule identification based on behaviour data	
Expert 10	easy 1 2 3 4 5 hard					

Fig. 2 Documentation of the EPM *learned carelessness*

computes the 'Return on Investment' (ROI) for the HUMAN project associated with a given ET (and its underlying EPMs). ETs with a high level of interestingness and whose EPMs are interesting and easy to implement have a high ROI. Second, the ROI value obtained for each ET is then processed to determine if the ET should be considered of high priority (ROI above a threshold P_{ET}) and therefore addressed early in the project, or of a lesser priority, to be addressed at a later stage. The final selection has been performed by the whole HUMAN consortium. The implications of the selection of specific ETs and their EPMs, in terms of developments for the cognitive model and the experiments with human pilots have been discussed by the consortium. The final selection was interestingly close to the recommendations determined by the formulas.

Results and Discussion

We claim that this method has the advantage that it is very exhaustive in determining the relevant error types and error production mechanisms, and that the final objects are selected according to explicit requirements.

The result of this method is the list of ETs and EPMs that are investigated in HUMAN, see Table 1. Please note that the list is of course specific to HUMAN, because they fit the specific requirements and objectives of the project.

As mentioned before, we have tried to be exhaustive, rational, explicit, democratic and efficient, at all steps of the selection process. We however encountered some difficulties. First of all, the definition of what constitutes a human error is controversial and the object of many discussions. For the HUMAN project, we have favoured a definition that relies on the notion of deviation from prescribed or acceptable activities. Error production mechanisms on the other hand are the mechanisms by which error types occur. The mechanisms are related to normal cognitive processes that do not perform optimally (variance of human performance), for a large variety of exogenous and endogenous causes, such as high workload, fatigue, inappropriate design of information display, and contribute to the occurrence of the error types.

Table 1 Overview of selected ETs and EPMs

	Learned carelessness 1	Cognitive lockup 1	Loss of information in working memory 2	Action priming 2	Routine capture 2	Selective attention 2	Saliency bias 2	Recency bias 2	Simple omission 2	Distraction due to external events 2
Entire task omitted	×		×		×				×	
Step(s) in task omitted	×		×		×				×	
Attentional slips		×		×		×				
Application of bad rules	×	×			×					
Biases							×	×		
External activation errors		×				×				×
Misordering of action sequences errors		×								
Failure to monitor or observe data		×				×			×	

In addition, the taxonomies obtained after surveying the literature were coming from very different sources, they were aimed at rather different objectives, and were relevant to multiple domains. The Error Types (ETs) and Error Production Mechanisms (EPMs) found in the source taxonomies were not always homogeneous or equivalent: identical or similar ETs or EPMs were sometimes described with different names, or identical names were used for different things. The levels of granularity within the taxonomies were also sometimes very different.

The distinction between ETs and EPMs is not a clear one. EPMs cause ETs, but sometimes EPMs cause other EPMs. The more we progressed in the project, the more we understood that we were faced with causal chains or trees, not solely with a simplistic dissociation between two categories (ETs and EPMs). It was too late, given the constraints of European projects, to get back and redo our initial structuring of ETs and EPMs. We therefore decided to pay more importance to the EPMs than to the ETs for the remaining of the project. The EPMs are central to the project, since they are the error mechanisms we have to describe and implement in the cognitive model.

We have tried to respond in the most optimal way, given our local constraints, to each of these difficulties, always having in mind the principles mentioned above. We believe the resulting list of targeted ETs and EPMs to be far more appropriate to the peculiarities, limits and constraints of our project than it would have been if the selection process had been made in a more implicit and subjective way, by a local set of two or three participants in charge of this specific task.

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Modelling Driver Behaviour in the Case of Failures in a Steer-by-Wire System

Jeroen Hogema and Paul Wewerinke

Abstract In the design and development of advanced vehicle control systems such as X-by-Wire (XBW), system safety is a crucial aspect. Failures in XBW can easily result in accidents. Therefore, methods and tools are needed to ensure fault-tolerant systems. Quantifying the consequence of an error is far from trivial, since the consequence is determined not only by the vehicle and the XBW system, but also by the driver's response. This chapter describes a driver model for the case of a Steer-by-Wire system. A rather good match between the model and the experimental results from a driving simulator study could be obtained for all configurations considered. The resulting model can be used to predict driver's response to tasks, similar to the type of failure tasks considered here, providing a useful method to answer a variety of design questions related to fault-tolerant system design.

Keywords Steer-by-wire • Driver model • Optimal control model • System safety • Driving simulator

Introduction

The 'by-Wire' technology—as in drive, brake and steer—introduces new possibilities optimising for handling and comfort. Selecting driver-specific settings becomes possible, and furthermore, 'by-Wire' systems can lead to reduced production costs and packaging advantages. At the same time, 'by-Wire' introduces new challenges in terms of system safety. A technical failure in a 'by-Wire' system can have severe safety consequences. Fault-tolerant design methods are needed to ensure that a single failure will not lead to a catastrophic event. This necessity is

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reflected in the development of FlexRay, a communication protocol for automotive applications, which has not only high performance, but also fault-tolerance and redundancy as main features [1].

In general, both the probability and the consequences of system errors have to be considered. Obviously, errors with ‘serious’ consequences need to have a ‘low’ probability, whereas errors with ‘innocent’ consequences can occur with a ‘somewhat higher’ probability without endangering safety (although trust in the system may still suffer). However, quantifying the consequence of an error is far from trivial, since the consequence is determined not only by the vehicle and the by-wire system, but also by the driver’s response. Embedding the driver’s response to such errors in a driver model will facilitate the design process.

This chapter describes driver model for the case of a system failure in steer-by-wire systems. An existing validated driver model for the lane keeping task was used as the starting point. For a detailed description, the reader is referred to [2]. In parallel to the driver modelling work, a driving simulator study was to provide empirical data for calibration and validation of the driver model. The responses to the system errors were analysed in terms of the extremes of the path deviation, the yaw rate, the heading angle and the steering wheel angle.

Method

Steer-by-Wire and Errors

The Steer-by-Wire (SBW) system consisted of a conventional steering wheel as the input device and two main control systems: a rack actuator that controlled the wheel angle and a torque actuator to provide the driver with a steering wheel feedback torque. The steering wheel torque setpoint of the SBW system was based on a simple spring-damper system, i.e. with the torque setpoint proportional to the wheel angle and the wheel angle angular velocity. The wheel angle and the steering wheel angle were related via a simple gear ratio. Two error types are described in this chapter, both consisting of a pulse on the wheel angle, defined by their amplitude and duration. For the first error type (‘Torque’), the error manifested itself in the vehicle motion *and* in the steering wheel torque. For the second error type (‘No torque’), the error on the wheel angle manifested itself only in the vehicle motion, not in the steering wheel torque. Four conditions are included: the two error types, and two pulse durations (50 and 200 ms), all with a fixed error amplitude of 2.3 deg.

Driving Simulator Study

A driving simulator study was conducted in the high-fidelity driving simulator of TNO (see [3] for more details). In this study the participant was seated in a BMW

318I mock-up, which was placed on a motion base with six degrees of freedom. A high-quality control loader provided the steering wheel torque. The participant watched a large radial screen on which the environment was projected. The road environment in the experiment consisted of one straight lane of 3.40 m wide with solid markings on both sides and no obstacles along the road, without any other traffic.

Driving speed is a factor that affects the impact of a SBW error: the effect of a given error on the vehicle path is more severe as driving speeds increase [4]. Thus, the most critical situation is at high speeds. In the current experiment the driving speed was kept constant at 120 km/h.

To incorporate the driver's expectation of errors, we distinguished two separate groups. The first group ('expecting') consisted of 16 subjects who received multiple errors and who were informed that errors would occur. In total, there were 88 errors for each participant. The second group ('surprised') consisted of 36 subjects who each only received one error, without knowing beforehand that this would occur.

Driver Model

The modelling approach was based on the Optimal Control Model structure, in line with the work of e.g. [5], based on a linear system theoretic approach. The fundamental hypothesis is that the human operator behaves optimally, according to a certain criterion, given his inherent limitations and constraints. A global diagram of the model components is shown in Fig. 1.

The *System model* describes the dynamics of the system controlled by the driver. A linear model formulation is used. The system state x is related to the driver control input u (in this case the steering wheel torque). The system state is also influenced by the system disturbance w, which includes the deterministic system errors as well as random inputs to account for wind, road surface effects, etc.

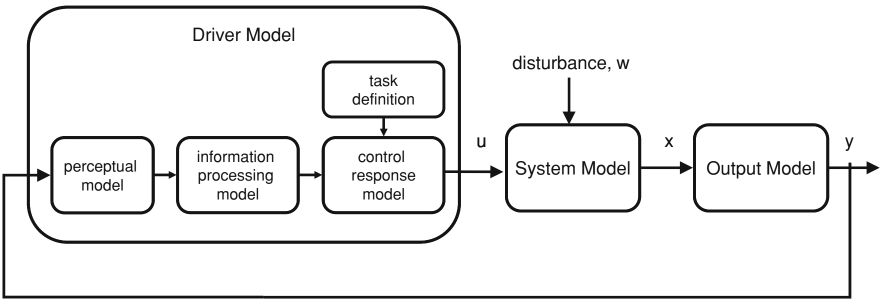

Fig. 1 Overview of the model

The *output model* determines the variables that are perceived by the driver (y) from the system state x: visual cues (lateral position, heading) and proprioceptive cues (power steering).

In the *perceptual model*, it is assumed that the driver perceives information with a certain inaccuracy and with a given delay. This part contains a lumped time delay and a neuro-motor component. Other components are perception and indifference thresholds, an overall attention level, and attention sharing concepts.

The *information processing model* contains an internal representation of the system, a 'mental model', based on which the driver estimates the system state.

The *control response model* determines the driver output, based on the estimated system state and the optimal feedback gains, i.e., feedback gains such that a performance index is minimised.

Results

Initial Results

The overall results of the simulator and the driver model are summarised in Fig. 2. Looking at the simulator results, we found a clear effect of error amplitude: the maximum path and steering deviations are larger for the 200 ms error than for the 50 ms error. The driver model results were in the same order of magnitude as the driving simulator results, showing a similar effect of pulse duration.

The effect of error type differed between the model and the simulator. In the driver model, the error type had no effect. In contrast, the driving simulator results showed that changing the error type from 'Torque' to 'No torque' gave an *increase* of the maximum path deviation, and a *decrease* of the steering amplitudes. Looking more closely to the short (50 ms) error, the model results typically exhibited a somewhat smaller path deviation and somewhat more steering activity.

Based on these results a plausible driver model parameter adjustment will be discussed in the next section.

Model Matching

A limited attempt was made to improve the agreement between the model and experimental results. As discussed in the previous section, the model results typically exhibit a somewhat *smaller* path deviation and somewhat *more* steering activity for the short (50 ms) errors. This suggests one possible discrepancy between model and experiment: the driver model adopts a slightly different trade-off between the control response and lateral position. This hypothesis has been investigated, but did not result in a clearly different response.

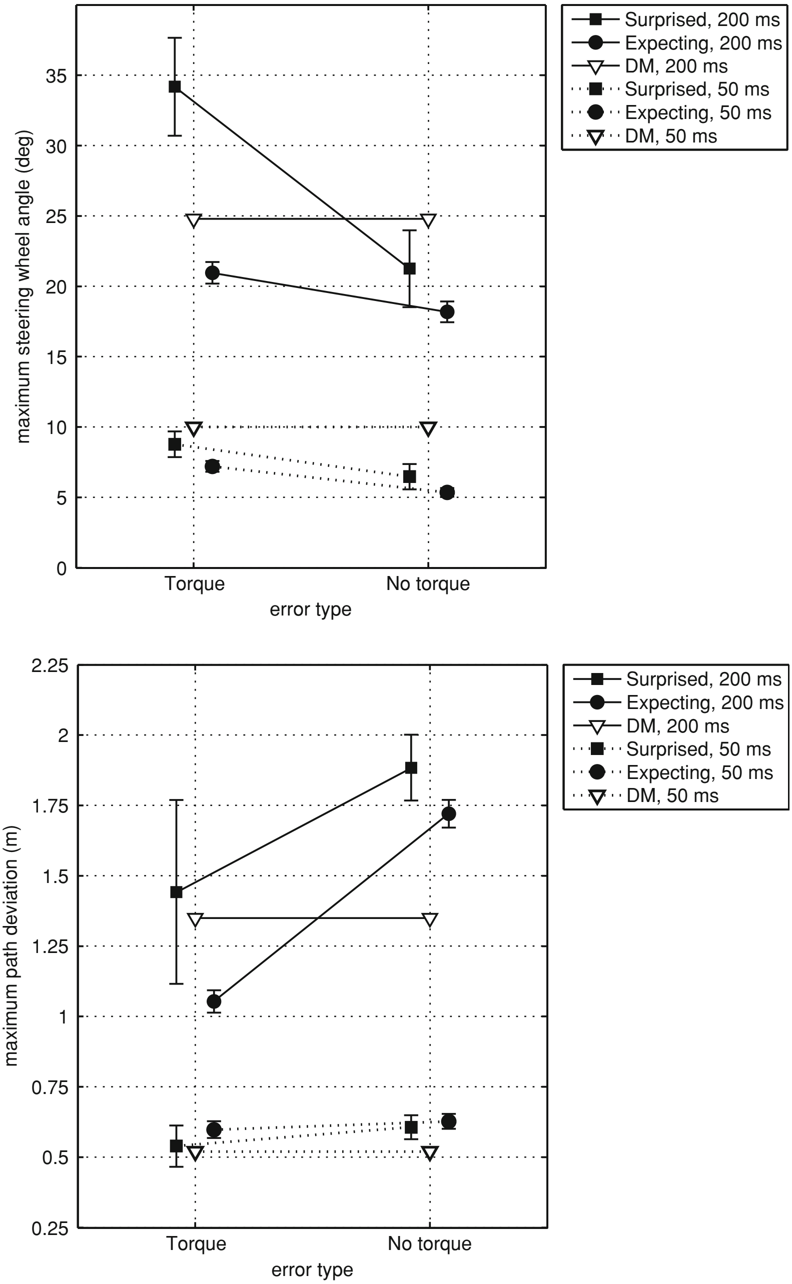

Fig. 2 Maximum steering wheel angle and path deviation (initial results): driving simulator (mean and SE) and driver model (DM) results as a function of error type and pulse duration

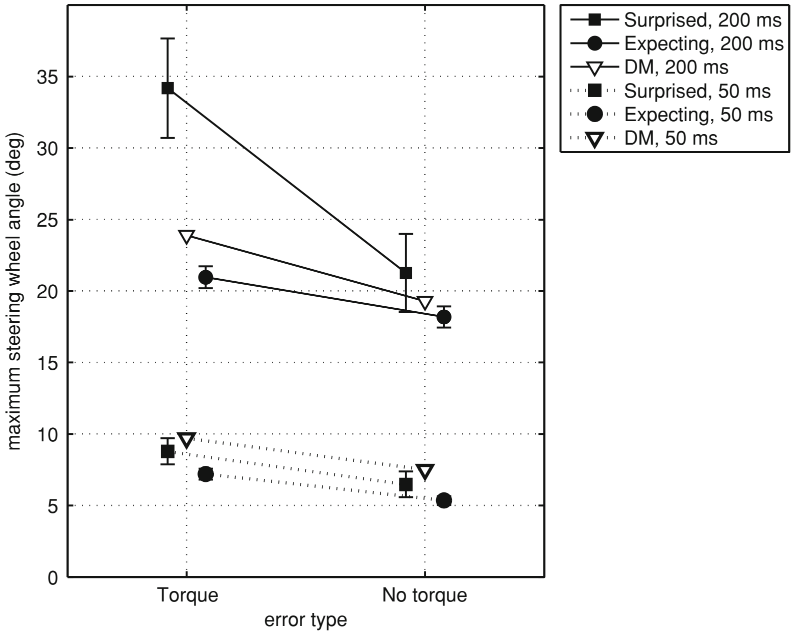

Fig. 3 Maximum steering wheel angle and path deviation (after model matching): driving simulator (mean and SE) and driver model (DM) results as a function of error type and pulse duration

Another explanation could be that the effective moment of inertia of the steering wheel, as reflected by the parameter $K_{1.}$ This parameter can be interpreted as the inverse of the moment of inertia of the steering wheel system. In the driving simulator, open-loop tests yielded a value for K_1 of 800 deg/s^2/Nm). However, in case of the closed loop situation, the driver holds (somehow) the steering wheel, and the effective (overall) moment of inertia will then be larger. Based on preliminary closed-loop tests, a value of K_1 of 100 deg/s^2/Nm was selected. Looking at the current results, this value should possibly be somewhat smaller (corresponding with 'holding the steering wheel somewhat tighter'). A value of 50 deg/s^2/Nm was considered for the 'No torque' error type. For the error type with Torque, it seemed that the force feedback, combined with the opposite yaw rate, 'encouraged' the driver to respond somewhat quicker (at least for the participants who were expecting the errors, and who were thus, to some extent, 'used' to this condition). In driver model terms: the driver is willing to move the steering wheel somewhat quicker, i.e. a somewhat larger value of the parameter K_1. Therefore, the original value of $K_1 = 100$ deg/s^2/Nm was maintained here.

Furthermore, a somewhat smaller neuromotor time constant (T_N) was assumed. Also this adjustment is plausible for the present simulation of suddenly occurring system errors, requiring a rapid driver response. Therefore, a value of 0.12 s is assumed for all configurations instead of the default value 0.15 s.

Figure 3 shows that now the agreement between the model and the experimental results are generally better. A closer match to the experimental results could possibly be obtained, e.g., by adjusting the reaction time. However, as we aim at maximum predictive capability for all configurations rather than an ad hoc model match for individual configurations, no further model adjustments were made.

Discussion and Conclusions

The driver model applied here was originally developed to model the lane keeping task. This model was now applied to investigate how well it could describe the driver's response to various Steer-by-Wire system errors. For various error conditions (two error types, combined with two error pulse durations), the driver model results were predicted and compared with the corresponding experimental results from the driving simulator, using default settings for the driver model parameters.

The (transient) driver response to the considered system errors was analysed in terms of the extreme of the lateral path deviation and of the steering wheel angle. Generally, the agreement was relatively good for the 50 ms pulse configurations, although the model results typically exhibited somewhat smaller path deviation and somewhat more steering activity. For the 200 ms pulse configurations, the lateral path deviation and steering wheel angle clearly did not match very well (discrepancy was approximately up till 30% for the lateral path deviation).

In the model matching phase, the values of two plausible model parameters were adjusted based on the comparison between the model predictions and the experimental results. The effective moment of inertia of the steering wheel, as reflected by the parameter K_1, was assumed to be somewhat smaller (corresponding with 'holding the steering wheel somewhat tighter') for the error type with no torque. In addition, a somewhat smaller neuromotor time constant was assumed in all conditions. Also this adjustment is plausible for the present simulation of suddenly occurring system errors, requiring a rapid driver response. Using these adjusted driver model parameter values, a rather good match between the model and the experimental results could be obtained.

The general conclusion can be drawn that the overall agreement between the driver model and the experimental results is rather good. Even though the model was originally developed for a stationary lane keeping task, the model has shown to adequately describe driver's response to suddenly occurring system failures and can be used for this type of tasks, providing a useful method to answer a variety of design questions. For example, the predicted relationship between error amplitude, for a given error pulse duration, and acceptable maximum lateral deviation allows the specification of acceptable failure characteristics. Another interesting question is the driver's expectation of failures, which can be investigated in a straightforward manner with the model.

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Flexible Design and Implementation of Cognitive Models for Predicting Pilot Errors in Cockpit Design

Jurriaan van Diggelen, Joris Janssen, Tina Mioch and Mark Neerincx

Abstract This paper describes an integrated design and implementation framework for cognitive models in complex task environments. We propose a task- and human-centered development methodology for deriving the cognitive models, and present a goal-based framework for implementing them. We illustrate our approach by modelling cognitive lockup as an error producing mechanism for pilots, and present the outcomes of the implemented cognitive models that resulted from applying our methods and tools.

Keywords Aviation · Congitive lockup · congitive modeling

Introduction

The HUMAN project seeks to use a cognitive architecture for simulating and predicting pilot errors in the aviation domain [3]. An ambitious endeavour such as this one poses many challenges for the project team, such as eliciting domain information, developing plausible psychological models of motor, sensing and thought processes, developing realistic scenarios, and implementing the cognitive model using state-of-the-art Artificial Intelligence (AI) techniques. Each research activity must be performed in close collaboration with the others, such that

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opportunities and constraints are properly observed and propagated throughout the project.

This principle also applies for the AI implementation of the cognitive architecture. We cannot expect to implement the architecture in a one-shot fashion, but must be prepared for continuous adjustments of the implementation due to changing requirements, functionality, and scope. In other words, the implementation must be flexible. The purpose of this paper is to show a flexible method for designing and implementing the cognitive layer using the HUMAN architecture and to report on our experiences modelling cognition using this methodology and architecture in the aviation domain.

The HUMAN project has adopted a multi-layered architecture where each layer processes information on a different level of abstraction, and functions relatively independent of the other layers. This has a number of benefits. Firstly, it allows for a much more flexible implementation (by different parties) than a monolithic architecture would. By distinguishing different relatively independent components, developers can focus on more simple parts of the model, which makes it easier to comprehend and adjust.

Secondly, the different layers correspond well with cognitive engineering theory as proposed by Rasmussen [6], which makes implementation of psychological models more straightforward.

However, modelling mental processes in such a layered architecture also poses a number of challenges for design, implementation and evaluation. A design challenge is to make sure that domain and human factors knowledge are properly identified and used throughout the development process. For this purpose, we have applied the Situated Cognitive Engineering methodology [5].

Implementation challenges are to ensure interoperability between the layers (i.e. making sure that the output of one layer is properly understood by the other layer) and to decide which cognitive processes should be modelled in which layers, by which AI techniques. Also, we would like to separate domain-specific knowledge from general reasoning mechanisms, which allows the framework to be reused for different domains and easily altered when implementation requirements change. For the cognitive layer, we solved these implementation issues by coupling multiple AI technologies such as Protégé-ontologies, CLIPS expert systems, and goal hierarchies.

The evaluation challenge consists of validating the cognitive layer by comparing event traces from the computational model, with real data gathered from experiments with human pilots. We discuss how we could use these outcomes for refining the cognitive layer.

The paper is organized as follows. The next section describes the Situated Cognitive Engineering methodology as a way to iteratively design, implement and evaluate cognitive models. The generic software architecture is described in Software Architecture. In the fourth section, we describe how we have applied the architecture to implement the cognitive layer using a specific case. Fifth section provides a conclusion and future work.

Situated Cognitive Engineering

The cognitive models are developed using the situated Cognitive Engineering (sCE) methodology [5], as depicted in Fig. 1.

The methodology is characterized by the following properties:

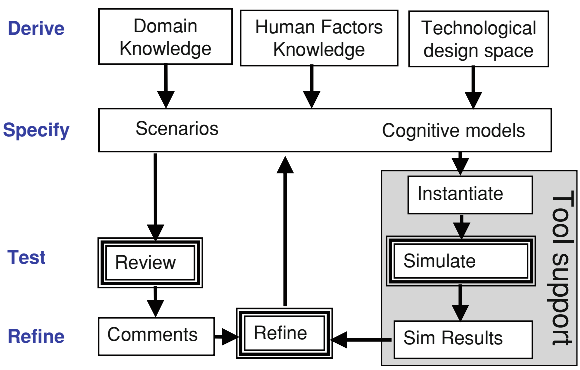
- Cognitive models are developed incrementally, in an *iterative* process of specification, refinement and testing.
- Human factors, domain aspects, and technological issues are studied early in the engineering process, and used throughout the entire development process, leading to a *situated* cognitive engineering approach.
- The approach offers tool-support for implementing the cognitive models, running simulations, and obtaining results.

As can be seen in the figure, the development of situated cognitive models occurs in four stages: Derive, specify, test, and refine. Each of these phases is further explained below.

In the *derive* phase, domain knowledge and human factors knowledge is collected using several techniques, such as field observations, critical incidents analyses and interviews with domain experts. For example, in the HUMAN project we have investigated the aviation domain, by literature reviews and performing interviews with pilots. Additionally, we collect human factors knowledge which is relevant for this domain. For example, we have identified *cognitive lockup* as a potential serious error causing mechanism for airplane pilots.

The next phase is the *specify* phase, where the knowledge obtained in the previous phase is made more concrete in scenarios and cognitive models. We can distinguish between two types of scenarios: scenarios which illustrate normative behavior, and extreme scenarios which illustrate potential errors occurring under certain conditions. The first type of scenarios results directly from the domain study. The second type of scenarios results from domain knowledge which is combined with human factors knowledge of error causing mechanisms. For example, we could develop operationally relevant scenarios in which the pilot is

Fig. 1 Situated Cognitive Engineering (sCE) for cognitive modelling



faced with a combination of context factors from which we know (from a human factors perspective) that cognitive lockup is likely to occur. Simultaneously with the scenarios, we develop conceptual cognitive models which can be used to simulate the pilot's behavior which is described in these scenarios.

In the *test* phase, the cognitive models are evaluated. This can be done by obtaining feedback from colleagues, e.g. in scientific conferences or workshops. A more objective way of testing is to implement the cognitive models, and instantiate them with appropriate data, and obtain simulation results.

In the *refinement* phase, the simulation results can be compared with the actual data, which leads to a further refinement of the model.

Software Architecture

The tool-support we have developed for simulating cognitive models, is included in the general HUMAN architecture. The HUMAN architecture is based on Rasmussen's three behavior levels in which cognitive processing takes place: skill-based, rule-based and knowledge-based behavior [6]. The levels of processing differ with regard to their demands on attention control dependent on prior experience:

- Autonomous layer: this layer models reflexive behavior.
- Associative layer: this layer models procedural behavior in terms of signs.
- Cognitive layer: this layer models deliberative behavior in terms of symbols.

In addition to the three levels, Rasmussen also assigns a type of information to each level. Information is categorized into signals, signs and symbols. At the skill-based level, signals represent the information as it has been perceived, e.g. altitude is 200 feet. Signals can then be enriched with further contextual information, e.g. altitude <1000 feet, and transformed into signs, to be used at the associative layer. These signs can then be associated to semantic information and general knowledge and transformed into symbols, to be used at the cognitive level. For more details on the general architecture see [3].

Because the mental processes which are of interest to this paper are high-level processes, they are modeled at the cognitive layer. Most cognitive agent reasoning processes can roughly be divided in three phases: a *sense* phase, a *reason* phase and an *act* phase [7]. We can apply the same distinction for our cognitive simulation tool.

In the sense phase, the right knowledge is gathered which serves as a basis to make appropriate decisions. In the cognitive layer, new knowledge can be created in two ways. Firstly, new knowledge can arise from perceptions in the environment. In our framework, this knowledge enters the cognitive layer via the associative layer. For this purpose, a translation is needed from knowledge represented in the form of signs, to knowledge represented in the form of symbols. Secondly, new knowledge can be a result of reasoning with existing knowledge. This is performed by a knowledge reasoning component. We refer to both of these functionalities as *knowledge management*.

In the reason phase, the agent uses its knowledge to decide which action to perform next. Following the intelligent agent paradigm, we use a *goal hierarchy* to describe which actions must be executed, given the agent's *goals* and *beliefs*. Unlike many other approaches for goal-based agent deliberation, we do not only strive for efficiency and effectiveness, but also for realism (i.e. analogue to human deliberation). In this way, we can use the framework for modeling human errors as well. We refer to these functionalities as *decision making*.

In the act phase, the agent performs the action, or task. In the context of this paper, tasks are restricted to *mental tasks*. This means that a reasoning step is performed, resulting in some piece of new knowledge. We refer to this functionality as t*ask execution.*

For each of the three functionalities described above, we have developed a separate module as depicted in Fig. 2.

DMM: The decision-making module is also called goal management, and determines which goal is executed. Each goal contains *preconditions* which specify when the goal is *active*. To check the truth value of a precondition, it consults the knowledge represented in the KMM. Which of the active goals will be selected to be executed is determined by the goal-prioritization mechanism. In the human factors analysis phase of the cognitive engineering method, we identified Cognitive Lockup (see [4]) as a relevant error producing mechanism (EPM). In the decision-making module, we have modeled this by introducing *task switch costs* (TSC) representing the difference that goal priorities must have before switching goals.

KMM: The knowledge management module communicates with the Working Memory (WM) in both directions. Signs are sent from WM to the KMM to enable translation from signs to symbols. Symbols are sent from KMM to WM to store

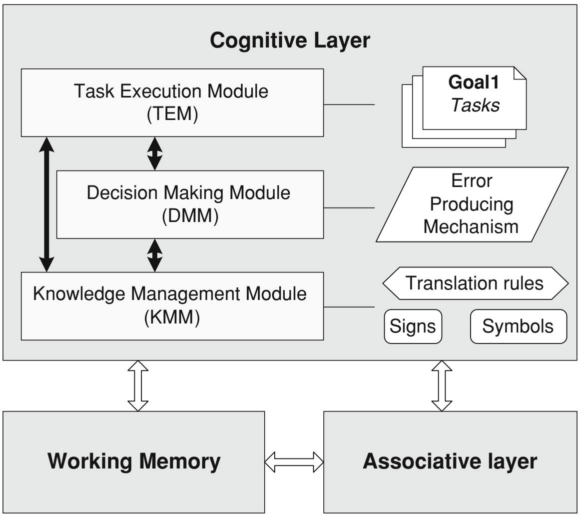


Fig. 2 The components in the cognitive layer

these newly derived symbols for future use by the cognitive layer. We apply two types of technology: ontologies and expert systems. Ontologies make syntactic and semantic assumptions of signs and symbols explicit to facilitate implementation and communication [2]. To convert signs in AL into symbols in CL, we have implemented a sign-symbol translator using the rule-based language CLIPS [1].

TEM: The task execution module executes tasks that can lead to fulfillment of the goal which has been selected by the DMM. Tasks (or lower-level goals) that the AL can handle are passed to the AL. Tasks that involve sign-symbol translations or involve other kind of deductive reasoning are passed to the KMM.

Case

To demonstrate the functionality of the cognitive layer, we describe a case which shows the occurrence of cognitive lockup.

Scenario

The scenario development is the result of the domain analysis and the application of human factors knowledge (see Fig. 1). During the domain analysis, pilots were interrogated about possible tasks and events that match the human factors knowledge about cognitive lockup. For example, as we are modeling tasks on the cognitive layer, only tasks which the pilot executes consciously and non-routinely should be chosen in the scenario. In addition, pilots could provide an idea of importance and priority of different tasks.

This has resulted in a scenario where during the cruise phase, the pilot is flying towards his destination. At one point a thunderstorm appears on the weather radar, close to the destination airport. As it is not clear whether the thunderstorm affects the current trajectory and the pilot needs to redirect to the alternate airport, the pilot watches the storm closely to decide on its importance and development over time. This task can be seen as an engaging task, which demands attention of the pilot. During this monitoring task, the system indicates a malfunction with one of the aircraft engines. The pilot recognizes this event (at timestep 1), but does not immediately try to solve the issue. Instead the pilot continues the monitoring task of the thunderstorm (at timestep 2). After a certain time (at timestep 3), the urgency to handle the problem with the engines is realized by the pilot and the pilot starts solving the system malfunction.

Implementation

As described in earlier, three modules need to be instantiated to implement a scenario. First, the decision-making module needs to be set to the cognitive-lockup bias. Second, the Knowledge management module and the task execution module need to be implemented.

For the TEM, this means that the top-level goals and the low-level goals need to be defined. The top-level goals for this scenario have been identified by the domain experts to be the goals to monitor the thunderstorm (*WatchStorm*), and to handle the system malfunction (*HandleSystemMalfunction*).

Event Traces

During the execution of the case scenario, the model runs and produces traces to show its activities. Figure 3 shows the priority value of each of the goals over time. At timestep 0, the model is executing the *WatchStorm* goal. At timestep 1, the virtual pilot notices the system malfunction, so the goal *HandleSystemMalfunction* becomes active. The initial priority of the goal is higher than the current priority of *WatchStorm*. The model does not switch goals, however, since the priority added with additional task switch costs is clearly higher than the priority of *HandleSystemMalfunction*. At this point in time, cognitive lockup occurs. At timestep 3, the total priority of *HandleSystemMalfunction* exceeds the total of *WatchStorm*. This is the case because additional priority is added if a goal is active for some time but not selected. The execution of *WatchStorm* is interrupted and *HandleSystemMalfunction* is started. Watching the storm is still relevant, so the goal stays active and can be executed further on in the scenario.

The output of the model shows the occurrence of cognitive lockup. It prevents the model to switch goals immediately, but instead the model chooses to continue pursuing the current goal.

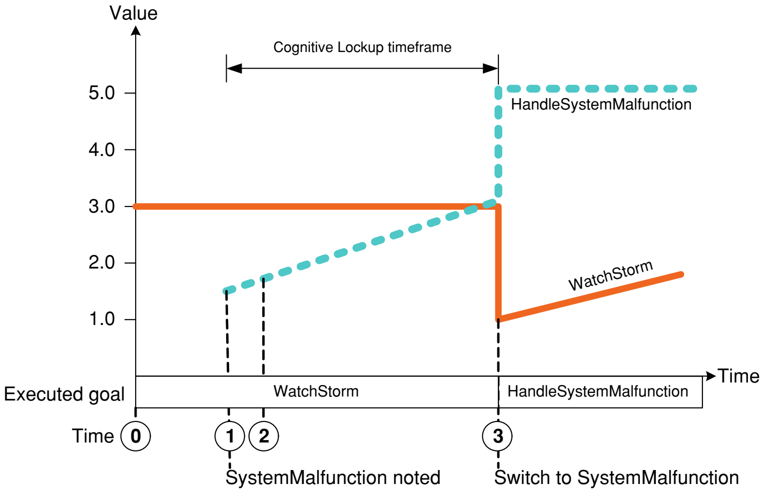


Fig. 3 Goal priorities during storm-avoidance scenario

Conclusion

In this paper we have discussed methodological and developmental aspects of modelling cognition in complex task environments. In particular, we have argued for a flexible development approach, enabling iterative design of the cognitive model, tailored to realistic settings, and led by human factors knowledge.

For this purpose, we adapted the situated Cognitive Engineering development approach, and presented a modular goal-based support tool for implementing cognitive models. We believe that the combination of these two frameworks have been successful in deriving and modelling the aviation scenarios in which cognitive lockup was a source of human error.

In the future, we would like to perform more development iterations of the cognitive model. Also, we intend to perform more thorough testing of the cognitive model by comparing simulated behaviour traces with real pilot behaviour. This allows us to better incorporate the *lessons learned* from the previous iteration in the next version of the cognitive model.

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Effective and Acceptable Forward Collision Warning Systems Based on Relationships Between Car-Following Behaviour and Reaction to Deceleration of Lead Vehicle

Genya Abe, Makoto Itoh and Tomohiro Yamamura

Abstract This study mainly forcused on unnecessary alarms for forward collision warning systems (FCWS) and two driving simulator experiments were conducted to investigate whether considering individual driving characteristics is reasonable for decreases in unnecessary alarms when determining alarm timing. The results indicate that if the average characteristics of car-following behaviour are taken into account when determining alarm timing, unnecessary alarms are not a problem except for drivers who tend to follow a lead vehicle with the short distance between vehicles. Alarm timing based on the particular characteristics of individual car-following behaviour thus has the potential to further decrease unnecessary alarms, independent of driving speed.

Keywords Forward Collision Warning System · Alarm Timing · Unnecessary Alarms · Car-Following Behaviour

Introduction

In order to improve road safety, automobile manufacturers have been developing forward collision warning systems (FCWS). FCWS has been thought to be of great

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benefit to drivers who fail to pay sufficient attention to the road ahead, resulting in a decreased number of accidents.

The criteria that determine alarm activation are critical to the system design of FCWS for deciding system effectiveness, as forward collisions normally occur in time-critical situations [2]. As a human factors issue in FCWS, concern has been expressed about unnecessary alarms [1]. They occur when a system works as designed but when the situation does not constitute a true collision threat. The problem with unnecessary alarms is that drivers may no longer respond to alarms appropriately if the frequency of unnecessary alarms becomes too high. On the one hand, it may be possible to decrease unnecessary alarms by providing drivers with later alarms. On the other hand, however, early alarms have the potential to provide more effective warning of imminent collisions than later alarms in some situations [3]. It is therefore important to determine appropriate alarm timings in order to simultaneously decrease unnecessary alarms and improve road safety.

When drivers become aware of the danger of rear-end collisions may vary according to the individual driver. If driving characteristics are related to a perceived collision threat, then it may be possible to decrease unnecessary alarms by taking the driving characteristics of individual drivers into consideration when determining alarm timing.

In order to investigate whether considering driving characteristics is reasonable for determining alarm timing for FCWS for decreasing unnecessary alarms, we conducted two experimental driving simulator studies.

In the first experiment, we investigated how a driver maintains his/her distance from the car ahead to clarify the characteristics of car-following behaviour. Next, a method for applying the identified characteristics of car-following behaviour to alarm timings for FCWS was proposed using the obtained data. Two alarm timings were then prepared based on the proposed method. In the second experiment, we compared these two alarm timings to investigate whether considering the characteristics of driver behaviour when determining alarm timing can decrease the number of unnecessary alarms. We also investigated how differences in alarm timing might influence car-following behaviour.

Driving Simulator Study I

Method

Apparatus and Participants

This experiment was conducted with a driving simulator owned by the Japan Automobile Research Institute. The simulator has six-degrees-of-freedom motion and uses complex computer graphics to provide a highly realistic driving environment. Computer-generated visual and auditory stimuli accurately represented environmental changes resulting from driver actions. Twelve participants, ranging in age from 23 to 61 years (Mean = 31.9, SD = 9.3), took part in the experiment. All were licensed drivers with everyday driving experience. Each participant was assigned a number from 101 to 112.

Movement of the Lead Vehicle

In this experiment, a lead vehicle was used to estimate car-following behaviour. The velocity of the lead vehicle was controlled based on data obtained from real traffic environments

Two types of velocity pattern for the lead vehicle were used in this experiment: designated speed pattern I and speed pattern II. Table 1 presents the characteristics of the lead vehicle's velocity for each pattern. Although the frequency of decelerations and accelerations was less in pattern I than in pattern II, there was great variation in velocity and acceleration.

Experimental Design, Procedure and Dependent Measures

Drivers followed lead vehicles with velocity patterns I and II, twice for each pattern, so that in total each driver completed four trials. Each trial comprised 7 min of car-following driving. The order of the experimental conditions was counterbalanced across the drivers.

All drivers were required to confirm their informed consent and were then briefed on the task requirements by the experimenter. Each driver was then given a 10-min practice drive to become familiar with the simulator. After a 5-min break, the experimental trials were started. All drivers were instructed to follow a lead vehicle in their usual manner.

The following dependent measure was recorded in this experiment.

THW (time headway) was defined as follows: the distance between the following vehicle and the lead vehicle (m) divided by the following vehicle's speed (m/s). It is known that drivers maintain a target THW independent of their vehicle speed when following a lead vehicle [4]. Thus, it is possible that the characteristics of car-following behaviour can be estimated using THW.

Table 1 Characteristics of variation in lead vehicle's velocity

	Velocity pattern I	Velocity pattern II
Velocity (Max.–Min.)	22.4–16.5 m/s	23.6–8.3 m/s
Acceleration (Max.–Min.)	0.49–0.33 m/s^2	0.78–0.43 m/s^2
The number of times for repetition of acceleration and deceleration	23	15

Results

Figure 1 illustrates median values of THW during car-following for each driver under the experimental condition of velocity pattern I. A difference of about 3 s was observed between the two drivers (102 and 112) who had the longest and shortest median values of THW. Moreover, the variance in THW was different among drivers, indicating that drivers who maintain a short THW can maintain a fixed THW compared to drivers who maintain a long THW. The same trend was observed for velocity pattern II.

Next, we considered how car-following behaviour might influence driver response to the lead vehicle. Figure 2 illustrates relationships between mean values of THW during car-following and delay times to movement of the lead vehicle for each driver. Delay times for each driver were calculated by considering the cross correlation between the lead vehicle's velocity and following vehicle's velocity for trials in which the lead vehicle used velocity pattern I. A positive correlation was found ($r = 0.91$, $p < 0.01$).

Alarm Timing Setting of FCWS

As mentioned earlier, in order to investigate whether considering driving characteristics is reasonable for determining alarm timing for FCWS for decreasing

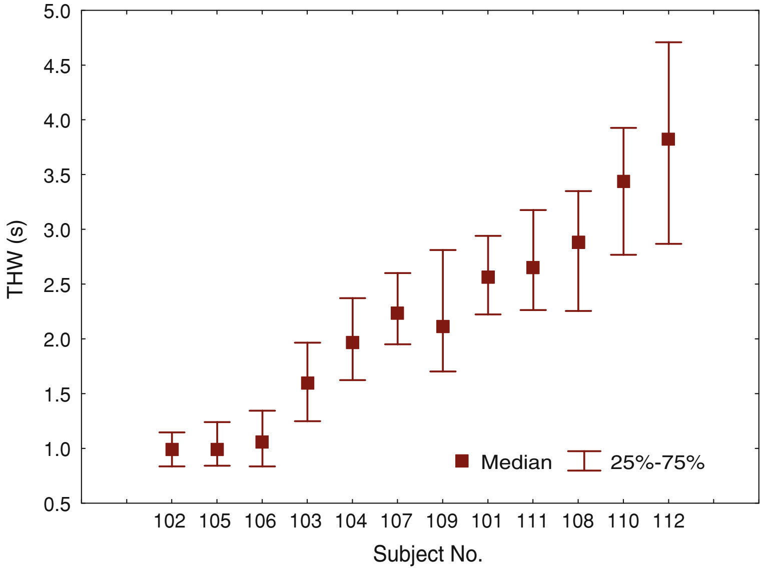


Fig. 1 THW for each driver during car-following

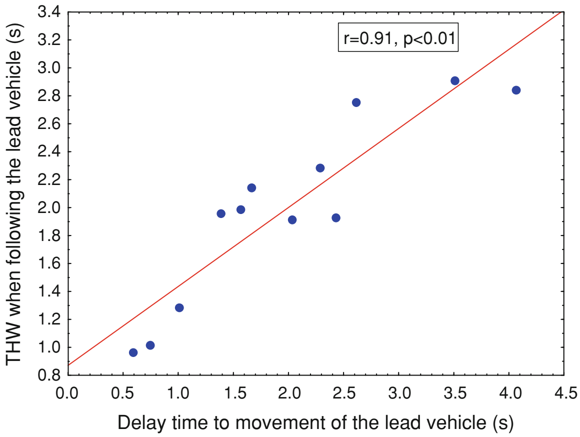


Fig. 2 Relationships between THW and delay time to the lead vehicle

unnecessary alarms two alarm timings were compared for this experiment. One was for applying typical characteristics of car-following behaviour of individual drivers into alarm timing setting. The other was for applying average car-following behaviour into alarm timing setting.

Both alarm timings were determined on the basis of the stopping distance algorithm (SDA), which is one of the preventative alarm trigger algorithms used for FCWS. This algorithm has three parameters: reaction time (*RT*), assumed deceleration of the leading vehicle (D_l) and assumed deceleration of the following vehicle (D_f). *RT* is the assumed reaction time of the driver of the following vehicle. The warning distance (D_W) is determined by these parameters along with the velocities of the leading (V_l) and following (V_f) vehicles as follows:

$$D_w = V_f RT + {V_f^2}\Big/{2D_f} - {V_l^2}/{2D_l} \tag{1}$$

An alarm is trigged when the current headway distance is less than the warning distance (D_W). As a method for integrating characteristics of car-following behaviour into the design of alarm timing, the THW obtained for each driver in study I was considered. More specifically, the parameter *RT* for SDA was determined on the basis of the distribution of THW. Based on the results of study I, it is possible that how drivers maintain THW during car-following reflects how they respond to a lead vehicle (see Fig. 2). Therefore, it seems reasonable to use the THW of drivers to determine their *RT*, the details of which are explained below using the value 5.88 m/s^2 for D_l and D_f, the other parameters of SDA.

- Adaptive alarm timing for each driver

In order to determine adaptive alarm timing, the 10 percentile value of THW for each driver in study I was used as the value of *RT* in Eq. 1. All the 10 percentile values of THW were found using data recorded under the two velocity patterns of the lead vehicle. The resulting minimum and maximum values of *RT* were 0.65 and 1.93 s, respectively.

It has been confirmed that the 10 percentile value of THW for each driver is slightly shorter than their observed timing of applying breaks in response to a lead vehicle.

- Common alarm timing for all drivers

In order to determine a common alarm timing for all drivers, the mean value of the 10 percentile value of THW for all drivers was used as the value of *RT*. The specific value of *RT* was 1.30 s. Therefore, all parameters of SDA were common to all drivers.

Driving Simulator Study II

The aim of this experiment was to investigate the effect of differences in alarm timing of FCWS on car-following behaviour and drivers' perceptions of the necessity of alarms by using the two alarm timings discussed in the previous section. FCWS provided drivers with a simple auditory beep sound in this experiment.

Method

Apparatus, Participants and Movement of the Lead Vehicle

The same driving simulator and driving environment were used as in driving simulator study I. The same participants took part in this experiment as in driving simulator study I. Moreover the same data for controlling the lead vehicle's velocity were used in this experiment as in driving simulator study I (velocity pattern I and velocity pattern II).

Experimental Design, Procedure and Dependent Measures

The drivers experienced the two types of velocity patterns for the lead vehicle and the two alarm timings (adaptive alarm timing and common alarm timing). Each participant completed four trials: one for each combination of velocity pattern and alarm timing. Each trial comprised 7 min of car-following driving. The possible orders of the four trials were evenly distributed among the drivers.

All participants were briefed on task requirements by the experimenter. They were instructed to follow a lead vehicle in their usual manner. In addition, they were informed of the presence of alarms following the alarm timings discussed above. Each driver was given a 10-min practice drive to become familiar with the simulator. After a 5-min break, the experimental trials were started. Before the start of each trial, drivers were informed which alarm timing (adaptive or common) was being used in that trial.

Two dependent measures were recorded in this study.

THW: This is the same measure as used in driving simulator study I.

Subjective ratings of unnecessary alarms: The degree to which a driver subjectively felt that triggered alarms were unnecessary was measured using an 11-point rating scale, in which 0 indicated “not at all”, 5 indicated “neither nor” and 10 indicated “very much”. Immediately after finishing each trial, the drivers gave a verbal response to the following question: “In general, how unnecessary did you feel that the alarms were for avoiding imminent collisions?”

Results

Subjective Ratings of Unnecessary Alarms According to Alarm Timing

Figure 3 illustrates drivers’ subjective ratings of unnecessary alarms according to alarm timing and velocity pattern of the lead vehicle. It seems that, compared to adaptive alarm timing, the effects of differences in velocity pattern of the lead vehicle on the subjective ratings of unnecessary alarms were more obvious for common alarm timing. There was a significant interaction between the factors of alarm timing and velocity pattern ($F(1, 47) = 5.971$, $p < 0.05$). A Tukey’s post hoc test revealed a significant difference in subjective ratings of unnecessary alarms between the two velocity patterns for common alarm timing. The main effect of velocity patterns was also significant ($F(1, 47) = 12.017$, $p < 0.01$).

Figure 4 illustrates frequency distributions of the velocities for the following vehicle when alarms were triggered according to alarm timing and velocity pattern

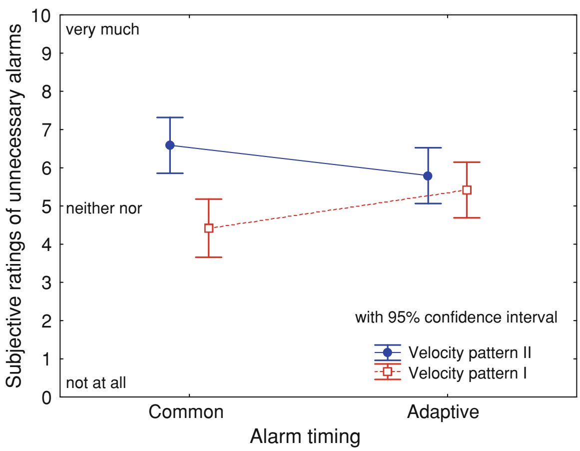


Fig. 3 Subjective ratings of unnecessary alarms according to experimental conditions

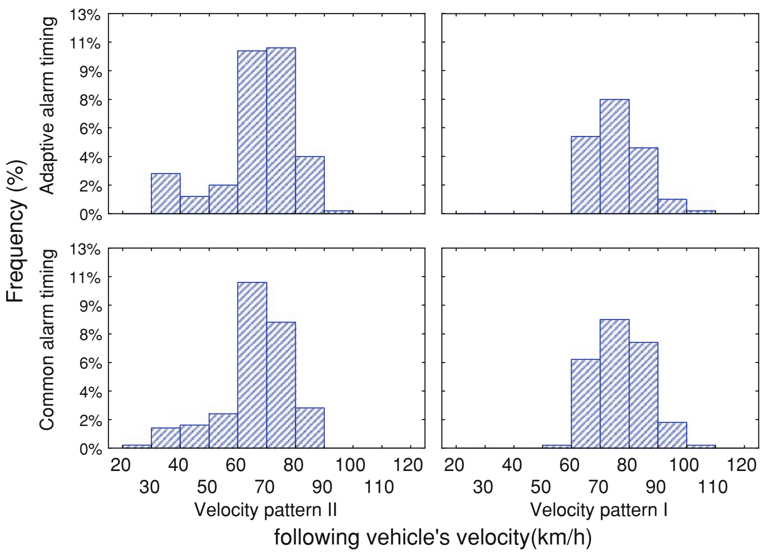


Fig. 4 Frequency distributions of the velocity for the following vehicle when alarms were triggered according to experimental conditions

of the lead vehicle. As can be seen in this figure, compared to velocity pattern I, alarms were frequently triggered when driving speed was low (less than 40 km/h) for velocity pattern II.

Interestingly, with adaptive alarm timing, alarms triggered when the following vehicle drove slowly did not cause increases in the ratings of perception of unnecessary alarms.

Figure 5 illustrates subjective ratings of unnecessary alarms for each driver by alarm timing. Both velocity patterns were included in this analysis. Drivers who showed a tendency to drive with short THW, specifically drivers 102 and 105 (see Fig. 1), gave higher ratings of unnecessary alarms for common alarm timing than for adaptive alarm timing. For other drivers, alarm timing did not dramatically affect the level of unnecessary alarms, except for driver 108. These results indicate that in order to decrease the level of unnecessary alarms for drivers who show a tendency to drive with short THW, it is necessary to determine alarm timing by considering the car-following behaviour of individual drivers.

Alarm Timing and its Influence on Car-Following Behaviour

Figure 6 illustrates relationships between mean values of THW during car-following in response to alarm timing (vertical axis) and mean values of THW without alarms during car-following (horizontal axis) for each driver. For drivers who show a tendency to follow a lead vehicle with short THW when no alarms are

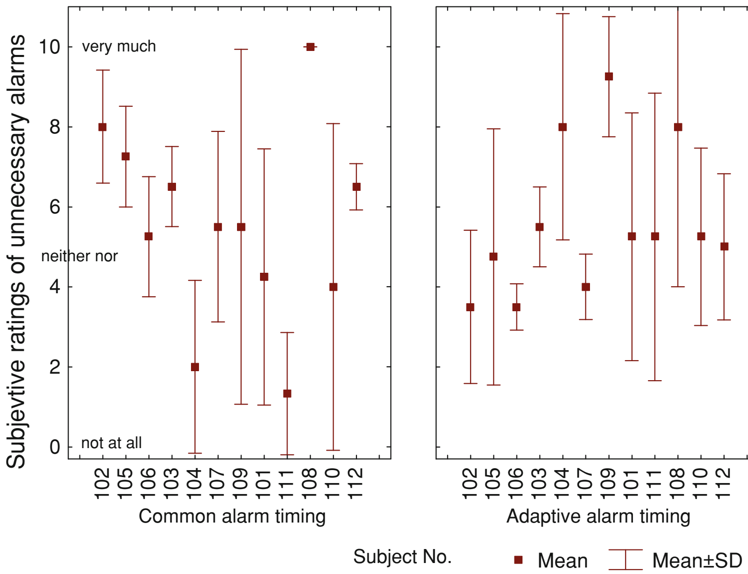
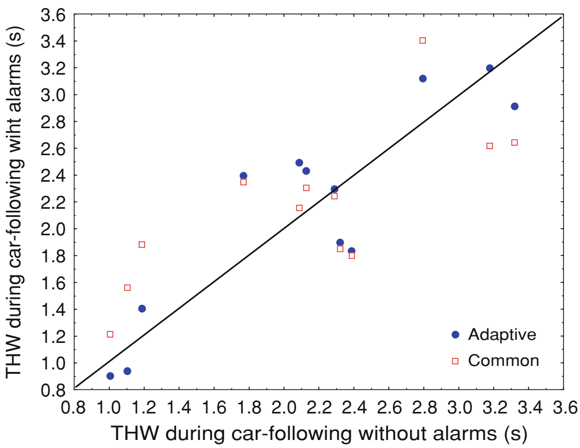


Fig. 5 Subjective ratings of unnecessary alarms for each driver according to alarm timing

Fig. 6 Changes in car-following behaviour due to differences in alarm timing



present, common alarm timing may induce longer THW than under usual driving conditions (that is, without alarms). Conversely, for drivers who show a tendency to follow a lead vehicle with long THW when no alarms are present, adaptive alarm timing may induce shorter THW than under usual driving conditions. For drivers who follow a lead vehicle with an average THW, alarm timing has no obvious effect on car-following behaviour.

Conclusion

A method has been proposed to design alarm timing for FCWS by extracting the distribution of THW and applying it to the parameter of SDA. The results of the experiments support the following conclusions:

1 For drivers who tend to follow a lead vehicle with short THW common alarm timing might have the potential to induce impaired subjective ratings of unnecessary alarms, compared to adaptive alarm timing.
2 Subjective ratings of unnecessary alarms varied according to driving speed, even thought the same alarm timing was used. Therefore, there is a possibility that subjective ratings of unnecessary alarms may be affected by driving speed.

Further research is needed, which mainly derive from the limitations of experimental methods employed in this study. That is drivers were not distracted but they concentrated their attention on driving, resulting in sensitive estimation of unnecessary alarms compared to distracted drivers. Moreover, THW was only considered when determining alarm timing. Other factors, such as driving speed might be assessed to find methods for decreasing unnecessary alarms efficiently.

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Modelling and Validating Pilots' Visual Attention Allocation During the Interaction with an Advanced Flight Management System

Florian Frische, Jan-Patrick Osterloh and Andreas Lüdtke

Abstract This paper presents the results of our analysis of human pilot behaviour and of a cognitive pilot model. We have performed experiments in a flight simulator including a new 4D flight management system (FMS) in order to gather information about the interaction of human pilots with the new FMS and to validate the performance of the cognitive pilot model. This paper focuses on the visual attention allocation of human pilots and on the validation of the visual perception component of the pilot model.

Keywords Cognitive Modelling · VisualAttention · Advanced Flight Management System

Introduction

The European project HUMAN (7th Framework Programme) aims at developing virtual testers, in order to improve the human error analysis of new cockpit systems. The virtual testers should allow simulator-based testing of new cockpit system software and annunciation concepts in early design phases, as a supplement of simulator tests with human pilots in later design phases. In HUMAN, a 4D Flight Management System (Advanced Flight Management System, AFMS) and its user interface (Advanced Human Machine Interface, AHMI), developed at the German Aerospace Center (DLR Braunschweig), have been selected as system

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under investigation. The virtual testers are based on a cognitive architecture named CASCaS (Cognitive Architecture for Safety Critical Task Simulation). The general goal of the research is to make psychological knowledge about human–machine interaction (including human errors) readily available to system designers to foster human-centred design. Although we focus on the AHMI in this study, CASCaS is independent of specific systems and can be used to predict the visual attention of all kinds of systems. Humans mainly gather information from the environment via visual perception. Thus, there is a need to model and to validate the visual attention allocation of the virtual tester in order to simulate human-like interaction between a pilot model and a virtual cockpit. In this paper we will briefly describe the visual component of CASCaS and how we performed experiments with human pilots and with the cognitive pilot model (virtual pilots). The main part of this paper focuses on the analysis results of the experiments and on the comparison between the visual attention allocation of the human pilots and the virtual pilots.

Modelling Visual Attention Allocation of Pilots

The cognitive architecture CASCaS has initially been developed in the 6th European Commission Framework Programme project ISAAC (see [7]), and has been widely extended within the HUMAN project (e.g. [8]). The visual attention allocation of CASCaS is determined by two processes, a top-down process and a bottom-up process. In the top-down process the normative behaviour, i.e. the tasks of the pilot, influences the visual attention. CASCaS is a multi-layered architecture, as depicted in Fig. 1.

Multi-layered means that the normative behaviour is processed on three different layers, which are based on Rasmussen's three levels of skill-based, rule-based, and knowledge-based behaviour, cf. [11]. In [1] Anderson defined corresponding levels, but named them autonomous layer, associative layer and cognitive layer. In the following, we will use Anderson's terminology. Each layer

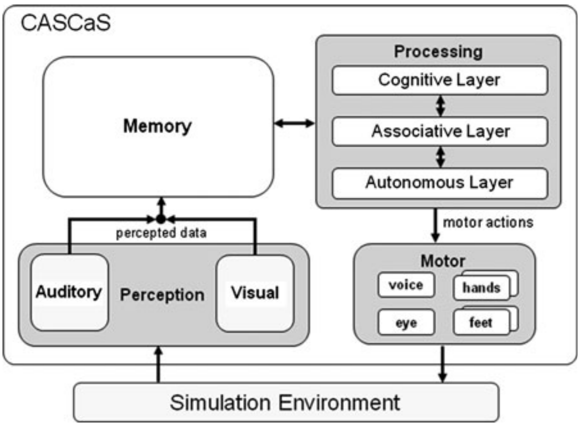

Fig. 1 The multi-layered architecture of CASCaS consists of components for perception, memory, knowledge processing and motor actions. The knowledge-processing component is based on Rasmussens three levels of knowledge processing

can be distinguished by the level of consciousness that has to be used to process the normative behaviour. While nearly zero consciousness is needed on the autonomous layer, almost full consciousness is needed on the cognitive layer, where decision making, planning and problem solving are located. In standard situations, pilots act mostly on the associative layer, using well-learned rules as normative behaviour. These rules define also visual percept actions, e.g. a rule request to percept the altitude during the monitoring task.

In contrast, the bottom-up process is an unconscious process within the perceptual component of CASCaS, which can be referred to as Selective Attention. Selective Attention is an effect where salient objects, e.g. flashing lights, moving objects, or high contrasts, cause an automatic shift of attention towards this object [2]. This effect may be restrained by the top-down process or by the saliency of other objects nearby, which suppress, with their own high saliency, other salient objects. This process was modelled within the percept component of CASCaS, as described e.g. in [10].

While bottom-up attention is used in modern cockpits—e.g. each mode change of an autopilot is highlighted by a flashing element—the main driving factor for the visual attention is the normative behaviour, i.e. the rule-based procedure on the associative layer. Therefore, it is possible to use CASCaS for prediction of visual attention independent of a target system like the FMS presented in this paper, as long as it is part of the normative behaviour.

Experiments

Experiments have been conducted with human pilots, in order to validate the behaviour of the cognitive model. In the following sections, we will describe how the experiments have been carried out.

Flight Simulator Setup

For the experiments with our subject pilots, we used the GECO (Generic Experimental Cockpit) Simulator, which has been build and is maintained by the German Aerospace Center (DLR, Braunschweig, Germany). The layout of the simulator has been derived from the Airbus A350 XWB aircraft. It is equipped with freely programmable wide-screen LCD displays and modern input devices like side sticks and a Keyboard Cursor Control Unit (KCCU), as used in the A380. The flight dynamics are derived from a VFW 614 (ATTAS), as used by the DLR as a test aircraft. The outside view is generated by three video projectors on a spherical screen with a diameter of 6 meters, providing highly realistic outside view. The GECO is a fixed-based flight simulator that is equipped with a visual head tracker (AR-tracking), and an SMI iView-X eye-tracker system. In addition, we recorded pilot voices and all flight parameters.

Scenarios

The experiments consisted of eight scenarions, each 30–45 min with up to five events (e.g. re-planning due to a thunderstorm or a system malfunction). The scenarios have been designed to introduce as much interaction with the target system as possible, in order to induce pilot errors, see [11] for more details on the error types and error production mechanisms. The scenarios have been divided into three phases, cruise, approach and final approach. All scenarios started in the cruise phase, and ended with the touchdown on the runway. Communication between pilots and ATC has been restricted to non-auditive communication via the AHMI.

Participants

Thirteen male and two female German line pilots have been recruited from german airlines. None of the pilots had experience with the AHMI. All subjects participated as the pilot flying (PF). The crew was completed by a scripted pilot, who acted as a pilot monitoring (PM). In addition to the normal duties of the PM, the scripted pilot was responsible for the training, and he supported the debriefing and analysis by taking notes during the flight.

Procedure

The experiments were distributed over 2 days: The first day started with a training session in order to train basic skills on the AHMI. The training ended with a procedure-talk-through to ensure that the procedures were well-trained. If necessary, training was repeated. After the talk-through was performed successfully, the subjects started flying the scenarios. After each scenario pilots took a short break. The cognitive model flew the same scenarios, each of them twelve times. The first datasets have been used to capture errors in the implementation and to improve the model’s performance. Thus, only the data sets for two scenarios were available for the final model setup which have been used for the data analysis described in this paper.

Results

Recent research in the field of visual attention allocation in cockpits provides information about gaze distribution (see [9, 12]) and scanning patterns (see [3, 6]) of human pilots in modern aircraft cockpits. In this section the results of our analyses towards visual attention allocation of human pilots will be presented and compared to results of human experiments found in the literature and to the performance of CASCaS.

Our results are based on eye-tracker data, which has been recorded during the experiments with human pilots, and on log files for the cognitive architecture. The output of both data sources has been pre-processed into a comparable format containing timestamps $t_{1,\ldots,n}$ and areas of interest (AOI) $\mathrm{aoi}_{1,\ldots,m}$ describing where pilots have looked at a specific time. We focussed on a set of seven AOIs: AHMI, PFD, NAV, gear, ENG, EFCU and windows.

Gaze Distribution

The gaze distribution of pilots during flight can be seen as the main indicator of how important specific areas are for flying an aircraft—from a pilot's point of view. Huettig et al. [6] revealed the dominance of the PFD in a modern glass cockpit with a value of around 40% before the NAV display with a value of 20%. This result was confirmed by Mumaw et al. [9, 12] who analysed the monitoring behaviour of pilots on an automated flight deck with 35% on the PFD and 25% on the NAV. In contrast, our results reveal a dominance of the new introduced AHMI with a value of around 53% aggregated over all flight phases. The PFD is with a value of 16% far behind the AHMI. This emphasizes the role of the AHMI during our flight tasks. AHMI, PFD and NAV sum up to a value >75%.

We have shown that the introduction of the AHMI has a major influence on overall gaze distribution of pilots. We also analysed the influence of the flight phases cruise, approach and final approach on the attention allocation. The most prominent result is that the AHMI is used in cruise phase very extensively. We have measured a value of 60% aggregated over all pilots for the AHMI. This high value is decreasing in the lower flight phases to a value of around 40% during the approach phase and finally to 22% in the final approach phase. The attention of human pilots to the PFD and to the NAV is changing in the opposite way. The attention to the PFD is increasing from 12% in cruise phase to 26% in approach phase and finally to 35% in during final approach. This means that the PFD becomes the dominant display during the final approach phase. The visual attention of pilots to the outside world does not change from cruise to approach phase, but doubles from approach to final approach phase. This was not surprising and is also reported by Sarter et al. [12]. The results of the influence of flight phases on pilots' gaze distribution are shown in Fig. 2.

We will now focus on the performance of the cognitive model in flight tasks, which we call virtual pilots contrary to human pilots. The main focus of attention was on the AHMI with an aggregate value of 56%. The second dominant AOI was the PFD with a value of 43%. Due to an incomplete virtual system model the interaction between the virtual pilots and the NAV has not been simulated.

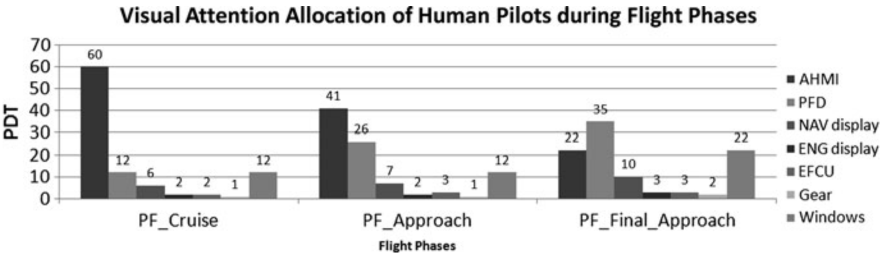

Fig. 2 Visual attention allocation of human pilots during cruise, approach and final approach phases (*PDT* Percent Dwell Time)

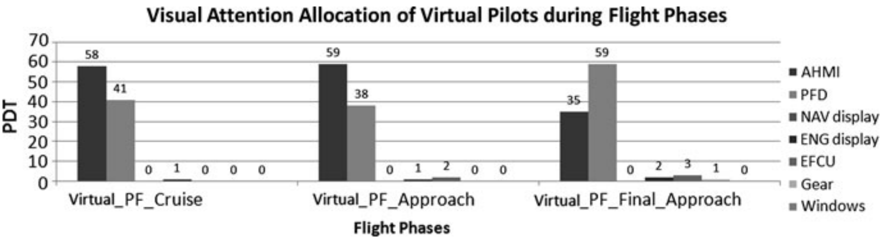

Fig. 3 Visual attention allocation of virtual pilots during cruise, approach and final approach phases (*PDT* Percent Dwell Time)

Thus the visual allocation of attention to the NAV is 0%. The dwell time of the virtual pilots on the AHMI captures the visual performance of the virtual pilots but not the functional performance of the NAV. Summing up the gaze distribution of the AHMI and the PFD virtual pilots have spent 99% attention to these displays. Only 1% remains on other areas. In accordance with the human pilots' experiments, the visual performance of the virtual pilots has been inspected in cruise, approach and final approach phase. The results are depicted in Fig. 3.

While the visual performance of the virtual pilots changes only marginal, the values of AHMI and PFD switch in the final approach phase. This is similar to the performance of the human pilots. In contrast to the human pilots, the virtual pilots do not perform any outside world checks during any phase due to the fact that the model is currently not able to percept outside world objects in front of the windows.

Scanning Paths

Scanning path analysis focuses on transitions between AOIs [5]. For a set of AOIs a list of all possible permutations with a length of three (three-series paths) has been prepared and the occurrence of each series has been counted per run. Example: For a set of 2 AOIs (1, 2) and a given AOI sequence 21212 the result is

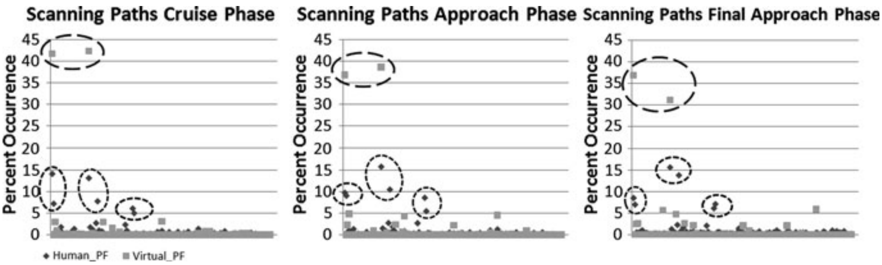

Fig. 4 Comparison of scanning paths of human pilots and virtual pilots during cruise, approach and final approach phases

#121 = 1 and #212 = 2 (see also [4]). We have not found comparable analyses in the literature, thus we only describe our results for the human pilots and for the virtual pilots.

Our analysis of scanning paths has focussed on 6 AOIs (AHMI, PFD, NAV, ENG, EFCU and gear), which are 6^3 combinations in total. Figure 4 depicts the relative occurrence values (%) of each three-series scanning path of human pilots and virtual pilots during the flight phases cruise, approach and final approach.

The main scanning paths detected in all flight phases are those involving the main displays (AHMI, PFD, NAV). The spatial positions of these displays in the simulator are NAV (left), PFD (centre), AHMI (right) in a line and close to each other. As Fig. 4 shows, most transitions are far below the 5% level. The most important scanning paths are highlighted with dotted cycles. These are (AHMI, PFD, AHMI) and (PFD, AHMI, PFD) in all flight phases for the virtual pilots, and (AHMI, PFD, AHMI), (AHMI, PFD, NAV), (PFD, AHMI, PFD), (PFD, NAV, PFD), (NAV, PFD, AHMI) and (NAV, PFD, NAV) for the human pilots in all flight phases.

The highest values in human pilots' performance are measured for scanning paths between AOIs that represent often used displays located close to each other. Scanning paths between less frequently used displays (such as ENG, EFCU) have not been optimized. Thus, we assume that human pilots tend to optimize their scanning paths for often used displays. The analysis of virtual pilots' scanning paths reveals that the model is fixed to a very small set of transitions.

Summary and Next Steps

The experiments showed that the AHMI attracts a lot of attention. This can be explained by two main factors. First, the AHMI provides redundant information from the PFD, e.g. altitude, heading and speed. Second, our scenarios have been designed to cause as much AHMI interaction as possible. In addition it is possible, that the subject pilots have been curious for the new system.

In summary, the visual performance of the model has to be improved. The main potentials for improvements detected are (1) the integration of a functional NAV, which has been detected as one of the most important displays and (2) an expansion of the specific normative flight phase tasks in the procedural knowledge of the model. Therefore, an in-depth task analysis is necessary. This will result in a more realistic gaze distribution and scanning behavior in the flight phases. In addition, a wider set of scanning alternatives could be added to the model. Primary, this concerns transitions involving the main displays and secondary all other displays in the cockpit.

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Estimating Traffic System Wide Impacts of Driver Assistance Systems Using Traffic Simulation

Andreas Tapani

Abstract There is a need to estimate impacts of proposed driver assistance systems already at early stages of the system development process. Estimations of the impacts of new technologies have to be based on laboratory studies and modelling. This paper presents a traffic simulation based framework for estimation of the traffic system wide impacts of driver assistance systems. The framework includes a two-step methodology. In the first step of the analysis, the considered driver assistance system's impact on driver behaviour is observed. The second step of the analysis consist of traffic simulation modelling taking into account the system functionality as well as the observed driver behaviour of the considered driver assistance system. Driver behaviour studies for use of the data for traffic simulation modelling is discussed and traffic simulation modelling of different types of driver assistance systems is exemplified by modelling of an overtaking assistant, of in-vehicle virtual rumble strips and of adaptive cruise control.

Keywords ADAS · Traffic simulation · Driver behaviour

Introduction

From society's perspective, to increase traffic safety and to remedy congestion and pollution problems, it is important that driver assistance systems (ADAS) lead to real benefits. Scarce resources require prioritisation and as a consequence ADAS need to be evaluated already at early stages of the development process. To assess

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impacts of already well-tried measures to improve the traffic system, one can conduct before and after studies or cross-sectional studies based on field data. Road safety analysis of traditional safety measures can for example be conducted based on the actual accident turn out. New technologies such as ADAS can however not be reliably evaluated based only on field data. Even though some ADAS already have been introduced in the traffic system, the proportion of equipped to unequipped vehicles is still too small for conclusions to be drawn. Instead, evaluations of ADAS have to be based on laboratory studies and modelling.

The aim of this paper is to present a traffic simulation based framework for estimation of the traffic system wide impacts of ADAS. Studying driver behaviour for use of the data for traffic simulation modelling is discussed and traffic simulation modelling of ADAS is exemplified.

The remainder of this paper is organised as follows. The framework for estimation of traffic system wide impacts of ADAS is presented in "A Framework for Estimation of Traffic System Wide Impacts of ADAS". "Observing Driver Behaviour for Traffic Simulation Modelling" contains a discussion on studying driver behaviour for use in traffic simulation modelling. Examples of how driver assistance system functionalities and the associated driver behaviour can be represented in a traffic simulation model are given in "Traffic Simulation Modelling of ADAS". Last section brings the paper to an end with conclusions and suggestions for further research.

A Framework for Estimation of Traffic System Wide Impacts of ADAS

Several authors have applied traffic simulation to estimate impacts of driver assistance systems, e.g. [1–3]. Many studies have considered the system functionality of longitudinal control ADAS. Driver behaviour adaptation to the ADAS is commonly not considered. The framework presented in this paper takes into account the combined impact of the ADAS functionality and the driver behaviour associated with the ADAS. The central component of the framework is the ADAS under consideration. This ADAS's effects on driver behaviour are studied in the first step of the analysis. In the next step of the analysis, a traffic simulation model is extended with vehicles including the ADAS functionality and the observed driver behaviour. The final step of the analysis consists of calculation of performance indicators based on the simulation results. A flow chart of the evaluation framework is shown in Fig. 1.

The basic result from a microscopic traffic simulation model run is a set of vehicle trajectories. To use these vehicle trajectories to estimate traffic performance, the trajectories need to be aggregated into performance indicators that are related to the traffic properties that are of interest in the current study. For example, quality of service is commonly measured by indicators such as "average journey speed", "queue length" and "time spent following". Similarly, if the goal

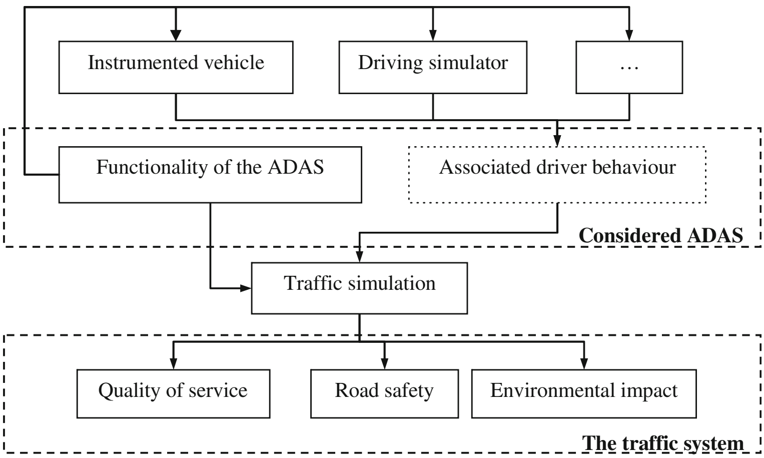

Fig. 1 ADAS evaluation framework

is to assess the resulting road safety effect then safety related indicators are needed. The basis for environmental impact analysis of road traffic is the analysis of vehicle emissions. Vehicle emission models use vehicle trajectories as the fundamental input. The environmental impact of the ADAS can therefore be estimated via vehicle emissions modelling using the resulting vehicle trajectories from the simulation as input.

The use of traffic simulation to "aggregate" the individual driver/vehicle behaviour to traffic system wide impacts makes it possible to study the ADAS impact for alternative ADAS introduction scenarios. For example, effects of different ADAS penetration levels can straightforwardly be studied by varying the proportion of ADAS-equipped vehicles in the simulated traffic. Moreover, if different behaviour has been observed for different driver categories then this can be taken into account in the simulation by using different categories of ADAS-equipped vehicles. Another important effect of ADAS introductions in the traffic system is that the ADAS may have an effect also on surrounding non-equipped vehicles. As an example consider systems that reduce driver reaction times, such a system may also be beneficial for non-equipped vehicles since more time will be available for corrective actions. These effects can also be studied using traffic simulation.

Observing Driver Behaviour for Traffic Simulation Modelling

Many of the tools used for studying driver behaviour have in common that they consider test drivers' behaviour in a laboratory situation. Since the ADAS under consideration can be assumed not to be widely available in the traffic system it is not possible to measure data directly in the field. However, if test persons are allowed to drive an ADAS-equipped vehicle in real traffic then it is still possible to observe the test persons behaviour under real traffic conditions. A drawback of this approach is that it is not possible to control the traffic situations that the test person is exposed to. An alternative approach is to implement the ADAS system functionality in a driving simulator. This approach has the advantage that it is possible to control the traffic situation completely. Possible drawbacks of the driving simulator approach concern the realism and validity of the simulator. There are also other alternatives for studying driver behaviour, e.g. stated preference methods. The current practice of driver behaviour studies is however not ideal to allow use of the findings for traffic micro-simulation modelling. Driving simulator experiments are for example often designed to reveal the test persons' reactions in relation to isolated critical situations. Driver behaviour studies performed for subsequent use of the results for traffic simulation modelling involve observation of the driver's continuous actions and reactions. There is, for this reason, a need for research on the design of experiments for collection of driver behaviour data for traffic simulation modelling. Ongoing research within the European project ITERATE [4] focused on observation and modelling of driver behaviour is one interesting step in this direction.

Traffic Simulation Modelling of ADAS

The traffic simulation model that is utilized to simulate traffic including ADAS equipped vehicles has to be capable of describing traffic in the road environments that the ADAS gives support in. Implementation of ADAS system functionality and driver behaviour for ADAS-equipped vehicles in a traffic simulation model involves modification of the driver/vehicle sub-models. It is consequently important that these sub-models are appropriate for simulation of ADAS-equipped vehicles. In this section, examples are given of how different types of ADAS can be modelled. The microscopic traffic simulation model RuTSim [5] is in the examples adapted to represent driver/vehicle units equipped with different types of ADAS.

An Overtaking Assistant

A traffic simulation based evaluation of an overtaking assistant is presented in [6]. The overtaking assistant considered in the study assists the driver in the judgement of whether or not an overtaking opportunity can be accepted based on the time gap to the next oncoming vehicle. This functionality was implemented in RuTSim by modification of the overtaking decision process in the simulation model. The overtaking decision-making process in RuTSim is governed by four conditions;

the vehicle's ability to overtake, the possibility to overtake considering the surrounding traffic, possible overtaking restrictions and the driver's will to overtake. Stochastic functions of the following form are used to determine a driver's willingness to overtake

$$P[s] = \begin{cases} \exp[-A\exp(-ks)], & s > s_{\min}^{\text{flying/acc}} \\ 0, & s \le s_{\min}^{\text{flying/acc}}, \end{cases} \tag{1}$$

where $P[s]$ is the overtaking probability given a clear sight distance, or distance to the next oncoming vehicle, s. The threshold $s_{\min}^{\text{flying/acc}}$ is the minimum clear distance for flying or accelerated overtaking and A and k are parameters. The probability functions of the equation above are fitted to empirical data collected on two-lane roads in Sweden. Distinct functions are estimated for different road widths, types of overtaking, overtaken vehicle and sight limiting factor, i.e. natural obstacles or oncoming vehicles.

The overtaking assistant has been modelled in RuTSim under the assumption that the assistant influences only the assisted drivers' willingness to overtake. For equipped vehicles in the simulation, the stochastic overtaking probability functions have been replaced by a deterministic procedure:

$$P[t, s] = \begin{cases} 1, & \{(t, s) : t > t_{\min}^{\text{assistant}}, s > s_{\min}^{\text{flying/acc}}\} \\ 0, & \text{otherwise}, \end{cases}$$

where $P[t, s]$ is the overtaking probability given distance s and time t to the next oncoming vehicle. The parameter $t_{\min}^{\text{assistant}}$ is the overtaking assistant threshold and $s_{\min}^{\text{flying/acc}}$ is the minimum clear distance for flying or accelerated overtaking. Vehicles equipped with the overtaking assistant will accept an overtaking opportunity if the time to the next oncoming vehicle is longer than the overtaking assistant threshold. This simple model corresponds to full driver compliance with the overtaking assistant.

In-Vehicle Virtual Centre Line Rumble Strips

Systems that give active support and thereby take over or actively interfere with parts of the driving process, e.g. adaptive cruise controls and speed limiters, will have an impact on both vehicle properties and driver behaviour. Assistance and information systems that do not give any active support can be assumed to only influence driver behaviour. Neither infrastructure based milled centre line rumble strips nor in-vehicle virtual rumble strips give active support. Consequently only the observed driver behaviour needs to be considered in the traffic simulation modelling of centre line rumble strips. In a combined driving and traffic simulator study of milled versus in-vehicle virtual rumble strips indications were found of impacts of the rumble strips on drivers' free driving speeds, reaction times and overtaking behaviour [7].

RuTSim applies a concept of a basic desired speed that vehicles in the simulation will strive for under ideal conditions, i.e. on a straight and wide road without speed limit. This basic desired speed is reduced with respect to the speed limit and the road alignment to a desired speed that vehicles will strive for along the simulated road. Individual vehicles in the simulation are assigned basic desired speeds drawn from vehicle type specific normal distributions, the resulting desired speeds will therefore vary within the population of simulated vehicles. The simulated free driving speeds depend on both the vehicles' desired speeds and acceleration capabilities. Free driving simulation runs, with only vehicle–infrastructure interactions and no vehicle–vehicle interactions, were used to tune the free driving speeds to the observed values for different rumble strip conditions.

Acceleration updates for the vehicles in the simulation were delayed to model the observed reaction times. RuTSim applies an acceleration model of the following form

$$a_n = f(\Delta x_n, v_n, \Delta v_n)$$

where $a_n, \Delta x_n, v_n$ and Δv_n denotes acceleration, distance to the vehicle in front, speed and speed difference with respect to the vehicle in front for vehicle respectively. Reaction times were modelled by evaluating the right hand side of the acceleration equation one reaction time earlier than the left hand side, i.e.

$$a_n(t) = f(\Delta x_n(t-T), v_n(t-T), \Delta v_n(t-T)),$$

where t is the current simulation time and T is the reaction time.

To model the observed difference in overtaking behaviour, the clear sight distance s in the right hand side of Eq. 1 was replaced by $\alpha \cdot s$. The parameter α was tuned to allow the model to reproduce the observed changes in overtaking behaviour.

Adaptive Cruise Control

An Adaptive Cruise Control (ACC) system influences the longitudinal movements of the equipped vehicle. Longitudinal vehicle movements are in a traffic simulation model governed by a car-following model. It is therefore necessary to modify the car-following model to allow simulation of ACC vehicles. Many commonly applied car-following models are in essence controllers that determine acceleration/deceleration rates given distance and speed difference to the immediate leader [8]. Hence, car-following models and models of ACC systems have the same input data. ACC system functionality can therefore straightforwardly be taken into account by changing parameters or functional form of the car-following model. The car-following model should also include parameters controlling speeds and car-following headways to allow modelling of observed driver behavioural changes. Delayed reactions in situations when the driver need to resume control of the longitudinal driving task should also be modelled if such situations are to be studied. The importance of this aspect is however likely to decrease as "stop-and-go" ACC systems are introduced.

More important for the analysis of future impacts of ACC is probably the modelling of non-equipped vehicles in simulations of mixed traffic. The most obvious difference between ACC and human driving is the longer reaction time of human drivers. Human drivers are also likely to estimate the position and speed of the leader vehicle with less accuracy than an ACC system's sensors. Limited perception capabilities are however compensated for by the drivers through anticipation of future traffic situations. This anticipation can, to be more precise, be described as consideration of multiple vehicles ahead and accounting for future speeds and positions.

In a study of vehicle trajectory impacts of ACC [9] the Intelligent Driver Model (IDM) [10] was used as the basic car-following model for both ACC and standard vehicles. For standard vehicles, limited human perception and reaction capabilities and anticipation to compensate for these limitations have been taken into account by extending the IDM model with the Human Driver Model (HDM) [11]. HDM is a meta-model that allows modelling of delayed reactions, perception inaccuracies and anticipation of the future traffic situation. The ACC system response time was also taken into account in the study.

Conclusions

A traffic simulation based framework for estimation of traffic system wide impacts of driver assistance systems has been presented. In the presented framework, the functionality and the driver behaviour adaptations associated with the considered ADAS are taken into account and implemented in a traffic simulation model. Traffic system wide impacts can then be estimated through simulations of traffic with different proportions of ADAS equipped vehicles. With the purpose of exemplifying traffic simulation modelling of different types of ADAS, the modelling of an overtaking assistant, of in-vehicle virtual rumble strips and of adaptive cruise control have been described. Driver behaviour studies for use of the results for traffic simulation modelling often place different demands on the experimental design than the traditional driver behaviour research. That is why an important topic for further research is collection of driver behaviour data for traffic simulation modelling.

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Modelling Aspects of Longitudinal Control in an Integrated Driver Model

Detection and Prediction of Forced Decisions and Visual Attention Allocation at Varying Event Frequencies

Bertram Wortelen, Malte Zilinski, Martin Baumann, Elke Muhrer, Mark Vollrath, Mark Eilers, Andreas Lüdtke and Claus Möbus

Abstract Simulating and predicting behaviour of human drivers with Digital Human Driver Models (DHDMs) has the potential to support designers of new (partially autonomous) driver assistance systems (PADAS) in early stages with

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regard to understanding how assistance systems affect human driving behaviour. This paper presents the current research on an integrated driver model under development at OFFIS within the EU project ISi-PADAS. We will briefly show how we integrate improvements into CASCaS, a cognitive architecture used as framework for the different partial models which form the integrated driver model. Current research on the driver model concentrates on two aspects of longitudinal control (behaviour a signalized intersections and allocation of visual attention during car following). Each aspect is covered by a dedicated experimental scenario. We show how experimental results guide the modelling process.

Keywords Driver model · Behaviour Classification · Attention allocation · Car following · Traffic light

Introduction

The number of driver support systems in cars is constantly increasing. Some of these systems influence drivers' attention and might change drivers' behaviour. Investigations on the probability of different factors to provoke inappropriate behaviour can lead to improved system designs. Driver models can help to systematically evaluate new driver assistance systems by doing closed loop simulations of drivers, systems and environments. The advantage of this simulator experiment based approach with human participants is (1) the reduction of costs for simulations and (2) to have a defined basis for comparison of design alternatives. However the main disadvantage is the incompleteness of driver models. As a matter of course they do by far not cover the great variance of human behaviour.

In a first step we create a valid DHDM without interaction to any assistance system. First results of this step will be shown in this paper. In future work the second step will be to extend the model to also handle interaction with an exemplary PADAS. Current research on our DHDM concentrates on two aspects of longitudinal control: behaviour at signalized intersections and allocation of visual attention during car following. For each aspect a dedicated experiment was conducted. We refer to the experiment for behaviour at signalized intersections with TL and for visual attention allocation with VA. Each will be described in the dedicated section. At the end we will show how the resulting models can interact by integrating them into CASCaS (Cognitive Architecture for Safety Critical Task Simulation) as executing framework, resulting in one integrated DHDM.

Detection and Prediction of Forced Decision at a Traffic Light

The TL scenario is used to investigate human driving behaviour at signalized intersection approaches. In this scenario participants approached a signalized intersection where the traffic light turned from green to yellow shortly before the driver reached the intersection. At the specific time when the yellow phase triggers drivers have finally to decide whether to stop at or to pass through the intersection. Depending on their decision different behaviour will be triggered. As shown later vehicle state and driver behaviour allow prediction of driver's decision prior to the yellow phase change.

The basic scenario was a short trial in an urban area with a single-lane priority road with low traffic density, no vehicles on the same lane, and some oncoming traffic. Pedestrians were randomly placed on the sidewalk. The whole section had a length of about 1,000 m. Behind a short curve there was a straight road of 160 m till the critical intersection. At this intersection was a traffic light, which switched from green to yellow in a moment, when the driver has the possibility either to pass or to stop. The traffic light was positioned 5 m before the intersection. The light turned from green to yellow 28 m before the traffic light. If the drivers stopped at the intersection, the traffic light switched back from red to green after 10 s. In the simulator, driver actions (position of gas and brake pedal) and the resulting car parameters were recorded with a frequency of 60 Hz.

The first step for our analysis of braking decisions is to identify the relevant observable variables that allow the prediction of the future decision. Psychological motivations of drivers to find reasons why they behave like they do are not investigated.

For the prediction itself we use different classification techniques, such as Naïve Bayesian Classifier[1] (NBC), Logistic Regression, and Support Vector Machines[2] (SVMs). We do not use decision trees (C4.5) since their performance in terms of AUC and accuracy are lower as stated by [2]. The selection and the size of the learning and testing data sets are systematically varied to get an overview of the prediction quality for different parameter sets. For every parameter set a cross-validation estimates the performance of the predictive model.

The parameters recorded by the simulator were used to calculate Distance To Intersection (DTI), Time To Intersection (TTI), and a combined variable for brake/gas position. The latter variable was calculated so that it gets a positive value [+1,0) when the gas pedal is pressed, a negative (0,−1] for brake pedal pressed and zero when the driver did not use either pedal. The data acquired does not cover information about when and why a driver at some point in time decides to brake at the intersection.

All simulation drives have been classified in terms of approach of drivers who stop at the traffic light (brakers) and drivers who do not stop at traffic light (passers). To distinguish the dichotomic groups from each other it was sufficient to check whether the car slowed down under 5 km/h at any time in the approach. The classification was appended to the time series and is used by the applied supervised classification algorithms for the learning and verification step.

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[1] See [1].

[2] See [1].

The driver is able to see the traffic light from about 150 m distance. The traffic light is observable in green phase over a section of about 120 m while drivers approach with a mean speed of approx. 51 km/h, which equals a TTI of approximately 8–9 s measured 120 m before the intersection. After the drivers have seen the yellow traffic light and start to brake (or in the other case continue at travelling speed, in some case also accelerate), it becomes easy to differentiate between the classes braker and passer. Also before the yellow phase triggers it is possible (with a particular level of error rate) to predict the future behaviour.

A measure of the predictive quality of a model is error rate. Error rate is calculated by dividing the sum of false predictions through the sum of all cases. The prediction models applied are trained with a subset A of data and a different subset B to test the predictive quality with the measure of error rate. A and B are subsets of the traffic light approaches constrained by specific starting and ending points and $A \cap B = \phi$. To estimate the performance of a predictive model cross-validation technique is used.

An issue which arises in the modelling process is the selection of the data. When dealing with time series starting and ending points which represent the relevant subset have to be chosen. Grid search for different selection parameters is applied in order to find those areas with low error rates.

Classification Procedure

The following classification procedure gives an overview on how the models have been calculated and validated:

1. Discretisation of data if required by prediction model
2. Define parameters for the selection of data for grid search
   (a) Starting points [−50 m, −48 m,…, 0 m] to intersection
   (b) Interval length [2 m,4 m,…, 30 m] (defining ending points)
3. Start cross validation loop for each parameter with 10 iterations
   For each iteration:
   (a) Train model using a specific model with subset A of data
   (b) Predict class for subset B of data ($A \cap B = \phi$)
   (c) Calculate error rate
4. Calculate mean error and standard deviation of all iterations
5. Plot results

As stated by Rakha et al. [3] TTI can be used to predict the probability of braking decisions for the instant when the traffic light switches to yellow phase. For classification in the scenario at hand velocity and brake/gas pedal have been chosen for training of the prediction model. By using velocity instead of TTI no discretisation issues (discretisation is needed for some models) arise when the speed converges to zero and therefore TTI converges to infinity.

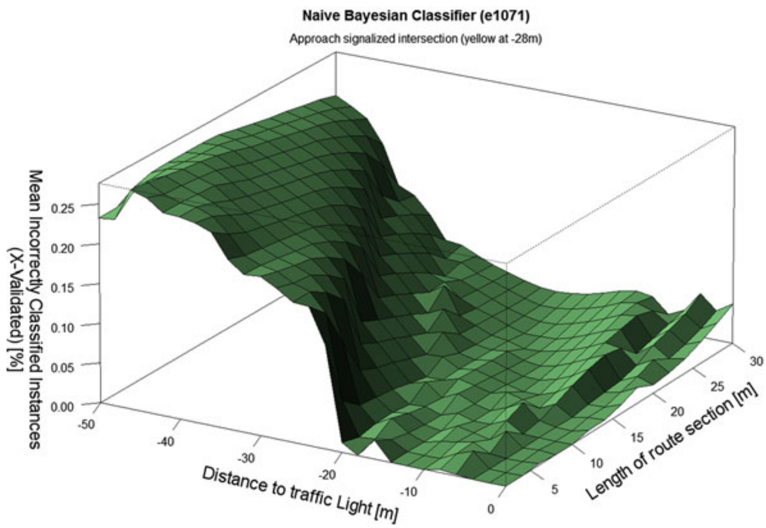

Fig. 1 Classification of braker/passer using na bayesian classifier (equal width interval discretisation)

Figure 1 shows the mean error rate of the NBC model for all subsets of the time series of the intersection approach defined by the grid search parameters. The model only uses velocity and brake/gas pedal as predictors. The x-axis shows the starting point of the selected data [−50 m, −48 m,…, 0 m] the y-axis represents the length of the interval [2 m, 4 m,…, 30 m]. On z-axis the mean error rate for the predicted area is shown. The prediction quality improves when the distance to the traffic light reduces. But also 50 m in front of the traffic light the error rate is already below 25%. A SVM model performs slightly better than the NBC, but the run of the curves are very similar. An advantage of the SVM in comparison to the implementation of the NBC (e1071[3]) is the fact, that no discretisation is required. Anyhow using only ten bins for each variable (equal width interval discretisation) the NBC is a very simple model with good performance, which is capable of giving levels of certainty[4] for the prediction (in contrast to SVMs[5]).

Visual Attention Allocation

Visual attention allocation is a crucial part in many aspects of the driving task. In our second line of research our modelling effort concentrates on how drivers

[3] Misc Functions of the Department of Statistics (e1071), TU Wien (http://cran.r-project.org/web/packages/e1071/index.html).

[4] Probability prediction is an inherent property of NBCs.

[5] Note: This could bypassed by using the hyperplane target function as scores.

distribute visual attention among different areas of interest while executing longitudinal control.

In the following we will present layout and first results of the VA experiment that has been performed to investigate visual scanning behaviour in a car-following task. Afterwards we show how the process of visual information acquisition is modelled in CASCaS.

Driving Experiments

According to the SEEV (Salience, Effort, Expectancy, Value) model of Wickens [4], information frequency is one of the main influence factors for visual scanning behaviour. To investigate the effect of different information frequencies on drivers' behaviour, driving simulator experiments in a dynamic driving simulator have been conducted at DLR [5]. For the VA experiment an urban scenario was realised in which 20 participants had to follow a leading car. The scenario consists of 24 straight road segments with a length of 600 m, divided by intersections where the drivers had to follow the passing or turning leading vehicle. Information frequencies have been varied for two Areas of Interest (AoI): the leading vehicle and a secondary task display showing the SURT (Surrogate Reference Task) [6].

To vary the amount of information the driver perceives from the lead car, the experiment has been executed with two different speed profiles of the lead car: (1) lead car driving constantly and (2) lead car varies speed with a given pattern (see [5] for details). The amount of information for the second AoI has been varied by using different interstimulus intervals (3 and 6 s).

Figure 2 shows percentage dwell times and gaze frequencies for one participant during the complete VA experiment, independent from the experimental condition. From this it is easy to observe, that the main sources of information are the front view (for the driving task) and the secondary task display (for solving the artificial in-vehicle task).

Visual Perception Process in CASCaS

Processes involved in visual information acquisition for any model in CASCaS are very shortly described here. For a more complete description see [7].

The main influencing factor for perceiving new information for any model developed within CASCaS is the internal representation of the task to be accomplished. A task like car driving is structured for the model by a set of hierarchically organized goals. Prominent examples in the driving domain are shifting gear and keeping lane, speed or distance. For the last three of these the driver has to permanently monitor the current state of car and environment to keep the car in the lane and to keep speed and distance within an acceptable range of values.

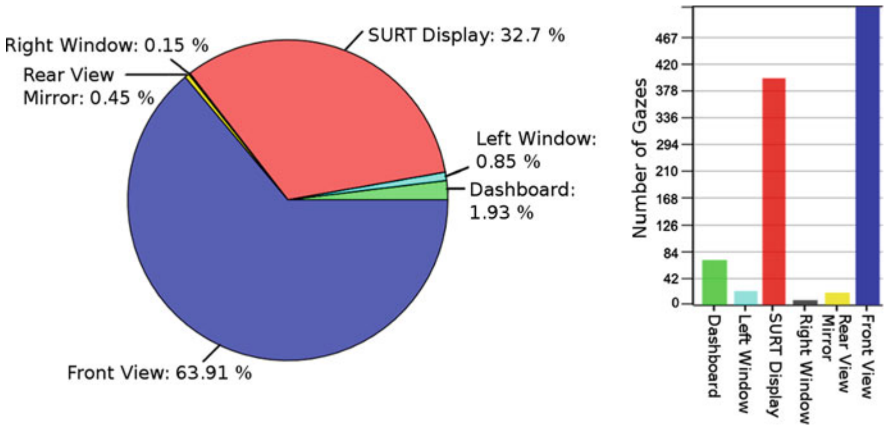

Fig. 2 Percentage dwell times and gaze frequencies for all recorded AoI's

At any time there are several goals that the driver model has to serve simultaneously. These are referred to as active goals. The set of active goals changes over time. This is due to the fact, that new goals emerge from the driving situation or existing ones are achieved or interrupted.

The goal the model is currently working on is referred to as selected goal. As each goal normally requires different kind of information, a goal switch also means a switch of visual attention, because the model has to get relevant information for the selected goal from the environment.

CASCaS derives which information is relevant for a goal from the task description. The main formalism used for the task structure are GSM-rules (Goal, State, Mean). A GSM-rule is a 3-tuple $r = (g_r, s_r, A_r)$, with g_r, being the goal, which this rule shall serve, s_r being a Boolean condition defining in which cases r shall be applied, and A_r being a set of actions to be carried out, when r is applied. The condition s_r is defined on a set of information I_r stored in the models memory. The model sequentially selects rules, for which g is equal to the selected goal, and s holds. If no rule condition holds for the selected goal, there are two possible reasons. (1) Every information in I_r is available for all rules associated to the selected goal, but no state description fits. In this case the model will apply no rule and just switches the selected goal. (2) The model cannot access all information elements of I_r. This can be, because it has not received the information yet, or it forgot the information, or due to additional timing constraints defined in s_r. Such constraints are used to describe the maximum allowed age for information used for the specific goal.

In the latter case when information is missing, the model will try to perceive it from the environment. Where it can find specific information is defined in a topology structure of the environment. The model questions this structure and moves its gaze to the place defined in the topology. In doing so the visual focus is driven by information demands of the selected goal (top-down-attention) and the strategy used to dynamically select goals drives the visual scanning behaviour of the model. We refer to this as the multitasking strategy. CASCaS contains also a mechanism for bottom up attention [7], which will not be further described here.

The current multitasking strategy just maintains a queue of active goals and executes them in strict sequential order. For three exemplary goals A (keeping lane), B (hold speed) and C (read navigation system) this results in static execution sequences of A-B-C-A-B-C-A-B-C-…, which is not very realistic. To overcome this we changed the multitasking strategy.

SEEV Visual Attention Model

For an initial improvement of this strategy we took implications of the SEEV model of Wickens [4], which states that there is a proportional relationship between information frequency of an AoI and probability of visual attention to it.

Besides the probability of attention the SEEV model does not state anything about fixation times and sequences on a small time scale. To account for this we changed the algorithm for goal selection. Goals are now selected on a probabilistic and not sequential basis. The probability of selecting a specific goal g_i is determined by:

$$P(g_i) = \frac{V(g_i) \cdot f(g_i)}{\sum_{j=1}^{n_{\text{goals}}} \left(V(g_j) \cdot f(g_j)\right)} \tag{1}$$

With *V(g)* being the value of goal g, f(g) being the event frequency of goal *g*, and n_{goals} being the number of active goals. In this way the model accounts for both knowledge driven factors of the SEEV model. Furthermore with equal and constant V parameters the model is identical to the idea of the Random Constraint Sampler of Senders [8]. The event frequency can be statically assigned or can be derived from the amount of information events appearing during simulation for each goal.

Like Senders already stated the resulting model is simple and in some points unrealistic. Parameters can easily be found to fit aggregated human data like percentage dwell times on a large time scale, but it especially does not consider the effect of what Senders called rising uncertainty about the current value of the signal, which is more related to changes of attention probability on a small time scale (few seconds). At the moment we are working on a second visual attention model which also accounts for this aspect.

Conceptual Integration into a Hybrid Simulation Model

The partial driver models presented in this paper will be integrated into one hybrid driver model, using CASCaS as executing framework.

The classification model for braking prediction presented in this paper will be used in CASCaS to decide which strategy (braking/passing) the model will select. This will be done by selecting one out of a set of rules, each initiating a different strategy. The selection of a rule will be guided by the classification model.

As previously described, the visual attention model is implemented in the goal module to guide the goal selection of permanent monitoring goals.

In a subsequent step all models will be used concurrently in one driver model, to account for different aspects of the longitudinal control task of driving.

Discussion and Conclusion

We showed how different modelling techniques can be utilised to generate partial and specialized driver models focussing on different aspects of longitudinal control behaviour. The next step will be to instantiate an integrated driver model in CASCaS as executing framework. We will investigate how such integrations can lead to a more holistic model of drivers.

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Towards Model-Based AHMI Automatic Evaluation

Juan Manuel González-Calleros, Jean Vanderdonckt, Andreas Lüdtke and Jan-Patrick Osterloh

Abstract Aircraft cockpit system design is an activity with several challenges, particularly when new technologies break with previous user experience. This is the case with the design of the advanced human machine interface (AHMI), used for controlling the Advanced Flight Management System (AFMS), which has been developed by the German Aerospace Center (DLR). Studying this new User Interface (UI) requires a structured approach to evaluate and validate AHMI designs. In this paper, we introduce a model-based development process for AHMI development, based on our research in the EUs 7th framework project "Human". The first goal is to rely on this structured approach to perform automatic evaluation of the User Interface.

Keywords User Interface · Advanced Human Machine Interface · Model-Based User Interface Development · Cockpit design

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Introduction

Aircraft cockpit system design is an activity with several challenges, particularly when new technologies break with previous user experience. This is the case with the design of the advanced human machine interface (AHMI), used for controlling the Advanced Flight Management System (AFMS), which has been developed by the German Aerospace Center (DLR). The interaction between the pilot and the AHMI is through the User Interface (UI) composed of traditional control objects (buttons, spin button, menu) and non-traditional (compass rose, aircraft). The transformation of the existing character-based UI (left in Fig. 1) for the AFMS into a graphical User Interface (middle in Fig. 1) encounters new defies for the development process (analysis, design, implementation, evaluation) and their future usage.

Integrating evaluation in the loop of the design of the AHMI imply the use of pilots and a physical simulator. Thus this is costly and it would be hard to perform traditional UI tests considering that pilots are assets hard to find not just for their cost but also their availability. Moreover, flight simulators, located mostly in aeronautics research centers, are of limited access for long testing sessions. This stresses the need for a new approach, partially substituting pilots and the physical simulator, to conduct research on the AHMI evaluation. The focus of this work is to describe how to perform automatic UI evaluation of the AHMI.

Studying this new UI requires a structured approach to evaluate and validate AHMI designs. We claim that AHMI design is an activity that would benefit from relying on a model-based UI development (MBUID) approach, which offers, in principle, the opportunity to test different AHMI configurations. This chameleonic capacity of the UI in the MBUID context permits us to consider the evaluation of different layouts or the replacement of interaction objects of the AHMI without changing the source code just the models.

In this paper we rely on a structured reference framework, Cameleon, a User Interface Description Language, UsiXML, and a formal representation of the models, meta-models, to express the different aspects of the methodology. The UI

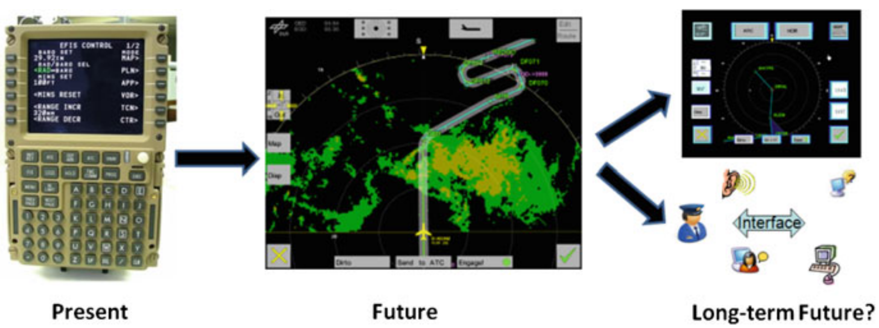

Fig. 1 AFMS evolution

of the AHMI is expressed using UsiXML formalism. Usability guidelines are also stored in the same formalism. The UI is checked against the guidelines and violations are listed and a solution is proposed. For instance, the text messages should always start with upper case and the rest of the words in the message, although it is a reserved word, should be in lower case. This kind of features can be evaluated automatically thanks to the use of software tool developed for this purpose, the Usability Adviser. The results of this evaluation complement the research on AHMI cockpit system design that is conducted with more sophisticated techniques where some other tools (virtual simulation platform of the aircraft) and techniques (cognitive modelling of pilots) are used to analyze pilots behaviour in order to identify why they commit errors. Another benefit of relying on the MBUID is that different modalities of interaction could be, in principle, also evaluated, if the models and the transformational knowledge needed exist. We explore this dimension to generate an alternative graphical (3D) representation of the AHMI (2D) or vocal interaction, see right side in Fig. 1. The goal of this work is to perform some traditional usability evaluation on the preference between the two different renderings with users.

The reminder of this paper includes the review of the state of the art in the newt section. Followed by, the description of the proposed methodology. Next, the methodology is exemplified through a case study. Finally, the conclusions and future directions of this research are exemplified.

State of the Art

Interactive Cooperative Objects (ICOs) used to model aircraft interactive systems [1], such as: air traffic workstations, civil aircraft cockpit and military aircraft cockpit. The formal description for interactive cockpit applications uses Petri nets to describe dynamic and behavioural aspects of systems in the cockpit. A formal model of pilot-automation interaction and the characteristics of the UI are described in [1]. This work compared the effects and benefits of visual cues (labels, prompts, messages) to support mission tasks. However, there is a limitation on the widgets models and guidelines. The design knowledge in the methods is described to support the design of highly interactive systems such as the AHMI as they just model classical WIMP interfaces [1].

There have been some attempts, in the avionics context, to standardize formal methods of some aspect of the UI. The ARINC standard [2] defines protocols to communicate the dialogue and the functional core of cockpit display system [3]. This standard also considers the presentation level, i.e., a set of widgets are included as a recommendation but no design guidelines, no method to design UIs are considered in the standard [3]. Even more, the ARINC standard is not used for primary cockpit applications [1], such as Primary Flight Display and Navigation Display. It only deals with secondary applications involved in the management of the flight such as the ones allocated to the Multiple Control Display Unit [1].

Formal methods have been used in aviation but limited has been its use specifically when addressing the UI design. Existing attempts are partial or limited in their formalisation as they just denote the UI functionality in terms of state transitions but do not go further in the modelling particularly to evaluate multiple UIs.

Even more, among all the User Interface Description Languages (UIDL) complaints with the MBUID, a complete review can be found at [4], we are not aware of any attempt to rely on a MBUID to prototype avionic displays.

Model-Based AHMI Design

There is a global consensus about the components of a MBUID methodology [5], which are: a series of models, a language, an approach and a suite of software engineering tools. We rely on the USer Interface eXtensible Markup Language (UsiXML) [6], a formal methodology for describing a MBUID process. Relaying in a language engineering approach [7], UsiXML considers three levels of the language aspect: the syntax, semantics and stylistics of the language. The semantics are expressed as UML class diagrams that correspond to meta-models of the AHMI. The meta-models are transformed into a XML specification, which considers XML Schemas (abstract syntax) for the definition of valid XML. Finally the stylistics is the visual syntax mainly used to depict meta-models.

The proposed method is compliant with the structured CAMELEON reference framework [8]. Largely used in the literature for UI development, the CAMELEON reference framework adheres to the MBUID that has been applied widely to address the development of complex systems. As the frameworks promoted the use of different UI abstractions, in this paper we just focus in the layer that concerns to the concrete description model. The *Concrete UI Model* (CUI) allows both the specification of the presentation and the behaviour of an AHMI with elements that can be perceived by the users [6]. The CUI model is an abstraction of AHMI elements some of which are independent of programming toolkit. For instance, in Fig. 2a the AHMI is rendered in VRML while in Fig. 2b in openGL.

Evaluating the AHMI User Interface

The evaluation of the AHMI UI considers static aspects (UI layout, position of objects) and dynamic concepts (state of a button during the interaction, colour of the label). UI models are stored and then are object of further evaluation, automatic or manual. In this scenario, usability guidelines over the UI objects (distribution of the widgets composing the UI) could be evaluated.

We have used the semantics of the AHMI formalised with UsiXML to evaluate the UI against guidelines. Special attention was paid to those guidelines for standard certification and quality assurance and to express them in the Guideline Definition Language (GDL) [5], a XML-compliant language that is directly linked to UsiXML.

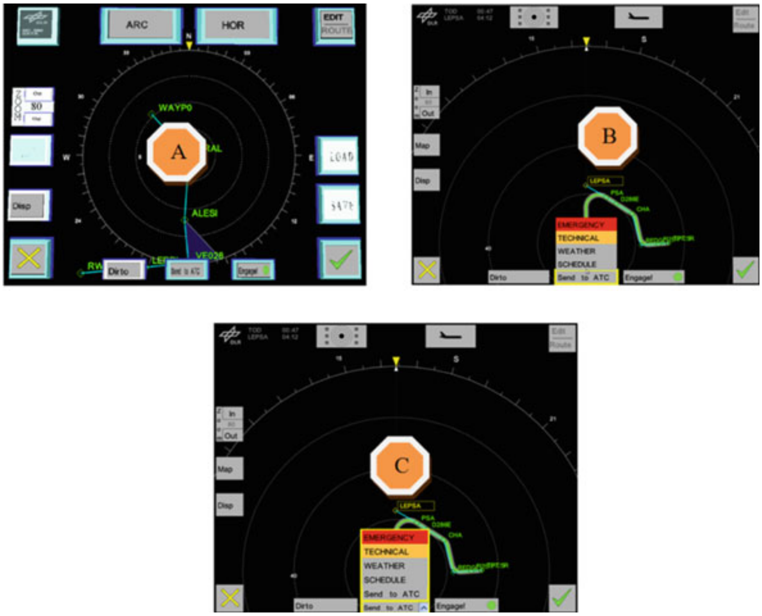

Fig. 2 Exploring diversity of widgets representation for the same task, A) VRML 3D rendering, B) OpenGL 2D rendering, C) Widgets replacement a combo box is used instead a menú (B)

Integrating UI Evaluation in a Simulation Environment

Different methods exist for evaluating a UI which mainly are divided in two categories: qualitative and quantitative approaches. Crew preferences and all kind of subjective data are gathered using different means, for instance questionnaires. There is always the need for crew members to provide feedback on the UI. Unfortunately, pilots are assets that are hard to find, so include them in the loop for constant UI evaluation is not feasible [9].

In the context of a simulation environment [10, 11] where pilots are substitute by cognitive models, and a physical simulation platform by a virtual simulation environment, automatic evaluation of the UI can be done by including a UI evaluation layer to the simulation environment. In Fig. 3, the Symbolic AHMI (SAHMI) architecture in the context of a virtual simulation platform is shown. A repository with UsiXML formalism describing the AHMI UI is used. This file is read using a parser that validates the specification and transforms this into a machine readable structure called model merger. The UI is complemented with dynamic and static data accessed via the simulation system. The Cognitive Architecture (CA) is used to simulate pilots' interaction with the AHMI. More details on the CA or the experiments are out of the scope of this paper, they can be found in [11]. Simulated pilots actions over the UI are passed as messages that are processed in the model merger. These data from the simulation system must be transformed to be compatible with UsiXML format. This data is store as a log File history (Fig. 3a).

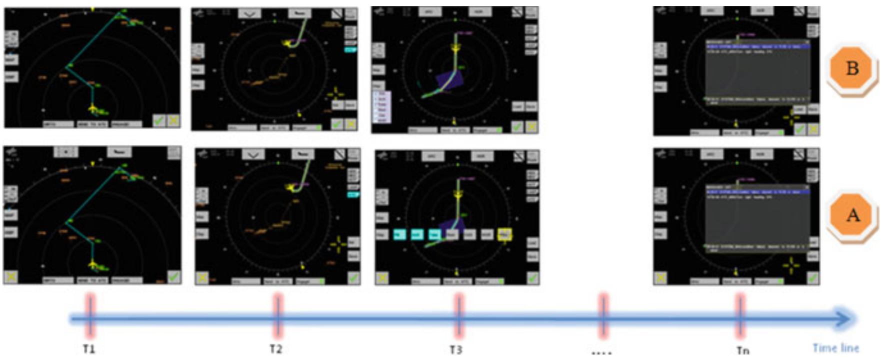

Fig. 3 AHMI UI evolution over time (**a**) and modified version over the same UI evolution (**b**)

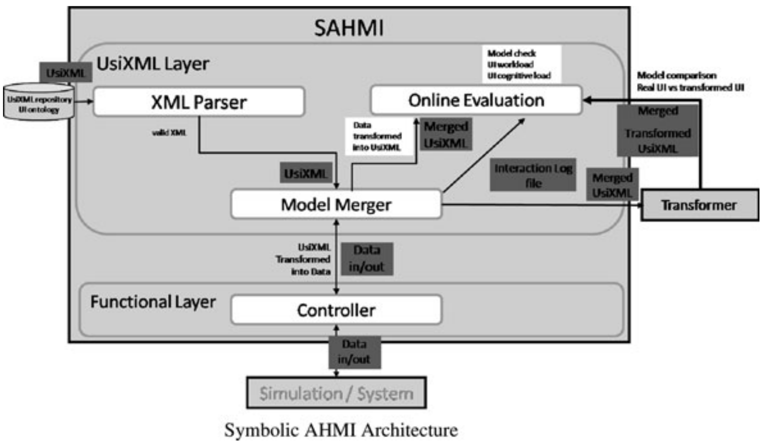

Fig. 4 Symbolic AHMI architecture

The transformer module (Fig. 4) modifies the specification of the UI trying to test multiple configurations. For instance, in Fig. 2c a combo box is used instead a menu (Fig. 2b) for selecting the negotiation type with the ATC. Thus as result the UI timeline could be composed of different version of the UI to perform the same task. The first timeline corresponds (Fig. 3b) to the real simulated system as it is. The second timeline and subsequent would be the result of investigating different renderings of the same UI over time. For instance in Fig. 3 the timeline B shows changes in the location of widgets (T_1, T_2, and T_n) and replacement of a widget (T_3). The evaluation layer of the SAHMI keeps a trace of the evolution of the UI during the interaction. The Model Merger layer reconstructs the UsiXML and sends it to store it in the online evaluation tool.

User Interface Evaluation

Guidelines evaluation can be automatically performed with the Usability Adviser [12]. Such evaluation can be automatically evaluated with the Usability Adviser [12], a tool to determine the ergonomics characteristics of a UI when it is specified in UsiXML. This tool evaluates ergonomic rules to determine, for instance, visual obstruction, colour coding. The software expresses usability guidelines as logical grammars. For example, a usability guideline that selects appropriate color combinations for the label on a slider, is described as follows: i ∊ Slider: ¬ [Slider-Color(i, white) ^ LabelColor (i, yellow)].

The AHMI must not differ from a traditional UI. The traditional set of widgets must be used for the AHMI UI as much as possible by imitating their behaviour and graphical representation. This is needed as future pilots would be used to the computer interaction, thus, cockpit display systems should at least be consistent with systems of our daily life [13]. Even more important, traditional UI usability guidelines such as those listed in the ISO 9126 standard can be used to evaluate elements of the AHMI UI. There are some which have been corroborated in the avionics domain, for instance, messages should follow always the nomenclature: first letter in capital and the rest in lower case [9]. There are some other that refers to specific AHMI display systems such as the consistency in the roll index in the compass rose [14].

Conclusion

The AHMI is a new innovative system that introduces new challenges for the development of cockpit systems. Development steps including design and evaluation, among others, are normally limited addressed when it refers to the UI. Design knowledge is normally hidden and evaluation is mostly focused on the system functionality rather than of the usability of the system. In this paper we propose to rely on a model-driven approach for the development of AHMI that, among other advantages, can be coupled in a simulation environment. Modeling the SAHMI showed to be an option for UI evaluation. The model of the UI, as described in the paper, can be modified in order to test different UI configurations. Traditional measurements can be assessed like UI workload, color combination. Finally, the modality of interaction of the UI can be object of evaluation. While in this paper we showed how the original 2D rendering can be equally rendered in 3D. A future plan is to automatically generate the AHMI from its model and to submit it to run-time analysis. For the moment, only automated guideline review in perform through the UsabilityAdvisor.

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Darmstadt Risk Analysis Method (DRAM)

A Generic Method for Modular, Systematic, Quantitative and Interdisciplinary Risk Assessments Considering Human Behavior

J. Stefan Bald and Frank Heimbecher

Abstract DRAM (Darmstadt Risk Analysis Method), is a structured and effective approach to do risk assessments and other evaluations on complex systems, especially if they are influenced by human behavior. The method is quite general. It does not imply any specific findings. To integrate findings is the task of the different research groups who are using DRAM. The method comprises a language to describe and document findings, to combine them to a bigger entity and to exchange them between different research groups. As in most natural sciences, the method is model-oriented. The vision of DRAM is to provide an overall model of the driver–vehicle–road-system, which is fed from most of the disciplines and research groups and may be used by them. This paper describes the structure of the method and its components and demonstrates its application by an example.

Keywords Road system modelling · Multidimensional · Human behaviour · Risk assessment · Probability distributions

Introduction

Aim of this report is to introduce Darmstadt Risk Analysis Method (DRAM). DRAM is a structured and effective approach to do risk assessments and other evaluations on complex systems, especially if they are influenced by human behavior. The general method does not imply any specific findings. To integrate

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findings is the task of the different research groups which are using it. The method uses some sort of language to describe and document findings, to combine them to a bigger entity and to exchange them between different research groups. One could consider it as being an illustrative and modular numerical representation of arbitrary very complex Bayesian networks.

DRAM has been designed to enable researchers from different research groups to model complex systems in a modular, clear, integrative and interdisciplinary way. In particular, the method shall enable them to analyze seldom combinations of system states, which may lead to dangerous situations, even or especially if the system depends on human behavior. The modular approach supports and stimulates cooperation between different research groups, and it makes it possible to enhance and refine single modules without having the need to build a completely new model from the scratch.

The method has its roots in research of the late 1980 [1, 5], when better methods for accident analysis were searched in Germany. For some reasons, there was not much progress during the following years. From 2003 to 2006, the method was revived and integrated into IN-Safety (http://www.insafety-eu.org), an European 6th framework project [2–4] . Actually, Technische Universität Darmstadt is about to finish a project from the German Highway Federal Research Institute BASt using DRAM for risk assessment in road tunnels with consideration of human behavior. The following general explanation of the method and its components will be accompanied by an example, which is taken from this current research.

Complex System

Road systems are very complex, non-linear and widely governed by human behavior and subjective feelings. They are covered by many disciplines: road and vehicle engineers, psychologists, educationalists, etc. Despite their high absolute numbers, from a statistical point of view, accident are rare events, a fact, which causes high dispersion. And accidents mostly are results of unfortunate combinations of events, which in itself are not necessarily unfortunate and occur quite often without negative effects. DRAM enables to analyze such systems.

Model Orientated Approach

As in most natural sciences, the method is model-oriented: The result of the model is a prediction for the reality dependant on certain parameter combinations (boundary conditions). If this prediction has been correct for situations in the past (with certain parameter combinations, which have been watched; “verification”), one can assume, that the prediction will be valid also for situations in the future (with other parameter combinations): the model may be used for failure analysis or for design processes.

Models can be used to identify problematic areas of a system (e.g. where does a human driver needs assistance by a technical system) or to elaborate and evaluate new policies and technologies (e.g. balance the advantages and disadvantages of ADA-Systems) before their realization.

The vision of DRAM is to provide an overall model of the driver–vehicle–road-system, which is fed from most of the disciplines and research groups and may be used by them. Each group concentrates on an area (one or more modules) of the whole model, in which it feels competent. If there is more than one approach for a certain area, the model shall provide all of them alternatively (with the user to decide, which of them shall be used for his specific analysis).

Components

Figure 1 gives an overview over DRAM. It shows, how the different components of the method are used to address the objectives: dealing with uncertainty, integration of all available data, modeling the cause-and-effect chain, improvability and upgradeability as well as cooperation and multidisciplinarity.

DRAM uses probability values, to deal with uncertainty, and especially the probabilities of consequence values to sum them up to risk values. It describes the system systematically with a modular structure of active and passive elements to reproduce cause-and-effect chains and to enable selective enhancement and refinement. It uses Numerically Described Multidimensional Probability Distributions (NDMPD) and a supporting computer tool (DRAT) to describe system states ("situations") and relations between these situations. And with its Database

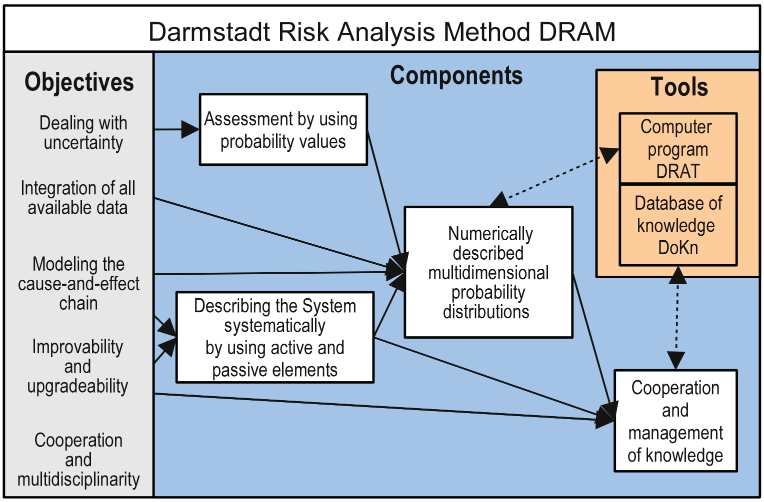


Fig. 1 Objectives, components and tools of DRAM

of Knowledge (DoKn), it gives the possibility to collect modules and to redistribute them to other researchers.

The components of DRAM are described in more detail below and in Bald et al. [3, 4].

Network of Active and Passive Elements

The complexity of the system is addressed by describing it systematically as a network of active and passive elements. Active elements are modules which describe and model the behavior of a certain part of the system. Passive elements are interfaces between the active elements. If these interfaces are defined in an appropriate way, the modules may be analyzed, replaced, upgraded etc. rather independent, e.g. by different research groups even from different disciplines. Active elements (modules) may be individually replaced or detailed in order to improve and upgrade the model.

For an example of a more complex system structure with some dozens of elements see Fig. 5 of Bald et al. [3], first published in Bald [1]. In the current research for tunnel safety, similar structures describe the occurrence of a dangerous event (e.g. a vehicle failure, its effects (e.g. traffic jam, fire), escape and consequences. Unfortunately, these diagrams are very extensive, so they cannot be reproduced within this paper.

Figure 2 gives a microscopic view on the tunnel example. It is part of the escape phase.

The analysis is organized in time steps. Figure 2 shows three elements, which form one iteration. The outermost two (with rounded edges) represent passive elements, which describe the tunnel situation at two consecutive time steps. Appropriate data are: the position, the speed and the direction of the people in the tunnel. The third element, an active element, connects the other ones and describes, how position, speed and direction are changing over time.

Numerically Described Multidimensional Probability Distributions (NDMPD)

Data are described by Numerically Described Multidimensional Probability Distributions (NDMPD). The following example shall demonstrate the advantage of this approach.

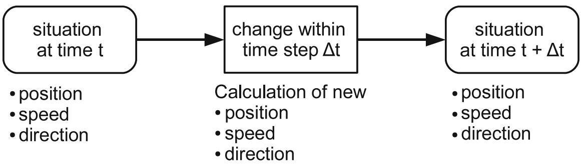


Fig. 2 Part of the structure of the escape phase in a road tunnel

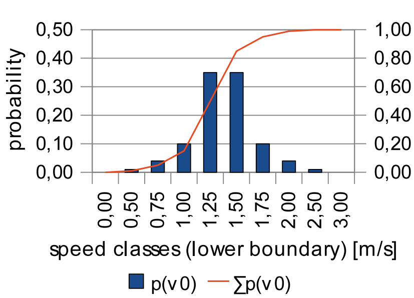
In a real case of fire in a road tunnel, people have only few minutes to save themselves. Current approaches assume, that they escape with a constant speed, in Germany assumed to 1.3 m/s, being on the safe side. According to physics, one can calculate the place of a person with this speed at time t with formula (1). E.g., after 30 s, the person will be 30 s · 1.3 m/s = 39 m away from his original place s_0.

$$s = s_0 + v \cdot t \tag{1}$$

In reality, this speed is not the same for all persons, and it may vary according to the physical ability, to the awareness of danger, to panic reactions. In fact, this speed is even not the speed of a typical person. It is some sort of characteristic speed. The medium speed characterizes the average behavior of the whole group; quantile values of the speed distribution the behavior of faster or slower subgroups. For example, a v_{85} quantile characterizes some sort of "medium fast persons", a v_{95} quantile "medium very fast persons" etc.

This approach is permissible and applicable, if there are only few parameters to consider. If there are more, it is unknown, what the result is standing for. For demonstration a second parameter "reaction time" t_R (time between the accident and the start of the escape) shall be considered. It is not for sure, that fast running persons are reacting fast, too, and vice versa. If one chooses $t_{R,95}$ and v_5, one will probably overestimate the risk. Is it appropriate to calculate alternatively with ($t_{R,50}$; v_5) and ($t_{R,95}$; v_{50})? Or with any another combination? The situation is quite more complex, if there are five or more of such variables to consider.

For this reason, DRAM is using probability distributions instead of single values, which cover the whole range of values. It is using numerically described probability distributions to allow arbitrary shapes of distributions. Fig. 3 shows up, which speed distribution has been chosen for the following tunnel example, and how such a distribution may be expressed to enable the computer program DRAT (see below) to process it (still in German language, an international version is under preparation). The value list includes probability values for undefined, very small (the first two) and very large (the last) variable values.

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@ D G
N: V0
S: K
B: Grundwerte Fluchtgeschwindigkeit
E: m/s
@ D S
N: V0_s
G: V0
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* 0.00 0.50 0.75 1.00 1.25 1.50 1.75 2.00
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S: V0_s
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* 0.0 0.0 0.0 0.01 0.04 0.10 0.35 0.35 0.10
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Fig. 3 Example of a speed distribution and its representation for DRAT

Using distributions helps to deal with uncertainty, especially of the human behavior. In order to take into account the complexity of the data structure, the concept of the numerical description is multidimensional: each “value” is described by a set of such distributions, which depends on no, one or more arbitrary other variables and is called Numerically Described Multidimensional Probability Distribution (NDMPD). In fact, each NDMPD is a huge set of numbers, organized as a set of Bayes’ distributions. A tool, called DRAT (Darmstadt Risk Analysis Tool) is provided to handle these sets. The user needn’t to care about the internal structure. He/she can describe his/her knowledge in the mentioned language (see Fig. 3), and the tool accepts these descriptions and is able to combine them along the instructions of the user. Active and passive elements are described by such NDMPD; active elements may also be described by arithmetic formulas (in which the variables are substituted by NDMPD). The result is a NDMPD again, which may serve as input for the next steps and modules.

DRAT will consider, whether variables are dependant or independent to each other, and numerically combine them. Considering the limited space of this paper, it is not possible to illustrate it here in detail. Bald [1] gives more information.

Modeling a Simple, but a Little Sophisticated Behavior Model

In the following example, a simple, but little more sophisticated behavior model shall be presented. The basic assumptions are:

- at the beginning, the persons are distributed along the tunnel after a given distribution;
- the incident is located at position $s = 0$; smoke is visible after 30 s and after another 90 s, it starts to move in positive direction with 6 m/s;
- the persons in the tunnel react according to the following rules:
  - if they don’t see any smoke (no smoke or smoke more than 200 m away), they wander around with limited speed;
  - if they see smoke, most of them will try to get away from it, though some of them go back (to fetch something?);
  - if the smoke approaches (smoke distance < 50 m), they panic and escape with higher speed;

The situations in Fig. 2 are described by two NDMPD: one, which describes the position of the persons, and another one, which gives the actual direction of the persons in relation to their position (“+1”: moving away from fire, “-1”: moving towards the fire).

The active element of Fig. 2 is described by formula 1, with the speed v modified by two factors describing human behavior. These two factors are described by two NDMPD (see Fig. 4): the first “FF_RICHTW” describes, how people, who

```
@ D S
N: DS_RAUCH_F_RW_s
G: DS_RAUCH
n: 2
* 0 50 200
@ D S
N: F_RICHTW_F_RW_s
G: F_RICHTW
n: 0
* 0
@ D G
N: FF_RICHTW
S: K
B: Richtungswechselfaktor fuer
Fluchtgeschwindigkeit
E: -
@ D S
N: FF_RICHTW_s
G: FF_RICHTW
n: 4
* -1.0 -0.99999 0 0.99999 1.0
@ D H
S: FF_RICHTW_s
A:2
*DS_RAUCH_F_RW_s
*F_RICHTW_F_RW_s
W:
* 1.0  0.0  0.0  0.0  0.0  0.0  0.0
* 0.0  0.0  0.15 0.4  0.4  0.05 0.0
* 0.0  0.0  0.05 0.4  0.4  0.15 0.0
* 1.0  0.0  0.0  0.0  0.0  0.0  0.0
* 0.0  0.0  0.0  0.0  0.0  1.0  0.0
* 0.0  0.0  0.0  0.0  0.0  1.0  0.0
* 1.0  0.0  0.0  0.0  0.0  0.0  0.0
* 0.0  0.0  0.0  0.0  0.0  1.0  0.0
* 0.0  0.0  0.0  0.0  0.0  1.0  0.0
* 1.0  0.0  0.0  0.0  0.0  0.0  0.0
* 0.0  0.0  0.50 0.0  0.0  0.50 0.0
* 0.0  0.0  0.02 0.0  0.0  0.98 0.0
* 1.0  0.0  0.0  0.0  0.0  0.0  0.0
* 0.0  0.0  0.15 0.4  0.4  0.05 0.0
* 0.0  0.0  0.05 0.4  0.4  0.15 0.0

-----

@ K Panikfaktor
@ D S
N: DS_RAUCH_F_PANIK_s
G: DS_RAUCH
n: 1
* 0 50
@ D G
N: F_PANIK
S: K
B: Panikfaktor
E: 0..1
@ D S
N: F_PANIK_s
G: F_PANIK
n: 3
* 0.9999 1.00 1.2 1.4
@ D H
S: F_PANIK_s
A: 1
*DS_RAUCH_F_PANIK_s
W:
* 0.0  0.0  1.0  0.0  0.0  0.0
* 0.0  0.0  0.1  0.2  0.7  0.0
* 0.0  0.0  0.1  0.2  0.7  0.0
* 0.0  0.0  1.0  0.0  0.0  0.0
```

Fig. 4 Description of human behavior by two factors: FF_RICHTW (1st part) defines, how the direction changes depending on the distance of smoke (DS_RAUCH) and the previous direction (F_RICHTW); F_PANIC (2nd part) defines, how speed changes, if smoke approaches

move in one direction will change to the other (or not), depending ("in Abhängigkeit"; "A:") on the distance of the smoke; the second "F_PANIK" describes, how the speed behavior changes due to panic, depending on the distance of the smoke.

After a calculation with these assumptions and time steps of 2 s, one gets a distribution of the positions of the person after each time step. Fig. 5 gives a illustrative impression of the result. To the right, one can see the length of the tunnel section (divided into classes of 10 m resp. 20 m), to the back 120 time steps of 2 s and upwards the probability for persons at this position (at this time step). The picture is composed of distributions for each time step.

The calculation of the 120 time steps took about 10 min with a non optimized program on a standard desktop computer. This makes it possible to change and test different parameters and approaches, until the overall behavior fits to observations. It is exactly this procedure, how natural sciences find out parameters, which are not accessible for direct observation (as in our case many parameters, which describe human behavior).

It is for sure, that the demonstrated model has many inaccuracies. But compared to the current approach (with the assumption of a constant speed), it is an enormous improvement: one can derive distributions, how persons reach the emergency exits,

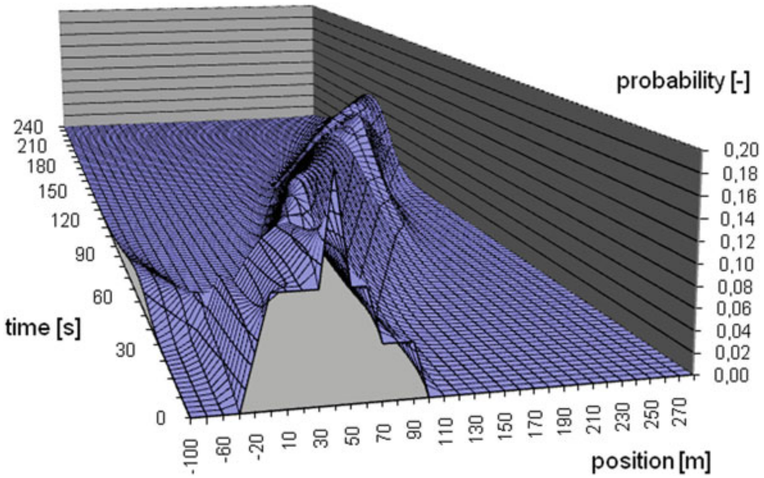

Fig. 5 Illustrative representation of the result of a first calculation of the road tunnel example (for each of the 120 time steps one distribution of persons along the tunnel)

how they are caught by the smoke etc. But such models need (and allow) the cooperation of many research groups, often from different disciplines. DRAM is a tool for such cooperation.

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Modeling Pilot Situation Awareness

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Abstract

Introduction The Man–machine Integration Design and Analysis (MIDAS) human performance model was augmented to improve predictions of multi-operator situation awareness (SA). In MIDAS, the environment is defined by situation elements (SE) that are processed by the modeled operator via a series of sub-models including visual attention, perception, and memory. Collectively, these sub-models represent the situation assessment process and determine which SEs are attended to, and comprehended by, the modeled operator. SA is computed as a ratio of the Actual SA (the number of SEs that are detected or comprehended) to the Optimal SA (the number of SEs that are required or desired to complete the task).

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Method A high-fidelity application model of a two-pilot commercial crew during the approach phase of flight was generated to demonstrate and verify the SA model. Two flight deck display configurations, hypothesized to support pilot SA at differing levels, were modeled.
Results The results presented include the ratio of actual to optimal SA for three high-level tasks: Aviate, Separate, and Navigate.
Conclusion The model results verified that the SA model is sensitive to scenario characteristics including display configuration and pilot responsibilities.

Keywords Situation awareness (SA) · Human performance model · Pilot model · Man–machine integration design and analysis system (MIDAS)

Introduction

In the Next Generation [1] of aviation operations, it is anticipated that there will be substantially more information available to pilots on the flight deck (e.g., weather, wake, terrain, traffic trajectory projections) to support more precise and closely coordinated operations. Safe and efficient task performance within complex sociotechnical systems depends on operators acquiring and maintaining appropriate levels of situation awareness (SA) [2], and as such, a critical issue is how well the flight deck will support the pilots' ability to acquire and maintain SA of relevant information in the NextGen environment.

Arguably, the most commonly accepted definition of SA is that offered by Endsley [3] who defined SA as the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future. To date, efforts to computationally model and predict SA have been few [but see 4–6].

This paper describes recent enhancements to the Man–machine Integration Design and Analysis System (MIDAS) to enable improved predictions of pilot SA. MIDAS is a human performance modeling and simulation environment that facilitates the design, visualization, and computational evaluation of complex human–machine system concepts [7–9]. MIDAS links a virtual human, comprised of a physical anthropometric character, to a computational cognitive structure that represents human capabilities and limitations. The cognitive component includes decision-making, task management, perception, visual attention, and memory mechanisms.

Modeling Situation Assessment and Situation Awareness

The MIDAS SA model was first developed by Shively, Brickner, and Silbiger [10] and is augmented here to enable improved predictions of multi-operator SA in

NextGen aviation concepts. In MIDAS, the *situation context* defines what information is important to the modeled operator in the situation [10]. At a minimum, in NextGen applications, the context is defined by the phase of flight (taxi, departure, cruise, approach, or land), but may be broken down to finer levels of granularity, or along other dimensions such as nominal and off-nominal operations. For each context, the operators' high-level tasks are defined. For NextGen aviation models, the default high-level tasks adhere to the following hierarchy of task importance[1]: Aviate, Separate, Navigate, Communicate, and Systems Management [see 11]. For SA, these can be subdivided; for example, the task of Separate can be divided into "Separate from traffic" and "Separate from terrain". The importance of each task is defined (as high, medium, or low) for each operator and each context.

Within each context, the environment is broken down into '*Situational Elements*' (SEs), which are pieces of information that are necessary to support the operator's high-level tasks [10]. For example, for the task of 'Aviate', the SE 'attitude' is *required*, but the SE 'angle of attack' (which is a display that presents the angle of the wing relative to the wind and warns of stall conditions) is *desired*. Although angle of attack supports pilot performance and makes the task easier, it is not strictly necessary, or required. The *accessibility* of each SE is defined by the analyst using a set of design heuristics that address: display modality (visual, auditory), legibility (size, contrast), permanence (always visible, automatically presented, requires key strokes), and format (text, graphical). For example, spatial information that is conveyed by a text display would be classified as less accessible than information that is conveyed graphically.

In the current implementation of MIDAS, perception is a three-stage (undetected, detected, comprehended), time-based perception model for objects inside the workstation (e.g., an aircraft cockpit). The model computes the upper level of detection that can be achieved by the average unaided eye if the observer dwells on it for a requisite amount of time. Once an SE is comprehended, the operator is assumed to have acquired SA of the SE. An SE with low accessibility requires longer time to comprehend, and thus has a corresponding decrement in SA. After an SE is comprehended, it is subject to the constraints of the memory sub-model, which degrades SA as a function of time since last accessed. The memory model in MIDAS causes the perception level of a 'comprehended' display to drop to 'detected' after the retrievability threshold of working memory (5 s) has been surpassed, and perception drops fully to 'undetected' after the retrievability threshold of long-term working memory (300 s) has been surpassed. As the maximum perception level for an SE drops, there is a corresponding drop in SA.

The information in the environment flows through the situation assessment process (including visual attention, perception, and memory sub-models) and

[1] Schutte and Trujillo [11] define a four-level workload management hierarchy: Aviate, Navigate, Communicate, and Systems management. Separate is added here to accommodate new flight-deck responsibilities anticipated in the NextGen environment.

yields a metric of SA for each operator's high-level task (Aviate, Separate, Navigate, Communicate, and Systems Management). The SA metric in MIDAS computes the ratio of SEs that are detected or comprehended (Actual SA) to the SEs that define the ideal state (Optimal SA).

Actual SA. For each high-level task (i), at time (t), Actual SA (See Eq. 1) is calculated as the weighted sum of m Required SEs and n Desired SEs multiplied by the perception level (p). Note that if an SE is available on more than one display simultaneously, the highest perception level attained is applied. For SEs within the cockpit, p has values of 0 if the SE is undetected, 0.5 if detected, and 1.0 if comprehended. *Required* SEs have a weight of 2 and *desired* SEs have a weight of 1.

$$SA_{Actual}(t_i) = \underset{\substack{\downarrow \\ required\,SEs}}{\sum_{r=1}^{m} 2 \cdot p_{irt}} + \underset{\substack{\downarrow \\ desired\,SEs}}{\sum_{d=1}^{n} 1 \cdot p_{idt}} \tag{1}$$

where p_{irt} and p_{idt} have values: 0 for undetected SEs, 0.5 for detected SEs, and 1.0 for comprehended SEs.

Optimal SA. Optimal SA (see Eq. 2) reflects awareness the operator would have if he/she comprehended all the information that is required and desired for the task at any given moment. Therefore, for each high-level task (i), at time (t), Optimal SA is the weighted sum of m Required SEs and n Desired SEs multiplied by p; where p is always equal to 1.0. Required SEs have a weight of 2 and Desired SEs have a weight of 1.

$$SA_{Optimal}(t_i) = \underset{\substack{\downarrow \\ required\,SEs}}{\sum_{r=1}^{m} 2 \cdot p_{irt}} + \underset{\substack{\downarrow \\ desired\,SEs}}{\sum_{d=1}^{n} 1 \cdot p_{idt}} \tag{2}$$

where p_{irt} and p_{idt} have values of 1.0.

SA Ratio. SA Ratio (See Eq. 3) is the ratio of Actual SA to Optimal SA. It yields a value from 0 (no SA) to 1(maximal SA) that reflects the proportion of SEs of which the operator has awareness.

$$SA_{Ratio}(t_i) = SA_{Actual}(t_i)/SA_{Optimal}(t_i) \tag{3}$$

Application Scenario

A high-fidelity model of a two-pilot crew flying an approach into an airport was developed. The model included pilot tasks such as manipulate flight controls, monitor flight instruments, maintain separation from traffic, monitor aircraft system status, and communicate with ATC. For the purposes of this model, the Captain was assumed to be the pilot flying (left seat) and the First Officer was the pilot-not-flying (right seat). The scenario started with the aircraft at 2,200 ft altitude on a normal approach into Dallas/Fort Worth International Airport. The scenario was run with two configurations (Current-day and Augmented) that varied both the flight deck display configuration and pilot responsibilities in a manner expected to impact the time to comprehend information, and, in turn, SA.

Current-Day Configuration. The flight deck was equipped with a minimal set of current-day glass-cockpit displays including a Primary Flight Display (PFD) that depicted altitude, speed, pitch, bank, and heading and a Navigation Display (ND) that graphically depicted the current and commanded flight path. Consistent with current-day operations, both pilots shared the same hierarchy of importance for the tasks of Aviate, Separate, Navigate, Communicate and Systems.

Augmented Configuration. The Captain was equipped with a head-up display (HUD) that superimposed primary flight instruments and a highway-in-the-sky (HITS) display over the out-the-window view [12] and a current-day ND. The First Officer was equipped with a current-day PFD and an advanced 3-D ND [13] allowing for improved visualization and predictive information about traffic and weather trajectories. Each pilot had a unique task hierarchy. The Captain's emphasis was placed on the tactical task of Aviate and Separate (from immediate hazards). The First Officer's main responsibility was the strategic planning tasks of Navigate and Separate (from global hazards).

Results

Figure 1 presents the SA ratio for the tasks of Aviate, Separate (*from* hazards), and Navigate (*to* waypoints) in the Current-day and Augmented configurations. In the Current-day configuration, there were only negligible differences between the

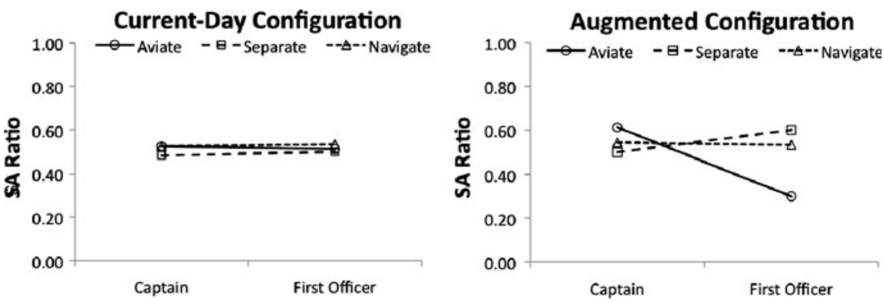

Fig. 1 Captain and First Officer SA ratio for the tasks of Aviate, Separate and Navigate as a function of display configuration (Current day, left and augmented, right). SA ratio is presented on a scale from 0 (no awareness) to 1.0 (maximum awareness)

Captain and First Officer's SA for each of the three high-level tasks. This was expected, since both pilots shared a similar display configuration and shared equal responsibility for maintaining awareness of all SEs in the environment.

The Augmented configuration demonstrated a different pattern of results, again consistent with expectations. Recall that in the Augmented scenario, it was assumed that the Captain would place highest priority on the tactical tasks of Aviate and Separate from immediate hazards as supported by a HUD with a HITS display. This is clearly reflected in the Captain's SA for the Aviate task, which was higher in the Augmented condition than the Current Day condition. Likewise, in the Augmented condition, the Captain's SA of the Aviate task was higher than that of the First Officer. Further, recall that in the Augmented scenario, the First Officer had an advanced 3-D ND that supported strategic Navigate and Separate tasks. This is reflected in the First Officer's increased SA for the tasks of Separate and Navigate, relative to the Captain, in the Augmented configuration.

Comparing the Current-day to Augmented configurations, it is clear that the distribution of SA has changed in a manner consistent with expectations as a function of the procedural and display manipulations in the Augmented conditions. System-wide, the Augmented configuration enabled a higher level of SA for the task of Aviate (by the Captain) and Separate (by the First Officer) than was attained in the Current-day scenario.

Conclusion

The MIDAS model was augmented yielding improved predictions of multi-operator SA. The SA metric was augmented to allow for the prediction of SA as a function of the operator's high-level tasks (such as shown above, Aviate, Separate, and Navigate). The model also allows for SEs to be characterized according to their level of importance for task completion (required or desired) and for SA to be degraded as a function of information accessibility. It is acknowledged that this model is limited in it's focus to the first of Endsley's three stages of SA [3]—specifically, the perception of elements in the environment. Future research efforts will be aimed at addressing the subsequent two stages of SA: comprehension and projection.

The SA model was verified using a high-fidelity simulation model of a two-pilot crew conducting an approach into an airport. The model output revealed that the SA model was sensitive to differences in display configurations and pilot responsibilities. While future efforts will undertake a formal validation of this model by comparing the model output to human-in-the-loop data, this work represents preliminary steps toward the development of a model-based tool that can be used to predict operator SA as a function of procedures and display configurations.

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Review of Models of Driver Behaviour and Development of a Unified Driver Behaviour Model for Driving in Safety Critical Situations

David Shinar and Ilit Oppenheim

Abstract Driver behaviour can be modelled in one of two approaches: '*Descriptive*' models that describe the driving task in terms of what the driver does, and '*Functional*' models that attempt to explain why the driver behaves the way he/she does, and how to predict drivers' performance in demanding and routine situations. Demanding situations elicit peak performance capabilities, and routine situations elicit typical (not necessarily best) behaviour. It seems that the optimal approach might be a hybrid of several types of models, extracting the most useful features of each. In recent years, a variety of driver support and information management systems have been designed and implemented with the objective of improving safety as well as performance of vehicles. To predict the impact of various assistance systems on driver behaviour predictive models of the interaction of the driver with the vehicle and the environment are necessary. The first step of the ITERATE project is to critically review existing Driver-Vehicle-Environment (DVE) models and identify the most relevant drivers' parameters and variables that need to be included in such models: (a) in different surface transport modes (this paper deals with road vehicles only, other transport domains are detailed in D1.1 & D1.2 of the ITERATE project), and (b) in different safety critical situations. On the basis of this review, we propose here a Unified Model of Driver behaviour (UMD), that is a hybrid model of the two approaches. The model allows for individual differences on pre-specified dimensions and includes the vehicle and environmental parameters. Within the ITERATE project this model will be used to support safety assessment of innovative technologies (based on the abilities, needs, driving style and capacity of the individual drivers). *In this brief paper we describe only the behaviour of a single test driver, while the environment and vehicle are*

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defined as parameters with fixed values (and detailed in D1.2 of the ITERATE project). The selected driver characteristics (and variables used to measure them) are culture (Country), attitudes/personality (Sensation Seeking), experience (Hazard Perception Skills), driver state (Fatigue), and task demand (Subjective workload).

Keywords Driver behaviour models · Culture · Attitudes/personality · Experience · Driver state · Task demand

Introduction

Hundreds of articles on driving and driver behaviours have been published during the past years, and substantial improvements in driving safety have been made within the past 50 years [11]; safety systems (e.g. collision warnings) promise substantial safety benefits by enhancing driver performance and behaviour, but their effectiveness hinges on the drivers' appropriate use of these systems. The implications of new vehicle technologies have been intensely investigated only with the past 25 years as these technologies became much more practical and implementable.

Driving a vehicle may be described as a dynamic control task in which the driver has to select relevant information from a vast array of mainly visual inputs to make decisions and execute appropriate control responses. Although there are occasions when the driver has to react to some unexpected event, in general, drivers execute planned actions which are shaped by their expectations of the unfolding road, pedestrian and traffic scenario in front of them and the reality that they actually observe.

This paper starts with a brief review of existing models of driver behaviour, and culminates in a proposed integrative functional model: the UMD. The dependent variables used to evaluate behavior and performance are errors and response time. Factors influencing driving safety that are being considered in this model (and the operational measures used to test their effects) include: attitude and personality (as measured with the Sensation Seeking Scale), experience (as measured by Hazard Perception Test), driver state (as measured in terms of time-on-task based fatigue), task demands (as reflected in variations in traffic and roadway geometry) and culture (as reflected by inter-country differences). Because the focus of the model and simulation is mainly on the driver, the environment and vehicle models are not detailed in this paper.

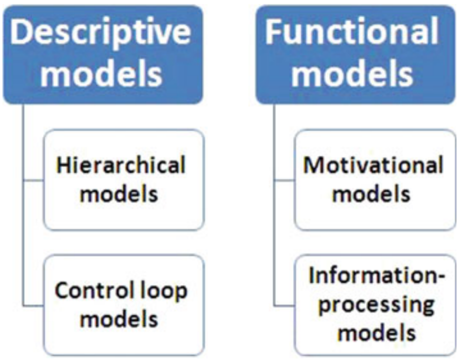
The aim is to model the effects of the independent variables listed above on the driver's information processing as reflected in the speed and correctness of responses to various emergency situations, and how these responses are modified by various in-vehicle driver support systems, also known as ADAS (Advanced Driver Assistance Systems). The ADAS can serve both as a sensor of driver, vehicle, and environmental states AND as an activator of interventions that affect the driver, vehicle, and environment.

Models of Driver Behaviour

Figure 1 (based in part on [30]) describes one way of classifying the different models. Descriptive models *describe* driving behaviours within various driving tasks or *what* the driver does. The principal limitation of this approach is that it has very little predictive power. An alternative approach, the functional approach, models behavior relative to the driver's tasks or *functions*. This approach attempts to predict driver behavior by focusing on *why* drivers do what they do; i.e. what situational and motivational factors are involved in the risk management of driving. One advantage of these models is the potential to implement them, either by generating a simulation of the driver, or by integrating them into some already existing traffic simulation tools or driver assistance devices, such as collision warning systems.

Descriptive models attempt to describe the entire driving task or some components of it in terms of what the driver does or has to do. The predictive power of such models is very limited, because they do not take into account the forces that shape the different behaviors such as driver motivation, skills, capabilities and limitations in different situations [1]. Despite this severe limitation these models have provided a strong impetus to driving safety research [11, 17, 19, 24, 26, 27]. The descriptive models can be divided into **Hierarchical models** (e.g. [17]) and **Control loop models** (e.g. [16]). The hierarchical modeling approach describes behavior in terms of a hierarchy of three distinct types of behaviors: the lowest level is an operational, control level. At this level most behavior are automatic and consist of quick responses to the changing environment (such as braking when a lead car slows down). The second level is a tactical, vehicle maneuvering level referring to how traffic situations are mastered. The behaviors are less reflexive and consist of conscious decisions in the driving, such as a decision to change lanes before exiting a highway. The third and highest level is a planning or strategic level, and consists of long-terms decisions such as which route to choose, or even if to drive at all. Thus, the three levels can be distinguished by the task requirements, the time frame needed to carry them out and the cognitive processes

Fig. 1 Taxonomy of driver behavior models



involved at each level. The second type of descriptive models, are the Control loop models. These models describe the operation of the driving task in terms of inputs, outputs and feedback. Control loop models deal primarily with the steering control aspect of driving in order to follow a specified route [15]. These models of driving have traditionally been couched either in terms of guidance and control or in terms of human factors. Unfortunately expanding these models to accommodate the rapidly growing complexity and sophistication of modern cars is a very daunting task. Within limits, due to their quantitative approach, such models can provide coherent and consistent ways of describing driver performance in ways that help engineers develop and validate technical concepts for semi- and fully automated systems in cars [7].

Functional models investigate the mental activities executed during driving; attempt to explain why the driver undertakes certain actions. These models are necessary to understand human errors and difficulties, and to design driving assistance adapted to driver needs [10]. These models strongly emphasize the driver's cognitive state and have incorporated important psychological concepts such as motivation, and risk assessment. **Information processing models** involve interactions between different components of the driving system [17]. These models consist of different stages, which include perception, decision and response selection, and response execution. Each stage is assumed to perform some transformation of data and to take some time for its completion [20, 31]. The driver in such models is viewed as a passive information transmission channel, who performs different acts within capacity limitations, two more crucial components are the attention allocation mechanism and a feedback loop [28]. Much experimentation has been directed at determining which types of processing can occur simultaneously and which must occur sequentially. Rasmussen's model of information-processing [21] serves as a starting point. Furthermore, a feedback loop was integrated to the model of Driver-Vehicle-Environment, helping to adapt task difficulty or the desired amount of strain experienced by coping with the stressors that originate from drivers' behaviour, showing the influence of the drivers' actions upon the future situations he has to cope with. Generic information-processing models of the human driver are valuable in seeking to predict asymptotic limits of human performance. However, as a means of understanding why specific individuals on a particular day in a particular set of circumstances behaved (or failed to behave) in a particular way, such models are very limited and have little to offer [14]. **Motivational models** focus on what the driver actually does in a given traffic situation. The main assumptions of these models are that driving is self-paced and that drivers select the amount of risk they are willing to endure in any given situation. The driver is viewed as an active decision maker or information seeker [6], rather than the passive responder implicit in many information-processing models. The risk associated with possible outcomes is seen as the main factor influencing behaviour; however, these models also assume that drivers are not necessarily aware of the risks associated with other outcomes. Examples of motivational models include risk compensation models [32], risk threshold models [18] and risk avoidance models [5]. Motivational models take into account interactions between driver and environmental states and individual differences.

Driver Factors and Variables Influencing Driving Safety

We have focused on five driver characteristics that are considered relevant to driving safety and to the impact of in-vehicle safety systems. These are culture, personality, experience, driver state, and task demands. In our model each factor is represented by one variable only.

Culture—Represented by Country

The rules of the road, the social environments (e.g. values, beliefs), and the norms of behavior may vary significantly from country to country and can influence the attitudes and behaviours of drivers [12, 29].

Although cultural aspects are difficult to measure and to manipulate, it is possible to investigate their effects on road safety. One project that specifically focused on inter-culture similarity and differences in driving is the EC project SARTRE (Social Attitudes to Road Traffic Risk in Europe) that describes drivers' attitudes and reported behaviours in over 20 different countries [25].

Attitudes/Personality—Represented by Sensation Seeking

Personality factors that have been investigated in the context of driver behavior include, sensation seeking [9, 22], aggression and risk taking [3]. Sensation Seeking is defined as "seeking of varied, novel, complex and intense sensations and experiences and the willingness to take physical, social, legal and financial risk for the sake of such experience" [33]. There is a correlation between Sensation Seeking & some aspects of risky driving [30].

Experience—Represented by Hazard Perception Skills

Experience is a factor whose value changes over time but is fixed for a given trip. Thus, with experience the driver learns to effectively select the cues to attend to, quickly perceive their meanings, and on the basis of these cues quickly identify the situation and project its implications into the immediate future [28]. Hazard perception skills distinguish experienced drivers from novice drivers [8]. Yet, the issue whether driving experience provides better performance when the driver uses in-vehicle systems is debatable [13, 23].

Driver State—Represented by Fatigue

Driver state is the driver physical and mental ability to drive (e.g. fatigue, sleepiness). Fatigue is one state that is significantly involved in crashes. It changes systematically over the time of day and with time-on-task (time behind the wheel). Fatigue can be either **State induced,** from sleep deprivation such as poor or lack of sleep, or **Task induced** as a result of a monotonous task or extended 'time-on-task' [2]. Within the ITERATE project we will evaluate only task induced fatigue in the model validation studies.

Task Demand—Represented by Subjective Workload

The Driving Task Demand is presumed to be a function of two factors: the *roadway baseline requirement* and the proximity to the navigation choice point also called *Maneuver Proximity*. The roadway baseline requirement determines a general level of attentional demand that is more or less constant over a section of freeway. The second factor is the increase in demand as the vehicle approaches a navigational choice point which requires a change in driving (e.g. exit areas), imposing additional load. The balance between the drivers' capabilities and the demands of the driving task is critical in safe driving behaviour [4].

Conclusions

ITERATE attempts to create a structured model that can be used in real time, in particular by a driver assistance system to monitor driver state and performance, predict how momentary risk is changing, and anticipate problem situations.

This paper describes the Unified Model of Driver behaviour (UMD) and defines key parameters for specific applications to cars (other transport domains are detailed in D 1.1 & D 1.2 of the ITERATE project). To be useful, the model should include as inputs, factors that have been shown to influence risk, risk-taking and errors. The selected driver variables whose effects have been selected for the ITERATE evaluation include *culture* (as measured by inter-country differences), *attitudes/personality* (as measured by sensation seeking), *experience* (as reflected in hazard perception skills), *driver state* (as measured by fatigue), and *task demand* (as measured by subjective workload. The proposed ITERATE model designed to serve the remaining tasks in the project is presented in Fig. 2. It summarizes the

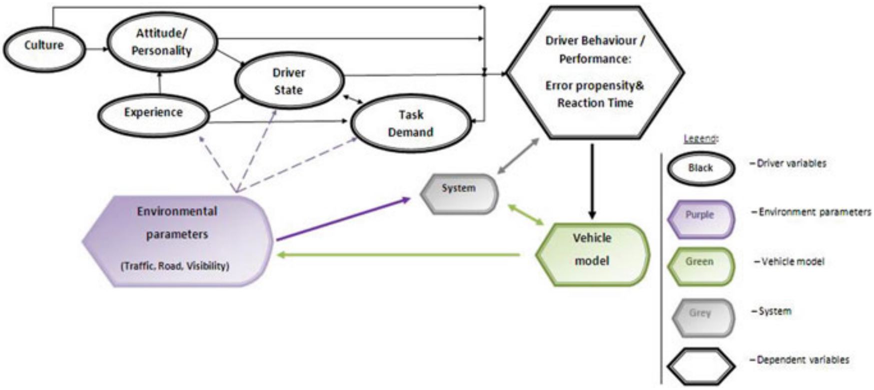


Fig. 2 The proposed ITERATE model

interactions between the driver variables, the environmental parameters, and the vehicle model. In this driver-centered model, driver states, skills, and limitations, environmental and vehicular variables all serve as inputs to driver behaviour. Though all the variables quantifiable, the current literature does not provide empirically tested values for all of them.

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Integrating Anticipatory Competence into a Bayesian Driver Model

Claus Möbus and Mark Eilers

Abstract
Background We present a probabilistic model architecture combining a layered model of human driver expertise with a cognitive map and beliefs about the driver-vehicle state to describe the effect of anticipations on driver actions.
Methods It implements the sensory-motor system of human drivers with autonomous, goal-based attention allocation, and anticipation processes. The model has emergent properties and combines reactive with prospective behavior based on anticipated or imagined percepts obtained from a Bayesian cognitive map.
Results It has the ability to predict agent's behavior, to abduct hazardous situations (what could have been the initial situation), to generate anticipatory plans, and control countermeasures preventing hazardous situations.
Conclusions We demonstrated that the Bayesian-Map-extended BAD-MoB model has the ability to predict agent's behavior, to abduct hazardous situations (what could have been the initial situation, what could be appropriate behavior), to generate anticipatory plans, and control countermeasures preventing hazardous situations. It was demonstrated that the selection of action and goal evidence has to be planned by a higher cognitive layer residing on top of the BAD-MoB model. An implementation with real expert and novice data has to follow this conceptual study.

Keywords Anticipatory planning · Bayesian cognitive map · Probabilistic driver model · Bayesian autonomous driver model · Mixture-of-behavior model ·

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Visual attention allocation · Anticipatory plans and control · Reactive and prospective behavior · Risk and hazardous prevention

Introduction

Driving is a skill with high inter- and intraindividual variation [1]. So, the human or cognitive centered design of intelligent transport systems requires digital models of human behavior and cognition (MHBC) which are *embedded, context aware, personalized, adaptive,* and *anticipatory*.

We present a probabilistic model architecture combining a layered model of human driver expertise with a cognitive map and beliefs about the driver-vehicle state to describe the effect of anticipations on driver actions. It implements the sensory-motor system of human drivers in a psychological motivated *mixture-of-behaviors (MoB)* architecture with *autonomous, goal-based attention allocation* and *anticipation* processes [5, 6, 13].

Our Bayesian autonomous driver mixture-of-behaviors (BAD-MoB) model offers sharing of behaviors in different driving maneuvers and is able to decompose complex skills into basic skills and to compose the expertise to drive complex maneuvers from basic behaviors [4, 11, 12]. The 2-time-slice template of the basic dynamic *reactive* BAD-MoB Model is shown in the left part and a 4-time-slice roll-out in the total view of Fig. 1. This roll-out is made under the Markov and the stationary assumption.

We call the basic model *reactive* because the Areas of Interest (AoIs) *directly* influence actions. The model embeds two naive Bayesian classifiers: one for the *behaviorsB* and one for the *states S.* This simplifies the structure of the architecture. Time slices are selected so that in each new time slice a new *behavior* is active. A *sequence* of behaviors implements a single *maneuver*. The *basic* model was discussed in detail in [11, 12].

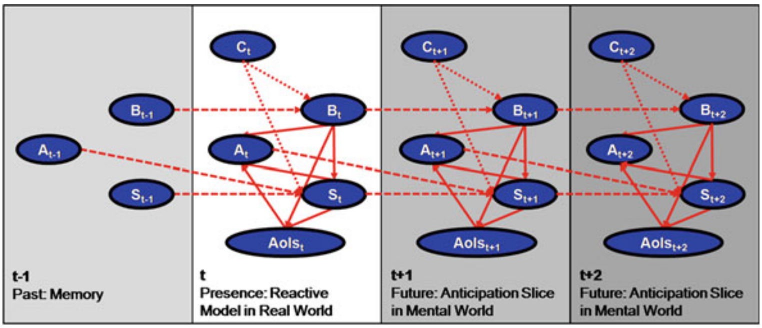

Fig. 1 4-time-sliced (4-TBN) Anticipatory BAD-MoB Model

Time slices (t-1) and t are used for the dynamic *reactive* part of the model. This part uses percepts of the real world and some information from the most recent slice (t-1) to select appropriate behavior and actions for time slice t. It describes a driver who is driving a scenario the first time in a *visual* driving style, so that he can stop the car in the assured clear distance ahead. This driver has *no* imagination or anticipations about the course of the road beyond his vision field. The cognitive Bayesian map is represented in the model by adding model slices to the right according to the level of expertise or competence C augmenting the anticipation horizon into the future. Perception is then substituted by imagination obtained from the Bayesian cognitive map. This information is learnt by memorizing former drives. To get the parameters of the anticipatory model we need at least one replication of the training drive for each expertise level: at least 3 training drives for the model in Fig. 1.

Here, we give a proof of concept for the operating mode of the cognitive Bayesian map and anticipatory planning with plausible but artificial data. The model contains 2,105 (two thousand one hundred five) parameters. These have been hand-coded into the model to test the plausibility of the concept model. We demonstrate that a BAD-MoB model based on Dynamic Bayesian Networks (DBNs) shows some *emergent* competencies: it has the ability to *predict* agent's behavior, to *abduct* hazardous situations (what could have been the initial situation), to *generate* anticipatory plans and control countermeasures *preventing* hazardous situations. The distinction between *prediction* and *anticipation* is defined by: *Prediction is a representation of particular future events. Anticipation is a future-oriented action, decision, or behavior based on a (implicit or explicit) prediction* [13, p. 25].

Method: Bayesian Autonomous Driver Mixture-of-Behaviors Models with a Bayesian Map Extension

BAD models [8–10] are developed in the framework of Bayesian (Robot) Programming [2, 7]. They describe phenomena and generate motor control on the basis of the joint probability distribution (JPD) of the variables of interest and their factorization into conditional probability distributions (CPDs).

A BAD-MoB model is able to decompose complex skills (scenarios, maneuvers) into basic skills (= behaviors, actions) and vice versa [4, 11, 12]. The basic *behaviors* or sensory-motor schemas could be shared and reused in different *maneuvers*. Context dependent complex driver behavior will be generated by mixing the pure basic *behaviors*. BAD-MoB models are embedded in DBNs. Under the assumption of stationarity their *template models* (Fig. 1, left two slices) are specified as *2-time-slice DBNs* (2-TDBNs). The template model can be unrolled so that their *interface variablesBehaviors* and *State* are glued together producing an rolled-out DBN over T time slices (T-TDBN) like the 4-TDBN in Fig. 1.

The degree of roll-out defines the anticipation horizon of the model. This is controlled by the level of the binary expertise or competence variable C_t. If $C_t = 1$, then the conventional transition probability matrices $P(B_{t+j} \mid B_{t+j-1})$ and $P(S_{t+j} \mid S_{t+j-1})$ are used. When $C_t = 0$, then all $C_{t+i} = 0$ ($i \geq 1$) and the probability distributions $P(B_{t+j} \mid B_{t+j-1})$ and $P(S_{t+j} \mid S_{t+j-1})$ are replaced by static distributions $P(B_{t+j})$ and $P(S_{t+j})$. Hence, C_t can be seen as a switch to activate and deactivate anticipatory time slices.

Learning data are time series of the pertinent domain-specific variables *percepts, AoIs*, *goals*, *behaviors*, *actions*, *observablestates*, and *actions* combined with *posthoc annotations* of maneuvers, scenarios, and the replication number of the training drive.

Information can be propagated within the T-TDBN in various directions. When working *top-down*, goals emitted by higher cognitive layers of the agent activate a corresponding *behavior* which propagates *actions*, relevant *AoIs*, and expected *perceptions*. When working *bottom-up*, percepts trigger *AoIs*, *actions, behaviors*, and *goals*. When the task or goal is defined and there are percepts, evidence can be propagated *simultaneously* top-down and bottom-up, and the appropriate *behavior* can be activated. Furthermore, evidence can be propagated for *predictions* from the past to the future and vice versa for *abductions*. This flexibility is used for *anticipatory planning* (Figs. 3, 4, and 5).

The BAD-MoB Model (Fig. 1) implements a Bayesian Map (BM). The structure of a BM is defined in (Fig. 2). The location variable L is redefined in our model as the belief state S. The belief state of future slices defines the Bayesian cognitive map.

A BM is capable to answer three kinds of questions:

- Localization (Where am I, if I have percept P ?): $P(L^t \mid P) = ?$
- Prediction (Where do I go, when I generate action A?): $P(L^{t'} \mid A, L^t) = ?$
- Control (What actions should I generate, to reach/avoid $L^{t'}$?): $P(A \mid L^t, L^{t'}) = ?$

The model in Fig. 3 is a rolled-out version of our basic template (Fig. 1). It answers the control question $P(\text{Actions}_{t-1}, \text{Actions}_t \mid \text{State}_{t-1} = \text{is\_in\_right\_lane}, \text{State}_{t+1} = \text{is\_in\_middle-lane})$. The model recommends actions with $P(\text{Actions}_{t-1} = \text{left\_turn} \mid \text{State}_{t-1} = \text{is\_in\_right\_lane}, \text{State}_{t+1} = \text{is\_in\_middle-lane}) = 0.59$ and

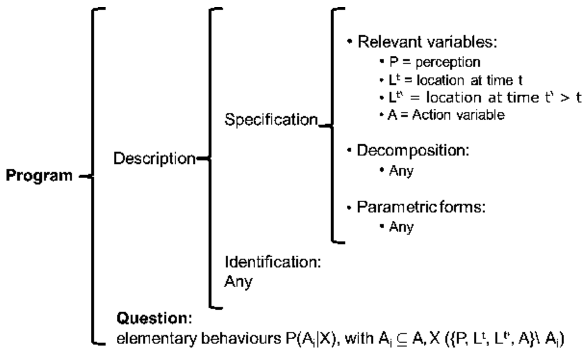

Fig. 2 The Bayesian Map model definition expressed in the Bayesian (Robot) Programming (BRP) formalism [3, p.165]

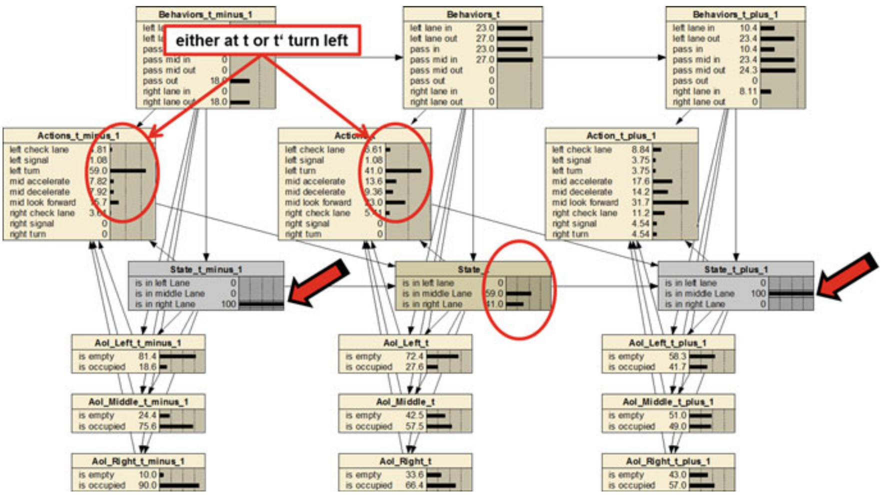

Fig. 3 The BAD-MoB gives an answer to the control question $P(A^{t-1},A^{t} | s^{t-1}, s^{t+1})$

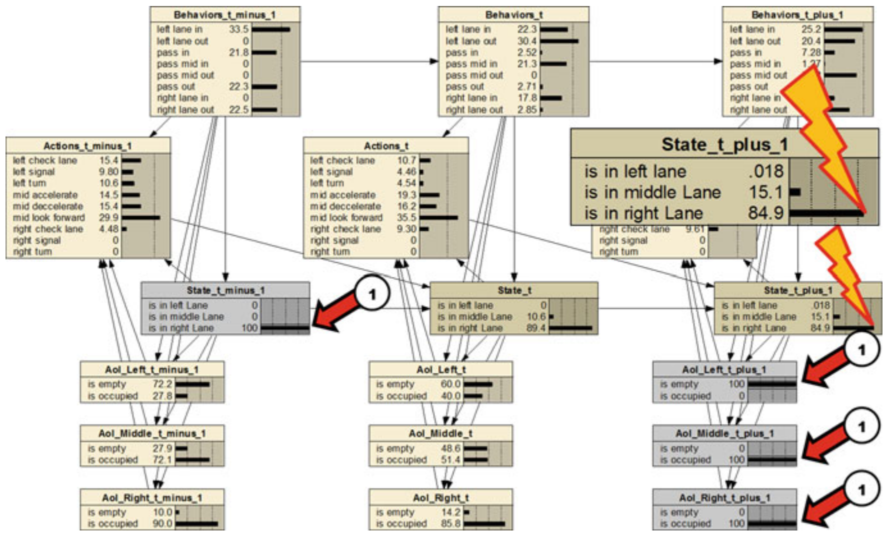

Fig. 4 3-time-sliced roll-out of BAD-MoB model with belief state and Bayesian map with Anticipatory Planning Steps 1 (NETICA implementation)

P(Actions$_{(t-1)}$) = left_turn | State$_{(t-1)}$ = is_in_right_lane, State$_{t+1}$ = is_in_middle-lane) = 0.41 (circled in Fig. 3). If the spatial goal at time t+1 is changed to the *left lane* the corresponding conditional probabilities are changed to P(Actions$_{t-1}$ = left_turn | State$_{t-1}$ = is_in_right_lane, State$_{t+1}$ = is_in_left-lane) = 1.0 and P(Actions$_{(t)}$) = left_turn | State$_{(t-1)}$ = is_in_right_lane, State$_{t+1}$ = is_in_left-lane) = 1.0.

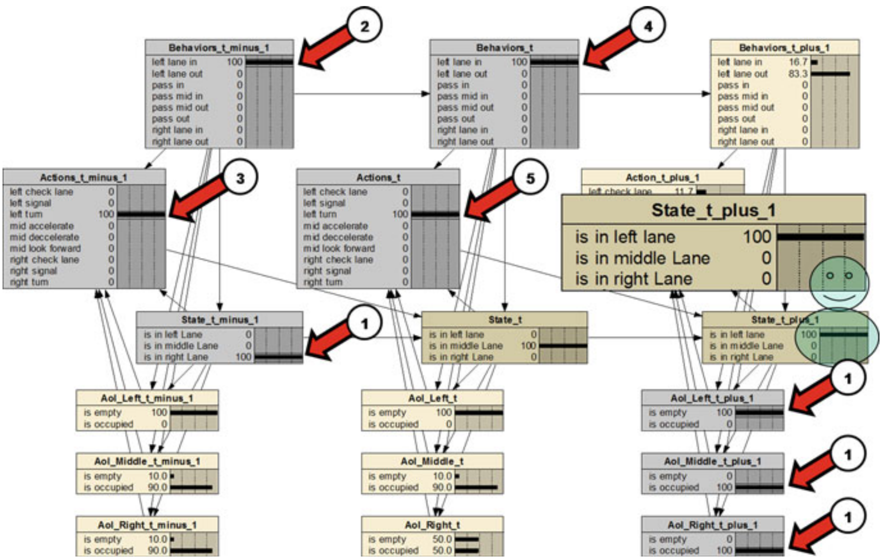

Fig. 5 3-time-sliced roll-out of BAD-MoB model with belief state and Bayesian map with Anticipatory Planning Steps 1-5 (NETICA implementation)

Method: Anticipatory Planning of Countermeasures with our BAD-MoB Model

> *Generally, anticipatory systems are those that use their predictive capabilities to optimize behavior and learning to the best of their knowledge…* Anticipatory behavior may be defined as: […] *a process or behavior that does not only depend on past and present but also on predictions, expectations, or beliefs about the future. …While reactive systems can functionally be described with STIMULUS → ACTION (S-A) behavioral patterns, anticipatory systems have instead (STIMULUS +) EXPECTATION → ACTION (E-A) behavioral patterns, which is permitted by the explicit prediction of a stimulus or an action effect (STIMULUS → EXPECTATION (S-E), or STIMULUS, ACTION → EXPECTATION (S-A-E))* [13, p. 24].

Our BAD-MoB model is an instance of an anticipatory system. The model in Figs. 3, 4, and 5 uses partly perceptual and partly imaginary evidence. If perceptual evidence is included in time slice t or (t-1) the beliefs about the driver-vehicle state S will revise the beliefs based on pure imagination obtained from time slices $t' > t$.

The process of anticipatory planning consists of five steps (Figs 4 and 5):

- Step 1: Anticipation and Prediction in (t-1) of Hazard and Collision for (t + 1) and abduction of appropriate behaviors or goals in (t-1)
  The model in Fig. 4 realizes in the current time step (t-1) that it is in the *belief* $State(t\text{-}1) = in\_the\_right\_Lane$ and that it will stay there including the future time slice (t+1) with the conditional probability $P(State(t + 1) =$

in_the_right_Lane | ….) = 0.849. This is an unfavorable state of affairs, because it "expects" at the same time, that only the left lane will be empty. These expectations are fed into the model as virtual evidence for t+1. The reason for this evidence has to be obtained from a higher cognitive layer of the model. Appropriate behaviors and goals could be inferred backwards by an abduction process: *left_lane_in, pass_in* in time slice t-1, etc.

- Step 2: Proactive Goal Activation in (t-1) and Collision Prediction for (t + 1)
  The BAD-MoB model gets from a higher cognitive layer a goal activation for the *left_lane_change* maneuver. This maneuver starts with the *left_lane_in* behavior. This means that the goal *Behavior*(*t*-1) = *left_lane_in* is injected in the model as evidence for t-1. As a consequence the conditional probability drops down to *P*(*State*(t+1) = *in_the_right_Lane* | …. *Behavior*(*t*-1) = *left_lane*) = 0.696, which is far too high.
- Step 3: Proactive Action Selection in (t-1) and Crash Prediction for (t+1)
  The model "knows" that some actions (like *signal left* or *look to the left*) do not change the belief state. So it activates and executes the state changing Action = *left-turn*. As a consequence the conditional probability drops down to *P*(*State*(*t*+1) = *in_the_right_Lane* | …. *Behavior*(*t*-1) = *left_lane, Action* (*t*-1) = *left_turn*) = 0.000. Because *P*(State(t+1) = *in_the_left_Lane* | …. *Behavior*(*t*-1) = *left_lane, Action*(*t*-1) = *left_turn*) = 0.012 the model "decides" that the state of affairs will be still unfavorable.
- Step 4: Anticipatory Goal Activation for (t) and Collision Prediction for (t+1)
  The models freezes the goal activation up to the next time slice with *Behavior*(*t*) = *left_lane_in*. As a consequence the conditional probability increases slightly to *P*(*State*(*t*+1) = *in_the_left_Lane* | …. *Behavior*(*t*-1) = *left_lane, Action*(*t*-1) = *left_turn, Behavior*(*t*) = *left_lane_in*) = 0.031 which is still far too low.
- Step 5: Anticipatory Action Selection for (t) and Good Luck Prediction for (t+1)
  This "motivates" the model to select the *Action*(*t*) = *left_turn* a second time (Fig. 5). Now the conditional probability increases to *P*(*State*(*t*+1) = *in_the_left_Lane* | …. *Behavior*(*t*-1) = *left_lane, Action*(*t*-1) = *left_turn, Behavior*(*t*) = *left_lane_in, Action*(*t*) = *left_turn*) = 1.000, which is a good state of affairs because it promises the avoidance of a collision.

Conclusions

We demonstrated that the Bayesian-Map-extended BAD-MoB model has the ability to *predict* agent's behavior, to *abduct* hazardous situations (what could have been the initial situation, what could be appropriate behavior), to *generate* anticipatory plans, and *control* countermeasures *preventing* hazardous situations. It was demonstrated that the selection of action and goal evidence has to be planned by a higher cognitive layer residing on top of the BAD-MoB model. An implementation with real expert and novice data has to follow this conceptual study.

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JDVE: A Joint Driver-Vehicle-Environment Simulation Platform for the Development and Accelerated Testing of Automotive Assistance and Automation Systems

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Abstract As virtualization of design methods in general becomes more and more relevant, one of the main goals of the EU FP7 Project ISi-PADAS is the development of a Joint Driver-Vehicle-Environment Simulation Platform (JDVE) which enables the designers of Advanced Driver Assistance Systems (ADAS) to validate their design with driver models as well as with "real" drivers. In order to cover both test cases, it is necessary to have a highly modular software platform able to be connected to various driving simulators, or even real test vehicles, but also capable of running with a virtual driver model on a single desktop PC. As virtual driver models do not need to act in real time it is beneficial to accelerate their timing in order to cover more test cases, e.g. as application of the Response 3 Code of Practice. This paper explains the modular approach of the JDVE and describes the accelerated time feature. Furthermore it briefly sketches some possible use cases for the JDVE.

Keywords Advanced Driver Assistance Systems · Automotive environment · Driver modelling · Simulation platforms · Field studies

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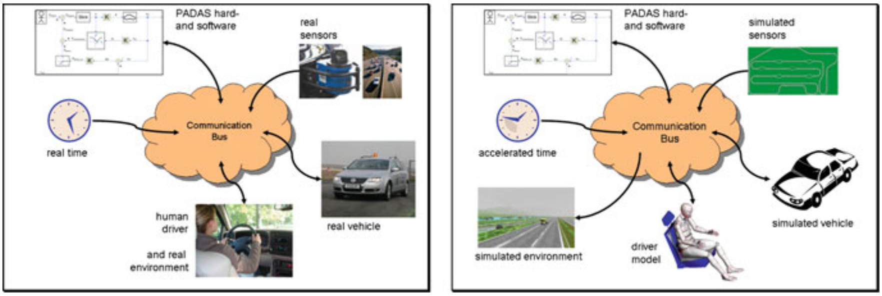

Fig. 1 Joint DVE Simulation Platform in real time (*left*) and accelerated time (*right*) mode, also showing the exchangeability of attached modules

Introduction

Since computers where able to simulate more and more complex issues, and since it became possible to simulate real looking environments, simulation platforms spread everywhere in the world. This is especially true in the Aviation and Automotive Domains, as scientific interest focuses on pilot's and driver's behaviours, and as experiments "in the real world" were quite expensive or too dangerous.

In the Automotive domain today we have a lot of different simulation platforms, all focusing on slightly different aspects of simulation, e.g. there are simulation platforms aiming at a good validity of simulated sensors, others focus on a high grade of immersion, and again others focus on the agility of development of complex systems (see e.g. [2, 3], or [8]).

Within the ISi-PADAS consortium the same was true: Each partner of each work-package had already pre-existing simulation capabilities focussing on the subject of each work-package, e.g. the creators of driver models had simulation platforms focusing on mental structures, the creators of assistance systems had already platforms focusing on the agile development of assistance strategies, and the psychologists responsible for experiments and evaluation had already platforms with a higher grade of realism.

In order to keep the avoidable workload of re-implementations for all the partners as small as possible, a work-package was instantiated which aims at the creation of a joint simulation platform able to bring the simulation capabilities of each of the partners together, to harmonize the systems as far as possible and to jointly develop on one single platform which is shared between the consortium (Fig. 1).

Therefore, the Joint Driver-Vehicle-Environment Simulation Platform (JDVE) was created, merging the already existing service oriented platform DOMINION [1, 2] developed by DLR's Institute of Transportation Systems and selected components from the Straightforward Modular Prototyping Library in C ++ (SMPL ++, [3, 4]). In general, the JDVE is a standalone simulation platform able to run on a single desktop PC. It includes several basic processes, which where derived from former existing and widely tested tools, like a vehicle model, a viewer for the virtual world, a traffic simulation etc. But each of these processes can easily be replaced by another one, e.g. with a higher fidelity. Exchanging more than one process brings the possibility of attaching e.g. different driving simulators up to large motion based simulators, other simulation platforms like SiVIC (a simulation software developed at INRETS, commercialized by the company CIVITEC sarl, [5]) or SILAB (developed by wivw, [6]), or even real test vehicles, while the other processes work unchanged.

This modular approach is only working when all the attached processes stick to a concrete interface definition, which is closer described in Modular Approach.

As ISi-PADAS focuses on the interaction between driver models and newly created assistance systems there is not always the need to run the simulation platform in real time. In order to cover as many test cases, e.g. as application of the Response 3 Code of Practice [7], it would be beneficial to accelerate the testing procedure by running the simulation platform as fast as possible. Therefore, an accelerated time feature has been integrated into the JDVE, which is closer described in Accelerated Time Testing.

Modular Approach

The JDVE builds up on an architecture for the development of in-vehicle services called DOMINION [1], developed by DLR's Institute of Transportation Systems. Part of DOMINION uses modified versions of business standards, like VSDL (in-Vehicle Service Description Language) and VPEL (in-Vehicle Process Execution Language). This concept integrates model-driven aspects like code-generation for real-time targets as well as the deployment of very flexible SOA (Service Oriented Architecture) services. This chapter briefly describes the code generation which includes the interface definitions between the services in general.

Afterwards, the modules included in the JDVE are depicted and the interaction with different simulators and other simulation platforms is exemplarily described.

Ontology-based Module and Interface Definition

The aim of easily exchangeable modules is reached by applying ideas of SOA for the JDVE. SOA is a paradigm for organizing and utilizing different functionalities in a structured architecture with a very strong view of re-usability. That aim is followed by dividing functions in isolated and atomic function elements, called services, with a clearly defined interface and description.

For that purpose there is a central service description for the JDVE, in which all services, their interfaces and exchangeable variables are registered. This document is XML based and uses a format called VSDL, which is specifically designed to describe services and their characteristics for in vehicle environments. So, if a module provides the same interface as another one, it can takeover its part and replace it without modifications of the remaining parts of the runtime environment modules.

Furthermore, there is an OWL-ontology of the VSDL service description, which allows formally describing the elements specified in the VSDL. Because of the open world assumption of OWL, these elements can be linked and further described by other ontologies to be described from another point of view.

Usage of VSDL significantly improves productivity of module implementations, because on base of the specification already basic applications can be directly generated. In that way aspects of model driven development (MDD) are integrated into the development process. Such a newly created application skeleton already implements the specified interface, completely encapsulates inter-module communication and exchanged variables can be transparently accessed.

By the already provided integration in the runtime environment, general functionalities like module management, synchronization or time acceleration are available. So, the programmer can just concentrate on implementing functional aspects of his module and is not concerned with other distracting tasks. On the other hand a specialized programmer has always the possibility to change the behaviour of the "deeper" layers of the code as needed.

Modules Included in the JDVE

As described, the JDVE is able to run standalone on a single desktop PC. Therefore it is necessary that the JDVE includes all the modules needed for

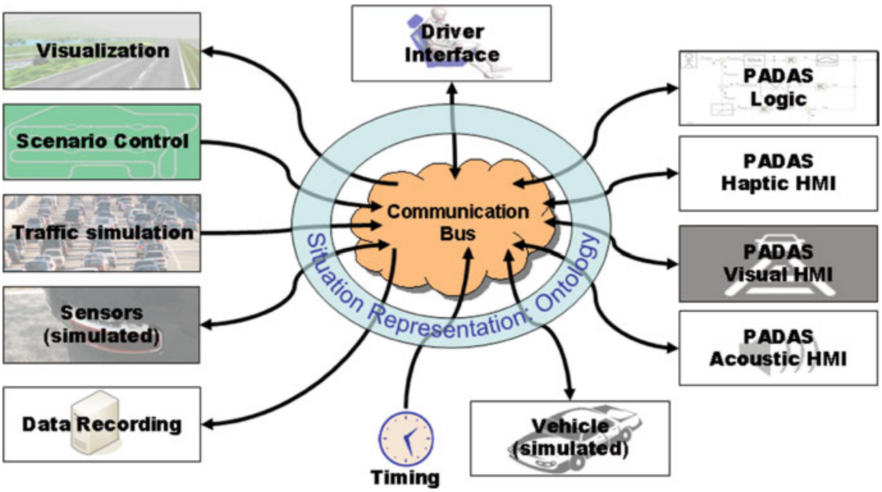

Fig. 2 The general setup of the JDVE showing all the attached modules when running standalone

simulation and, as the JDVE is highly embedded into the ISi-PADAS project, all the modules needed inside the project. Figure 2 shows the general setup of the JDVE and all the modules connected besides the ones needed for administration, like a Server application.

As shown in Fig. 2, there are basic modules attached to the blackboard which are e.g. a viewer based on OpenSceneGraph responsible for showing the virtual world, a tool for controlling the scenario (including traffic car behaviour as well as environmental changes, like e.g. traffic lights), a traffic and a sensor simulation and a data recorder which is able to directly store the data directly on databases.

In addition, a non-linear two track vehicle model is simulated, bringing enough realism for a desktop simulation while still being lightweight software not consuming much PC power.

The Driver Interface is a dummy module which can be instantiated in different ways: When working on a desktop PC it is simply a GUI making it possible to emulate the acceleration and brake pedal movements as well as the steering wheel by using the mouse. On the other hand it is always possible to replace this module by an interface module to your favourite inceptors. In case of ISi-PADAS the Driver Interface can also be a driver model directly commanding the vehicle.

As ISi-PADAS also aims at the integration of assistance systems, there are also modules attached which include the logic of the system as well as interfaces to the different HMI modalities *haptic*, *visual* and *acoustic*.

Interaction with Simulators and Other Simulation Platforms

In the context of ISi-PADAS, the JDVE has been connected to different driving simulators and simulation platforms in order to make experiments using the integrated PADAS possible all over the consortium. A connection has been applied to the following systems:

- Motion based driving simulator located at DLR-ITS
  As the ontology of the JDVE is a subset of the ontology of DOMINION used in DLR-ITS simulators, it was very easy to connect the JDVE. Figure 3 shows the components used in the experiments.
- Driving Simulator located at the Technical University of Braunschweig using SILAB
  This simulator uses SILAB as simulation platform. In order to connect SILAB and the JDVE, interface processes have been created which exchange the inceptor and environment information. The PADAS system and the vehicle model where completely located in the JDVE.
- Simulateur Véhicule-Infrastructure-Capteurs (Vehicle-Infrastructure-Sensors Simulator, SiVIC)
  Concerning SiVIC it is currently planned to bundle the platforms closer than done with SILAB. A possible integration of the two platforms is the integration

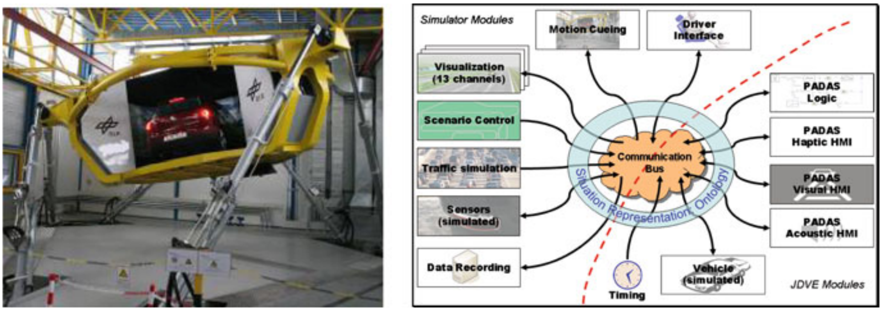

Fig. 3 Motion based driving simulator at DLR-ITS and the used component configuration

of the sensor simulation of SiVIC into the JDVE in order to benefit from the features of the COSMODRIVE [8] driver model.

Accelerated Time Testing

This chapter describes the standard timing used within the JDVE for real time application. Furthermore, it describes the steps taken to achieve the feature of accelerated timing enabling accelerated time testing of PADASs and Driver Models.

Standard Timing

The JDVE modules are divided in the Application itself (built on top of the application skeleton) and the Application Controller. Besides other features, the Application Controller controls the timing of the application. As shown in Fig. 4 (left), it monitors the current time provided by the used operating system and triggers the application in a well-defined constant frequency (every N ms. in Fig. 4).

When the application itself is in the need of knowing the exact time, it directly uses the functionality of the operating system. In order to assure more or less exact timing, the operating system clocks where synchronized.

Creation of the Feature of Accelerated Timing

One possibility to speed up the system could be to increase the applications frequencies and to include the factor of increase in the applications algorithms. This solution has the disadvantage that it has to assure that all data used by applications is most recent. One could imagine that an application with a simple

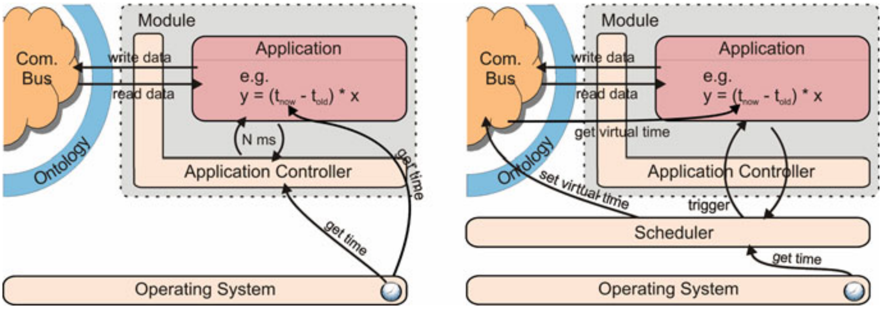

Fig. 4 *Left* Standard Timing of a single application, *Right* Virtual accelerated time implementation using a scheduler

functionality can work with a much higher frequency than an application with complex functionality. If the factor of increase would be set to high, so that the system cannot provide the output of the complex application in time, the clocks of both applications would begin to differ and the calculated results would not be valid. Furthermore, inconsistencies would appear when the factor is changed, because it cannot be guaranteed that all applications change in time.

An even better solution is the use of a scheduler which triggers the applications and manages the virtual accelerated time, like presented in Fig. 4 (right). In each run, the scheduler updates the virtual time by a specified amount and writes it into the blackboard, so that all attached applications can use it.

In a second step all (registered) applications are triggered by the scheduler directly via the Application Controller. When all applications finished, this is indicated to the scheduler that now can start a new run. This approach guarantees the highest possible acceleration of the applications, even when they run on a distributed system.

For optimization reasons, debug processes which are not affected by accelerated timing can be decoupled from the scheduler and run on their own. Example it is not necessary to have a tool like the viewer in the loop of scheduling, as it is only displaying the simulation world as it is.

In addition to this, it is possible to change the timing behaviour during runtime, so only some phases of each run can be accelerated and other phases can be performed in real-time. The toggling of the timing behaviour is done in a console window. As all timing applications (including changes between the different timing behaviours) are fully encapsulated within the Application Controller, the time is always increasing for the application itself.

Conclusion

Within ISi-PADAS a jointly used simulation platform has been created which is able to serve as backbone for usability assessments with real drivers in real time as well as for testing of PADAS functionality with driver models in accelerated time. While working also standalone, this platform has been successfully attached to different driving simulators and other simulation platforms, allowing to test the same PADAS prototypes in different environments.

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Effects of Distraction and Traffic Events Expectation on Drivers' Performances in a Longitudinal Control Task

Luca Minin, Lorenzo Fantesini, Roberto Montanari and Fabio Tango

Abstract

Background In recent studies it has been investigated how the decrease of situation awareness is related to the level of drivers' attention dedicated to the road and to drivers' incorrect expectation on traffic events. This paper is aimed at investigating the effects of a distracting visual research task and drivers' expectations on traffic behaviour on drivers' on-road performances.

Methods Twenty drivers were involved in a driving experiment where they were asked to perform several car followings, with and without interacting with a visual research task. Expectations of traffic behaviour were reproduced by varying (i) the lead vehicle speed: proceeding at a variable speed and sudden brake and (ii) size: a car for predictable conditions, a bus (obstructing follower sight) for unpredictable. Average Time Headway and Brake Reaction Time were selected as on-road performance indicators.

Result Results confirmed literature findings in terms of driver behaviour impairment in the visual research task conditions; at the same time, the unpredictability of lead driver behaviour negatively influenced the longitudinal behaviour, in particular when drivers were asked to also deal with the secondary task.

Conclusion The interesting aspect of the results is the negative effect on the longitudinal behaviour of the reproduced unexpected events. Even if this is a small scale experiment, significant differences have been found, even worst if drivers also have to deal with a secondary task. Data collected and experiment findings have also been used to design a driver model for the prediction of driver's distraction, currently under development.

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Keywords Advanced Driver Assistance Systems · Automotive environment · Modelling distraction · Driver vehicle interction

Introduction

Situation awareness during driving involves being aware of what happens around your car to understand how the information perceived from the context will impact the driving task in the near future [2]. In the recent years the lack of situation awareness has been investigated as one of the primary factors in car accidents [6]: among them, rear-end crashes are one of the frequently occurring types [10].

According to Beirness et al. and Houtenbos et al. [1, 5] the decrease of situation awareness is related to the level of drivers' attention dedicated to the road and to drivers' incorrect expectation on traffic events. In the analysis conducted in Muhrer and Vollrath [9], authors found that one possible reason for rear-end crashes is, in fact, the generation of inadequate expectations about the future behaviour of a preceding car: the driver does not expect the vehicle ahead to slow down as the situation contains no cues activating this expectation. Concerning driver attention, in [7] the analysis on the causes of 6.177 rear-ends events showed that in 2006 more than 1.600 crashes involved a distracted driver. The effects of these impairments are reflected on drivers' behaviour and can be assessed by monitoring drivers' performances and reaction time to traffic events. One of the main reasons of understanding drivers' behaviour in these critical conditions is to collect relevant information to design enhanced driving assistance systems.

In this paper we focused on the assessment of the effects of traffic events expectation and of a secondary distracting task on drivers' performances; the investigation has been conducted involving real drivers in near-car following conditions, considering the relevance of these factors in the impairment of drivers' situation awareness in rear-end crashes.

Methods

Participants

Twenty participants were involved in the study, specifically: 10 young in the age between 20 and 25 years old and 10 middle-aged, between 30 and 45 years. There were 3 females and 7 males in each age group. All participants stated they had valid Italian driving licenses, a minimum of 2 years of driving experience, driving a minimum of 6000 km per year. All of them usually use an IVIS (In-Vehicle Information System, like navigators) while driving. Drivers were collected among students and researchers of the University of Modena and Reggio Emilia (Italy).

Apparatus

An Oktal SCANeRII fixed driving simulator (www.oktal.fr) was set up to perform the test: the cabin was equipped with traditional control (e.g. steering wheel, pedals) and a digital instrumental dashboard. The vehicle position and dynamics were logged by the driving simulator at a frequency of 20 Hz: data logs were saved as text files for post-processing analysis.

Secondary Task Settings

A 13 $\times$ 17 cm touch screen display (resolution 800 $\times$ 600 pixels) was mounted on the dashboard to the right of the steering wheel, where IVIS are usually installed.

The SuRT (Surrogate Reference Task, [8]) was chosen as secondary task to evaluate the interferences caused by a generic visual search task rather than a specific IVIS. The SuRT (like most commercial IVIS) requires visual perception and manual response: such activities, according to Wickens' multiple resources model [11] require the same mental resources of the driving task and will therefore be more likely to interfere, possibly causing a performance degradation. SuRT is therefore a good compromise between an experimental distraction task, easy to set up and to manage, and a more ecological distraction, similar to the actual devices that drivers use everyday.

A two column SuRT was set up: participants were required to double-click on the portion (left or right) of the screen where the target circle is located.

Two difficulty levels were used: a light one with fewer distractors (small circles), and a harder one with more distractors. In both difficulty levels, targets (large circles) had a diameter of 1.4 cm (while distractors 0.7 cm).

Drivers where asked to perform this task each time it was presented during the driving session. The frequency the task was presented was varied between two ranges: (i) High—between 3 and 5 s, (ii) Low—between 6 and 9 s.

The frequency identified the time distance between the activation of two consecutive tasks. The test also included driving sessions without secondary task condition, where the SuRT was switched off and the driver had to deal only with the car-following.

Primary Task Settings

A three lanes highway with high radius curves was designed; traffic flow was reduced in order not to interfere with driver manoeuvres. According to Lee et al. [7] one of the most common pre-incident manoeuvre for the follower vehicle in a car following context involved in rear-end crashes is decelerating in traffic lane: this accounted for 44.4% of the rear-end crashes. The authors also state that the abrupt onset of the brakes activated by the lead vehicle is one of the second causes of these crashes, accounting for more than the 10% of the total amount of accidents.

Taking such results into account, we reproduced two car following scenarios which participants have been asked to carry out [4]:

- Car following with lead vehicle proceeding at a variable speed. The follower (i.e. the vehicle driven by test participants) is asked to proceed in the same lane of the lead vehicle, while the lead vehicle drives at a pseudo-random speed.
- Car following with a sudden brake of the lead vehicle. As above mentioned, the follower proceeds in the same lane of the lead vehicle that drives at a pseudo random speed. At a pre-defined coordinate on the road the lead vehicle activates a full brake decelerating from its actual speed to 5 km/h.

The pseudo-random variation of the lead vehicle speed has been designed in order to reproduce a smooth acceleration/deceleration of the vehicle as it happens on highway roads at high speed.

In order to assess expectations of lead vehicle behavior we introduced two types of vehicles in the two conditions listed above, specifically: a car and a bus. The level of predictability was reproduced as follows:

- Predictable lead vehicle behavior: the lead vehicle is a car, the small size of the vehicle allows the driver of the following vehicle to see through the lead vehicle and predict its deceleration.
- Un-predictable lead vehicle behavior: the lead vehicle is a bus, the road has very high radius curvature, and the big size of the vehicle does not allow the driver of the following vehicle to see through the lead vehicle and predict the reasons of its deceleration.

During the test, each driver was asked to follow one of the two vehicles he/she always encountered ahead, driving at speed in the range between 90 and 120 km/h. In order to reproduce the traffic conditions for rear-end crashes, drivers were asked to keep a reasonable short distance to the preceding vehicle.

Experimental Design

All participants were provided with a brief explanation about the purpose of the experiment, its procedure, equipment and expected duration. They were also informed about the opportunity to quit the experiment at any time without any consequence. All participants gave explicit consent about all data recording and analysis.

Participants were asked to drive for 45 min on a simulated three lane highway with a total length of 60 km.

The design was within subjects with each subject experiencing 24 combinations of the two independent variables: Expectations (4—two speed conditions and two size conditions) X Distraction (three frequencies: high, low, off) X Repetitions (2). To cover all the combinations each subject participated to the three sessions.

Each driver was asked to drive each of these sequences. In order to avoid possible learning effect, the three sequences have been presented to the drivers in a partially randomized order.

Dependent variables: Brake Reaction Time and Time Headway

Drivers' performances have been measured by means of two longitudinal behaviour measures: Time Headway (TH) and Brake Reaction Time (BRT).

Time headway has been computed as the difference between the time when the front of a vehicle arrives at a point on the road and the time the front of the next vehicle arrives at the same point (in seconds). The mean value of TH has been adopted as indicator of longitudinal performances in particular for the car following conditions with the lead vehicle proceeding at a variable speed. According to Östlund et al. [12], small mean headways values are related to high risk of collision: values higher than 3 s can be considered safe, while values less than 1 s can be considered risky, even if the subjective estimation of safe headway varies a lot between drivers. An increased headway may indicate that the driver decides to increase the distance to the lead vehicle in order to compensate for a concurrent secondary task inducing distraction.

Brake reaction time has been computed as the interval time between lead vehicle brakes onset to the follower brakes onset: the time instants of both brake events have been recorded in the simulator log file. In this study the mean value of brake reaction time has been computed as longitudinal performance indicator especially for the car following with a sudden brake of the lead vehicle conditions. According to Östlund et al. [12] this value is intended only for safety critical situations requiring very quick brakes reaction, usually within two seconds - to avoid incident or crash, like the ones reproduced in this work.

Results

The effects of driver expectations on lead vehicle behaviour have been analyzed with a t-test comparing mean values of the BRT and TH indicators in the predictable vs un-predictable lead vehicle behaviour conditions. The same analysis has been conducted to evaluate the effect of secondary task frequency on BRT and TH performances. Results were discussed separately for the two scenarios described in Table 1. Grouping factors like gender and age have not been taken into consideration in this analysis but they will be further investigated to evaluate their effects on TH and BRT with reference to expectations and secondary task frequencies.

With regard to the car following task with lead vehicle proceeding at a variable speed, the mean BRT was higher in the un-predictable than in the predictable condition (3.3 vs 2.5 s, $p < 0.01$), suggesting drivers' difficulties in anticipating

Table 1 Twelve car-following combining secondary tasks levels (3), Leading Vehicle behaviour predictability (2) and Leading Vehicle (LV) speed (2)

Secondary task frequency	Predictable (Car)	Not predictable (Bus)
High	1 LV variable speed	7 LV variable speed
	2 LV braking	8 LV braking
Low	3 LV variable speed	9 LV variable speed
	4 LV braking	10 LV braking
Off	5 LV variable speed	11 LV variable speed
	6 LV braking	12 LV braking

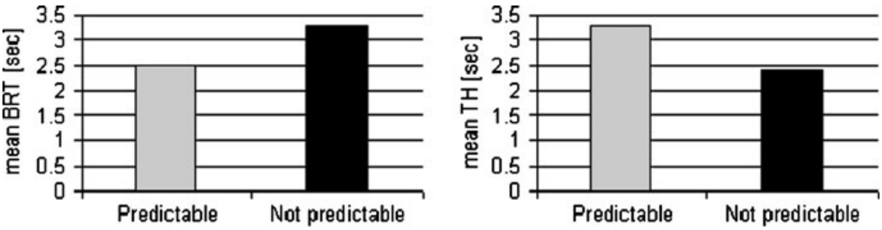

Fig. 1 Mean values of BRT and TH in the car following task with lead vehicle proceeding at a variable speed: comparison between predictable and un-predictable lead vehicle behaviour conditions

the lead vehicle deceleration. This result was also confirmed by the mean TH: the value of this indicator was lower in the un-predictable than in the predictable task (2.4 vs 3.3 s, $p < 0.01$) revealing an impairment of the driver in keeping a safety reasonable time distance to the lead vehicle: according to Fiorani et al. [3] this distance has been identified in the range between 3.5 and 4.5 s. In fact, according to the authors the time needed by the following vehicle to completely stop the car at a speed of 33.3 m/s (i.e. about 120 km/h, the maximum speed allowed during the test) giving a deceleration capability of 9 m/s^2 is about 3.7 s. Then, the range we identified let the driver stop the car in time to reduce the risk of rear-end crashes (Fig. 1).

In the car following task with a sudden brake of the lead vehicle the mean value of BRT measured in the un-predictable condition still confirmed the trend of the previous findings (2.65 s for un-predictable vs 2.2 s for predictable, $p < 0.01$). This result was also confirmed by TH even if it did not reveal significant differences between the conditions.

The t-test analysis of driving performances in the *with* and *without* secondary tasks revealed that, when active, the mean BRT was higher in the former than in the latter (2.7 vs 2.0 s, $p < 0.01$), then confirming expectations and literature findings [12] on drivers' impairment in vehicle longitudinal control during the interaction with a visual research task. However, no significant differences were found between mean BRT values in the two secondary task conditions (high and low frequency): this indicator was not able to discriminate driver performances between the two conditions of secondary task frequency.

Furthermore, the t-test carried out to assess how the activation of the secondary task influences the TH revealed that the mean TH was higher (3.7 vs 2.4 s, $p < 0.01$) when the secondary task is activated; even higher in the high frequency condition compared to the low frequency one (2.55 vs 2.30 s, $p = 0.051$). This reveals that drivers dedicated more effort to the in-vehicle task, then reducing the attention to the vehicle speed and the distance to the leading car as expected.

Finally, a two-way Analysis of Variance was conducted grouping TH and BRT data by (i) lead vehicle behaviour predictability/un-predictability and (ii) secondary task (low and high frequency) with the aim to assess how the interaction between predictability and secondary task levels influences driving performances. We found that this interaction significantly affected both BRT ($p < 0.001$) and TH ($p < 0.01$); we observed that the p-values of these interactions have been mainly affected by the predictability grouping factor, then revealing good performances of BRT and TH in identifying significant drivers' behaviour variations between predictable and un-predictable conditions.

Discussion and Next Steps: A Model to Detect Driver Distraction

The results related to the effects of the secondary task on drivers' performance agree with the literature; the interesting aspect of the analysis is the negative effect on the longitudinal behaviour of the reproduced unexpected events. Even if this is a small scale experiment, significant differences have been found, even worst if drivers also have to deal with a secondary task.

From the recorded data, three datasets have been created (training, validation/checking and testing), in order to implement a model for the distraction detection and classification basing on vehicle dynamics. These datasets includes inputs to the model (vehicle dynamic data like Speed, Time to Collision, Time to Lane Crossing, Steering Angle, Lateral Shift, Position of the accelerator and brake pedals) and target values inputs should be mapped to. Detected distraction has been kept as the target variable, computed as the time drivers eyes (measured by post-processing video recording data of driver sight) looked on the SuRT: according to Klauer et al. [6] if the drivers look away from the road for more than 2 s, they can be regarded as distracted. For each mentioned parameter in the list, the mean on different mobile window has been computed, as a method to group the data. Window size denotes the period over which eye movement and driving data were averaged.

Two Machine Learning (ML) techniques have been considered: Feed-Forward Neural Networks (FFNN) and Support Vector Machines (SVM). Preliminary results showed that FFNN was able to classify distraction for certain subjects with a Correct Rate up to 89.7%. Considering the SVM classifier we obtained even better results, with a Correct Rate up to 96.4%...

Potential applications of this research include the design of adaptive IVIS and of "smarter" Partially Autonomous Driving Assistance Systems (PADAS), as well as the evaluation of driver's distraction.

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Part III
Human Behaviour, Error and Risk Assessment

Human Driver Modelling and Simulation into a Virtual Road Environment

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Abstract This paper presents the driver model developed by INRETS in the ISi-PADAS project, with the aim to dynamically simulate driver's mental activities carried out while driving. The methodology supporting this model development is based on empirical data collection on driving simulator, in the frame of a car-following task. After presenting the theoretical foundations of the modelling approach and the empirical data analysis, the functional architecture of our COgnitive Simulation MOdel of the DRIVEr (COSMODRIVE) will be described, and the type of results liable to be obtained through simulations on a virtual Vehicle-Environment platform (SiVIC) will be presented. Then, the conclusion will briefly examine the perspectives of the model applications for driving aids virtual design.

Keywords Driver model · Cognitive simulation · Car following · Visual scanning · Situation awareness · Mental represention · Virtual design · Driving schemas · COSMODRIVE

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Introduction

The general objective of this research is to design, develop and implement a cognitive simulation model of the car driver, able to virtually simulate the human drivers' mental activity carried out while driving, through an iterative "*Perception-Cognition-Action*" regulation process. This model is more particularly focused on three following functions: (1) *Perception* of the road environment and of the other road users behaviours, (2) *Cognition*, integrating elaboration of *mental representations* of the road scene (corresponding to driver's situational awareness) and *decision-making* processes (based on these mental models of the driving situation and on anticipations assessed from dynamic mental simulations) and (3) *Action*, corresponding to behavioural performances as decided at the cognitive level and then effectively implemented via actions on vehicle commands, in order to dynamically progress into the road environment. Moreover, the aim of the model is not only to simulate these perceptive, cognitive and executive functions in an optimal way, but also to generate human errors in terms of non-perception of event, erroneous situation awareness, or inadequate driving performances.

Theoretical Foundations

From a theoretical point of view, this research is based on the COSMODRIVE model (i.e. *COgnitive Simulation MOdel of the DRIVEr;*2, 3) dedicated to driver's mental activities modelling. Basically, driving a car requires (i) to select relevant information in the environment, (ii) to understand the current situation and to anticipate its change in the more or less long term, (iii) to take decisions in order to dynamically interact with the road environment and the other road users, (iv) and to manage owns resources (physical, perceptive and cognitive) in order to satisfy the time constraints of the task, inherent to the dynamic nature of the driving situation. The selective dimension of information collection is especially important as drivers cannot take in and process all the information available in the road environment. This information selection mechanism is the result of a complex process whose keystone are the driver's mental representations of the driving situation. Mental representations correspond to the driver's *Situation Awareness*, according to Endsley [7] definition of this concept. These mental models are dynamically produced through a matching process between pre-existing *operative* knowledge and the perceptive information extracted in the road scene. At the *tactical level* [13], these mental representations provide ego-centred and goal-oriented visual-spatial models of the driving situation, which are dynamically produced and continually updated, as and when the drivers carry out their activity. One of their core-functions is to support cognitive anticipations, through mental simulations, providing expectations of future situational states. Moreover, driver modelling requires to consider two different levels of activity control:

an automatic and implicit mode *versus* an attentional and explicit mode. This dichotomy is well established in the literature with the distinction put forward by Schneider et al. [17] between *controlled processes*, requiring cognitive resources and which are only performed sequentially, and *automatic processes*, which can be performed in parallel without any attentional effort. In the same way, Rasmussen [16] distinguishes 3 levels of activity control according to whether the behaviours implemented rely on (i) highly integrated abilities (*Skill-based behaviours*), (ii) decision rules for managing familiar situations (*Rule-based behaviours*), or (iii) more generic knowledge that is activated in new situations for which the driver have not any prior experience (*Knowledge-based behaviours*). Regarding the functioning of the human cognitive system while driving, a large share of the driver's activity relies on heavily integrated and automated empirical know-how partly escaping to conscious control, but nonetheless relying on an implicit form of awareness and activity monitoring, to guarantee that the goals explicitly defined are reached. Thus, these two levels of control support themselves, and are embedded in each other [4]. By considering this theoretical background, the computational version of COSMODRIVE implemented on the SIVIC platform during the ISI-PADAS project is composed of three functional modules (i.e. *Perception*, *Cognition*, and *Action* modules) and is able to drive a virtual car on a virtual road from 2 synchronized "*Perception-Cognition-Action*" regulation loops: (i) an attentional control loop, based on COSMODRIVE *Driving Schemas*, and (ii) an automatic control loop, simulated through the *Envelope Zones* strategy and the *Pure-Pursuit Point* method.

Modelling the Tactical and Explicit Cognition: The Driving Schemas

Based on both the Piaget's concept of operative *scheme* and the Minsky [14] *frames theory*, driving schema is a computational formalism defined at INRETS for driving knowledge modelling at the tactical level [2, 3]. They correspond to prototypical situations, actions and events, learnt by drivers from their practical experience. From a formal point of view, a Driving Schema is composed of (i) a functional model of road *Infrastructure*, (ii) a *Tactical Goal* (e.g. turn left), (iii) a sequence of *States* and (iv) a set of *Zones*. Two types of zone are distinguished: *Driving Zones*, corresponding to the driving path of the vehicle as it progresses on the road, and the *Perceptive Exploration Zones*, in which the driver seeks information (e.g. potential events liable to occur). Each driving zone is linked with *Actions* to be implemented (e.g. braking or accelerating, in view to reach a given state), with a set of *Conditions* for performing these actions, and with perceptive zones that permitting to check these conditions. A *State* is defined by a vehicle *Position* and *Speed*. The different sequences of the driving zones make up the *Driving Paths* that progress from the initial to the final state (i.e. achievement of the tactical goal). Once activated in the working memory and instantiated with the characteristics of road environment, the active driving schema becomes the *tactical mental representation* of the driver, which will be continuously updated as and when s/he progresses into the road infrastructure. This representation corresponds to the driver's explicit awareness of the driving situation and provides a mental model of the road, functionally structured according to the tactical goal followed by the driver in the current context (e.g. turn left).

Modelling the Operational Skills and the Implicit Cognition

At the operational level, corresponding to the automatic control loop, the COSMODRIVE model regulation strategy is jointly based on the *envelope zones* and the *pure pursuit point* approaches. The concept of *envelope zones* recalls two classical theories in psychology [3]: the notion of *body image* proposed by Schilder [18], and the theory of *proxemics* defined by Hall [10], relating to the distance keeping in social interactions with other humans. Regarding car driving, envelope zones refer to *safety margins* [8]. At this level, our driver model is based on Kontaratos' [11] work who distinguished a *safety zone*, a *threat zone*, and a *danger zone*. Envelope zones correspond to the part of the path of driving schemas to be occupied by the car in the near future. As an "hidden dimension" of the social cognition, as suggested by Hall's [10] theory, these proxemics zones are also mentally projected to other road users, and are then used to dynamically interact with them, as well as to anticipate and manage collision risks. This virtual skin is permanently active while driving, as an implicit awareness of the expected allocated space for moving. As with Schilder's body schemas, it belongs to a highly integrated cognitive level (i.e. implicit regulation loop), but however favours the emergence of critical events in the driver's explicit awareness. Therefore, the envelope zones play a central role in the regulation of "social" as well as "physical" interactions with other road users under normal driving conditions (e.g. inter-vehicle distance keeping), and in risk assessment if a critical situation occurs (commitment of emergency reactions).

A second "hidden dimension" of the implicit cognition as implemented at the operational level of COSMODRIVE concerns the executive functions of lateral and longitudinal controls of the car, to be carried out in order to dynamically progress along the driving path of the driving schema. This automatic control loop is based on the *Pure Pursuit Point* method. The *Pure-Pursuit Point* method was initially introduced by Amidi [1] for modelling the lateral and the longitudinal controls of automatic cars along a trajectory, and has been adapted by Sukthankar [19], and then Mayenobe [12], for driver's situational awareness modelling. Mathematically, the pure-pursuit point is defined as the intersection of the desired vehicle path and a circle of radius centred at the vehicle's rear axle midpoint (assuming front wheel steer). Intuitively, this point describes the steering curvature that would bring the vehicle to the desired lateral offset after travelling a distance of approximately l. Thus the position of the pure-pursuit point maps directly onto a recommended steering curvature: $k = -2x/l$, where k is the curvature (reciprocal of steering radius), x is the relative lateral offset to the pure-pursuit point in vehicle coordinates, and l is a parameter known as the look-ahead distance. According to this definition, the vehicle-control abilities of COSMODRIVE for driving a virtual car are implemented as a dynamic regulation loop that permanently keeps the Pursuit Point on the driving path of the current driving schema, to a given speed assigned with each segment of the current tactical driving schema, as instantiated in the mental representation.

Methodology for Model Design and Data Collected

The methodological specificity of the driver modelling approach implemented in this research was to use the SiVIC virtual Platform [9] as (i) a driving simulator for empirical data collection with real drivers, and then, as (ii) a virtual road environment to be interfaced with the driver model for future virtual simulations. According to this approach, human drivers' behaviour and driver model performances will be observed for the same driving scenarios of car following, in the same virtual road environment. From these similarities, it is expected to facilitate the model validation and to increase its validity.

Participants

Twenty experienced drivers of middle-age (from 23 to 56 years old) have participated to the experiment. All the drivers have a minimum of 5 years of driving experience and they drive a minimum of 5,000 km per year.

Driving Scenarios and Visual Secondary Task (ST)

The participants' driving task was to follow a lead car in different driving conditions. Four main sources of variation have been more particularly investigated: (1) the driving context (i.e. motorway, rural road and urban area), and consequently the vehicle speed required (respectively 130, 90, and 50 km/h), (2) the nature of the car-following task (i.e. free *vs* imposed car following distance at a given Inter-Vehicular Time [IVT] of 0.6 s), (3) the lead car behaviour (having a steady *vs* irregular speed), and (4) the necessity to perform a secondary task (ST) while driving. Concerning more specifically visual distraction, the ST to be performed by the participants was the following: a set of 3 visual pictograms, accompanied with an auditory beep, were displayed on an additional screen (situated on the right side, near the usual position of the radio). Some seconds later (from 3 to 4 s), one of this three pictograms appeared under the first set, and the driver had to use a 3-buttons command for indicating which pictogram was replicated.

Main Results

The results presented here only concern the negative impact of a visual ST on the drivers' performances, more particularly by considering the driving behaviour modifications in normal conditions (e.g. inadequate following distance), and the accident risk increasing for critical scenarios (i.e. when the lead car brakes).

In *normal driving conditions*, two main differences due to visual distraction have been observed: (i) a significant reduction (T-test, $p < 0.001$) of the safety margins in *free following conditions* (without ST, mean value of IVT is of 3 s without ST *vs* 2.65 s with ST) and (ii) a significant degradation ($p < 0.05$) of the following performance in constrained following conditions (in these scenarios, drivers have to follow the lead car at an imposed IVT of 0.6 s, and the percentage of time when this value is performed is of 57% without ST, *vs* 44% with ST). These results show a negative effect of visual ST for short following distance keeping.

In *critical driving conditions*, the two main negative impacts of the visual ST on drivers' performances are (i) an increasing of Reaction time for braking (the differences are only significant for the constrained following task: 0.89 s *vs* 1.1 s; $p < 0.05$), and (ii) a risk of crash increasing: Table 1 presents the percentage of collision with the lead car/total number of required emergency braking, for the different driving conditions investigated. It appears that the risk of collision due to a ST is significantly increased for 4 of the 10 driving scenarios requiring an emergency braking. The highest negative impacts of visual ST are observed for the *constrained unsteady car following* scenarios, in both urban and rural areas.

Table 1 The percentage of collision with the lead for critical scenarios

Context	Driving scenario	Without ST (%)	ST-Visual (%)
Highway	Free steady lead car following	55	50
	Free unsteady lead car following*	**35**	**50**
	Constrained steady lead car following	65	70
	Constrained unsteady lead car following	70	70
Rural	Free unsteady lead car following	60	60
	Constrained unsteady lead car following*	**55**	**80**
Urban	**Free steady car lead following***	**20**	**30**
	Free unsteady lead car following	30	30
	Constrained steady lead car following	30	30
	Constrained unsteady lead car following*	**25**	**90**

(*Bold values indicate significant differences between without-ST vs ST conditions; T-test, $p < 0.05$)

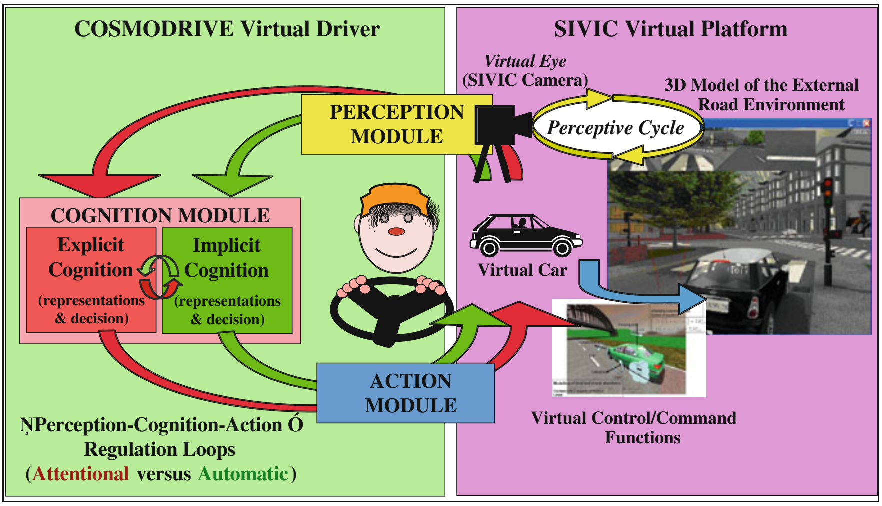

Fig. 1 COSMODRIVE model interfaced with the SIVIC Virtual Environment

Fig. 2 The COSMODRIVE virtual eye, as implemented on SIVIC

Driver Model Description

The functional architecture of the version of the COSMODRIVE model implemented into SiVIC is composed of three main modules (Fig. 1): a Perception Module, a Cognition Module, and an Action Module.

By implementing COSMODRIVE into the SiVIC Platform, it becomes possible to generate dynamic simulations of the driver model interacting with a virtual road environment, through actions on a virtual car.

Perception Module

The Perception module is based on a *virtual eye*, designed as a new type of SiVIC virtual sensor, adapted from the virtual camera model pre-existing in this platform.

This virtual eye includes three visual field zones (Fig. 2): the *foveal vision* (solid angle of 2.5° centered on the fixation point) with a high visual acuity, *para-foveal vision* (from 2.5° to 9°), and *peripheral vision* (from 9° to 150°). Visual strategies implemented by the driver model are simulated through a dynamic visual scanning of the road scene by the virtual eye. The visual strategies, modelled as a sequence of fixation points, are implemented by progressively considering *perceptive queries* received by the Perception module from the Cognition module. Each query requires to focus the virtual eye on a specific area of the road scene. Perceived data is then integrated into the implicit and the explicit mental representations of the Cognition Module.

However, two complementary perceptive processes have been implemented. The first one is the *perceptive integration* (that is a data-driven process, i.e. bottom-up integration of perceptive data), allowing the cognitive integration of the *perceptible* data in the mental representations of the Cognition Module. The second process is the *perceptive exploration* (that is a knowledge-driven process based on Neisser's theory of perceptive cycle [13]) in charge to move the virtual eye in the road scene, from a point of fixation to another one, according to the perceptive queries received by the Perception module.

Cognition Module

The Cognition Module is implemented through two regulation processes: an attentional control process, based on an explicit awareness of the driving situation requiring cognitive resources for sequential reasoning, and an automatic process, based on an implicit situational awareness and cognitive skills liable to run in parallel. Moreover, two main cognitive functions are implemented in this module: mental representation elaboration and decision-making. Concerning mental representations elaboration, this process is based on *driving schemas* instantiation with the external environment characteristics. As visual-spatial models of the environment, mental representations modelling required to use several instances of the SiVIC 3D graphical engine (i.e. *representation* of current the driving situation, and *anticipated representations* corresponding to the driver's expectations on future situational states). These internal models of the external environment are continually fed by the *perceptive integration* and the *perceptive exploration* processes implemented in the *Perception module*. It is thus possible to simulate human errors in terms of inadequate mental representations (e.g. non-integration of perceptive data or event false-updating due to distraction). Concerning Decision-Making, this process is dually implemented in the Cognition Module. At the attentional level (i.e. *explicit* decisions), this process is based on State-Transition rules integrated into the *driving schemas*. At the automatic level (i.e. *implicit* decision-making), the decisional process is implemented via the *envelop-zones* regulation mechanism. Moreover, in order to support decision based on cognitive anticipations, a process of *mental*

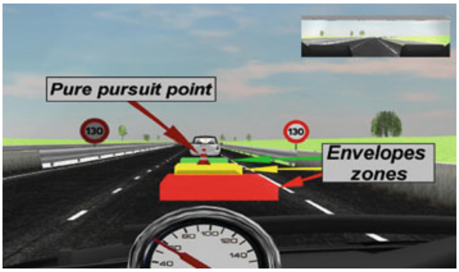

Fig. 3 Pursuit Point and Envelope Zones on SIVIC platform

deployment [4] of the current driving schemas has been implemented, by using a third specific instance of SiVIC.

Action Module

The Action Module is in charge to perform vehicle-control skills, according to the driving actions decided, anticipated and then planned at the representational level by the Cognition module. The two core regulation mechanisms implemented in the Action Module are the (i) *Pure-Pursuit Point* method and (ii) the *Envelope-Zones* regulation process. These vehicle-control abilities have been implemented on the SIVIC platform as a new type of the pre-existing SIVIC models of *vehicle controls* [8].

Indeed, a new class of "*COSMO-CAR*" has been defined, integrating the *pursuit point* and the *envelope zones*. Figure 3 illustrates such a regulation strategy in a car-following task: the pursuit point determines the cap to be followed by the ego-car, and the envelope zones are used for keeping the IVT distance with the lead-car.

Model Results

In its current status, the COSMODRIVE model implemented on the SiVIC platform is able to observe, mentally analyse, decide and dynamically progress into a virtual road, through continuous actions on a virtual car. Indeed, model results take the form of dynamic simulations of the driver's activity at four levels.

At the visual level (i.e. Perception module), by dynamic simulation of a sequence of visual fixation points, corresponding to the areas of interest successively explored by the driver while progressing on the road, according to its own tactical intentions, or as influenced by a visual secondary task while driving, requiring to alternate the road scene scanning and an on-board screen observation.

At the cognitive level (i.e. Cognition module), by dynamic elaboration of mental representations (i.e. situational awareness simulated through 3-Dimensional mental models of the road scene, integrating *driving schemas*, *envelope-zones* and *pure pursuit points* abilities), and decision-making processes simulations in charge to determine which relevant action should be implemented in the current driving context, as perceived, understood and anticipated by the driver model.

At the behavioural level (i.e. Action module), corresponding to the driver's action actually performed on the virtual car commands (e.g. presented in Fig. 9 through the curve describing the brake pedal status) for dynamically progressing into the virtual road environment and interacting with the other road users.

At the performance level as a whole, corresponding to the consequences of a dual "Perception-Cognition-Action" loop of regulation, continuously implemented by the driver model (e.g. respective speeds and positions of the vehicle and thus, Inter-Vehicular distances keeping), and which is dynamically simulated through the actual effects on driver's action on the current driving situation, as virtually modelling into the SiVIC environment.

This last level of global performance, including potential critical consequences of human errors, is more particularly connected with the practical objectives of the Risk-Based Design methodology of driving aids to be implemented in the Isi-PADAS project, and that is focused on the human reliability issues. However, by considering the respective underlying simulations implemented by the *Perception*, the *Cognition*, and the *Action* modules, it becomes possible to investigate in detail human errors and thus to open the door for an "in-depth" understanding and analysis of the human driver's reliability *versus* unreliability issues.

Conclusion: Model Use for Virtual Design

The research presented in this paper takes place in the frame of a Human Centred Design approach, aiming at setting up a virtual simulation platform to design and evaluate in-vehicle systems interest and potential impact on road safety (Bellet et al. 2010a). In this objective, it was proposed as to implement a cognitive simulation model of the driver on a Vehicle-Environment platform, in order to provide a simulation platform liable to support virtual design of vehicle automation technologies. This driver model implemented on the SiVIC platform aims to simulate human drivers' perception, cognition and behaviour in order to dynamically progress in, and interact with, a virtual road environment. One objective during the second phase of the ISI-PADAS project will be to contribute to the Risk Based Design methodology defined by Cassini and Cacciabue [5], and requiring human errors simulation results. Indeed, like a human driver, this model is not only able to simulate the driving performance in an optimal way, but is also able to generate *human errors* (e.g. non-perception of events, erroneous situational awareness and thus, decision-making, or inadequate behavioural performance in terms of safety margin keeping or reaction time), liable to occur in particular driving conditions. According to these functionalities, the model interest for driving assistances design will more particularly concern the initial design phases corresponding to the driving aid concept definition. At this earlier stage, our driver model could thus be used for virtual simulations allowing the designers to estimate human drivers' performances in case of unassisted driving, in order to identify and specify the most critical driving scenarios for which the target-system to be developed should provide a palliative assistance. These critical scenarios will correspond to driving situations where the human driver reliability—as assessed from our driver model performance—seems not sufficient to adequately manage the risk. Through these scenario simulations, it could be thus possible to provide ergonomics specifications of drivers' needs in terms of assistance. Then, during the driving aid testing phases, coming later in the design process, it could be therefore possible to evaluate the assistance effectiveness for the specific sub-set of most critical scenarios, as selected through the model simulations, in order to test the efficiency of this device (and, therefore, its interest for the drivers) in these particular driving conditions. These isues will be investigated in the ISI-PADAS project.

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Driver Behaviour and User Acceptance of Cooperative Systems Based on Infrastructure-to-Vehicle Communication

Robert Kölbl and Susanne Fuchs

Abstract

Background In the area of Intelligent Transport Systems (ITS) the development of co-operative systems is seen as one of the key means to ensure safe and efficient driving. The European Integrated Project COOPERS (Co-operative systems for intelligent road safety, http://www.coopers-ip.eu) focuses on the I2V communication systems transmit accurate, high-quality traffic information directly to vehicle groups in order to achieve the above objectives.

Methods As a framework, the model of human information processing has been used with the integration of driver behavior and user acceptance. The former should show the short time effects such as driver reaction to certain events and the latter should assess the long-term behavior and its usage. The same methodology has been applied in a simulator study and in field tests.

Results In the simulator study the driver reduced the speed in all events. A reduction in speed could also be found in the field studies. In terms of user acceptance, the objective measurements could also be found in the subjective questionnaire results and fulfilled the expectations where the post-questionnaire results outperformed those of the pre-questionnaire.

Conclusions The COOPERS system can provide a contribution to safe and efficient driving through the information provision and the raising of the attention at critical incidences. However, this can only be achieved if the provided information can be transmitted accurately, i.e. in time and in location, and with a high degree of certainty.

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Keywords Driver behaviour · User acceptance · Information technology · Telematics · Human informationprocessing · I2v communication

Introduction

One of the main focuses of worldwide research and development (R&D) projects in the area of Intelligent Transport Systems (ITS) is the development of co-operative systems, where three areas can be distinguished: autonomous in-vehicle systems, vehicle-to-vehicle (V2V) communication systems and infrastructure-to-vehicle (I2V) communication systems. The European Integrated Project COOPERS (Co-operative systems for intelligent road safety, http://www.coopers-ip.eu) focuses on the I2V communication systems and plans to link vehicles to the road infrastructure via continuous bidirectional wireless communication. For the I2V communication no specific communication technology has been developed but existing networks have been analyzed and tested in terms of their abilities to transmit accurate, high-quality traffic information directly to the vehicles on a motorway. COOPERS attempts to provide vehicles and their drivers with real-time, safety-related services in relation to their current location of driving and to the actual traffic status, i.e. a concept that is also followed by the Vehicle-Infrastructure Integration (VII) [1] and the Japanese Advanced Cruise-Assist Highway System Research Association (AHSRA) [2]. It is expected that I2V communication has the potential to improve traffic management and to enhance road safety [3].

For the increase in road safety the first technological challenge is to establish a faster exchange of information from the infrastructure side and the traffic control centre (TCC). Currently in Europe, the delivery of information from the road operator to the drivers is done via broadcasted digital information using the Traffic Message Channel (TMC) [4]. This information provision takes up usually more than 10 min, which is too long for safety applications. Within COOPERS this information gap is attempted to be reduced to 30 s from the generation of the information within the Traffic Control Centre (TCC) until its delivery to the end user. Below this 30 s threshold it is anticipated that V2V communication will take over.

The second challenge is to improve information accuracy. Information is sourced from various sensor technologies and fused intelligently with external information such as weather forecasts. For cooperative systems, messages need to be assigned to the location, either in relation to the point of an event (e.g. an accident or the dynamically moving end of a congestion) or in relation to the start and end point for a road segment-specific information (e.g. slippery road surfaces or speed restrictions).

The traffic information depicted to the driver will also be language independent, ensuring that all drivers in a multi-lingual Europe have the possibility to obtain the messages as in their home countries and in their mother tongue. Within the COOPERS project the following safety relevant information services have been defined [5]:

- Accident/Incident Warning (drivers are warned on an accident/incident ahead)
- Weather Condition Warning (drivers are made aware of environmental related problems ahead e.g. black-ice, fog, heavy rain, storm)
- Roadwork Information
- Lane Utilization Information (drivers are made aware of the lane control policy applied and the lane utilization information)
- In-Vehicle Variable Speed Limit Information
- Traffic Congestion Warning
- Intelligent Speed Adaptation (ISA) with Infrastructure Link (in comparison to the In-Vehicle Variable Speed Limit Information; the information provided by motorway operators should be very accurate based on a continuous communication between infrastructure and vehicle)

The Information Processing of Driver Behaviour

Introduction

As the main objective of COOPERS is related to safety, especially to enhance safe driving through the influence of timely and locally accurate traffic information, it is generally anticipated that improved safety will be achieved primarily by helping drivers to avoid situations where the risks of accidents are greater due to environmental, roadway or traffic conditions [6]. However, traffic safety evaluation is a difficult task, primarily due to the relative infrequency of accident occurrences, i.e. the need for large samples to identify with reasonable confidence a modest change in safety, and that it is often difficult to attribute causes of accidents to particular factors. Thus, it is usually attempted to focus on the behavioural aspects of the driving task [7], where aspects are selected based on known adverse effects on traffic safety, such as insufficient safety margins in lateral and longitudinal positioning. Traffic safety effects are then confined to extrapolations from these test results, although even then it is doubtful whether complex and often contradictory results can be translated into reliable estimates of safety for a road network [8]. It should be noted that there is no scientifically established causal connection between technical equipment and driver behaviour, which implies that no direct calculation regarding the gain in safety based on a particular service provision can be made.

Evaluation methodologies for the assessment of ITS systems and thier performances are usually developed from a technical perspective. Here we start to develop the evaluation approach from the human behavioural perspective, since the human response is *the* crucial element in the whole driving process.

The model of human information processing is used as a framework, since it provides the linkage between perception of the external or input information (in terms of the driving task and information provision by the on-board unit)

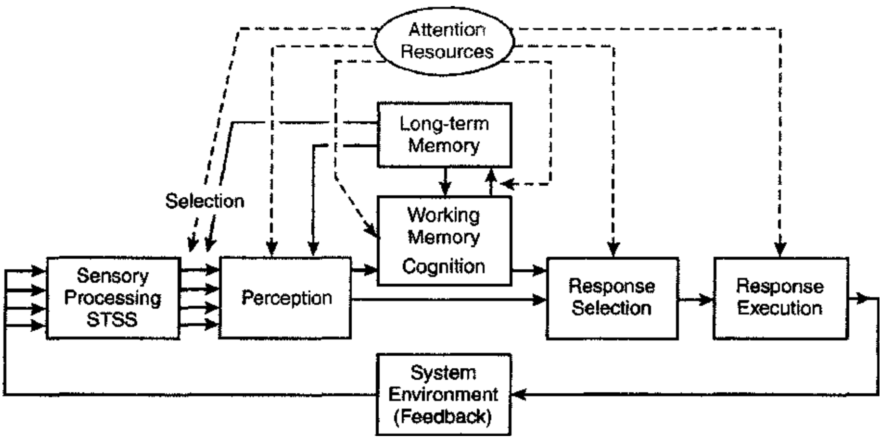

Fig. 1 A model of human information processing [9]

and the information processing within the human (i.e. the response of the driver or driver reaction) and the performance of the driver or driver reaction and performance of the car [9]. There are numerous feedback processes, which can have various influences (Fig. 1). Out of this complex scheme, we would like to group the following items of the framework to two terms: i) perception, working memory or cognition and response (selection and execution) which will be summarized under the umbrella of driver behaviour and ii) long-term memory, which will be evaluated in relation to user acceptance. This classification is assumed since the driver response and execution is within the range of up to two or three minutes (which equates to the information provided of around 2 km before an incident). User acceptance on the other hand, involves decision making which depends, for example, on the usefulness and ease of use of the information device over a longer time period and is usually addressed in economics, information systems and marketing research.

Driver Behaviour and User Acceptance Assessment

The assessment of driver behaviour and user acceptance has been divided into two stages, firstly a simulator study and secondly field tests. Simulator studies are very common to test cooperative system in a safe environment as well as simulated safety–critical driving scenarios. Similar simulator studies have been performed by the European Safespot project (http://www.safespot-eu.org) for the Intelligent Cooperative Intersection Safety System (IRIS) [10] or by the U.S. Department of Transportation for the Cooperative Intersection Collision Avoidance Systems (CICAS) research initiative [11]. Field tests have recently been carried out at various locations in Austria, Belgium, France, Germany, Italy and the Netherlands.

In relation to the methodology, the simulator study provides the repetitiveness of clearly defined and exactly the same traffic instances for each test driver and thus builds the basis for establishing firmer correlations between traffic circumstance, information provision and driver reaction. The field trials, on the other hand, cannot replicate this repetitiveness of the same traffic events but should show the driver reaction under real conditions. (Due to the scope here, only results from the simulator study will be presented below.) In order to establish a comparative basis, the tests have to follow the same principles and procedures of the methodology, the simulator study and the field tests, otherwise no coherent derivations can be attempted. An extensive list of parameters has been defined since different demonstration sites measure different units. The parameters have also been examined with alternative combinations, in order to establish a comparative basis from a unit point of view, which have additionally beens standardized or normalized.

The analysis of driver behaviour is based on the comparison of driving without and with the service information. Hereby several parameters are collected, starting from the usual vehicle performance measures (e.g. speed, headway) up to drivers' physiological measures, consisting of portable bio-signal data acquisition instruments out of which the heart rate signal has been used to assess the stress during driving. In addition, a driver behaviour and a user acceptance model is used in order to attempt a step beyond the exploratory level [12–15]. The testing procedure for both, the simulator and the field tests is laid down in Fig. 2.

The hypothesis of the testing was that the COOPERS technology can improve efficiency, effectiveness and safety of roads. User Acceptance (usually not considered in a telematics and network performance assessment) is measured by various factors, where the main predictors are ease of use and usefulness which account for up to 57% of all envisaged measures [16, 17]. Technology or user acceptance is thus defined as the degree to which individual users will use a given

User Groups	Group 1	Group 2
	Driver Selection with Filter Questionnaire	
Pre-test	Driving without and the with the provisional fitted physiological measurement equipment	
Test		
	Pre-questionnaire	Pre-questionnaire
Driving I	without Services	with Services
Break		
Driving II	with Services + GD	without Services + GD
	Post-questionnaire	Post-questionnaire
In-depth interviews	With selected drivers	

Fig. 2 Testing Procedure (GD = Ghost Driver scenario)

system when usage is voluntary or discretionary [18]. The acceptance of a product or service refers to the continuous usage of the system. It can be measured by two parameter values: frequency of use and intensity of use.

For user acceptance, a mixed method design is used: investigations are performed with both quantitative and qualitative approaches to account for the special conditions with COOPERS test sites across Europe. A validated and pre-tested questionnaire is used to test standard items in the Technology Acceptance Model—TAM [16]. In addition, qualitative interviews served as a basis for further understanding and source of information.

Results of The Simulator Study

The Test Persons

In total, 51 test persons participated in the COOPERS simulator study. The distribution between female and male participants was equal (49% female, 51% male). Of these test persons, 65% belonged to an age group between 30 and 44 years, 33% were between 45 and 59 years and 2% up to 29 years old. All of the participants had at least some driving experience on motorways-being the focus of the COOPERS investigations-, most of them (68%) stated that they drive daily or several times a week on motorways, 27% stated to drive on motorways mostly on weekends of holidays. Only 6% are driving rarely on motorways.

Driver Behaviour Results

One main reason for setting up the simulator study within COOPERS was to assess the boundaries of the driver response. The second advantage of the simulator study is the demonstration of dangerous events that cannot be tested under real conditions.

The following scenarios have been designed in the simulator study:

- Accident/incident warning with an approaching ambulance from behind. Here an intermediate reaction of the driver is expected.
- Accident/incident warning with a wrong way driver warning. Here, a very quick reaction is very short and a very quick reaction is required.
- Weather conditions warning with upcoming heavy fog, where a slow driver reaction is expected.
- Traffic Congestion Warning indicating the end of a congestion-zone with an expected fast driver reaction.

As described above (see also Fig. 2) one simulator drive of around 30 minutes was done twice, one time with the COOPERS system on, the other with the

COOPERS system off. The order of the events has been changed between the single test drives to ensure comparable results that rely merely on the services and not on the sequencing and other factors.

Driver behaviour can further be distinguished into objective driver behaviour and subjective user acceptance, which can be related to short and long term behaviour respectively. The objective driver behaviour deals with direct measurable data (e.g. speed of the vehicle, lateral position of the vehicle), actions taken by the drivers (e.g. lane changing, braking) and physiological measurements as described above. For the subjective measurements, a questionnaire deals with the discerned sensation of the driver concerning the driver's behaviour (e.g. actions taken) and the test person's opinion on how they were influenced by the COOPERS system during the simulation drive.

Objective Driver Behaviour Results

In all scenarios the service information of the upcoming dangerous event was given to the single drivers 2 kilometres ahead of the trouble spot (except the wrong way driver warning, which was displayed only seconds before the incident). In Fig. 3 it can be seen that the drivers reduce immediately after the receipt of the fog warning their driving speed by 10 kph and approach the dangerous motorway section with a 15 kph lower speed than without the system; the average speed is 5 to 15 kph lower, which can be seen as a positive safety impacts of COOPERS.

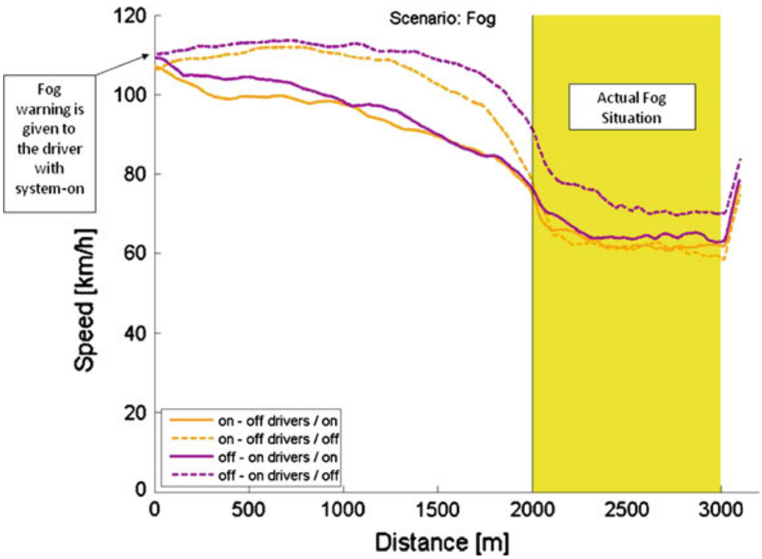

Fig. 3 Driver behaviour with fog warning according to the

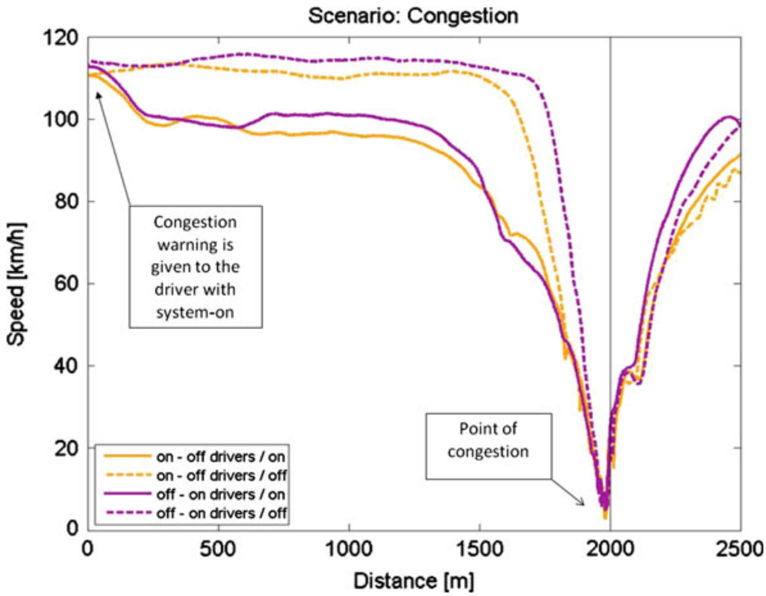

Fig. 4 Driver behaviour with congestion warning

The congestion scenario provides an additional feature regarding timeliness of information provision. Although an immediate speed reduction can also be observed with the congestion information given (Fig. 4), in contrast to the fog scenario the average driving speed was reduced immediately after the event-information but then the speed was kept up to a distance of 800 m prior to the event. With this distance a continuous reduction of the speed can be observed up to the congestion zone, where the average speed is drastically lower than without congestion warning (up to 30 kph lower!). This reaction of the drivers can be seen as an influence of an information provision, which might be too early but raises the driver's alertness and thus decreases the required deceleration.

If the two figures are compared, the common feature in both figures is that the drivers reacted nearly the same irrespectively of the order of information provision, i.e. for half of drivers the system was first off and then on, and for the other half, the system was first on and then off. This feature would raise the question regarding the learning curve, since drivers may have seen the scenario already once, thus having prior knowledge and reacting differently to without the system. The reasoning could be that driving is mainly based on a trained behaviour with a low-level of consciousness and thus requires only the basic driver information processing from perception. This would also explain why people, on the other hand, can listen to the radio during driving. From a scientific point of view, however, a more structured approach between discerning and undiscerning behaviour is required which would mean that other disciplines such as human behaviour science or neuroscience should be considered in future research.

Table 1 Subjective Driver behaviour according to different scenarios

Congestion	• 92% of the drivers felt that the system affected their behaviour • 54% felt support for a decision • 63% were calmed by the system
Ambulance	• 100% of the drivers felt that the system affected their behaviour • 69% felt support for a decision • 69% were calmed by the system
Fog	• 92% of the drivers felt that the system affected their behaviour • 42% felt support for a decision • 67% were calmed by the system
Ghost driver	• 100% of the drivers felt that the system affected their behaviour • 63% felt support for a decision • 58% were calmed by the system

Subjective Driver Behaviour Results

In all scenarios the drivers felt that the COOPERS system affected their driving behaviour. This was mainly the case in the fog and congestion scenario, where 92% of all test persons concluded, that their driving behaviour was changed by enhancing their attention to the upcoming event. In the other two scenarios (i.e. the ambulance approach and the wrong way driver scenario) all drivers felt they were supported in a difficult driving situation as they were informed in time about the upcoming dangerous event.

The test drivers were calmed by the COOPERS system in all driving situations, which can be seen in Table 1. The reduction of the subjective stress level was between 58% (for wrong way driver warning) and 69% (for the ambulance scenario); for the wrong way driver warning (or Ghost driver warning) the subjective stress level can especially be reduced, but is still very high. In combination with the decision support of the COOPERS system, it is possible to positively support drivers in such dangerous situation.

User Acceptance Results

As discussed in the methodology section, perceived usefulness and perceived ease of use of a system investigated are the strongest predictors of actual system use and thus user acceptance. For this reason, the measures of the COOPERS simulator study for perceived usefulness and perceived ease of use as well as the intention to use are described here in more detail.

The results for the indicator “perceived usefulness” show that the test persons had very positive expectations towards the COOPERS system already before they actually experienced it. The post questionnaire (after system experience) revealed, that the actual COOPERS system experience outperformed the test drivers expectations: on average they found the system even more useful during driving than expected and that the system enables them to accomplish driving tasks more quickly; they also found that the system increases driving safety more than expected, and so on. Only for the questions "using the system I can move from A to B more quickly" and "using the system I can better conform to traffic rules" the experience was lower than the expectations.

Ease of Use is besides Usefulness the strongest indicator of Technology Acceptance. The results show that in every single question in connection with how easy the system use is perceived, the already quite high expectations of the users were outperformed by the actual system experience. On average the test persons stated that they strongly agree that the interaction with the system was clear and understandable and that they find the system easy to use.

As described above, the expectations of the test drivers towards the system were outperformed by the system performance in terms of how easy the system is to use and how useful the system is for driving. The test drivers were also asked, whether they intended to use a COOPERS system in the future. Figure 5 shows the results for the "Intention to Use" of the COOPERS system. Again, the answers given to the questions after experiencing the system were even more positive than expectations before experiencing the system. After using the system, the respondents agreed that on average they would buy the system when commercially available.

Overall, the test drivers reacted in a very positive way towards the COOPERS system. All major indicators for User Acceptance rank very high, and are positive in a before/after comparison. Especially the easy to use interface and the usefulness of the COOPERS services seem to have a good impression on end users. The results achieved in the simulator study were promising but it can be assumed that the results of the field test may not reach the same levels due to the more complex conditions of a real motorway.

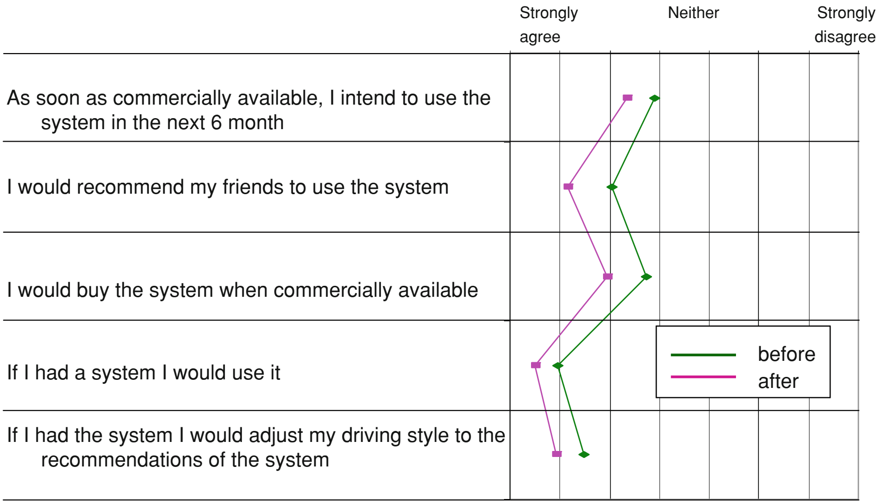

Fig. 5 Results for "Intention to Use" of the COOPERS system

Conclusions and Limitations

First results concerning driver behaviour and user acceptance of cooperative systems achieved in the simulator study conducted in the European COOPERS project, give very promising findings in both, user acceptance and driver behaviour. Especially driver behaviour is positively influenced in safety critical situations by speed and driving stress and simultaneously enhancing driver attention and thus road safety. Technology Acceptance measurements of the COOPERS system show that the end user's expectations are high towards co-operative services. Experiences in the simulator outperformed these expectations and test persons were keen to buy a COOPERS system as soon as it becomes commercially available.

In a cross-discipline analysis, the COOPERS team will provide more evidence, whether user acceptance has an influence on driver behaviour. We will show whether test drivers have a positive attitude towards the system and adapt their driving style better to the information given by the system.

Long-range adaptive behaviours might reduce the benefits of some ITS services [19]. This effect has not been investigated in the current study and needs to be looked at in future, i.e. in methodological designs of ITS simulator and field tests. Furthermore, the effects of error in the ITS system and its potential impact on driver behaviour and user acceptance have not been investigated in this study but are important aspects for future research.

Field tests carried out, for example, in Sangubashi (Japan) by AHSRA support our results [2]. Tests on major motorway sections across Europe will show, if the simulator results will be validated under real life conditions.

From a methodological point of view, it can be seen that there is a need for combining objective and subjective methods in order to assess driver behaviour and human behaviour on the whole. This could be shown in respect to short term driver behaviour and long term user acceptance. This opens up the need for integrating more general or interdisciplinary approaches of human behavioural research, where the interfaces between the different disciplines would need to be redefined.

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Exploratory Investigation of Vibration Floor as Potential Collision Warning

Christine Mégard, Margarita Anastassova and Daphné Repain

Abstract This paper investigates the possibility of using the floor of a car as potential locus of vibratory collision warnings. Arrangements of three actuators were used to provide vibrating floor patterns. DC motors with eccentric mass and suspended on leaf springs were fixed longitudinally at the center of a metallic structure. The actuators can be activated independently to provide different haptic patterns with different possible amplitudes and temporal frequency parameters. Continuously activated patterns, provided by the simultaneous activation of the actuators can be suggested for high level urgency collision warning as they are considered to be mostly associated to unpleasant, urgent and intrusive judgments. Low level amplitude patterns can be proposed for the advice collision warning.

Keywords Haptic interaction · User-centered design

Warnings in PADAS Systems

ISi-Padas project proposes an original risk-based methodology based on driver-vehicle-environment modelling approach for the design and evaluation of Partially Autonomous Driver Assistance Systems (PADAS). PADAS systems are aimed to mitigate human errors and driver distraction. Driver distraction contributes to a high proportion of serious crashes [7]. When the car is equipped with PADAS, the

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driver is either informed on potential risks of collisions by alarms (Forward Collision Warning Plus: FCW+) or the speed of the car is regulated in order to keep a safe distance and temporal values with cars ahead (Autonomous Cruise Control Plus: ACC+). The area between the ego car and the car ahead is split in four security regions: over 7 s there no particular danger, between 7 and 2 s, the car enters a yellow area indicating that the driver must be cautious and an advice warning is delivered, in the orange area between 2 and 0.7 s, reaction from the driver is required; urgent warning is delivered by FCW+ as well as ACC+ and. In the red area (< 0.7 s), emergency braking is provided. In both PADAS, FCW+ and ACC+ , information to the driver on the state of the PADAS is of paramount importance to ensure situation awareness.

Traditional warnings in car are generally delivered by the visual or the auditory channel. But as mentioned by Spence and Ho [7], there is a growing interest in using the haptic channel as information display in navigation displays [9] or to orient visual attention to spatial location during the detection of changes in complex visual scenes [2, 8]. Haptics refers to the sense of touch regarding tactile (vibrations) and proprioceptive/kinaesthetic information (force feedback). Haptic interaction in cars has already been considered in the literature and is considered as an interesting candidate for providing information, when vision or audition is overloaded [7]. Haptic priming in steering wheel for lane departure was found to be more efficient than seat vibratory warning produced by a lateral haptic stimulation [1]. Most haptic collision warnings are based on haptic feedback provided by the accelerator pedal. When approaching a vehicle ahead, the accelerator pedal becomes stiffer. As accelerating requires more strength to the driver, the driver is intuitively warned that he has to slow down [6].

In this study we focus on the design of new possible interactions using haptics on the floor of a car to cover situations where the driver has his feet off the pedals, either when using the FCW+ and a cruise control, either using the ACC+ . In the present study we investigate whether a haptic vibrating floor can provide possible collision warnings that can intuitively orient driver's attention to the locus of potential collision indicating different urgency levels; the study aims to provide the partners of the project with candidate haptic patterns for forward collision warning. The question is how to design efficient and acceptable haptic signals. The ISO 9241-920 [4] provides general guidance on specific haptic attributes for encoding information: Limiting the number of attributes, Combination complexity may be used to encode different information dimensions, Limiting complexity: a purposeful combination of attribute values within a system should be discriminable. Other general guidelines are available in the literature [5, 10] but do not provide a design methodology. Design strategy can be based on musical metaphors [3] or on rhythmic patterns composed by the combination of elementary vibrating signals defined by their duration, amplitude and frequency [11].

Haptic warning signals for PADAS must be salient to attract attention of the driver, especially during distraction and must provide at least two urgency levels. They must induce short reaction times, but nevertheless need to be acceptable to the driver.

Choice of the Methodology

We designed an experiment to explore the possibility of using haptic patterns located on a floor to warn the driver of potential risks of collisions. As we cannot anticipate how people can react to floor vibrations, we decided to gather their subjective judgments relative to the acceptability of haptic patterns before beginning a driving simulator study. Acceptability was assessed with subjective scaling on pleasantness and intrusiveness of the patterns. We also investigated whether some patterns can evoke different urgency level to be proposed for the two classes of warnings: advice and urgent warning and advice.

Procedure

Patterns were generated by the three eccentric mass motors located at the center of the floor on a custom made metallic structure (Fig. 1). The structure was covered with a rug during the experiment. Despite the fact that this type of actuators induces dependant control over amplitude and frequency, eccentric mass motors were chosen over voice coil motors as they might be used in cars for their low cost.

A preliminary selection of patterns was performed with five subjects to distinguish well identified and discriminating patterns. Low level amplitude patterns (150 out of 250) were rejected because the frequency was too low to be perceived by the subjects. Eight non directional Patterns were investigated during the study. We used three temporal patterns at different frequencies (1, 3, 5 Hz) and one continuously activated patterns (Fig. 2). All patterns were tested with two amplitude levels (185 and 225 out of 250). Only square shape signals were used as the actuators used in the study presented high inertia. The duration of each pattern was one second.

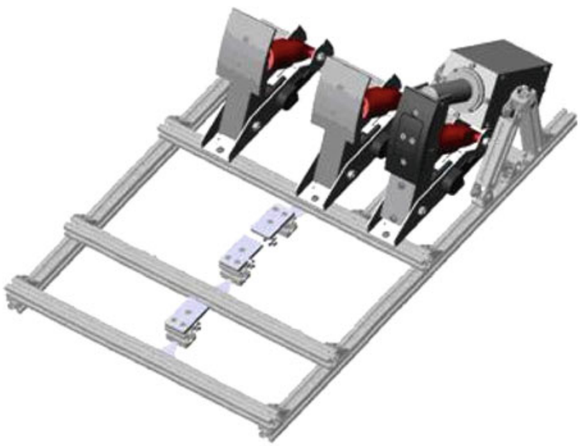
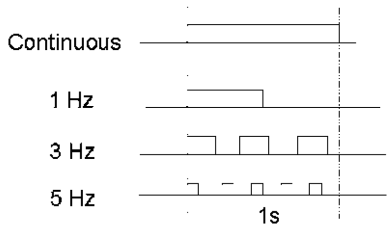


Fig. 1 Structure of mechanical haptic floor. Three actuators are located at the center of the platform

Fig. 2 Temporal properties of the patterns. The temporal patterns are activated according to their frequency (1, 3 or 5 Hz) or continuously during pattern duration (1 s)



After presenting the context of the study, the participants were informed that they would have to make judgments on the vibration patterns. Before the beginning of the experiment per se, the participants were introduced with an overview of the patterns. After this introduction, haptic patterns were presented randomly. We first asked participants to describe the vibration patterns to be sure there was no misperception. The number of presentations of the pattern was decided by the subject. Participants were then invited to use 10 points Lickert scales to estimate the perceived urgency level evoked by the pattern (10 on the scale is the more urgent level), to scale the perceived pleasantness of the pattern (10 is the more unpleasant) and the perceived intrusiveness (10 is the most intrusive note). The total duration of the experiment was about an hour per subject.

A within subject design was used with 25 voluntarily participants (17 males, 8 females). Mean age was 29. Five subjects over 25 had no driving license. All wore their regular shoes. Participants were seated in the context of a car without driving as for this first study we did not want any interference between the driving simulation and subjects' judgments.

Results of the Subjective Judgments

Description of the Patterns

Haptic floor patterns were generally well perceived. Patterns are well detected but their description is quite heterogeneous. Either subject focus on intensity aspects, or spatial aspects; but they rarely describe the patterns per se.

Subjective Judgment on Pleasantness

A repeated Anova was performed with Statistica on the results of the 10 points Likert scale on pleasantness, intrusiveness and urgency estimation of non-directional patterns. Patterns are generally judged pleasant (mean = 4.25; $F(7, 168) = 4.26$, $p = 0.00023$*). Patterns with the lowest amplitude (185) are systematically judged more pleasant (mean = 4.03) than patterns with higher amplitude (mean = 4.48) The Anova does not show a significant main effect of amplitude of the patterns on pleasantness estimation ($F(1, 24) = 2.22$, $p > 0.05$). Post-hoc Fisher, Test, confirms that the two continuously activated patterns are systematically judged more unpleasant than the others.

Patterns frequency has also a significant impact on the judgment on pleasantness ($F(3, 72) = 4.76$; $p = 0.004$*). The pos-hoc test shows that the only significant difference comes from the comparison between continuous and non continuous patterns, whatever the frequency.

Urgency Estimation

Pattern characteristics have a significant impact on urgency judgments ($F(7, 168) = 7.64$; $p = 0.00$*). Patterns with the lowest amplitude (185) are systematically judged less urgent (m = 4.6) than patterns with higher amplitude (m = 5.52). The amplitude of the patterns has a significant effect ($F(1,24) = 9.25$, $p = 0.0056$*). Post-hoc Fisher Test show that the two continuous patterns are systematically judged more urgent than the others.

High frequency patterns (5 Hz and continuous patterns) are associated with a higher level of urgency. Mean 1 Hz = 4.39, 3 Hz = 4.08, 5 Hz = 4.75, mean Continuous = 6.84 ($F(3,72) = 13.90$; $p = 0.000$*). Fisher Post-hoc test shows that continuous patterns are significantly judged more urgent than the other patterns ($p = 0.01$*).

Intrusiveness Estimation

Pattern characteristics have an impact on the judgment of intrusiveness ($F(7, 168) = 2.93$; $p = 0.0065$*). Patterns with high amplitude are systematically judged more intrusive (mean = 5.70), than low amplitude patterns (mean = 4.93) ($F(1, 24) = 4.885$, $p = 0.036$).

Patterns frequency has a significant impact on the judgment on intrusiveness ($F(3,72) = 5.703$; $p = 0.001$*). High frequency patterns are judged more intrusive than low frequency patterns. (mean 1 Hz = 4.81, 3 Hz = 4.22, 5 Hz = 5.24; continuous = 6.26). The pos-hoc test shows that the only significant difference comes from the comparison between continuous and non continuous patterns, whatever the frequency.

Geometrical Representation of the Judgment Space

A Principle Component Analysis (PCA) was performed to represent the different judgments on a geometrical space. Results are mostly explained by one axis:

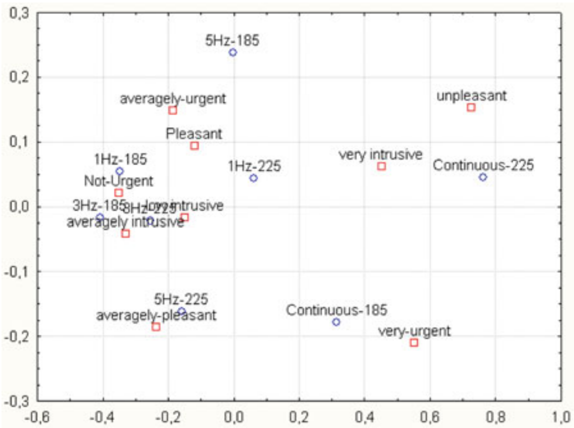


Fig. 3 Principle component analysis performed on the subjective judgment of pleasantness, intrusiveness and perceived for continuously activated patterns and temporal patterns

Dimension 1, contributes to 81.07% of the global inertia. Dimension 2 contributes to a less extent to the global inertia (9.17%). A multidimensional scaling (Fig. 3) shows that the first axis mainly opposes the two continuous patterns to all other patterns that are judged less intrusive, less urgent and more pleasant.

Interpretation of the Subjective Scales and Consequences on the Choice of Candidate patterns

Haptic patterns are well perceived, even if their description is heterogeneous. This result may be due to a high sensitivity of the sole, even if less than the hand's. Subjects may have perceived different behaviours of the eccentric mass motors and focused on that point. Haptic patterns seem to be well accepted by the subjects, even after an hour long experiment. Nevertheless not all of them are judged pleasant. Continuously activated patterns are systematically declared more unpleasant and intrusive than flickering haptic patterns.

The estimation of the urgency evoked by the patterns was an easy task for the subjects. Urgency estimation depends on the amplitude and on the temporal properties of the pattern. High amplitude levels generate higher urgency estimation than lower amplitude patterns. The effect of temporal frequency is less clear, and is probably due to the dependant control over amplitude and frequency for the actuators used in the display. The PCA analysis shows a clear distinction between the two continuously activated patterns compared to all the others. Continuously activated patterns are generated by three simultaneous actuators, creating a clear and strong percept, limiting side effects due to heterogeneous eccentric mass motors. These two continuously activated patterns can therefore be proposed as candidate haptic patterns, the high amplitude pattern as urgent warning and the low amplitude as advice warning. This proposition was confirmed by the subjects when asked to choose among the patterns presented during the experiment which could be used as warnings. However, affordance of haptic warnings when driving is of major importance in the choice of patterns and requires further studies.

Conclusion and Perspectives

The study presents the methodology used to explore the possibility of using haptic warnings embedded on the floor of a car. Judgments on urgency, pleasantness and intrusiveness show that continuously activated patterns with two amplitude levels can be warning candidates to advice and urgent warnings used in FCW+ and ACC+ . This study was a laboratory-based research and the evaluation of patterns requires further investigation, in simulator with critical driving scenarios. Multi-sensory warning needs also to be investigated in PADAS. Multisensory signals seem to more effective in capturing attention than unimodal signals [2]. Ecological investigation needs to examine how drivers behave with haptic and multisensory warnings.

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The Influence of Predictability and Frequency of Events on the Gaze Behaviour While Driving

Robert Kaul, Martin Baumann and Bertram Wortelen

Abstract One possible reason for rear-end crashes might be that the driver is distracted as the driver does not pay enough attention to the driving task. Therefore allocation of attention must be appropriate to the demands of the current traffic situation. According to the SEEV-Model allocation of attention is determined by the expectancy that there will be new information in a visual channel. According to the model expectancy is determined by the event rate of the information. To investigate to what extent allocation of attention is determined by the absolute frequency of events or by the expected event rate an experiment was conducted in a dynamic driving simulator. The current results show that the predictability of the behaviour of the lead car has a bigger influence on the allocation of visual attention than the frequency of speed changes of a lead car and the frequency of a visual secondary task.

Keywords Cognitive driver model · Allocation of attention · Frequency of events · Gaze behaviour · Car following

Introduction

Performance in dynamic situations like driving a car is highly influenced by how well the driver knows what is currently going on around him and how well he can

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predict the development of the situation in the near future. For safe driving it is necessary that drivers perceive, identify, and correctly interpret the relevant objects and elements of the current traffic situation and that they construct expectations about the future development of the current situation to adapt their own driving behaviour to the situation. The processes involved in constructing and maintaining a mental representation of the current situation that forms the basis for the driver's decisions and actions are described in the concept of situation awareness [2]. Models of situation awareness in the driving context have been developed to assess the impact of driving assistant and information systems on driver's situation awareness and their consequences for driving behaviour and driver's safety [1]. One possible reason for rear-end crashes is the generation of inadequate expectations about the future behaviour of the lead car [4]. Another possible reason for rear-end crashes might be that the driver does not process all information present in the traffic situation deeply enough to achieve a complete and accurate mental representation of the traffic situation because he is distracted as the driver does not pay enough attention to the driving task due to low demands of the driving task. Therefore the allocation of attention must be appropriate to the demands of the current traffic situation.

According to the SEEV-Model the allocation of attention to any visual information channel is determined by four factors [5]. A visual information channel might be the view to the front, an information display inside the car, or the rear view mirror. The first factor is the salience of information in that channel, which is related to the conspicuity of information or events that occur within a given information channel. The second factor is the effort to access information from this channel. This factor is the only one of the model that influences the allocation of attention negatively—the more effort necessary the smaller is the probability that this channel is attended. The third factor of the SEEV-Model is the expectancy that there will be new information in that channel being the result of the observed rate of events or changes of information in that channel. The higher the expectancy that new information will be present in that information channel the higher the probability that this channel will be attended. And the last factor is the value or importance of information for the driving task. Also the higher the value of an information channel for a task the more this channel will be attended according to the SEEV-Model. According to this model expectancy is determined by the observed event rate in a given channel. But it is not clear whether it is the observed event rate that determines expectancy and thereby visual attention allocation or rather the deviation from an expected event rate in this channel. The deviation from the expected event rate means that a driver expects some event rate (e.g. a low event rate for the front view channel on a straight lane with a lead car as usually a lead car on a straight road without obstacles does not brake abruptly) and if the observed event rate is different from the expected one (e.g. lead car brakes abruptly without obvious reason) the front view channel will get more attention in the future.

Research Question

To examine the objective how expectations in relevant rear-end crash scenarios are constructed and thereby the allocation of visual attention respectively the driver's gaze behaviour is influenced by predictability and frequency of traffic events while following a lead car an experiment in the dynamic driving simulator of the DLR Institute for Transportation Systems as part of the ISi-PADAS project was conducted. Based on the results of the experiment a computational cognitive driver model is developed to support the design of a Partially Autonomous Driver Assistance System (PADAS). To investigate the research question a driving scenario based on a description of relevant accident scenarios [4] was developed. The driver in the ego car follows a lead car on a straight road approaching an intersection. Given this scenario the following hypotheses about the allocation of visual attention can be postulated. First, if the lead car shows an unpredictable braking behaviour at an intersection the driver will pay more attention to it than if the lead car shows a predictable braking behaviour. Second, if the lead car shows a high frequency of speed changes on a straight road without obstacles the driver will pay more attention to it than if the lead car drives steadily. Third, the impact of an unpredictable braking at the intersection on attention allocation will be greater if the lead car drove steadily before than if the lead car showed a high frequency of speed changes before. That means that more visual attention should be allocated to a channel with a lower event rate. And fourth, more visual attention will be allocated to a secondary task showing stimuli with a higher frequency than to a secondary task with lower stimuli presentation frequency.

Method

Participants

A middle-aged driver group with a mean age of 36.6 years (sd = 6.46 years; min = 28; max = 47) of twenty participants was selected for the experiment. Gender was balanced among the participants so that 50% female and 50% male were included in the sample. The mean driving experience of the participants was 18.1 years (sd = 6.4 years; min = 10; max = 29) and 19,325 km/year (sd = 11,585.23 km; min = 5,000; max = 50,000). Due to the eye-tracking system emmetropic participants were recruited, i.e. participants neither wore glasses nor contact lenses.

Experimental Design

A within-subject design was realised to investigate the research question. Three independent variables were varied to examine their influence during car following.

The first variable is the predictability of the braking behaviour of the lead car (predictable vs. unpredictable). In the predictable case the ego and the lead car approaching an intersection being on the non-priority road and the lead car brakes as expected in front of the stop sign. In the unpredictable case the ego and the lead car are on the priority road but the lead car brakes nevertheless. The second variable is the frequency of speed changes of the lead car during car following (constant vs. varying). And third, the frequency of stimuli presented in a visual demanding secondary task (low vs. high) the driver had to react to while driving. As dependent variable gaze behaviour of the participants were recorded.

Driving Scenario

Two different driving scenarios were defined. The first driving scenario was a scenario with constant velocity of the lead car. A route with a total length of 17,200 m was designed. Sixteen priority road signs and thirteen stop signs were distributed on 37 intersections along the road. The route consisted of eight straight segments with a total length of approx. 2,200 m. Three to four intersections with a maximum distance of 600 m were arranged along one segment. After the end of one segment the participant had to turn left respectively right. Flanked by two intersections with the same traffic sign (priority road sign vs. stop sign) on each straight segment there is one intersection we refer to as critical intersection. Eight intersections had no traffic sign at all and were only used to turn left respectively right. The maximum speed of the lead car was 50 km/h. After a straight section of approx. 600 m the first intersection with a priority road sign respectively a stop sign was presented. The behaviour of the lead car at this intersection was according to road traffic regulations. After the next 600 m the critical intersection was presented. The lead car stopped at this intersection. After the next 600 m the third intersection was presented. The behaviour of the lead car at this intersection was also according to road traffic regulations. The distribution of critical intersections with priority road signs respectively stop signs along the different segments was randomized.

As visual demanding secondary task the participants had to perform a variant of the surrogate reference task (SURT) while driving [3]. The participants' task was to indicate on which half of the screen the target stimulus—a red circle among red and blue squares and blue circles—was located by pressing on that half of the screen. The interstimulus interval lasted for 3 s in the high frequency secondary task, and 6 s in the low frequency secondary task. The two secondary task variants were presented at different road segments. The assignment of route segment and secondary task stimulus frequency was randomized.

The second driving scenario was almost identical to the first one. Only the behaviour of the lead car differed and to avoid learning effects the assignment of the traffic signs to the corresponding intersections and the assignment of route segment and frequency of stimulus presentation in the secondary task were different. In this driving scenario the lead car showed unexpected breaking behaviour within the distances of 600 m between the intersections. Two braking manoeuvres were executed by the lead car per 600 m interval. During these braking events the speed of the lead car was reduced from 50 to 35 km/h with a deceleration of 2 m/s^2.

Apparatus

The participants were tested in the dynamic driving simulator at the DLR. Additionally video data of gaze location relative to the driving scene were recorded via the head-mounted eye-tracking system Dikablis (Ergoneers GmbH). The stimuli of the secondary task were presented in 15″ TFT screen, located at the passenger seat next to the participant. Each participant completed a demographical questionnaire at the beginning and a set of questions addressing simulator sickness at different points in time during the simulator experiment.

Procedure

After a demographical questionnaire the participants completed a familiarization drive that used urban and suburban sections of road, and lasted up to 15 min. During the familiarization drive the participants trained the secondary task. Before each driving scenario a calibration process synchronized the driver's gaze location with the driving scene and the TFT touch screen. For calibration of the eye-tracking system a calibration panel (25 cm height × 35 cm length) was used, which was mounted between front windshield and steering wheel. Three points of reference (diameter: 3 mm) were used for visual fixation during calibration. After calibration the panel was removed and the participants drove the first driving scenario. The sequence of the two driving scenarios was balanced across the participants and gender.

Results

The results presented here are based on a first analysis of 12 participants. For the analysis of the data the route was divided into two parts. The first part is the road before the critical intersection and the second part is the road after the critical intersection. Furthermore, the road was also divided. Each road part was divided into four intervals according to the speed changes of the lead car. First, the interval before the first braking manoeuvre of the lead car. Second, the interval after the first braking manoeuvre. Third, the interval after the second braking manoeuvre. And fourth, the interval before the intersection.

Predictability of Lead Car Behaviour at Intersection

The first variable which was examined is the influence of the predictability of the lead car behaviour at an intersection (predictable vs. unpredictable). In this case the ego and lead car approaching an intersection having either priority or not and the lead car either stops or passes the intersection. In case the ego and lead car are on the priority road the lead car either brakes and stops unpredictable before the intersection or passes the intersection predictable. In case the ego and lead car approaching an intersection with stop sign the lead car stops always predictable.

The important comparison regarding the effect of predictability on the allocation of visual attention is the comparison between the gaze behaviour after an unexpected braking at a priority sign compared to the gaze behaviour after an expected braking at a stop sign. The behaviour of the lead car is exactly the same in both situations but the predictability is completely different. Up to now only a few parameters describing gaze behaviour have been analysed. Among these is the maximum glance duration. The analysis shows no significant difference between maximum glance duration at the lead car after an unpredictable braking event at a priority road sign compared to a predictable braking event at a stop sign.

Frequency of Speed Changes of Lead Car on Straight Road

No significant effects of frequency of speed changes (constant vs. varying) on a straight road of the lead car on the maximum glance duration to the lead car could be found. Based on this first analysis of the gaze behaviour of only 12 participants the driver of the ego car does not pay more attention to the lead car if it shows a high frequency of speed changes on a straight road compared to the situation if the lead car drives steadily.

Frequency of Stimuli Presentation of Visual Secondary Task

A secondary task with a higher frequency of stimulus presentation was considered as visually more demanding than a secondary task with a lower frequency of stimulus presentation. The analysis of maximum glance duration was divided between segments where the driver was on a priority road and expectedly braking at the critical intersection and segments where the driver was on the non-priority road and expectedly braking at the stop sign. In both cases there is no significant effect of stimulus frequency in the secondary task on maximum glance duration to the lead car. But if the lead car brakes unexpectedly at an intersection there is a tendency that the maximum glance duration to the lead car is longer if the participant has to perform the high frequency secondary task than if the participant has to perform the low frequency task. But this pattern turns upside down if the lead car shows an expected braking behaviour at an intersection with a stop sign. After an expected braking of the lead car at the stop sign the participants' maximum glance duration to the lead car is higher if the participants performed the low frequency secondary task. Furthermore, there was no significant interaction between frequency of secondary task and the number of speed changes of the lead car.

Discussion

The objective of the experiment was to examine the research question how expectations in relevant rear-end crash scenarios are constructed and thereby the allocation of visual attention respectively the driver's gaze behaviour is influenced by predictability and frequency of traffic events while following a lead car. According to the SEEV-Model [5] expectancy is one of four factors that determine the allocation of attention to any visual information channel. One assumption of the model is the higher the expectancy that new information will be present in an information channel the higher the probability that this channel will be attended. To examine this assumption the predictability resp. the expectancy of the lead car behaviour at intersections was manipulated. Based on the preliminary analysis of the gaze behaviour of 12 participants the results indicate that the predictability of the lead car behaviour at intersections does not strongly influence the allocation of visual attention of the driver in the ego car after this event. If the behaviour of the lead car is unpredictable resp. the lead car shows an unexpected braking event at an intersection although it is on a priority road the maximum glance duration to the lead car after the intersection is not significantly longer compared to the maximum glance duration after an expected braking at a stop sign. Further analyses of other parameters of glance behaviour are currently carried out to examine whether this preliminary result is reliable.

Furthermore, the SEEV-Model postulates that expectancy is determined by the event rate of the information. But it is not clear whether it is the absolute event rate that determines expectancy and thereby visual attention allocation or rather the deviation from expected event rate. The results show no significant effects of frequency of speed changes on a straight road of the lead car on the gaze behaviour and thereby the allocation of visual attention. One possible reason for a missing effect is maybe due to the small sample size of only 12 participants which was analysed in a first step. Another possible explanation for none significant effects can be the fact that some participants kept a very long distance to the lead car and consequently the speed changes of the lead car on the straight road were might have been not relevant for these participants driving task. In this case the effective event rate in the "view to the front" channel was not greater than in the condition where the lead car drove with a constant speed.

Finally the influence of the frequency of stimuli of a visual demanding secondary task on the allocation of visual attention respectively the driver's gaze behaviour was examined. Whereas there was no significant effect of stimulus frequency in the secondary task on analysed gaze behaviour parameters, a tendency of an interaction between secondary task stimulus frequency and the predictability of event frequency was found. If the lead car shows an unpredictable braking event (unexpected braking at an intersection although it is on a priority road) the participants tend to show a longer maximum glance duration to the lead car after the intersection when performing the high frequency secondary task then when performing the low frequency secondary task. But this turns upside down if the lead car shows predictable braking behaviour at intersections. In this case the participants tend to show a shorter maximum glance duration to the lead car after the intersection when performing the high frequency secondary task than when performing the low frequency secondary task. One possible explanation might be that after an unexpected behaviour of the lead car the driver pays more attention to observing this lead car and neglecting the high frequency secondary task because it would need too much visual attention. On the other hand if the lead car behaves predictably enough visual resources are available to perform the visually more demanding high frequency secondary task. But before being able to draw firm conclusions from these results the entire sample of participants and more gaze behaviour parameters need to be analysed. These results will then be used to support the development of a computational cognitive driver model, that incorporates the SEEV-Model [5]. The structure of the driver model and how the SEEV-Model is integrated into this model is described in detail in [6].

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A Hierarchical Task Analysis of Merging onto a Freeway—Comparison of Driver's and Driver Model's Task Representation

Astrid Kassner, Martin Baumann and Lars Weber

Abstract This paper presents the results of a Hierarchical Task Analysis (HTA) that show how drivers represent the driving task of merging onto the freeway. These individual representations were examined to precise and improve a cognitive driver model which simulates freeway merging manoeuvres in a real-time driving simulator. It could be demonstrated that the goal hierarchy of the drivers corresponds to the goal hierarchy of the driver model in several critical aspects regarding the contents of the goals. However, both hierarchies differed regarding the process in which some goals are achieved. Probably a consideration of the processes that are part of the drivers' goal hierarchy will improve the validity of the driver model.

Keywords Hierarchical Task Analyisis · Merging onto a freeway · Derives model

Introduction

Driving is a highly complex task that consists of a huge amount of different subtasks which are composed of sets of subtasks. One can describe this hierarchical task structure analytically based on the objective requirements of the driving task and on normative rules. But when constructing a cognitive driver model one has to consider the drivers' mental representation of the relevant task structure and how they structure the driving task into goals, sub-goals, and actions. This mental

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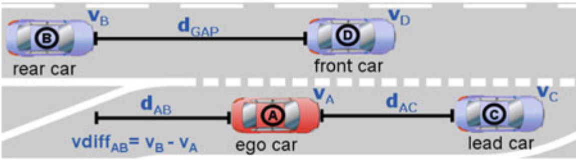

Fig. 1 IMoST freeway merging scenario: variations of distances, differential speed or gap size

representation is the basis for the driver behaviour. Therefore, to construct a valid cognitive driver model one has to represent the drivers' task structure and hierarchy in the driver model. The aim of this paper is to describe the drivers' mental representation of a specific driving manoeuvre—merging onto the freeway—by using the method of Hierarchical Task Analysis (HTA). This representation was used to precise and improve the task hierarchy of a cognitive driver model.

The cognitive driver model was developed within the IMoST (Integrated Modelling for Safe Transportation) project and is based on the cognitive architecture CASCaS [5]. The model is able to drive various freeway merging scenarios in a real time traffic simulator. Its task structure was initially based on Kassner [4] who described a normative driving behaviour for the merging process onto the freeway which based on interviews with driving instructors. Two tasks were identified as being critical for a safe merging process and were therefore integrated within the driver model. They concern the observation of the lead car on the ramp and the observation of the rear traffic on the right lane of the freeway. Additionally to this first basis a number of driving simulator experiments were conducted during the project to specify the parameters of the driver model. In these experiments the participants had to merge in situations with varying parameter values (Fig. 1) to measure the effects of certain situational characteristics, such as the distance to vehicles on the freeway (d_{AB}), the differential speed ($vdiff_{AB}$), the effect of other vehicles' behaviour (cooperative or not) on drivers' merging behaviour, and the kind of environmental information drivers use while merging [2].

In this paper we will first describe the resulting goal hierarchy of the driver model which simulates freeway merging manoeuvres in a real-time driving simulator. To precise and improve the driver model we decided to examine the goal hierarchy drivers have in mind about the merging task which was determined by using a HTA. The process of conducting the HTA and the resulting goal hierarchy will be described in the main part of this paper.

Weber et al. [7] used the statechart formalism [3] to model a driving task, associating states with goals. According to this Fig. 2 visualises Car Driving as the top level goal which contains the three goals Longitudinal Control, Lateral Control and the Lane Change Manoeuvre Task which are executed in parallel. This paper describes the model of the Lane Change Manoeuvre Task which merging onto the freeway is associated to.

Based on above mentioned experimental data two basic strategies how to start the Lane Change Manoeuvre Task could be identified and were integrated into the driver model. Drivers following the first strategy strongly accelerated the vehicle before their first glance into the left mirror and consequently before considering

Fig. 2 Top-level statechart for the driving task

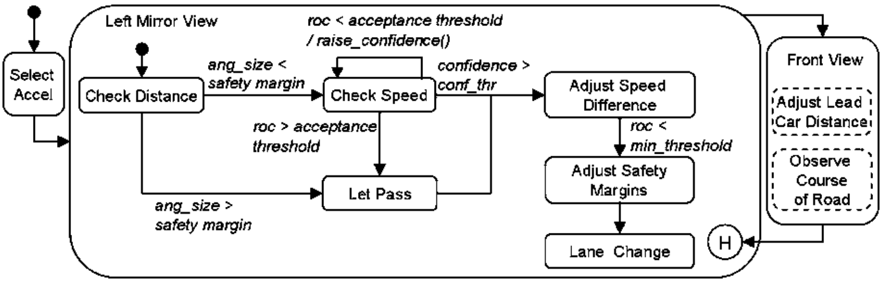

Fig. 3 Subchart for the lane change manoeuvre task

the traffic situation on the highway. Drivers following the second strategy did not or did accelerate only slightly before their first glance to the left mirror, but accelerated afterwards. The driver model's first sub-goal within the parent goal of the Lane Change Manoeuvre Task (shown in detail in Fig. 3) is consequently to select the acceleration strategy (*Select Accel*). The selection is based on a stochastic selection process provided by the CASCaS architecture and is modeled in the procedure language.

After the acceleration strategy is chosen, the next goal is activated (*Left Mirror View*) which serves to observe the rear traffic on the right lane of the freeway. This goal implements a sequential gap search consisting of several sub-goals. Given that there are several vehicles on the right lane of the freeway a gap is defined by the space between the front and the rear car (see Fig. 1). First, in sub-goal *Check Distance* the distance of the rear car to the driver is estimated based on the rear car's viewing angle. If the angle exceeds a maximum value (rear car is too near) the model immediately decides to let it pass and checks the successive gap. In case the distance of the rear car is large enough the sub-goal *Check Speed* is activated. Within this sub-goal the model checks the speed difference to the rear car based on the rate of change of the viewing angle (roc). If the roc threshold value is exceeded, that is if the speed difference is too large, the *Let Pass* sub-goal is activated and the model adjusts the ego-vehicle's speed to let the vehicle pass and tries to smoothly accelerate into the gap after the rear car. In case the speed difference is below the threshold the model's confidence in the current gap increases and the model accelerates if the slower acceleration strategy was selected in the beginning. The confidence is a parameter included in the driver model to simulate the fact that drivers in the experiments strongly differed in their times glancing into the left mirror before performing the lane change. A plausible explanation for this could be that drivers observe the rear traffic in the left mirror until they are confident enough to make a decision. If the confidence exceeds the threshold the model decides to merge into the current gap and switches to the goal *Adjust Speed Difference*. To achieve this goal the model reduces the speed difference to the rear car, e.g. by accelerating in case the rear car is faster than the ego-vehicle, until it is below a threshold value (based on roc). After achieving this sub-goal the sub-goal *Adjust Safety Margins* is activated where the model adjusts its speed in a way to keep minimum safety margins to adjacent vehicles. As soon as these safety margins are fulfilled the *Lane Change* sub-goal is set and the model performs the lane change.

For testing the model validity we compared the trajectories driven by participants with trajectories driven by the model and noticed that the lane changes of the model started later than several participants did and that the different trajectories of the model were in a smaller range than the trajectories of the participants. A possible reason might be an insufficient goal hierarchy or process represented in the driver model. Therefore we decided to examine the goal hierarchy of drivers about the merging process by using the method of a HTA.

Hierarchical Task Analysis

Task analysis methods comprehend a group of tools that describe and represent the performance in a specified task. HTA is one of the most popular task analysis methods originally developed by Annett and Duncan [1]. Within the driving domain only a few studies exist where HTAs were conducted, e.g. Walker, Stanton and Young [6] used HTA to describe normative driving behaviour.

The overall aim of the HTA is to identify actual or possible sources of performance failure and to propose suitable remedies, which may include modifying the task design or providing training. In contrast to other methods HTA starts analysis not by listing the activities of a task, but by identifying the goals of the task, since in complex tasks the same goals can be achieved by different means. Furthermore this procedure allows for depicting human behaviour as a goal-oriented behaviour.

The structure of a HTA mainly consists of the overall goal, different sub-goals, plans and operations. The overall goal is decomposed into a nested hierarchy of further goals and sub-goals in such a way, that the associated sub-goals together achieve the higher-level goal. Plans describe how sub-goals are carried out to attain their parent goal. They specify the conditions when sub-goals are applicable and the order in which they are carried out. Operations as a further part of the HTA constitute the fundamental unit of the analysis since they contain further specifications of the goals and sub-goals.

The process of carrying out an HTA starts with the definition of the task under analysis and collection of the data. Data may be derived from different sources like interviews, direct observations, manuals, verbal protocol analyses, questionnaires, safety records etc.

Procedure

Interviews with 10 participants were conducted (5 male and 5 female, average age 33.6 years). Each interview was videotaped and written down in a protocol. The interviews resulted in a goal hierarchy for each participant containing the goals and sub-goals each participant achieves when merging onto the freeway, the plans that are connected with the goals of each level and the operations regarding each goal. The individual interviews started by asking each participant to specify the main goals of the merging task. This set of goals constituted the higher level goals in each HTA. The identified goals were noted on cards and then discussed one by one. First, participants had to specify what sub-goals each goal contains. This set of sub-goals constituted the hierarchy of goals that have to be accomplished to achieve the parent goal. Further they had to describe in which sequence and under which conditions the goals and sub-goals have to be accomplished. This information was necessary to create the plans. Finally, each goal and sub-goal was specified by describing which information is necessary to perceive and what actions have to be executed to accomplish the goal. The necessary information and actions constitute the operations. The completed interviews were translated into ten individual goal hierarchies by two raters independently. In case of different results an agreement was achieved referring to the videotaped data.

Results

One of the ten resulting goal hierarchies is shown in Fig. 4. According to this hierarchy five goals have to be accomplished to achieve the main goal. First the driver has to *observe the traffic on the ramp*. This is followed by *observing the traffic on the freeway ahead and setting the indicator* until the end of the merging process. In case there is some traffic on the freeway *traffic behind him on the freeway is observed* repeatedly, finally the goal to *evaluate the situation* is activated and thereafter the *speed is adjusted*. Three of these goals are connected with sub-goals. For example the goal *Observe traffic on ramp* consists of two sub-goals that have to be achieved. One sub-goal is *Estimate the speed of the lead car,* the other one is *Observe speed and number of cars on ramp*.

In the next step of the analysis we derived a general set of goals from the individual goal hierarchies. We compared the goal descriptions of all individual hierarchies and assigned goals with the same content that served the same purpose on a more general level and were considerably different from other goals into clusters. For example, the goals observe traffic on the freeway in front and behind in Fig. 4 (second and third goals in Fig. 4) were clustered together with the goal to understand the traffic situation and the goal to look for gaps that were both part of other individual goal hierarchies. The resulting goal cluster was called *Observe possible gaps*. From this process eight goal clusters were obtained that comprise

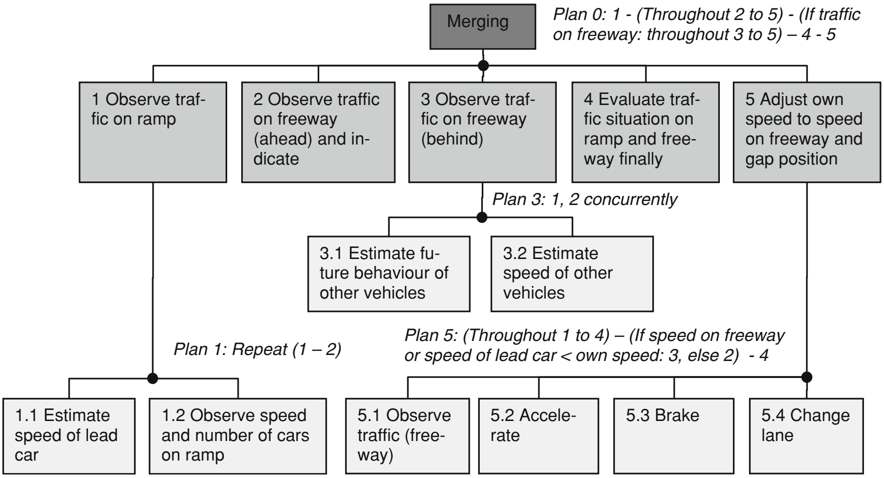

Fig. 4 Individual HTA of one participant. The merging task contains five goals on the higher level, which are sometimes connected with sub-goals on the lower level

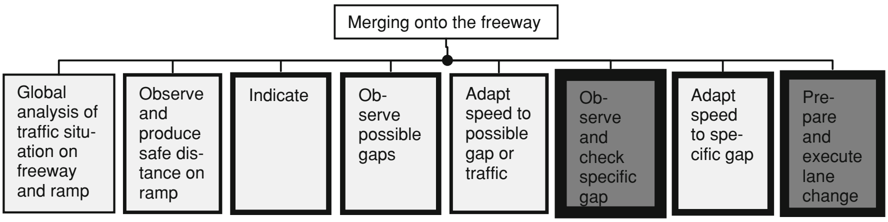

Fig. 5 General goal structure of the merging task containing eight goal clusters that comprise all goals of the individual HTA. The different thickness of the frames represents the different frequency with which the clusters were specified by the participants. Mandatory goal clusters are highlighted in dark grey and more optional goal clusters are highlighted in light grey

all goals of the individual hierarchies on the one hand and reduced the data base sufficiently to make comparisons between the individual hierarchies easier. Fig. 5 shows the eight goal clusters that describe which goals have to be executed in general when merging onto the freeway. The frequency with which the clusters were specified by the participants varied between two and ten participants. For example the goal cluster *Global analysis of traffic situation on freeway and ramp* was part of just two individual hierarchies, whereas the goal cluster "Observe and verify specific gap" was part of all individual hierarchies. There are several reasons possible why a goal was not specified by a person, e.g. the goal was not part of the mental representation, it was too trivial to be specified or it was simply forgotten. The different thickness of the frames in Fig. 5 represents the different frequency with which the goal clusters were mentioned in the individual hierarchies. The different frequency can be interpreted as an indicator of the different importance of each cluster. Therefore, we differentiated the goal clusters in mandatory and optional goal clusters. Mandatory clusters were specified by almost all participants and apparently have to be achieved when merging onto the freeway. From the two mandatory clusters highlighted in dark grey in Fig. 5 *Observe and verify specific gap* was the only cluster specified by all participants and seems to play a central role for achieving the main goal.

In the final step similarities between the individual goal sequences based on the defined goal clusters were examined. Since the individual sequences varied considerably and not all goal clusters were part of all individual goal hierarchies it was not possible to identify one common sequence. Nevertheless some similarities between sequences could be identified. Based on the nature of the task two goal clusters have the same position in all sequences: the merging process always starts with a *global analysis of the traffic situation* and ends with the *lane change* (left and the right goal cluster in Fig. 5). Examining the succession of pairs of goal clusters one can identify a common sequence present in many individual sequences. The evaluation of the situation always starts with an *observation of the global traffic situation*, followed by the *observation of possible gaps* and is finished by the *observation of a specific gap and the decision* to choose this gap to merge onto the freeway. Furthermore, the analysis of the relative sequences of the goal clusters showed that the perceptual processes were typically followed by adjusting activities. This means that both the *observation of a possible gap* and the *observation of a specific gap* were followed by some *speed adaptation* to reduce the speed difference of the ego-vehicle to the gap. In large parts merging onto the freeway can be described as a process of a more and more specific perceptual search for an adequate gap that is accompanied by behavioural adaptations to match with the identified gap.

Conclusions

The results of the HTA demonstrate that the goal hierarchy of the drivers corresponds to the goal hierarchy of the model in several critical aspects regarding the contents of main goals of the cognitive driver model. In both goal structures the observation of the lead car and the consideration of the traffic on the right lane of the freeway play the central role. Within the goal hierarchy of the drivers considering the traffic on the freeway involves the observation and checking of a specific gap which is followed by an adequate speed adaptation. The same structure can be found within the driver model. There the checking of the gap is achieved by checking the distance and checking the speed to the rear car and this checking is also followed by a speed adaptation. Differences between both structures concern the kind of the gap search. While in the drivers' goal hierarchy the gap search starts with a global analysis and ends with the specification of one concrete gap, in the driver model gaps are examined sequentially. This sequential strategy results from experimental data where only equal gap sizes between the cars on the freeway were presented. In this situation the participants and the driver model only had to check which gap can be reached safely in terms of distances and speed differences to the rear and front car of the gap. To extend the structure and the processes of the model for a wider range of situations will be the next natural step to increase the model's validity and scope.

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Predicting the Effect of Driver Assistance via Simulation

Martin Fränzle, Tayfun Gezgin, Hardi Hungar, Stefan Puch and Gerald Sauter

Abstract Developing assistance systems in the automotive domain involves several exploration and evaluation activities with potential users of the system. To replace the amount of human test subject involvement, executable models reproducing human behaviour are introduced. Together with models of the car, road, surrounding traffic and of course the assistance system, a complete representation of the assistance system in its application environment can then be constructed which may be used to predict effects of introducing the assistance without having to resort to experiments with humans. In this paper we present techniques concerned with the exploration of the behaviour spectrum of the combined models. We show how functionality and safety aspects of assisted driving can be evaluated in computer simulations already during early phases of the development process.

Keywords Driver assistance systems · Safety assessment · Software in the loop · Heterogeneous models · Co-simulation

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Background

The design of an assistance system in the automotive domain (and elsewhere) requires several exploration and evaluation activities with potential users of the system to assess the effect of the system under development. As a consequence, the development process is difficult to organize, it is expensive and time consuming. The goal of the IMoST [1] project is to reduce the amount of involvement of human test subjects through the introduction of executable models of the driver. These models shall be able to replace the driver in that they are capable of reproducing human behaviour. Combining them with equally executable models of the car and traffic scenario and of course the assistance system, a complete operational representation of the assistance system in its application environment can then be constructed and be used to predict effects of introducing the assistance without having to resort to experiments with humans.

While the construction of driver models is a both scientifically and practically challenging task which is addressed in a number of other reports, e.g. [2–4], in this paper we focus on techniques concerned with using these models, i.e., with evaluating functionality and safety aspects of driving with assistance. The evaluation is performed by studying the emergent behaviour of the integrated models. As the models are rather complex, the main means for assessing them must be simulation, Other analysis methods (e.g., computing all states the model may reach or even formal verification) are only applicable to much simpler classes of systems or smaller models.

Approach

We develop and exemplify our approach to improve the design of assistance system on a relevant case study.

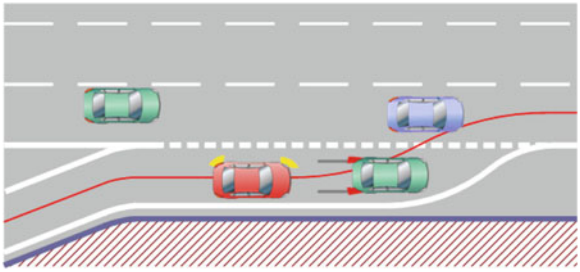
Application Scenario

The application scenario on which IMoST develops and tests its approach is that of an *advanced driver assistance system* (ADAS) supporting the driver in entering an expressway, including the gap selection and speed adaptation, illustrated in Fig. 1.

This scenario captures one of the most critical expressway manoeuvres. On the other hand, compared to other potentially critical traffic situations (e.g., crossings), it is limited in its variability and is thus suited for developing and assessing a new

[1] The full name of the project is "Integrated Modelling for Safe Transportation." Further information can be found in [1] and at the URL http://imost.informatik.uni-oldenburg.de/.

Fig. 1 Application Scenario Illustration



approach. Variables we considered were the number of other traffic participants, speed differences and gap sizes.

Co-simulation

The complete model consists of several software modules. These are provided from different sources—a commercial traffic simulation, the models of the driver and the assistance system developed in the project and components for monitoring and recording. The most convenient way to cope with continuing changes of these modules is to refrain from a deep integration into one system and rather combine them via a co-simulation environment. For that purpose, we use a commercial implementation of the IEEE standard 1516 [5] for coupling simulators (HLA, "High Level Architecture"). This standard defines how a joint run of different component simulators is orchestrated by a central component (RTI, "Run-Time Infrastructure").

The HLA term for a set of combined simulators is *federation*, and each partner is called a *federate*. HLA offers a time management service which enables to synchronize federates running at different and even variable step resolutions. A federate is time regulating, if it influences the advance of other federates, and it is time constrained if its own evolution is restricted by others. Time management permits to keep the data exchange in accordance with the progress of logical time, opposed to best-effort simulation where data are consumed as they become available during simulation. To limit variation between different simulation runs with the same parameters, i.e., to achieve a high degree of reproducibility, we used this time management. For technical reasons, in particular the nature of the commercial traffic simulation software, even this does not suffice for full reproducibility. It is, though, planned to replace that component with another one expected to remove these problems.

Fig. 2 depicts the structure of the main components and their integration by the RTI. Besides the RTI, there are models of the driver and assistance-system (Advanced Driver Assistance System, ADAS) on the left of the figure and a simulation of the ego car, which is the car controlled by the driver model, and the traffic environment on the right. Further components not shown in the figure are

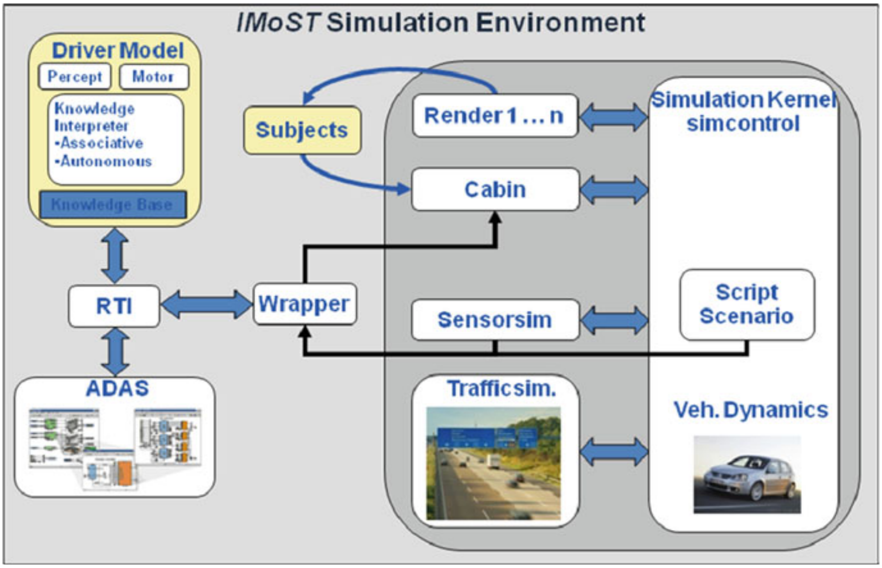


Fig. 2 Architecture of the federated simulation

property monitors (see below) and a recorder. The co-simulation is executed on a set of standard PCs.

Each component model evolves in discrete time steps, with temporal resolutions in the order of 20–35 Hz. Synchronisation and data exchange is managed by the RTI. The output behaviour of models of the ADAS, the ego car, and the environment depends deterministically on their input, where the traffic environment is parameterized by scripts defining the street layout and number and actions of other cars. A complete run of the scenario consists on average of about 2,700 discrete time steps.

The driver model controlling the ego car is probabilistic, reflecting the varying and in practice not predictable behaviour of the driver. Randomised decisions concern the driving strategy and manoeuvre starting points. More complex randomizations to be considered in the future will concern also the gaze and steering behaviour. The (deterministic) behaviour of the other traffic agents in the application scenario is defined in scripts.

Property Specification

To automate the evaluation of safety and functionality aspects via simulation, we use monitors which observe to which extent properties of interest are satisfied or violated. These monitors result via a translation from temporal logic specifications [6] and enter the simulation environment as additional federates.

In their basic observations, the properties refer to car positions, their speed, visible actions of the driver and so on. Typical safety criteria are *time to collisio*n and *time headway* (these involve the relative position and speed of two or more cars). For the functionality one may refer to, e.g., events indicating manoeuvres like steering wheel positions and turn signals, or to ADAS outputs.

These atomic observations enter temporal-logic formulas which permit to express their temporal extensions and sequential relations between observations. e.g., one would want to the express that at no point in time, the time to collision to a car ahead on the same lane drops below a certain value. Linear temporal logic provides a set of useful operators. With an adequate subformula defining "TimeToCollision", computed from distance and relative speed of a leading car, if there is any, the simple example property may be formalised as

$$\square\ (\mathrm{TimeToCollision} > 2.6\ \mathrm{s}).$$

The standard interpretation of temporal logic operators provides a truth value for each run. This would already be useful. But to decide whether the parameter settings of a particular run, compared to those of another, did increase or decrease the criticality, it would be more helpful to have the exact minimal values. Therefore, we chose a nonstandard, quantitative semantics [7, 8] which assigns a numerical value to a formula for each run: A positive number means that the formula was satisfied, and the result value gives the minimal distance in variable values which would have made the formula false (conversely for negative values). Thus, a formula defines a function which assigns a numerical value to each simulation run.

A program translates formulas of this logic into *observers* which may join the co-simulation as additional federates. Upon termination of the simulation, each observer provides the numerical evaluation of the property it stands for on the completed run. Thus, the run can be classified as good or bad according to the resulting numbers. Even better, the observers are capable of computing lower and upper bounds for the final value while the system is evolving [6]. That way, runs which can early be seen as irrelevant may be stopped, saving simulation resources.

Approach Summary

To sum up the essentials of our approach, we list its main ingredients.

- An application scenario addressing an open assistance problem
- Executable behaviour models of all constituents of the application scenario
- A co-simulation environment capable of orchestrating the execution of the joint models
- A mechanism for specifying relevant functional and safety properties which can be automatically evaluated online during simulation

In the following section we explain how we cope with the problem of reliably assessing the effects of the ADAS on driving.

Exploring the Behaviour Spectrum

It should be obvious that the variability of the scenario is too high to cover all its instances by simulation, let alone by experiments with human drivers. Also, the probabilistic nature of the driver model, together with the rare occurence of hatardous situations, does complicate matters. Therefore, a Monte-Carlo simulation will not a result in very reliable assessments. To overcome this problem, we propose the following, three-stage approach.

- A property of interest is specified by a temporal-logic formula.
- A batch of simulations is performed with the intent of roughly exploring the spectrum. For that, test points covering the value ranges of the scenario parameters are chosen, and similarly the otherwise randomised driver decisions are taken in a controlled way.[2] This batch of simulations provides a grid of sampling points for the property function from which an approximation of the function is derived by interpolation.
- Further simulation refines the approximation in areas of interest (i.e., in region with high function values, corresponding to high levels of satisfaction of the formula) by selecting input values accordingly.

Via such a guided simulation, maxima of the property function can be detected with far less simulation runs than by brute force.

In our case, guided simulation is instantiated as follows. The main parameters determining the course a simulation run takes are those of the traffic scenario to be explored and the decisions the driver model takes in reaction to the scenario. Let us assume that simulations are fully determined by these parameters. We will not describe here the adaptations necessary to cope with nondeterminism resulting from, e.g., race conditions in the simulators.

The traffic scenario inputs are easy to cover as they are set at the beginning of the run. The driver's probabilistic decisions are more difficult to handle as their occurrence depends on the history of the simulation. For a fixed set of scenario parameters, the set of possible runs forms a tree. Each node in the tree stands for a probabilistic decision, and each edge is labelled accordingly by a probability. A Monte-Carlo simulation would explore the runs according to the resulting distribution. This might be adequate for a functionality test, but it would not yield a thorough evaluation of the safety of a reasonable design, as critical situations would have a low probability of occurrence.

[2] For that, the otherwise internal randomized decisions of the driver model are resolved deterministically by an external procedure.

To assess the safety impact, a formula defining criticality (the example property given above specifies one aspect of uncriticality) will have been chosen in the first step.[3] The random tree of possible runs in a fixed scenario is by its nature accessible (only) in a top-down fashion. To explore it, paths are taken systematically. The branch probabilities encountered along the way are multiplied to compute the path probability. If a path probability gets below a minimum fixed at the beginning of the procedure, its further exploration is stopped. Completed runs yield values for the property of interest. These are used to annotate the branches which have been taken with estimations of maximal property values and reliability information, guiding the further exploration of the tree.

This criticality-guided simulation explores in a largely automatic fashion the complex model and provides the designer with meaningful information on potentially dangerous situations arising from the current ADAS design.

Summary

We have presented a way of exploring via simulation the functionality of assistance systems and their effect on safety, given executable behaviour models of the driver and all other constituents of the scenario. Our results on a relevant case study indicate that this approach may indeed be helpful in reducing the number of tests with human subjects and increasing the quality of the ADAS design. The techniques are yet to be explored on a larger scale, which we intend to do in the near future. We will be develop further techniques for speeding up the simulation and guaranteeing high assessment reliability. In particular, we will use the information about the internal states of driver and ADAS model for coverage and guidance.

We acknowledge the many fruitful discussions and in particular the work of the other participants in the IMoST project and further cooperating projects which provided the models whose behaviour we have set out to explore.

Acknowledgments The research reported here has been mainly performed in the project IMoST which is funded by the Ministry of Science and Culture of Lower Saxonia.

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[3] In our experiments, we used a combination of time-to-collision and time headway.

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Simulation Study for Driver Behaviour Analysis as a Basis for the Design of a Partially Autonomous Driver Assistance System

María Alonso, M. Henar Vega and Óscar Martín

Abstract This paper is presenting a driver behaviour investigation conducted within the framework of ISi-PADAS (*Integrated Human Modelling and Simulation to support Human Error Risk Analysis of Partially Autonomous Driver Assistance Systems*) FP7 European Project (September 2008–September 2011). This research has been developed at an initial phase of the project to support the conception of a new driver assistance system, aimed at improving longitudinal driving by means of information, warning and intervention strategies. In this research, the contribution to the system conception is based on providing a knowledge base of driver behaviour through the conduction of simulator experiments. In particular, this paper is aimed at providing a thorough description of the rationale behind the investigation, as well as at describing the methodology and the procedure used for the experiments conduction. Moreover, the main results achieved through this research and how these results are linked to the modelling phase inside the ISi-PADAS project, are covered within this paper.

Keywords Driver assistance system · Driver behaviour · Usal and cognitive distraction · Driving simulator

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Introduction

The research presented within this paper, framed under the FP7 European project ISi-PADAS (*Integrated Human Modelling and Simulation to support Human Error Risk Analysis of Partially Autonomous Driver Assistance Systems*) [3] is aimed at studying driver behaviour and investigating the visual and cognitive distraction effects in driving. This research is providing support to the conception of a new support system referred to as PADAS (*Partially Autonomous Driver Assistance System*), since it is able to automatically intervene in the vehicle control in case of an emergency. Given that this kind of systems represents an innovative step in the field of driving assistance systems available nowadays, its design implies a great challenge, since it requires an understanding of the potential implications and effects of PADAS introduction within the driving activity.

Along this document, the background, objectives and method used in the experiments are defined together with a description of the results and the derived conclusions, as well as the link and implications with the rest of the project.

Rationale

According to Lee et al. [4], rear-end crashes are one of the most frequently occurring type of collision (approximately 29% of all crashes), resulting in a relevant number of injuries and fatalities every year. The causes of this kind of crashes are usually found in driving related inattention to forward roadway (31%), fatigue (15%) or vehicle related secondary tasks (8%).

Distraction or inattention occurs when the driver is delayed in the recognition of information needed to safely accomplish the driving task because some event, activity, object or person within or outside the vehicle compelled or tended to induce the driver's shifting attention away from the driving task [6]. In this sense, the distraction caused by interacting with in-vehicle devices while driving has been shown to significantly impair driver's performance [7]. Nevertheless, findings suggest that drivers are not always aware of the detrimental effects of these secondary tasks on their driving performance [5] and often underestimate the risks.

There is clear evidence that visual distraction directly increases the risk of having an accident, due to the fact that the driver does not observe the road scene while driving. Consequently, driving performance is affected in its whole dimension, specifically through a reduction of lane keeping control and a reduction of speed, which can be interpreted as a compensatory effect in order to maintain driving performance on an acceptable level [1].

Nevertheless, cognitive distraction is usually underestimated. This type of distraction occurs when drivers attend to other non-driving tasks or events, failing to allocate sufficient attention to the driving task. Numerous studies have shown that cognitive distraction can affect visual behaviour and increase reaction times. On the other hand, it seems to have little or no effect on lane keeping performance and reduced effects on longitudinal control, although some studies found a significantly reduced speed [1]. This could be due to the fact that drivers are able to adjust their performance to partially compensate for cognitive impairments (and therefore, the increased risk), thereby maintaining their safety [2].

On the base of these results, an in-depth investigation of distraction effects, as a potential cause of human errors increasing the risk of having a rear-end accident, as a potential factor which can significantly modify driving behaviour or drivers' performance and as a potential negative effect of on-board assistance devices, was done through ISi-PADAS experiments.

Objectives, Research Questions and Hypothesis

The global objective of this study is to analyse the effects of distraction on driving behaviour and performance, particularly on the longitudinal control task, through the conduction of simulator experiments. The results obtained will contribute to the development of a model to diagnosis both visual and cognitive distraction in order to support the driving activity through PADAS, trying to eliminate or mitigate driver errors.

Therefore, the research questions selected were focused on the main effects of secondary tasks on driving and in addition, whether visual and cognitive load differ qualitatively. Thus, these research questions were translated in the corresponding research hypotheses to be studied during the experiments:

- H1V: *Visual distraction results in a reduction of speed*
- H2V: *Visual distraction impairs lane keeping performance*
- H1C: *Cognitive distraction does not degrade lane keeping performance*
- H2C: *Cognitive distraction does not affect significantly longitudinal control*

Method

Participants and Design

According to ISi-PADAS objectives, these experiments were addressed to a general average driver profile given that data to be collected for the development of models of the "Driver" was required at a generic level. Thus, a set of 24 drivers was selected for their participation in the trials, considering middle-age drivers (25–55 years old), equally distributed by gender (12 males and 12 females) and with a minimum driving experience of 6000 km/year.

Concerning the experimental design, a 2-factors model was selected for this study, considering gender and task condition (single or dual) as factors. Nevertheless, two different secondary tasks were independently included in the study (visual and cognitive), so two similar models were considered.

Tools

CIDAUT driving simulator (Fig. 1) was used for the experiments, which is a fixed base simulator platform that comprises an ordinary car with three axes motion system with X/Y rotation (roll/pitch) and Z movement. Furthermore, the driving simulator was equipped with two additional micro-cameras in order to record images from the control panel and the driver.

Each participant completed three questionnaires, one before the test and one after each of the two driving sessions.

The initial questionnaire aimed at assessing some of the participants' personal characteristics directly related to driving behaviour, including the following list of well-known questionnaires: DAS (*Driver Anger Scale*), T-LOC (*Traffic Locus of Control*), DBQ (*Driver Behaviour Questionnaire*), SSS (*Sensation Seeking Scale*) and BFI/Responsibility (*Big Five Inventory*). Additionally, after each drive participants had to complete a questionnaire where they had to assess the single and dual-task phases regarding the level of activity (physical and mental), attention, alertness, annoyance, tiredness and difficulty of the drive, perceived risk and safety levels and finally their driving performance, including errors committed and DQS (*Driving Quality Scale*). Moreover, in the last session, other general data related to demographic information was also gathered.

Driving Scenarios

The selected routes were mainly focused on highway and/or extra-urban contexts where several lanes existed. Specifically, the experiments were focused on the following particular scenarios: FD (*Free Driving;* the own vehicle is driving on a road and follows its course without any lead vehicle), ASV (*Approaching a Slower Vehicle*; the own vehicle is approaching a slower lead car driving on the same lane,

Fig. 1 CIDAUT driving simulator and control zone

being forced to reduce its speed) and O (*Overtaking*; the own vehicle is overtaking one or more vehicles driving with less speed).

Procedure

As a whole, each test lasted around 2 h, considering the driving sessions and the administration of questionnaires at the beginning and after each test drive. Firstly, participants completed a driving phase dedicated to make them familiar with the environment. After this, the first test drive started alternating phases where participants had to drive only (single-task condition) and other situations where they had to drive and perform a loading secondary task (ST) concurrently (dual-task condition). The driving session was repeated twice in order to have a different type of ST each time (visual and cognitive).

Regarding dual task conditions and in order to analyse distraction effects, participants had to perform a mental arithmetic task as cognitively loading secondary task during driving. On the other hand, SURT (*Surrogate Reference Task*) was selected as secondary visually loading task.

Results and Discussion

Driving Performance Analysis

Regarding driving performance, the first analyses were focused on the study of the differences between single-task and dual-task phases, considering the corresponding scenarios under study.

Therefore, for the cognitive task driving session, a T-test for paired samples was performed and the following statistically significant differences were found:

- Maximum speed in FD scenarios was higher ($T(23) = 3.47$ $p = 0.002$) and minimum distance in ASV was smaller ($T(23) = -2.80$ $p = 0.010$) when no other task was performed.
- Distance to lane centre variance in FD scenarios was higher in no ST conditions ($T(23) = 3.46$ $p = 0.002$).

As it was previously shown, longitudinal control seems to be little affected by cognitive load according to previous existing studies. However, in this experiment it was found that maximum speed in FD scenarios was higher when no ST was performed (although, no significant results were found in terms of mean speed). Additionally, the minimum distance in ASV was reduced in single-task conditions. This is also shown in the literature [2], where longer distances in car-following situations were found when driving with cognitively demanding tasks to compensate for cognitive impairments.

Most of the studies regarding cognitive load during driving have not found clear effects on lane keeping. However, in Engström et al. [1] results showed that a cognitive task resulted in improved lane keeping performance in terms of reduced lateral position variation. This is in line with the results shown in this article, since in this case, the variance of the distance to lane centre in FD was increased in no ST conditions and therefore reduced in dual task conditions, replicating previous studies. Evidences from literature, shown in the results of this experiment as well, demonstrate an adaptive compensation for cognitive dual task interference in car following scenarios and free driving conditions in order to maintain their target level of risk.

Similarly, considering the sessions where a visual task was considered in particular moments during driving, the following significant differences were found:

- Maximum speed in FD scenarios was higher without secondary task ($T(23) = 5.48$ $p = 0.0$)
- Mean distance to lane centre in FD scenarios ($T(23) = -2.51$ $p = 0.021$) and in FD left scenarios, as part of overtaking manoeuvres ($T(23) = -2.38$ $p = 0.027$) was higher in ST conditions

A significant increase of maximum speed in free driving scenarios was found in single-task conditions (together with an increase in mean speed in FD during no ST conditions ($T(23) = 1.76$ $p = 0.092$) with a 90% of confidence) and therefore, this result is in line with most of the existing work [1] which showed a reduction in speed as a compensatory effect in order to face the complexity of the driving task. However, no results were found in terms of headway distances.

On the other hand, regarding lateral control, many studies have found a strong relationship between visual demand and reduced lane keeping [1]. This experiment shows that in FD scenarios mean distance to lane centre was higher when performing a visual loading task. In the same way, mean distance in FD conditions was also higher when driving in the left lane (performing an overtaking manoeuvre). Moreover, considering a 90% of confidence, other results show that mean ($T(23) = -2.67$ $p = 0.014$) and standard deviation ($T(23) = -1.94$ $p = 0.066$) of the distance to lane centre during ASV was higher in ST conditions.

Finally, a comparison between visual and cognitive task driving sessions was performed using a T-test for paired samples as well. The only statistically significant result was the variance of distance to lane centre in FD scenarios, being higher in visual ST conditions ($T(23) = -2.32$ $p = 0.030$). However, considering a 90% confidence, mean distance to lane centre was also found higher for visual tasks ($T(23) = -1.82$ $p = 0.083$).

Subjective Driving Performance

This section shows the results obtained from the analysis of the final questionnaires applied after each test drive (i.e. both cognitive and visual sessions).

In relation to required activity while driving, subjects indicated that performing a cognitive secondary task required a higher physical ($N(0,1) = -2.69$ $p = 0.007$) and mental ($N(0,1) = -3.99$ $p = 0.000$) activity than just driving without any secondary task. In the same way, regarding visual secondary task, subjects reported that performing the secondary task while driving required a higher physical ($N(0,1) = -2.33$ $p = 0.020$) and mental ($N(0,1) = -3.67$ $p = 0.000$) activity.

On the other hand, performing a cognitive secondary task while driving was perceived as less pleasant ($N(0,1) = -2.44$ $p = 0.015$), more risky ($N(0,1) = -3.09$ $p = 0.002$), more tiring ($N(0,1) = -3.46$ $p = 0.001$), more difficult ($N(0,1) = -3.24$ $p = 0.001$), less safe ($N(0,1) = -2.99$ $p = 0.003$) and more annoying ($N(0,1) = -2.74$ $p = 0.006$) that driving without any secondary task. Moreover, subjects reported that they committed a higher number of errors when having a cognitive secondary task ($N(0,1) = -3.00$ $p = 0.003$). Thus, the most frequent errors reported were wrong estimation of other vehicle speed (overestimation or underestimation) (75% of the subjects), driving too close to other vehicles (66.7%), inappropriate speed for the situation (41.7%), not paying attention on road signs (41.7%) and lane exceedences (41.7%). No differences were reported in terms of attention paid to driving.

Likewise, performing a visual secondary task while driving was perceived as less pleasant ($N(0,1) = -2.81$ $p = 0.005$), more risky ($N(0,1) = -3.58$ $p = 0.000$), more difficult ($N(0,1) = -3.51$ $p = 0.000$), less safe ($N(0,1) = -3.15$ $p = 0.002$) and more annoying ($N(0,1) = -3.32$ $p = 0.001$) than driving without any secondary task. Furthermore, similarly to cognitive secondary tasks, subjects reported to commit more mistakes when performing a visual loading task concurrently with driving, namely wrong estimation of other vehicle speed (overestimation or underestimation) (70.8% of subjects), driving too close to other vehicles (62.5%), not paying attention on road signs (50%) and inappropriate braking (too harsh/too late) (50%). No differences were reported in terms of perceived tiredness and attention paid to driving.

These results are in line with previous data from literature. In Engström et al. [1], subjects rated their driving performance to be worse in dual-task conditions (both cognitive and visual tasks) compared with driving without any secondary task.

Comparing cognitive and visual tasks according to users opinions, cognitive secondary tasks required more mental activity ($N(0,1) = -2.13$ $p = 0.033$) and were more pleasant ($N(0,1) = -2.97$ $p = 0.003$) than visual tasks. Furthermore, subjects reported that cognitive tasks made them feel more tired than visual tasks ($N(0,1) = -1.93$ $p = 0.053$). Nevertheless, comparing the errors that drivers reported to commit during each driving session, no statistically significant differences were obtained comparing visual and cognitive tasks.

Finally, regarding perceived quality of driving performance during the test compared to normal driving, statistically significant results were found. Specifically, subjects reported a worse performance when driving in dual task condition (both with cognitive ($T(23) = 4.087$ $p = 0.000$) and visual tasks ($T(23) = 4.727$

$p = 0.000$)) than in the driving task alone. Additionally, drivers perceived their driving performance with cognitive ST worse than when performing the visual ST ($T(23) = -2.646$ $p = 0.014$).

Conclusions and Implications Towards Other Project Activities

When drivers have to perform a secondary task they tend to develop a strategy to reduce primary task load. This is shown by a reduction in driving speed during interaction with either cognitive or visual tasks. As for lateral control, visually and cognitively loading secondary tasks have different effects, being the former the situation where performance is more degraded. On the other hand, cognitive task leads to improved lane keeping performance, which could be considered as a side effect of the disabled visual scanning [1]. These results are in line with the ones obtained in the simulator experiments shown in this article.

Furthermore, subjective driving performance was also analysed. The findings show that subjects rated their driving performance more negatively in dual-task conditions, both for cognitive and visual tasks, compared with driving without any ST. In addition, users reported that cognitive tasks made them feel more tired, needed more mental activity and worsened their performance compared to visual tasks.

The analysis of driving behaviour shown above, provided input to the empirical investigation of driver behaviour carried out in the first phase of the project. This knowledge helped to describe drivers behaviour without any assistance system, as the basis for future developments in the framework of ISi-PADAS. Furthermore, this dataset has been used for driver modelling objectives in terms of distraction, both visual and cognitive. In fact, considering the data coming from the experiments on driver's distraction, together with vehicle dynamics and surrounding traffic information, a model is being developed in order to recognise, classify and predict this driver's status. Thus, all these data can be used to train the distraction model that can be integrated afterwards in PADAS strategies or directly provide feedback to the driver by means of a dedicated HMI (Human–Machine Interface), so that a holistic approach is adopted. This way, the design process of the PADAS is fully based on data coming from users, adapting the system to their needs and requirements, in order to support them in the driving activity, eliminating or minimizing potential driver errors.

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Application of Simulation Based Risk Assessment for Driver Assistance Systems Development

Jens Alsen, Mirella Cassani and Bertram Wortelen

Abstract This paper proposes the application of a new methodology for an improved human error risk analysis in the current design process of driver assistance systems to a specific case study. The basic ideas of the methodology are: (1) to use well-known and existing techniques; (2) to combine them with a quasi-static approach to account for the variability and dynamicity of Human–Machine Interaction; and (3) to utilise joint cognitive models to evaluate the consequences of the HMI as well as to derive probabilities of human inadequate performances. After a general overview of the risk based design methodology and the description of the driver Model, the proposed case study is developed. Specific attention is given to the application of the driver model within the methodology.

Keywords Driver model · Risk based design · Event tree · Expanded human performance event tree · Human error

Introduction

Modern vehicles are equipped with an increasing amount of assistance systems, aimed at improving safety and the quality of performance. However, they lead to changes in the driving task and in driver behaviour. Appropriate methods are

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consequently needed that enable to assess the new forms of safety and risk derived from the implementation of such new systems. In particular, the driver behaviour has to be explicitly considered in such methods.

This paper proposes the application to a specific case study of a new methodology for an improved Human Error Risk Analysis in the current design process of driver Assistance Systems (AS).

The basic ideas of the methodology for risk based design (RBD) are: (1) to use well-known and existing techniques, such as for example, Technique for Human Error Rate Prediction (THERP), expert judgment and possibly other techniques; (2) to combine them with a quasi-static approach (called Expanded Human Performance Event Tree, EHPET) to account for the variability and dynamicity of human–machine interaction (HMI); and (3) to utilise joint cognitive models to evaluate the consequences of the HMI as well as to derive probabilities of human inadequate performances.

The major advantage of this approach is the substantial gain in the speed of evaluation. Instead of time-consuming real-time tests in driving simulators or prototypes, the simulation approach enables virtual testing in highly accelerated time to define situations which are relevant for real-time testing with human subjects.

Besides this introduction, the paper is organised into four main sections:

"Overview on RBD Methodology" contains a brief overview of the methodology for Risk Based Design proposed within the EU Project ISi-PADAS. A more extended description of it is reported in [4].

"Overview on Driver Model" provides a general overview of the driver model. A detailed description of it is reported in [10].

"Exemplary Application of Case Study to RBD Methodology" deals with the description and development of the case study.

"Discussion and Conclusions" presents some topics for discussion and conclusions.

Overview on RBD Methodology

The RBD methodology consists of six steps.

First two steps are the definition of a scenario (i.e. a set of elements that represent a situation, including a dynamic evolution of environment and vehicle independently of the driver behaviour that may affect the overall sequence of events) and of an initiating event (i.e. an event which, within an event time line, is considered the triggering event of the sequence).

The third step deals with the creation of an EHPET, which includes both system events and driver's expected performances. The EHPET expands over the classical human error event tree [9] by considering an alternative to the simple binary possibility "success vs. failure" and enabling the possibility of introducing different expected performances at each branch of the tree. An example of EHPET will be provided in "Exemplary Application of Case Study to RBD Methodology" of this paper.

Both the fourth and fifth steps of RBD methodology are served by the simulation approach. The fourth step is the identification of frequencies of system and driver events of the tree. This numerical association of probability values to each event allows the calculation of probability of each sequence depicted in the tree itself. The fifth step is the evaluation of consequences and related severity of each predicted situation in the tree.

Finally, the last step of RBD methodology deals with the assessment of risk through the classical tool of risk matrix [6].

For a detailed description of the methodology, see [4].

Overview on Driver Model

A lot of research has been done in the last few decades on drivers' behaviour, resulting in a great number of driver models (DMs), most of which are very specialised models which take into account only few aspects of driver's behaviour. An example is Boer's longitudinal control model [2], which is theoretically able to produce suitable driver actions on gas pedals, but does not take into account how drivers obtain relevant information. A model of driver's visual attention distribution has been presented by Horrey et al. [5]. It predicts visual attention of the driver, without considering driver's actions on car control. Other models use a more holistic approach, trying to cover the most important aspects involved in producing driver's behaviour (see e.g. Bellet et al. [1], or Salvucci [8]). A good overview on the diversity of driver models can be found in [3].

The model used for the case study presented in the next section uses a holistic approach. It is based on the cognitive architecture CASCaS (Cognitive Architecture for Safety Critical Task Simulation), see Fig. 1.

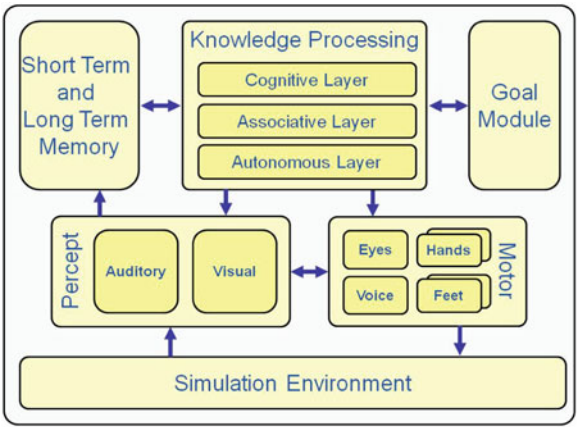

Fig. 1 High-level view on CASCaS

CASCaS consists of a set of components simulating different cognitive processes and limitations, which contribute to human behaviour, like perceptual and motor limitations, memory processes or the internal representation of a specific task. It allows the driver model to consider various aspects of cognitive processes that constitute driver behaviour.

The model has been developed on the basis of data from driving simulator experiments (see [7] for details) with a number of human participants. For a detailed description see [10].

Exemplary Application of Case Study to RBD Methodology

In the following sections it will be shown how the presented RBD methodology, step by step, can be applied to a car following case study.

Scenario and Initiating Event

The considered scenario is shown in Fig. 2: a car is stationary on the road (stationary vehicle—SV). The ego vehicle (EV) is following another car (leading vehicle—LV), while approaching the SV. The EV is equipped with an AS for the safety distance control, which gives a warning (sound) when a critical distance/time headway to an obstacle is reached. If a further level of criticality is reached, emergency braking is performed by the AS.

A variety of traffic conditions can be evaluated in relation to the possible manoeuvres of the LV. Typically, three dynamic situations can occur depending on the oncoming traffic: (1) the LV and consequently the EV have to stop beyond the SV waiting to overtake; (2) the LV can overtake the SV, whereas the EV has to stop; and (3) both LV and EV can overtake the obstacle. The initiating event (IE_0) considered in the case study corresponds to the first of these situations.

Expanded Human Performance Event Tree

The EHPET shown in Fig. 3 is characterised by the following expected performances (*EPs*), divided for each event family depicted in the tree:

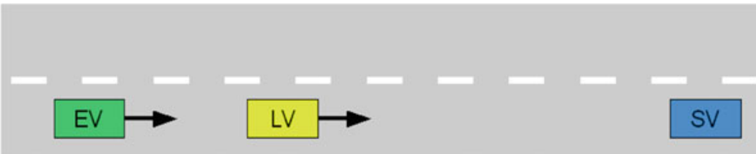

Fig. 2 Scenario of case study

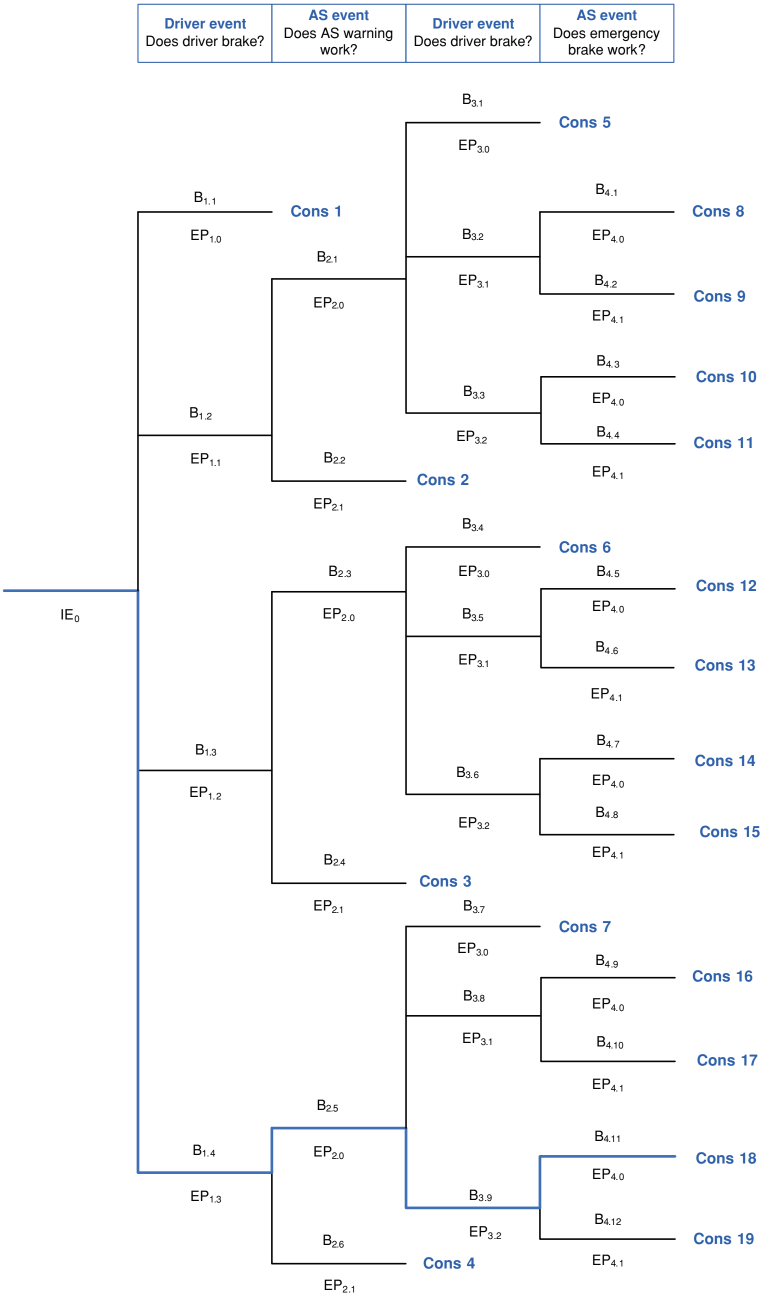

Fig. 3 Expanded human performance event tree

- Event Family 1 (Does driver brake before AS intervention?): $EP_{1.0}$ = Driver brakes sufficiently early and hard enough; $EP_{1.1}$ = Driver brakes sufficiently early, but not hard enough; $EP_{1.2}$ = Driver brakes hard enough, but not sufficiently early; $EP_{1.3}$ = Driver does not brake.
- Event Family 2 (Does AS warning work?): $EP_{2.0}$ = AS warning works; $EP_{2.1}$ = AS warning fails.
- Event Family 3 (Does driver brake after AS intervention?): $EP_{3.0}$ = Driver perceives the AS warning and brakes sufficiently early; $EP_{3.1}$ = Driver perceives the AS warning, but does not brake sufficiently early; $EP_{3.2}$ = Driver does not perceive the AS warning.
- Event Family 4 (Does emergency brake work?): $EP_{4.0}$ = AS emergency brake works; $EP_{4.1}$ = AS emergency brake fails.

Whereas the AS failures are represented "simply" by the classical binary alternative of success vs. failure, the human expected performances can take multiple different forms. Moreover, different possible expected performances are considered for the same event. For example, the Event Family 1 has four possibilities which focus on the action of braking and hence on the possible actions of the driver. On the other hand, for the same action ('Does driver brake'), the Event Family 3 has three possibilities, which focus not only on the execution of action, but also on the perception of AS. This distinction should not be possible with the classical event tree, because it considers only the simple binary possibility "driver brakes vs. driver does not brake".

Evaluation of Probabilities

One of the main ideas of the RBD process presented in this paper is to use driver models to predict probabilities for certain branches of the EHPET. For the case study presented above, a driver model based on the cognitive architecture CASCaS, developed at OFFIS, is used (see "Overview on Driver Model").

Given the scenario presented in Fig. 2 and, specifically, the sequence of the EHPET highlighted by thick lines in Fig. 3, the node $B_{1.4}$ of the Event Family 1 is first considered. For each simulation run, there is a certain time t, where the driver model perceives the obstacle. Doing a lot of simulations will give the probability distributions over time (see Fig. 4); so for each point in time t_1, a probability p_1 of perceiving the obstacle and for each time t_2 a probability for braking p_2 are given. The braking manoeuvre initialized by the detection of the obstacle has to lead to a certain deceleration a_t, which in the usual case should result in an avoidance of a crash. If, for example, $t_1 + t_2$ become large, a_t has to increase also to avoid the crash. Assuming that the behavioural predictions of the driver are sufficiently valid, a large number of simulation runs will give the mean probabilities for crash avoidance under the boundary conditions of the scenario.

The next node of the sequence ($B_{2.5}$) after the event "Driver does not brake" ($B_{1.4}$) in the EHPET (Fig. 3) is the AS event "AS warning works", which belongs

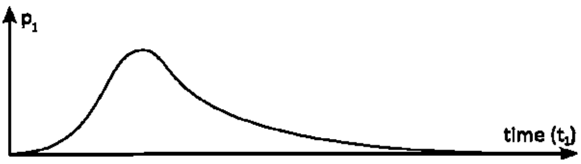

Fig. 4 Schematic illustration of expected probability density function for *detection of obstacle*

to the Event Family 2. Here the probability p_3 for the warning by the AS and its respective reaction time t_3 are obtained from AS specifications.

The following node ($B_{3.9}$) is again related to the driver, concerns the braking behaviour after the AS warning and belongs to the Event Family 3. For simulation, this node is divided into the event of perceiving the AS warning and the use of the braking pedal itself. For both sub events, mean probabilities p_4 and p_5 and the respective mean reaction times t_4 and t_5 can be determined in the same way as done for the node $B_{1.4}$.

If the driver does not brake after the AS warning ($B_{3.9}$), the final node of the sequence is the node $B_{4.11}$ of the Event Family 4 related to the intervention of the emergency brake of AS. Once again, for the possible AS actions, probability p_6 and reaction time t_6 will be determined.

Multiplying the probabilities and summing the reaction times for the actions in the branch will lead to an estimation of the mean probability and the mean severity of an accident following the initial event. The same approach will be used for all the nodes in the specific branch to compute the probabilities p_i for a driver action and the respective reaction times t_i ($i = 1,.., n$; n: Number of discrete action in the branch under examination).

To give the probability for the next branches after the nodes inside the EHPET, the simulation has to run multiple times. This is similar to collecting results with a number of human drivers. But since the simulations are run on computers, they can be speed up and do not have the disadvantage of being restricted to real time as experiments with human beings have. Moreover the simulation can be limited to run for specific event tree nodes of interest to allow more simulation runs for these nodes.

Evaluation of Consequences

Situations of high risks appear relative seldom. So these risky situations can become examined not often in standard tests using human participants. Since AS usually work in these situations of high risk, the interaction of the driver and AS and the respective behaviour of the driver can only be investigated rarely. In a closed loop simulation with driver models, the simulation can be focused on critical branches, even if these branches would not occur often in reality. This will allow to get information on the interaction between driver and AS in critical situations. To obtain estimations on the risk in a certain path in the event tree, besides its probability, also the final consequence (crash, no crash, driver state after the event, etc.) has to be known. If, for example, the sequence highlighted by thick lines in Fig. 3 is considered, the reaction time of the driver becomes to be an important variable for evaluating the final consequence.

Running the simulation often for this scenario will lead to the mean probabilities of braking, mean reaction time and mean brake power. These results allow estimation of the severity of the final situation in a more differentiated way than the classical RBD can do.

By fine tuning of the model with respect to the results of specific participant groups (e. g. grouped by age or gender), the model can be adapted to these specific groups to allow simulation focussed on them.

Assessment of Risk

The risk can be basically defined as the product of the frequency or probability of occurrence of a hazardous event and the potential criticality of the resulting harm or damage.

Specifically, with regard to the sequence highlighted in the EHPET (Fig. 3), the measure of risk can be obtained by combining probability and consequence estimates through specific tools, such as risk matrix [6]. An interesting and new point of this kind of simulation can be to come to decision lines, which respect the time of the situation development in certain branches. This will allow predicting the criticality of branches and situation inside them with a higher accuracy. For example, if a driver brakes early in a possible critical situation, the severity of a possible crash is less compared to a late or even not braking.

The use of driver models in the risk assessment will help to discover situations of high potential risk and will moreover allow finding situations in which the interaction of the driver with the cars assistant systems may lead to unforeseen situations. Moreover the division of events into sub events and the simulation of the respective course of actions allow to identify sequences of higher error susceptibility and risk and to optimize these courses of action. By running the simulations with or without the AS being part of the simulation, the benefit of the use of the AS in critical driving situations can be determined.

Discussion and Conclusion

In this paper a new RBD methodology has been proposed and its intended application to an exemplary case study through the use of a driver model has been shown. In future work, the presented proposal will be further investigated to identify advantages and disadvantages of the methodology and its interaction with driver models. In particular:

- Formal requirements for a preferably automatic use of driver models within Human Error Risk Analysis will be outlined. Problems arising from the use of driver models, especially concerning their validity of predictions and runtime complexity, will be investigated.
- The issue related to the dynamic aspects of the RBD methodology will be considered and developed. In fact, the approach includes the best aspects of the classical static methods and describes the time dependant Human–Machine Interaction process by means of a quasi-static approach. This issue implies the consideration of dynamic interplay between humans and machines and the generation of intentions that evolves during an HMI process.

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Human Factors Engineering in Train Cab Design—Prospects and Problems

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Abstract
Background The railway sector in Europe is currently going through major technical and organizational changes resulting in a more complex system with more interfaces between organizations and technologies. These changes require risk management of the interfaces between Hu**M**ans, **T**echnologies and **O**rganizations (MTO). The purpose of this paper is to discuss such changes and interfaces related to the train driver's work task.
Methods The paper presents some of the changes in the train driver's work task as well as risks identified related to these changes.
Results Examples of new risk situations for the train driver involves information overload and divided attention between information inside and outside the train cab.
Conclusions The paper highlights the need for a systematic work process within the railway sector in general to manage issues related to the interaction between MTO.

Keywords Train driver · Railway · ERTMS · Human factors Engineering · MTO

Introduction—Changes on the European Railways

The design and implementation of new technologies in the train driver's cab as well as in the signaling and traffic management systems is in progress. Major investments are made concerning infrastructure as well as in vehicles and in support systems. New systems are introduced and existing functions are added

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such as information and fault detection systems for train drivers and train traffic controllers. The most important new technical system is the European Rail Traffic Management System (ERTMS). The system will provide a new generation of standardized train control and signaling systems in Europe. It is introduced to support the EU policy of interoperability on the European railway system. Several standards, mostly technical, have been published in order to support the implementation of this policy. One of the standards specifies a new, standardized interface for the train driver, Driver Machine Interface (DMI) (e.g. [5]).

So far, ERTMS has been installed in Switzerland, Spain and Italy. In Sweden the implementation of the new system has begun. New and existing railway lines will in the future be equipped with ERTMS. Also new vehicles are being purchased with the new ERTMS Driver Machine Interface (DMI) and old ones are being retrofitted.

Purpose

The purpose of this paper is to discuss the effects of technical and organizational changes on the train driver's task and highlight prospects and problems. Furthermore improvements concerning processes to address the MTO and human factors/HFE issues as a part of change management will be suggested.

Major Change for the Train Driver—The ERTMS and its Prospects and Potential Risks

The introduction of the ERTMS system means a major technical and organizational change as well as a change in work processes for several professional groups, such as train drivers, train traffic controllers as well as maintenance workers. It will provide a standardized solution for the European railways. At present, in 2010, there is a mix of older train cabs and signaling systems in use on the European network and also somewhat different driver safety and support systems are used in different countries.

The changes that the new signaling system will bring about in the train driver's task will be further discussed in this paper. The new DMI interface will make it possible to present more information to the train driver and thus give better support for situational awareness. However, the safe and efficient use of ERTMS requires extensive use of human factors/MTO processes, knowledge and methods, in design and implementation. Important information which has not been available before can be shown in real-time, and information from different sources can be integrated. Information may be used by the driver for planning ahead. This means that the driver will have in-cab signaling information and a new driver–machine interface (DMI). The layout of the DMI interface [5] is standardized meaning that if a certain type of information is presented to the driver it must be presented in a certain way.

The ERTMS system will provide a great opportunity to give better support for train driver work. The need for improvements in these areas has previously been identified (e.g. [9]).

In addition new information systems, e.g. for fault detection and passenger door control will also be introduced into the train cab. A concept for an entire new train cab has been presented for example in the projects on European Drivers Desk (EUDD) meaning that more information will be presented on several other displays in the train drivers' cab. As of today there are no standards available which takes into account the interface in the entire driver's cab.

Introduction of ERTMS means that the driver will have in-cab signaling information, a new driver–machine interface (DMI), new support systems, a higher level of automation and considerably more information for the driving task. The layout of the DMI interface [5] is standardized meaning that if a certain type of information is presented to the driver it must be presented in a certain way. However as of today there is no standard or recommendation on how much information the line-side information system should present to the driver.

The new system introduces potential human factors problems and potential for new types of human errors. This is for example related to driver information overload but also to increased risk of driver distraction due to the demands for simultaneously attending to in-cab information and information outside the train. These are well known error inducing situations.

These changes require risk management of the interaction between systems related to HuMans, Technologies and Organizations. The focus on these issues in the railway sector has by tradition received relatively low attention and funding as compared to other sectors such as aviation and the process industry (e.g. [11]). Nevertheless, the MTO/human factors area is beginning to gain more attention and is now becoming a more important area also in the railway industry (e.g. [1, 2, 13].

The expansion of railway transportation across Europe has included major investments in new vehicles. In Sweden major investments has been made over the past ten years, in many cases in electric multiple units (EMU). Many of these vehicles have had major problems. The problems have been related to brakes, passenger doors, and the air conditioning system but also to the design of the train driver cab. In one case the problems were severe enough for the Swedish work environment regulator to impose restrictions and fines (summarized in [3]). The results of such problems are vehicle breakdowns, severe traffic disturbances and economic losses thus meaning negative consequences on quality, costs and safety.

Some of these problems are related to lack of systematic work processes for managing MTO or HFE/human factors issues in the design as well as in the deployment project phases.

Experiences from other projects have shown that problems may occur if human factors/MTO is not included in the early project phases such as in specification and design. The result can be maladaptive solutions, no regulatory approval, and that costly conversions must be made on the ready vehicle and also that vehicles must be taken out of the production process to be modified.

Results and Discussion

The primary task of the train driver is to integrate various sources of information in order to achieve the goal of moving the train within the limits of its authority, whilst maintaining an efficient speed profile, and making scheduled stops. The train driving task can be described as a real time dynamic control and decision-making task. It involves the driver's adequate allocation and shifting of attention in order to collect and integrate information to perform a braking task, in a short as well as a longer time frame. For this task the driver has to use and integrate information from several sources of information, lineside signals and signs, ATP/ATC Automatic Train Control information, route book and timetables, rule book and different kinds of safety messages.

Several studies emphasize the importance of route knowledge, expectations and knowledge of the next signal aspect and situational awareness for the driving task (e.g. [9]. Landmarks and lineside features are used to confirm that the train has been set up correctly for the next section. The drivers′ appear to be working from well-developed scripts for the various track sections. The driver integrates information from several sources outside and inside the cab. The information used varies for different parts of the route. Knowledge and prediction of next signal aspect is important for the driving plan. Knowledge of whether the next signal aspect will be red and knowledge of what route is set determine at what speed the train should be driven and thus the drivers planning of the task [4].

Attentional conflicts can occur in particular in platform situations where the driver must be fully concentrated on passengers boarding and leaving the train [7].

These results clearly show that there is a need to integrate data from different sources of information to support the driver. Integration of information should also support the driver's mental model. However, if more, integrated information is given to the driver it must be designed in order to avoid attentional conflicts.

Important factors in the work situation influencing train driver performance are the highly irregular work hours making it more difficult to get adequate rest and recuperation [6]. Occasional monotony with fluctuating demands for attention and communication are also typical for the work situation. Also, train driving is solitary work. A literature review on train driver models and performance is presented in Kecklund [8] and Oppenheim et al. [12].

In support of the Swedish ERTMS implementation a risk analysis project is currently working on analyzing risks related to the interaction between Hu**M**ans, **T**echnologies and **O**rganizations (MTO). The ERTMS DMI interface will provide additional and important information to the driver which will be a major improvement. However, the project has identified information overload and divided attention as some of the major problems and potential risks related to driver machine interaction.

Also, organizational issues which can be potential risks were for example lack of systematic human factors engineering processes in the design phase and lack of analysis of qualification requirements for different user groups [10]. These results indicate the need for a systematic process for considering user issues in the design and implementation of projects involving major technical changes.

In addition to this, an exploratory, interview study was previously carried out to collect experiences from a new vehicle purchase project concerning HFE/human factors and MTO [3]. End users (i.e. instructor drivers) as well as buyer representatives were interviewed. These included staff from the train operating company as well as from the buyer representatives. The results from this study indicated some problem areas.

The results showed that the communication and cooperation had worked quite well on the lower organizational level, e.g. that the technicians and engineers did take the drivers feedback into account. However, concerning the communication with the contractor at higher organizational levels (i.e. the management) the end users feedback was given lower priority or was considered at a very late state of the project. Some findings indicate that the difficulties were due to communication problems between different organizational levels within the contractor company. The general results indicates that the there is a need for an MTO/HFE process in rail vehicle projects.

Concerning the driver interface the results showed that the users experienced information overload ("Too much information is presented", according to one of the interviewees). They stated that much of the information was irrelevant ("Wrong information [is presented] by the system" in the words of another interviewee) and that some of the auditory warnings were distracting. This is probably due to a lack of overall concept for designing alarms (alarm philosophy). Also too much and irrelevant information, was given to the driver from the fault indication system. A common problem in such a situation is that much information which is to be used for maintenance purposes is also shown to the driver.

These problems may have quite serious implication such as the drivers' lack of trust in information and warning systems. The systems might be regarded as disturbances rather than as a support. This can result in that the fault indications are not taken seriously, thus creating a "cry wolf effect".

The drivers were pleased with the design of controls and the physical aspects of the driver's cab such as space and the driver's chair but not with the physical in cab climate in the driver's cab.

The results indicate the lack of a systematic process to include the end users in a systematic evaluation of the end product. Some end user representatives stated that they had been involved and others that they had only been given little opportunity to comment on the design.

Concerning quality of the train vehicle the staff interviewed expressed that there seems to be a general view among the contractors that the vehicles can be delivered with faults which could be continuously fixed over time. In this particular case the client did not accept to receive the vehicles until the faults had been corrected. The client staff interviewed considered this conduct by the client as positive. When this study was conducted the delivery of the vehicles was several months behind schedule.

One of the persons interviewed clearly stated that there exists a culture of a "trial-and-error" philosophy within the railway community which would not be accepted for example in the aerospace industry. In the interviewees own words: "I would like to see that airline which placed 400 passengers in some kind of 'flying cigar' whereas you do not have one hundred percent quality assurance on the product".

Conclusions

The results indicate that new interfaces and layout in new train cabs may introduce risks related to information overload, divided attention, lack of structure in presentation of alarm as well as improper use of visual and auditory alarms. Such problems and risks could be managed by use of professional expertise and a systematic work process for MTO/human factors.

Furthermore, the results demonstrate that there is a need for more systematic processes to include MTO/human factors in train cab design in particular and in the overall vehicle design in general. A systematic approach requires addressing MTO at an early stage of an engineering project. Also, an important prerequisite is to provide professional MTO/HFE/human factors competence as well as adequate resources for analysis and implementation of analysis results. The railway industry could benefit from experiences and processes from other areas of industry, e.g. aerospace engineering or the nuclear industry. Already existing standards and guidelines presenting principles for integration and handling of MTO issues could be used and adapted to the railway industry, for example, ISO 11064-1 (International Standards Organization, 2000) and ISO 13407 (International Standards Organization, 1999). Railway related studies based on an MTO/human factors approach are few, yet there are some good examples—see Davis [2], Bourne and Carey [1], or Reinach and Jones [13].

In conclusion, the following aspects are essential when forming a process for MTO:

Planning	Clarify the project goal and scope and identify the general MTO issues relevant for the project at an early stage of the project to ensure the timely inclusion of the important issues.
Screening	Select the most safety significant functions and systems for which the MTO process need to be applied.
Analyses and definition	Analyses needs to be conducted in order to clarify end user needs and requirements of the technical design before the design solutions are set. Examples of important methods are task analysis, to identify

	the information needed to carry out the task and to design information displays and controls.
Verification and validation	Evaluate the design regarding MTO issues in an iterative process in the different project phases.

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Assessment of Transportation System Resilience

Simon Enjalbert, Frédéric Vanderhaegen, Marianne Pichon, Kiswendsida Abel Ouedraogo and Patrick Millot

Abstract A transportation system like tramway or train is a system in which the functions of the human and the machine are interrelated and necessary for the operation of the whole system according to Human–Machine System (HMS) definition. Both human and machines are sources of system reliability and causes of accident occurrences. Considering the human behaviour contribution to HMS resilience, resilience can only be diagnosed if the human actions improve the system performances and help to recover from instability. Therefore, system resilience is the ability for a HMS to ensure performances and system stability whatever the context, i.e. after the occurrence of regular, unexpected or unprecedented disturbances. The COR&GEST platform is a railway simulation platform developed in the LAMIH in Valenciennes which involves a miniature railway structure. In order to study the human behaviour during the train driving activities with or without any technical failure occurrences, an experimental protocol was built with several inexperienced human operators. In railway transportation

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systems, traffic safety is the main performance criterion to take into account. Based on this criterion, authors propose to evaluate an instantaneous resilience indicator in order to assess the "local resilience" of HMS. As others performance criteria must be aggregated to reflect the whole studied HMS performance, the "global resilience" of HMS will be defined.

Keywords Human Machine Systems · Resilience assessment · Transportation system

Introduction

Resilience is a relatively new field of research although the concept has been first use in physics for Charpy impact test in the early XXth. Resilience was related to the ability of a material to recover from a shock or disturbance. The concept of resilience was next developed in the field of ecology and characterizes natural systems that tend to maintain their integrity when subject to disturbances [4]. It has generated much interest in different communities and has been applied to sociology, economy, informatics [1, 5] and:

- In psychology or psychiatry, the concept is linked to the invulnerability theory i.e. the positive capacity of people to cope with trauma and to bounce back.
- In biology, resilience is developed in the theory of viability i.e. ability for an organism to survive after disruption [7, 8].
- In industrial systems and automatic, resilience is related to the concept of robustness which is related to error-resistant and error-tolerant systems.
- In organisational and safety management, resilience is the capacity of a system to survive, adapt and grow face to unforeseen changes, even catastrophic incidents [16].

The analysis of the positive contribution to the system control relates to the concept of resilience. Hollnagel and Woods define the concept of resilience engineering as the *"intrinsic ability of an organization (system) to keep or recover a stable state allowing it to continue operations after a major mishap or in presence of a continuous stress"* [3]. This approach, which incorporates all components of HMS (machines, human, and organization) and their interactions, can be adopted as a definition for further developments.

Indicators to Assess Resilience

Human related performance, machine related performance or organisation related performance can be used to assess the human machine system performance. They can focus on the measurement of the occurrence or the consequence of the events that may affect this system performance. When a measure of the event occurrence is combined with a measure of their consequences, the risk of system performance is assessed. Several criteria can then be evaluated considering the human behaviour contribution to HMS resilience.

Several performance shaping factors are factors that may affect human performance. They are taking into account the internal physical, psychological and physiological state of the human operators or are based on the requirements or the impact of external events [10, 12]. External factors relates to events such as the demands of the tasks to be achieved, the interaction with other operators or with the technical systems, etc. Internal human state concerns for example personal motivation, trust, self-confidence, individual experience, workload, stress, etc.

Sometimes a limited number of factors can be assessed because of the correlations or the dependencies with other factors. For instance, some factors that may affect human performance can also maintain an optimal level of performance. Therefore, human factors such as stress, workload or task demand can generate positive or negative stimuli when controlling a given system [11, 15]. A low or a high level of stress, workload or task demand may lead to a degradation of the human performance, vigilance or attention whereas a medium level may maintain an acceptable level of performance, vigilance or attention. This hypothetical view also considers temporal and functional factors integrating the control of particular situations such as emergent or complex ones. Each of these factors can be assessed qualitatively or quantitatively by subjective or objective approaches. For instance, the human mental workload may be subjectively assessed by TLX or SWAT methods that assess the workload by taking into account factors such as the temporal, the cognitive or the physical requirements of the human tasks [9]. Objective methods can also be useful to calculate on-line the human workload related to the tasks demands assessment. There are methods such as the assessment of the functional task demand to identify the complexity level of controlled current situation or of the temporal task demand to identify the saturation of the human resource [13].

Other factors aim at assessing the erroneous behaviours and their consequences. For instance, there are interpreted in terms of the number of human errors per time unit or the number of human errors upon the total solicitations of the same task. Some human error assessment methods integrate several performances shaping factor that facilitate the occurrence of human errors [14].

In transportation systems, several performance criteria are assessed:

- The traffic safety in terms of barriers non violation, i.e. signals and speed limits respect,
- The departure quality related to the respect of trains departure time from stations,
- The arrival quality related to the respect of trains arrival time at stations,
- The human workload linked to the number of interactions between drivers and technical driving support systems.

Due to the importance of safety for railway transportation systems, the evolution of system safety under disturbances must be selected as the main indicator for HMS resilience.

System Resilience Classification

Several measurements of resilience based on the evolution of performances considered as indicators have been proposed in literature. In order to present these measurements, an example of evolution of system safety under a disturbance is presented in Fig. 1. The baseline in the figure presents the totally safe condition and the minimum acceptable threshold indicates an acceptable safety level for designers. E_{max} is the maximum amplitude of the effect of disturbance on safety and E_j is the amplitude of the effect of disturbance on safety at time T_j.

Resilience can be evaluated by the maximum intensity of an absorbable force by the system without perturbing its functioning. The measurement of the instantaneous resilience can also be linked with the speed of recovery from a disturbance. As these measurements do not consider on the same time disturbance period and effect, and recovery speed, another method will be proposed.

System resilience assessment requires the evaluation of two classes of indicators:

- The stability indicator of performances on a given time interval, i.e. the time period during which the performance improvement occurs or remains.
- The performance indicators of HMS related to the consequences of human actions in order to compare performance levels between two dates, i.e. the current one and a past one (sampling period).

Supposed that optimal performance level exists (initial and nominal HMS state, i.e. baseline situation), after any disturbance (intrinsic, like human or technical failure, or external, like environmental event), performances of the HMS will be degraded and several scenarios can be considered:

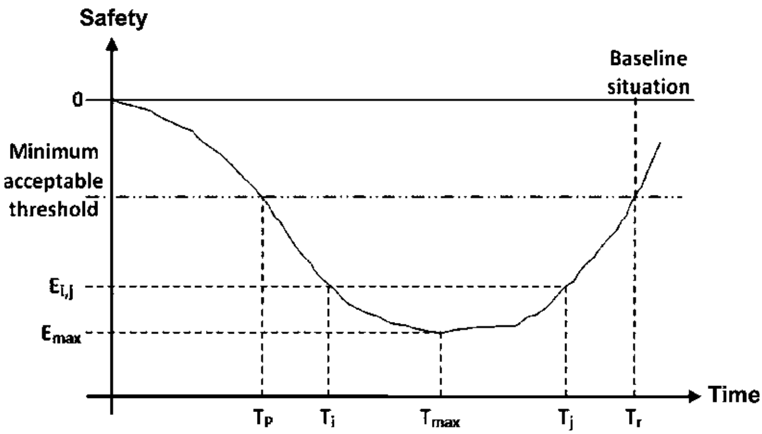

Fig. 1 Resilience measurement in literature

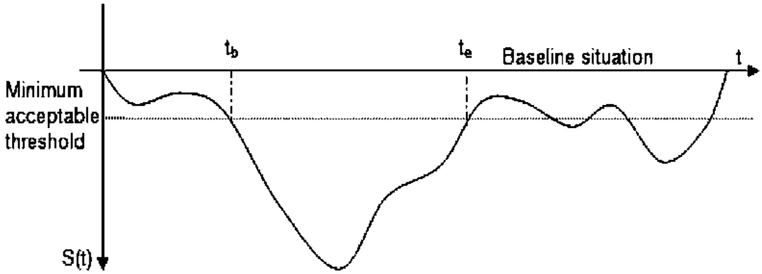

Fig. 2 Evolution of safety indicator for resilience assessment

- If the HMS is capable to return to the initial nominal performance (known disturbances situation), the system can be defined as resistant;
- If the HMS is capable to recover from a perturbation and to stabilize to another acceptable performance level (not optimal, unknown situations, e.g. unexpected or unprecedented disturbances), the system can be defined as resilient;
- Else, If the HMS is not capable to recover from perturbation (out of acceptable performance domain) or to stabilize itself, the system is nor resistant nor resilient.

HMS capable to recover from a perturbation and to stabilize to another acceptable performance level will be studied in next section in order to assess their resilience.

Application to Transportation System

The COR&GEST (French acronym for Railway Driving and Traffic Management) platform is used to simulate railway driving systems. System safety, in order to assess the system resilience, is determined by the sum of effect of factors which can affect the system safety like speed, braking distance, driver awareness, etc. [2]. For instance, resilience can be assessed between times t_b (beginning of disturbance effect, i.e. safety indicator below minimum acceptable threshold) and t_e (end of unacceptable performance) in Fig. 2.

Based on this safety indicator, "local resilience" evaluation Is proposed in Eq. 1:

$$\text{local resilience} = \frac{dS(t)}{dt} \tag{1}$$

The "local resilience" is an instantaneous measurement of resilience and its value depends on the effect of disturbance on the system. It can be negative if the performance decreases or positive if the system recovers from the disturbance.

Table 1 Resilience assessment results

	t_b	t_i	t_{max}	t_j	t_e
Local resilience	$S'(t_b)$	$S'(t_i)$	0	$S'(t_j)$	$S'(t_e)$
Total resilience	0	$\int_{t_b}^{t_i} S'(t)$	$\int_{t_b}^{t_{\max}} S'(t)$	$\int_{t_b}^{t_j} S'(t)$	$\int_{t_b}^{t_e} S'(t)$

The "total resilience" is the sum of "local resilience" during a sampling period as presented in Eq. 2:

$$\text{total resilience} = \int_{t_b}^{t_e} \text{local resilience} = \int_{t_b}^{t_e} \frac{ds(t)}{dt} \tag{2}$$

Table 1 presents results that can be obtained for times t_i (during safety performance decrement), t_{max} (maximum effect of disturbance) and t_j (during safety performance recovery):

Results from ITERATE European project experiments will be used in order to evaluate the proposed resilience assessment.

Conclusion

In this paper, indicators of human behaviour contribution to assess resilience in Human Machine System have been discussed. Then, a system resilience classification based on literature review of measurement methods is proposed. It has been applied on railway simulation platform and will be validated on ITERATE European project data.

Future works will deal with "global resilience" which can be evaluated as the merging of different indicators of "total resilience" such as workload or quality of service. Moreover, learning algorithm to achieve the selection of the most appropriate alternative for driving [6] and to define a new action plan, with its associated consequences, applicable to HMS in order to evaluate its effect in terms of resilience.

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Effects of Situational Characteristics on Drivers' Merging into Freeway Traffic

Martin Baumann, Rike Steenken, Astrid Kassner, Lars Weber and Andreas Lüdtke

Abstract

Background We explore a model-based approach for the design of advanced driver assistance systems (ADAS) where a computational cognitive driver model based on psychological theories of driver behaviour interacts in a simulated environment with the simulated ADAS to predict the positive and possible negative effects of the ADAS on driver behaviour early in the ADAS development process. Applying such an approach to the design of ADAS requires the availability of a valid driver model that can be used to assess the effect of system proto types on human driving behaviour in simulations.

Methods This paper presents two empirical studies conducted within the project IMoST (Integrated Modeling for Safe Transportation) focussing on drivers' merging into highway traffic and how the performance of this manoeuvre is influenced by the speed difference between the merging vehicle and the vehicles on the highway and their distance. These studies were the basis for the development of a cognitive driver model that is able to perform the merging manoeuvre comparable to human drivers.

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Results The empirical results of the studies show that both speed difference and the distance between the merging and the highway vehicles influence driver's decision making processes, attention allocation and driving behaviour while performing the manoeuvre. Furthermore, the results demonstrate large inter- and intraindividual differences in merging behaviour. In a first validation study the frequencies of drivers' decisions to merge before or after an oncoming faster highway vehicle and the trajectories of the human drivers when performing the merging manoeuvre were compared to the cognitive driver model's decisions and trajectories. The comparisons yielded a substantial match between human and model data.
Conclusions The positive results of the first validation studies of the cognitive driver model indicate the suitability of the approach as tool for ADAS development even though a lot of further research is needed on the way to a powerful and validated cognitive driver model.

Keywords Freeway merging · Cognitive driver model · Model-based ADAS design

The Model-Based Approach to Assistance and Automation Design

Future Advanced Driver Assistance Systems (ADAS) will be more and more able to control essential subtasks of the driving task. There are already systems on the market that actively support the driver both in longitudinal (e.g., ACC Stop and Go) and in lateral control (e.g., Lane Keeping Assistance). For such automated systems it is of high importance that the design methodology carefully investigates the complex aspect of driver–ADAS interaction. In the project IMoST (Integrated Modelling for Safe Transportation) the suitability of an alternative approach to traditional ways of evaluating the effects of new ADAS on driver behaviour is explored [1]. This approach is based on an integrated driver–vehicle-environment simulation as a tool to assess the effects of an ADAS on the driver and his/her performance. A cognitive driver model interacts in a simulated environment with the simulated ADAS to predict the ADAS effects on driver behaviour (see also [2]). A prerequisite for this approach is the availability of a computational driver model—a model that allows simulating normal and erroneous driver behaviour. A series of empirical studies was performed within the project to provide the data basis for a driver model that incorporates psychologically plausible and validated processes of human perception, cognition and action for the tasks that are specific to driving.

As traffic scenario merging into freeway traffic was chosen. This manoeuvre is complex and demanding as it involves many cognitive processes and resources at different levels of the driving task [13]: for example, situation assessment, attention allocation and decision processes (e.g., finding a suitable gap, deciding which gap to choose), and both longitudinal and lateral control. Merging into freeway traffic constitutes a multitasking situation. The driver has to simultaneously search for a suitable gap on the freeway and keep the vehicle safe on the road including keeping a safe distance to a lead car. Information from different sources has to be processed and integrated: The traffic situation on the freeway behind the driver, the road ahead and the behaviour of a possibly present lead car from the front, and the information about the current driver's speed from the speedometer.

This manoeuvre is associated with large workload and a relatively high error and accident frequency [3, 10]. Previous studies in our lab (e.g., [8]) suggest that errors in lateral and longitudinal control, speed estimation and attention allocation are the main causes for the occurrence of critical situations when merging into freeway traffic.

Therefore, this rather specific driving scenario is a very good starting point for constructing a cognitive driver model as it is safety relevant and requires the modeling and integration of essential cognitive processes to show valid driving behaviour. The model must possess lateral and longitudinal control capabilities, a mechanism for distance and Time-To-Collision (TTC) estimation, decision processes, a mechanism for the allocation of visual attention, memory processes, multitasking capabilities, and some form of situation awareness mechanism.

Experimental Basis for Model Construction

In a series of experiments conducted in a fixed-base driving simulator at the DLR Institute for Transportation Systems several characteristics of the merging traffic situation were examined to assess their effect on drivers' merging performance. In the experiments driver performance data and drivers' gaze behaviour were recorded. In this paper we will briefly report some results of two experiments performed in this project.

Experiment 1: The Effect of Distance and Speed Difference

Experiment 1 was designed to address the effects of the distance between the approaching freeway vehicle and the ego-vehicle and the effects of the speed difference between these vehicles on drivers' merging behaviour. Both variables obviously should have an effect on merging behaviour, but to construct the driver model a quantification of this effect is necessary. Accordingly, a scenario as shown in Fig. 1 was presented and drivers' decisions to merge before or after the approaching vehicle, driving behaviour on the acceleration lane and drivers' glance behaviour were recorded.

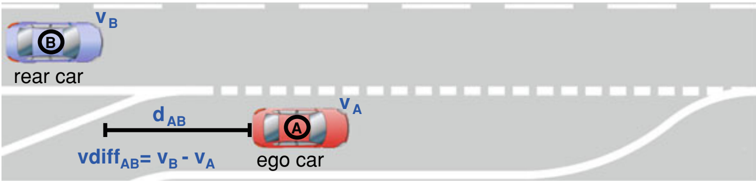

Fig. 1 Driving scenario of Experiment 1; distance d_{AB} and speed difference $vdiff_{AB}$ between approaching rear vehicle B and ego-vehicle A were manipulated

Method

Twenty participants (seven of them were female) took part in this experiment, all possessing a valid driving license. The participants' average age was 35.3 years. The critical part of the basic driving scenario is shown in Fig. 1. Each participant had to enter the expressway while a vehicle on the right lane of the expressway was approaching. There was no lead car. At the time the ego-vehicle entered the acceleration lane the vehicle on the freeway was either 20, 30, or 40 km/h faster than the participant and was either 20, 30, or 40 m behind the ego-vehicle. A full factorial combination of these two variables, the speed difference at start and the starting distance, led to nine different merging situations. Each participant drove each of the situation four times. The order of merging situations was completely randomized.

Results

Table 1 shows the relative frequencies of the participants' decisions to merge before or after the freeway vehicle in the nine different merging situations. Results indicate that both, distance and speed difference between the freeway vehicle and the driver influence the drivers' decisions whether to merge before or after the freeway vehicle. The proportion of trials where the driver decided to merge into the freeway in front of the approaching freeway vehicle increases with increasing distance between the two vehicles, but only if the speed difference between the two vehicles does not exceed a certain limit, that is if the speed difference is below

Table 1 Relative frequencies of participants merging before or after the vehicle on the freeway as function of speed difference and distance

Distance (m)	Speed difference					
	20 km/h merging		30 km/hm merging		40 km/h merging	
	Before	After	Before	After	Before	After
20	0.0875	0.9125	0	1.0	0	1.0
30	0.6125	0.3875	0.025	0.975	0	1.0
40	0.9125	0.0875	0.4375	0.5625	0	1.0

40 km/h. The analogue pattern can be found for the speed difference. With increasing speed difference the proportion of trials where the driver decided to merge before the freeway vehicle decreases.

Another important feature in the data is the variability in the driver decisions for certain combinations of speed difference and distance. In the situation 30 km/h speed difference and 40 m distance the proportion of decisions to merge before or after is nearly even. This variability derives from both inter-individual and intra-individual variations in the merging decisions. That is, whereas some drivers show in this situation some preference for one driving strategy other drivers decide in about half of the trials to merge before the vehicle and in about half of the trials after the vehicle. This variability had to be considered in the construction of the driver model.

Experiment 2: The Effect of Environmental Cues on Drivers' Entering Behaviour

In the second experiment it was examined which environmental cues drivers probably use to generate expectations about the future development of the merging situation and how these expectations influence their merging behaviour. More specifically, it was investigated which cues lead to the drivers expectation that the approaching freeway car will cooperatively clear the right freeway lane to support the drivers merging manoeuvres and their resulting behavioural effects. The underlying assumption here is that action schemata control the behaviour of the driver and are triggered by these environmental cues [11]. The more schema compatible cues are present the stronger the schema will be activated, in this case whether it is appropriate to merge before or after the approaching car. The following cues were manipulated: relative velocity, whether the approaching freeway vehicle shows cooperative behaviour by starting a lane change to clear the right freeway lane, and whether it sets the indicator (see Fig. 2). The drivers' expectations should lead to observable effects in driving behaviour during the entering

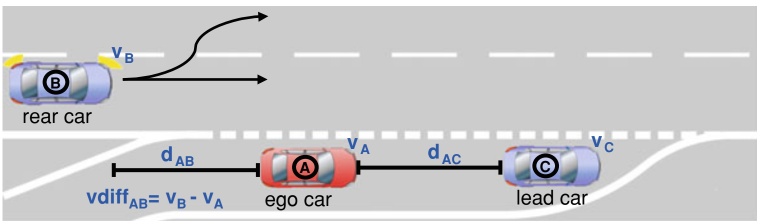

Fig. 2 Driving scenario of Experiment 2. *A* Ego-vehicle, *B* approaching rear freeway vehicle, *C* lead car; speed difference $vdiff_{AB}$ between *A* and *B* was either small or high, *B* had the indicator set or not, and performed a lane change or not

manoeuvre. Moreover, it is intended to integrate the effect of expectancy on drivers' behaviour in the driver model.

Method

Sixteen participants (seven of them were female) took part in the second experiment, all possessing a valid driving license. The participants' average age was 29.1 years. In contrast to the preceding experiment the Experiment 2 scenario was extended by adding a lead vehicle C (see Fig. 2). At the time the ego-vehicle entered the acceleration lane the vehicle on the freeway was either 20 (slow speed condition) or 40 km/h (fast speed condition) faster than the participant, activated its turn signal or not, and showed cooperative behaviour or not. A full factorial combination of these three variables—speed difference at start, turn signal, and cooperative behaviour—led to eight different merging situations. Each participant drove each of the situation four times. The order of merging situations was completely randomized.

Results

Results of Experiment 2 indicate that drivers indeed use environmental cues to generate expectations about the future development of the situation and base their driving decisions at least partly on these expectations. As can be seen in Fig. 3, generally, the speed of the approaching car has a great influence on drivers' decision to merge. If relative velocity between the driver and the approaching car

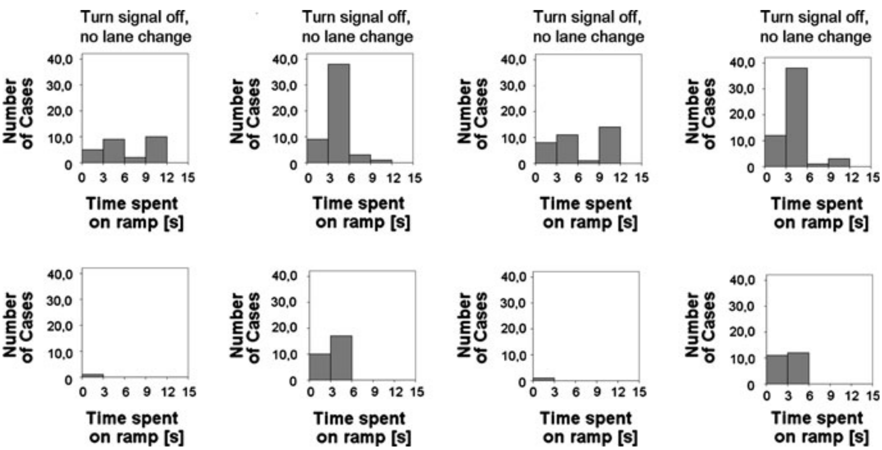

Fig. 3 Distribution of merging duration when merging before freeway vehicle as a function of speed difference (upper row small, lower row large), lane change of freeway vehicle and indicator use

is 20 km/h participants are more prone to enter the freeway before vehicle B. This is compatible to the results found in Experiment 1: with decreasing relative velocity an increase in the probability to merge before the approaching car can be observed.

Cooperative behaviour of vehicle B indicated by starting a lane change to clear the right freeway lane had great influence on drivers' behaviour both in the slow and in the fast speed condition. They entered the freeway before vehicle B more often. Moreover, the drivers significantly spent less time on the ramp and performed the lane change onto the freeway earlier. In other words, when the approaching car shows cooperative behaviour the action schema of the driver is activated faster. However, this influence of an environmental cue on drivers' merging behaviour before vehicle B is restricted to the cooperative behaviour. Setting the turn signal had no such effect. In conclusion drivers can use environmental cues to anticipate other drivers' future behaviour leading to a faster activation of action schemata and therefore to a faster execution of the entering process on the freeway.

The Driver Model

The general architecture of the cognitive driver model was presented in [9, 14]. In a nutshell, the model is based on the cognitive architecture CASCaS whose layered approach explicitly allows modeling of autonomous and associative behaviour using different techniques, e.g. control-theoretic approaches, bayesian modeling or rule based knowledge modeling. The associative layer which processes goal oriented, rule based knowledge enables a stochastic selection of goals which is very useful to implement a various number of action strategies. As data of Experiment 1 suggests, drivers do not behave consistently in the same situation. To adapt the model to the experimental results we first extracted different acceleration behaviours and their distributions of appearance in the data. The different behaviours were modeled in a number of rules associated to different goals, e.g. aggressive acceleration style or safety oriented driving style. At runtime a certain driving style is chosen using a probabilistic selection.

To decide whether a merging before an approaching car is possible, the model assesses the distance and the time to collision to the approaching vehicle on the highway by the angular size and its rate of change of the approaching car in the left mirror (see [5, 6]). Each time the model takes a look into the mirror it gets additional *confidence* in the assessment of the situation. This mechanism is based on models of belief revision that assume that new evidence increases respectively decreases the confidence in a given hypothesis (e.g., [7]). In our case the confidence that it is possible to merge before or after the approaching vehicle is revised according to the information perceived in the left mirror. If the confidence exceeds a predefined threshold the model chooses the current gap.

Merging into highway traffic is a multitasking situation as stated above. The driver has to monitor the road ahead to keep the vehicle safely on the road and the driver has to search for an appropriate gap on the highway by looking into the left mirror to monitor the highway traffic. These two goals have to be interleaved in a way that both tasks can be accomplished successfully. The model simulates the drivers' interleaving of these goals by implementing a multitasking concept based on deadlines. That means, each goal being relevant in the multitasking situation is associated with a certain time for being in control of the action. This reflects the empirical findings showing the temporal dependence of multitasking behaviour [4, 12]. A goal switch is initiated each time a deadline expires. As the deadlines associated with each goal can be modified by rules being sensitive to the current task demands and urgencies the scheduling of tasks can be adapted to changing demands of the traffic situation. By adjusting these deadlines for the two relevant goals (keeping the car on the road and searching for an appropriate gap) at runtime applying this mechanism we were able to simulate variations in the visual scanning patterns of the road ahead and the left mirror based on the dynamic switching of these two goals. Those variations in scanning patterns successfully reproduced the variety of the merging decisions in line with the experimental data.

Modeling the results of Experiment 2 is not finished yet because the variety of results could not be easily condensed into the model. So far we integrated a mechanism into the model that allows to model the effect of the lane change cue whose effect on merging behaviour was obvious. CASCaS offers a concept called *reactive rules* which can be used to activate new goals based on perception of external events. In case of detecting a lane change by lateral deviation the model assumes a free right lane and initiates its own lane change.

Conclusions and Discussion

The aim of this paper was to present some empirical results on driving behaviour when merging into freeway traffic and how these results have been integrated into a cognitive driver model. Both the empirical and the modeling activities were carried out within the project IMoST. The ultimate goal of these activities is to build a cognitive driver model that can be used in the process of designing new ADAS. Possible effects of ADAS on driving performance are evaluated reducing the necessity of empirical tests with human participants. The results achieved sofar are promising. The modeling of different driving strategies and the decision making based on confidence successfully led to a model which is able to replicate the merging decisions of the first experiment in all nine scenarios [14]. We are currently investigating other confidence functions to further improve the match of the merging decisions.

As previously stated the modeling and integration of the results of Experiment 2 are not finished yet. The model currently is able to detect certain environmental cues such as a cooperative lane change of an approaching vehicle on the freeway.

This mechanism allows the model to generate expectations about the future development of a traffic situation. The next step will be to integrate the reactive rule concept with the confidence mechanism to provide a more general mechanism modeling the effects of expectations on driving behaviour.

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A Reinforcement Learning Approach for Designing and Optimizing Interaction Strategies for a Human–Machine Interface of a PADAS

Fabio Tango, Maria Alonso, M. Henar Vega, Raghav Aras and Olivier Pietquin

Abstract The FP7 EU project ISi-PADAS (Integrated Human Modelling and Simulation to support Human Error Risk Analysis of Partially Autonomous Driver Assistance Systems) endeavours to conceive an intelligent system called PADAS (Partially Autonomous Driver Assistance System) for aiding human drivers in driving safely by providing them with pertinent and accurate information in real time about the external situation and by acting as a co-pilot in emergency conditions. The system interacts with the driver through a Human–Machine Interface (HMI) installed on the vehicle using an adequate Warning and Intervention Strategy (WIS). In this paper, the design of the PADAS HMI as well as a decision-theoretic approach for deriving an optimal WIS are described.

Keywords Human machine interface · Decision making support systems · Machine learning / reinforcement learning · Partially autonomous driving assistance systems · Optimal strategies

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Introduction

The FP7 EU project ISi-PADAS (*Integrated Human Modelling and Simulation to support Human Error Risk Analysis of Partially Autonomous Driver Assistance Systems*) aims at conceiving an intelligent system called PADAS (Partially Autonomous Driver Assistance System) in order to aid human users to drive safely, by providing them with pertinent and accurate information in real time about the external situation and by acting as a co-pilot in emergency conditions [1]. The system interacts with the driver through a Human–Machine Interface (HMI) installed on the vehicle using an adequate Warning and Intervention Strategy (WIS). Such a system constitutes an innovation in the field of PADAS, since it intervenes continuously from warning up to automatic braking in the whole longitudinal control of the vehicle (e.g., it can prevent a collision with a leading vehicle by bringing the vehicle to a halt independently of driver's action). This system is called LOSS (*Longitudinal Support System*).

Overview of ISI-PADAS Project

In this context, a specific PADAS has been developed and implemented in the simulator, including the interfaces between the driver and the system: different approaches for tactile, visual and acoustic interfaces are investigated, in order to provide the right information in the right way at the right time. This includes both the intervention of the assistance system and the warnings to the drivers.

Such a system is focused on the assistance to the user in longitudinal driving task and it is thereby called Longitudinal Support System (or LOSS, in short). Two types (or modes) of LOSS have been considered: the Advanced Forward Collision Warning (FCW+ , in short) and the Advanced Adaptive Cruise Control (ACC+ , in short) which are both constituted by 3 functions: Forward Collision Warning (FCW) or Adaptive Cruise Control (ACC); Assisted Braking (AB); Emergency Braking (EB). In particular, this PADAS can provide assistance through the whole longitudinal driving task, from warning the driver (FCW) up to automatic braking action (EB) in imminent critical conditions.

The Approach of HMI Design in the ISI-PADAS Project

Human–Machine Interaction (HMI) is the discipline concerned with the design, evaluation and implementation of interactive computing systems for human use and with the study of major surrounding phenomena. The interface is responsible of effectively translating between the human and the machine to allow the interaction to be successful and this effectiveness can be measured by the concept known as “usability” or “quality of use”: the extent to which a system, product or service can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use [3].

As a result, the need to keep users at the center of the process is outlined, which is the basis of the Human-Centred Design (HCD) approach. ISO 13407 (1999) [2] provides guidance on HCD activities throughout the life cycle and indicates the following considerations: an active involvement of users and a clear understanding of user and task requirements; an appropriate allocation of function between users and technology; the iteration of design solutions and a multi-disciplinary design. As a consequence, to realize LOSS following a HCD approach, the PADAS system is comprised of four capabilities: it can convey visual signals, it can emit audio signals in the form of beeps or alarms, it makes use of a specifically-developed tactile platform to provide hap-tic signals in the form of vibrations and it can decelerate the vehicle (being particularly useful if the driver is not providing adequate deceleration to avoid a collision).

The WIS of LOSS constitutes a set of rules in the form of a software module that determines, at each time step, the manner in which to exercise these HMI capabilities. In this paper, the design of the LOSS HMI as well as a decision-theoretic approach for deriving an optimal WIS for LOSS are described. This way, the HMI of the new LOSS is specified, identifying which information is made accessible to the driver at each time and in which way it is being provided. An optimal WIS achieves the objective of LOSS while being as discreet or as non-interfering as possible, thus attempting to minimize its interactions with the driver and its control over the vehicle’s deceleration. The decision-theoretic approach consists of modelling the driver-system interaction as a Markov Decision Process (MDP) considering that an optimal control policy for this MDP constitutes an optimal WIS for LOSS. The effects of PADAS interaction on the driver, when exercised, can be quite complex, hence requiring a robust, methodical yet adaptive approach to determine an optimal WIS. Driver’s reaction to the HMI of the host vehicle constitutes the “environment” of the MDP. The algorithm will then construct an optimal policy based on this data, meaning that the WIS for LOSS is optimal for the “average” human driver (averaged from all the human drivers who participated in the driving simulator experiments conducted within ISi-PADAS in which simulators were equipped with a PADAS system).

The HMI of LOSS Application

LOSS system is conceived to provide assistance to the driving task by supporting both tactical and operational levels [6], since its range of functionalities goes from informative messages to intervention actions. Taking this into account, LOSS HMI (FCW+ and ACC+) is defined, by specifying interface outputs and the kind of interaction mediating between the driver and the system.

FCW+ system

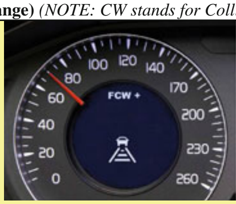
FCW+ warning icons in its various levels are consistent and based on FCW ISO Standard [4], adapting headway area and using red colour to convey urgency to the driver (Table 1). Additionally, text is used in danger and emergency situations, when the driver is requested to brake or is informed about a system intervention. Regarding the acoustic interface, a sound is used for the provision of collision warnings (with variable frequency and duration). Regarding haptics, patterns must be meaningful to the driver in high time constraint situations and thus, it is proposed to use middle temporal frequency for caution and high temporal frequencies for danger levels. Continuous haptic pattern (with high amplitude) is proposed for emergency level to indicate urgency.

ACC+ system

The case of the ACC+ HMI design (Table 2) follows the same principles as the ones used for FCW+ , keeping consistency and using ACC ISO Standard [5]

Table 1 FCW+ interface definition while system operation

<table>
<tr><th colspan="6">FCW + interface definition</th></tr>
<tr><th>HMI channels</th><th colspan="5">Situation criticality (from NORMAL-green to EMERGENCY-red through CAUTION-yellow and DANGER-orange) (NOTE: CW stands for Collision Warning)</th></tr>
<tr><td rowspan="2">Visual</td><td>

FCW + tell-tale / No warnings</td><td colspan="2">

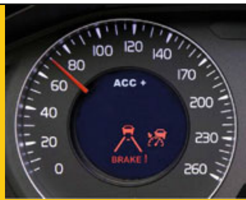
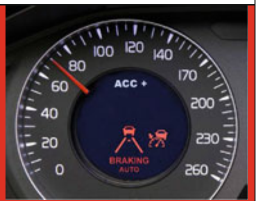
Pre-CW icon displayed for 10 s</td><td colspan="2">

CW icon displayed for 10 s</td></tr>
<tr><td colspan="3">

Danger icon displayed as long as the situation exists together with a text message: ‘BRAKE!’</td><td colspan="2">

Emergency icon shown as long as the situation exists, with the text: ‘BRAKING AUTO’</td></tr>
<tr><td>Acoustic</td><td>No acoustic warnings (an activation warning for ON/OFF)</td><td>No acoustic warning</td><td>Alarm BEEP issued for a brief period (to be defined during simulator experiments)</td><td>Urgent alarm BEEP issued for a longer period (to be defined during experiments) and with a higher frequency</td><td>Urgent alarm BEEP issued for a longer period (to be defined during experiments) and with a higher frequency</td></tr>
<tr><td>Haptic</td><td>No haptic warnings</td><td>No haptic warnings</td><td>On the floor
3 Hz vibrating haptic signal</td><td>On the floor
5 Hz vibrating haptic signal</td><td>On the floor
Continuous haptic pattern with maximum amplitude</td></tr>
</table>

Table 2 ACC+ interface definition while system operation

ACC + interface definition			
HMI channels	**Situation criticality (from NORMAL-green to EMERGENCY-red through DANGER-orange)**		
Visual	 ACC+ icon, current selected speed and headway with visual icon	 Red ACC symbol displayed as long as the situation exists together with a short headway icon and a text message indicating 'BRAKE!'	 Red ACC symbol displayed as long as the situation exists together with a short headway icon and a text message indicating 'BRAKING AUTO'
Acoustic	No acoustic warnings	Urgent alarm BEEP issued for a long period (to be defined during experiments) and with a high frequency	Urgent alarm BEEP issued for a long period (to be defined during experiments) and with a high frequency
Haptic	No haptic warnings	On the floor 5 Hz vibrating haptic signal	On the floor Continuous haptic pattern with maximum amplitude

as a basis. In addition, text is used along with the ACC+ informative icons either to indicate selected speed. Appropriate information in an emergency situation is provided to keep the driver in the loop, using visual information in combination with acoustic and haptic feedbacks that attract drivers attention to the road situation (specially, haptics are provided on the floor since drivers would not be pressing the accelerator pedal).

Thus, following a HCD view, the LOSS HMI design has been based on adopting two different but consistent solutions for FCW+ and ACC+ respectively.

An MDP Approach for Designing the HMI of LOSS

Thus far, the design of the actions, available to the system to help the driver in avoiding collisions, has been described. Now the attention is torn to the decision rules according to which the system employs these actions. The decision rules form a *warning and intervention strategy* (henceforth, a *strategy*).

A strategy must be seen as a function that constantly determines the system's interaction with the driver. As such it has set of inputs and a set of outputs, which is nothing but its set of actions. A strategy describes the following cycle: 1) Collect or sense input i; 2) Determine an action o according to the strategy and the input; 3) Apply o; 4) Go to 1.

An action of a strategy is a pair (h, b) where h is an integer representing a code for an audio-visual-haptic signal (as described in the previous sections) and $b \in [0, 1]$ represents a fraction of maximum brake pressure.

An *optimal* strategy is one that achieves the system's objective in order to minimize collision probability on a longitudinal route. In this section, a mathematical approach for determining an optimal strategy is presented. the problem is conceived as a *Markov decision process* (MDP) [7] an important mathematical model for formulating problems of sequential decision making.

In defining a problem as an MDP, it is characterized as the control of a Markov chain. The control unfolds over discrete time steps. In each step, the problem occupies a state from a set of N states and the decision maker (the controller) chooses one of the K actions available. The probability that the problem is in a given state in a time step is conditional only on the state of the problem and the action chosen by the controller in the previous time step. This is the *Markov* property. In each time step, the controller incurs a cost that is a function of the state and the action chosen in that time step. The objective of the decision maker is to take such actions as to minimize the expected (discounted) cost over an infinite number of time steps. The decision maker uses a *policy* for taking decisions, which is a function that maps actions to states. An optimal policy is one that achieves the decision maker's objective.

In modeling the LOSS system as an MDP, each time step as a duration of 300 ms. The state in a time step is defined as the *headway*, which is the ratio d/v, where d is the distance between the two vehicles and v is the velocity of the host vehicle. It is limited to be in the interval [0, 50 s] (headway above 50 s is considered to be 50 s). Thus the set of states in this MDP is an infinite one. In order to render it finite, the interval is exhausted into disjoint partitions of unequal sizes. As an example: [0, 0.5 s), [0.5, 1 s), [1, 1.5 s), [1.5, 2 s), and so on. These partitions are the states of the MDP.

As stated before, an action consists of a pair (h, b) where h is a signal code and b is the suggested fraction of braking pressure. h takes values from a set of integers representing the various signal codes available. b takes values in the interval [0, 1]. In order to render the set of actions finite, only a subset of points is considered from this interval. To be precise, the set is {0, 0.05, 0.1, …, 0.85, 0.9, 0.95, 1}. As for control costs, a cost of 1 is imposed for taking *any* action when the headway is less than 2 s, and 0 cost otherwise. For the LOSS system, thus, a policy is a function that maps each headway partition to a pair of the type (h, b). So, the policy for the MDP is a warning and intervention strategy. Let f be the strategy. Its functioning describes the cycle:

1. Compute the headway $\theta_t = d_t/v_t$
2. Determine the action $(h, b) = f(\theta_t)$ to be taken
3. Convert h into the corresponding audio-visual-haptic signal and transmit it to the driver via the HMI
4. Apply the suggested braking pressure b
5. Wait for 300 ms
6. Go to 1

Computing an Optimal WIS

An optimal policy for an MDP is one that minimizes the *β-discounted costs* and it can be determined as follows: for $\beta \in (0, 1)$, the β-discounted costs of the N states form an N-vector $(V_1, V_2, \ldots, V_N)$ such that for $i = 1, 2, \ldots, N$, the following equation is satisfied [7],

$$V_i = \min_{k=1}^{k=K}\left(C_{ik} + \beta \sum_{j=1}^{j=N} P_{ij}^k V_j\right)$$

where P_{ij}^k is the probability of moving to the jth state in a timestep if in the previous timestep it is in the ith state and the kth action is chosen and C_{ij}^k is the cost for taking the kth action in the ith state. This set of equations is called the set of *Bellman's equations*. It can be solved through dynamic programming (value iteration) or through linear programming. An optimal policy p^* can be then derived from the vector $(V_1, V_2, \ldots, V_N)$ as follows: for $i = 1, 2, \ldots, N$,

$$p_i^* = \arg\min_{k=1}^{k=K}\left(C_{ik} + \beta \sum_{j=1}^{j=N} P_{ij}^k V_j\right)$$

For the LOSS MDP, the costs C_{ik} is known, but not the probabilities P_{ij}^k. These can be calculated approximately from the *simulation data* as follows. The simulation data is organized in terms of episodes. An episode is a sequence of state action pairs. Thus, by running through each episode, for each pair of states i, j and each action k, the probability of moving to the jth state in a time step can be obtained, if in the previous time step it was in the ith state and the decision maker took the kth action as, $P_{ij}^k = B_{ij}^k / \sum_{j'=1}^{N} B_{ij'}^k$ where B_{ij}^k is the number of times the transition (i, k, j) was observed in the data.

Thus, the optimal WIS is computed as follows:

1. Model the problem as the MDP described above.
   Determine the probabilities P_{ij}^k through the data.
2. Find the β-discounted costs $(V_1, V_2, \ldots, V_N)$ using dynamic programming.
3. Extract an optimal policy p^* from $(V_1, V_2, \ldots, V_N)$.

The optimal policy p^* for the MDP is an optimal WIS.

Discussion and Conclusions

This paper has presented the approach followed by ISI-PADAS project, for the design and optimization of the warning and intervention strategies of the PADAS, called LOSS, using a Markovian Decision Process model. The HMI has been designed following the Human Centered Design methodology, which has defined the form of interactions between human driver and the system (that is, the visual information, the auditory signals and the tactile warnings). The MDP–LOSS has defined the contents of the information to be provided by the system to the driver and in particular: the risk associated to the external situation and based on 5 different levels; the value of deceleration (in %) needed to be applied on the brakes, in order to avoid (or at least to minimize the consequence of) the impact.

At the best of our knowledge, this approach is quite new in automotive domain and it is completely based on the driving and environmental data. At the moment, the optimal policy p^* has been obtained and it is now integrated into the two driving simulators (of DLR and URE). In the next experimental phase, it is necessary to prove and assess that such an approach allows a more "realistic" and efficient strategies for the continuous longitudinal support function, giving best performances with respect to more "traditional" methods and assuring higher acceptability by the user's point of view.

Concerning the future works envisaged into the project concern two main directions: one for the HMI strategies and one for the MDP topics. Following the mentioned HMI strategy, it is also relevant to refer to some research directions that may indicate future lines of investigation:

- How to provide the driver with useful and timely warning information that leads to high levels of comprehension and compliance
- Identify any long-term effects of PADAS use on driver behaviour.
- How to integrate these warnings from multiple PADAS while maintaining a manageable level of workload for the driver, identifying associated workload demands
- Investigate the impact of false alarm rates on driver behaviour and how to deal with them.

For what concerning the MDP, as aforementioned, the efficiency and the acceptability of the MDP–LOSS, implemented in driving simulators, has to be tested with human subjects. If the results will be positive, MDP–LOSS will be the first example of design warning and intervention strategies of a longitudinal support function, based entirely on the data and following a statistical approach. Moreover, other activities include:

- More detailed definition and assessment of the states and actions for the two modes FCW+ and ACC+
- Evaluation and assessment of other variables and parameters to define the states (e.g. the TTC can be merged with deceleration of the vehicles or with the HD variable)
- Investigation of other methods to solve the MDP system, like the Reinforcement Learning

Since the project is at the half of its duration, the experiments of the next months will start providing some good indications about the way to follow.

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The Multisensory Driver: Contributions from the Time-Window-of-Integration Model

Hans Colonius and Adele Diederich

Abstract In this paper, we sketch a specific framework developed to describe and predict crossmodal effects in orienting responses. The time-window-of-integration (TWIN) model postulates that a crossmodal stimulus triggers a race mechanism in the early peripheral sensory pathways, then followed by a compound stage of converging subprocesses that comprise neural integration of the input and preparation of a response. We describe the model in the context of a focused attention task and outline its potential for informing the design of multisensory warning signals.

Keywords Multisensory Integration · TWIN model · Focused attention · Reaction time

Introduction

Modeling driver behavior and designing efficient driver assistance systems depend on a clear understanding of the faculties and limitations of the human brain's processing systems. Over more than a century, experimental psychologists have studied perceptual and cognitive functioning at many different levels and in diverse domains, many of which have an obvious bearing on the driving task. Subsequently, notions like e.g. *spatial distribution of attention* or *mental workload* have become standard repertoire of psychological driver models. Nevertheless, one important, and relatively recent, development in basic research may not yet

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have found sufficient consideration in modeling driver behavior: Over the last 20 years, an extensive body of evidence in psychology and neurophysiology has emerged revealing that information received through different sensory modalities (especially vision, audition, touch) interacts in many ways, and at different levels of processing, in order to generate a coherent subjective representation of the external world (for a recent review, see [1]). In this paper, we sketch a specific framework developed to describe and predict crossmodal effects in orienting responses, and we outline its potential for informing models of driver behavior and for the design of driver assistance systems with an emphasis on warning signals.

Crossmodal Effects in Driving

Vision is clearly the dominant modality for the driving task, but there is growing evidence for an important role of information from other senses, in particular auditory, vibrotactile, proprioceptive, kinesthetic, and vestibular information, being delivered to the driver [12, 21].

Attentional Resources and Crossmodal Signals

Up until recently, the effect of processing sensory information in addition to the visual domain has typically been discussed in terms of allocation of attentional resources. For example, providing the driver with auditory signals has been seen as a possibility to increase the total amount of processing capacity, due to the driver having relatively independent pools of attentional resources for the processing of visual and auditory stimuli. This view, embodied in the influential multiple resources theory (MRT) by Christopher Wickens [24] has lately been criticized by proponents of contemporary multisensory integration research in experimental psychology [20]. Specifically, citing empirical evidence from studies on the use of mobile phones, talking to passengers, or listening to the radio, they demonstrated that there is unequivocal evidence that people find it difficult to divide their attention between different sources of information at the same time, even when the information is presented to separate modalities ([20], p. 192). Driver distraction, from some secondary task provided by recent in-vehicle technologies, has been identified as an important factor in serious car crashes [15]. Nevertheless, there is also some initial evidence that multisensory information displays, for example to provide route finding information, may be more effective than unimodal visual displays [14, 22].

Multisensory Warning Signals

Under laboratory-based conditions, RT facilitation typically decreases as a function of the spatial separation of the unimodal stimulus positions, sometimes even turning into inhibition (cf. [7]). However, it is not obvious that this result generalizes to real-world situations in which a driver's attention is normally engaged by multiple competing multisensory stimuli. Some studies find that the location of tactile and auditory warning signals does have to be controlled as precisely as the location of visual signals to facilitate a response to the critical visual event (cf. [11]). Other studies suggest that multisensory warning signals may be more effective in capturing a driver's attention depending, however, on a number of factors like the nature of the task being performed and on the spatial proximity of the cue and target positions (for a recent review, [19]). For example, [18] assessed the influence of multisensory interactions on the exogenous orienting of spatial attention by comparing the ability of auditory, tactile, and audiotactile exogenous cues to capture visuospatial attention under conditions of no perceptual load versus high perceptual load. They found that multisensory cues capture spatial attention more effectively than unimodal cues under conditions of concurrent high perceptual load. In a recent study, [13] showed that participants initiated head-turning movements and made speeded discrimination or braking responses significantly more rapidly following the presentation of a close rear auditory warning signal than following the presentation of either a far frontal auditory warning signal, a vibrotactile warning signal presented to their waist, or a peripheral visual warning signal. These results suggest that the introduction of peripersonal warning signals results in a significant performance advantage relative to traditionally designed warnings.

Time-Window-of-Integration (TWIN) Model

While there exists a multitude of crossmodal effects in performing the driving task, here we focus on those multisensory processes that occur in orienting responses, in particular toward a warning signal and, thus, typically unfold within less than 1 s. Multisensory integration manifests itself in a facilitation, or inhibition, of reaction time and a change of detection thresholds in orienting tasks, whereby the amount of crossmodal interaction critically depends on the exact spatiotemporal configuration of the stimuli from different modalities [10].

TWIN Model: Introduction

We have developed a quantitative modeling framework that affords the integration of crossmodal interaction results on performance speed and from which a host of empirical predictions can be derived. The time-window-of-integration (TWIN model) introduced in [3] postulates that a crossmodal stimulus triggers a race mechanism in the very early peripheral sensory pathways, which is then followed by a compound stage of converging subprocesses that comprise neural integration of the input and preparation of a response. The central assumption of the model concerns the temporal configuration needed for multisensory integration to take place : Multisensory integration occurs only if the peripheral processes of the first stage all terminate within a given temporal interval, the *time window of integration*. Thus, the window acts as a filter determining whether afferent information delivered from different sensory organs is registered close enough in time to trigger multisensory integration. Passing the filter is necessary, but not sufficient, for crossmodal interaction to occur since the amount of interaction may also depend on many other aspects of the stimulus set, like the spatial configuration of the stimuli. The amount of crossmodal interaction manifests itself in an increase or decrease of second stage processing time, but it is assumed not to depend on stimulus onset asynchrony (SOA) of the stimuli. Although the TWIN model assumptions oversimplify matters, many of its experimentally testable predictions have found empirical support in recent studies, e.g., the effect of stimulus intensity, of SOA, of the number of modalities involved, and of the type of paradigm utilized [5–9].

As for the neural underpinnings of the time window of integration, a promising direction has been taken by Rowland and colleagues [16, 17]. The classic way of assessing multisensory response enhancement by the change in the mean number of impulses over the entire duration of the response (of a single neuron) is a useful overall measure, but it is insensitive to the timing of the multisensory interactions. Therefore, they developed methods to obtain, and compare, the temporal profile of the response to uni- and crossmodal stimulation. For multisensory neurons in the deep layers of the superior colliculus in the cat, they found that the minimum multisensory response latency was shorter than the minimum unisensory response latency. This initial response enhancement (IRE), in the first 40 ms of the response, was typically superadditive and may have a more or less direct effect on reaction speed observed in behavioral experiments.

TWIN Model for the Focused Attention Paradigm

We consider the TWIN model in more detail here for a specific experimental paradigm type, referred to as *focused attention*.

Redundant Targets vs. Focused Attention Paradigm

In the *redundant target* (or, *divided-attention*) paradigm (RTP), stimuli from different modalities are presented simultaneously or with certain SOA), and the participant is instructed to respond to the stimulus detected first. Typically, the time to respond in the crossmodal condition is faster than in either of the unimodal conditions. In the *focused attention* paradigm (FAP), crossmodal stimulus sets are presented in the same manner but now participants are instructed to respond only to the onset of a stimulus from a specifically defined target modality, such as the visual, and to ignore the remaining nontarget stimulus, the tactile or the auditory, say. It has been shown that it may be harder to selectively attend to one sensory signal if an irrelevant (nontarget) signal from another sensory modality is presented from approximately the same spatial location. It seems obvious that results on crossmodal interaction have to be taken into account not only in modeling the driver in complex traffic situations but also in the design of effective warning systems and of driver-assistance systems in general [2].

TWIN Assumptions (Focused Attention)

In the focused attention paradigm, crossmodal interaction occurs only if (i) a *nontarget* stimulus wins the race in the first stage, opening the time window of integration such that (ii) the termination of the target peripheral process falls into the window. The duration of the time window is a constant. The idea here is that the winning nontarget will keep the system in a state of heightened reactivity such that the upcoming target stimulus, if it falls into the time window, will trigger crossmodal interaction. In the case of the target being the winner, no discernible effect on RT is predicted, like in the unimodal situation. For concreteness, we present this version of TWIN in a more formal way.

The race in the first stage of the model is made explicit by assigning statistically independent, nonnegative random variables V and A to the peripheral processing times for a visual target and an auditory nontarget stimulus, say, respectively. With τ as SOA value and ω as integration window width parameter, this implies that the event of multisensory integration, I_{FAP}, equals

$$I_{FAP} = \{A + \tau < V < A + \tau + \omega\}.$$

Thus, the probability of integration to occur, $P(I_{FAP})$, is a function of both τ and ω; it can be determined numerically once the probability distribution functions of A and V have been specified. Expected reaction time in the bimodal condition then is

$$\mathrm{E}[RT_{VA,\tau}] = \mathrm{E}[V] + \mathrm{E}[S_2|I^c_{FAP}] - P(I_{FAP}) \cdot \Delta \tag{1}$$

with $\Delta \equiv \mathrm{E}[S_2|I^c] - \mathrm{E}[S_2|I]$. Expected reaction time for the visual (target) stimulus condition, where no interaction may occur, becomes

$$\mathrm{E}[RT_V] = \mathrm{E}[V] + \mathrm{E}[S_2|I^c_{FAP}]. \tag{2}$$

Note that in the focused attention task, the first stage duration is defined as the time it takes to process the (visual) target stimulus, $\mathrm{E}[V]$. Crossmodal interaction (CI) is defined as difference between mean RT to the unimodal and crossmodal stimuli, i.e.,

$$\mathrm{CI} \equiv \mathrm{E}[RT_V] - \mathrm{E}[RT_{VA,\tau}] = P(I_{FAP}) \cdot \Delta. \tag{3}$$

According to TWIN, this equation expresses the separation of temporal and nontemporal factors for the observable CI: the first factor, $P(I_{FAP})$, depends on SOA whereas the second factor, Δ, depends on crossmodal properties, like spatial separation, but not on SOA.

TWIN Predictions (Focused Attention)

When the nontarget is presented very late relative to the target (large positive SOA), its chances of winning the race against the target and thus opening the window of integration become very small. When it is presented rather early (large negative SOA), it is likely to win the race and to open the window, but the window may be closed by the time the target arrives. Again, probability of integration, $P(I_{FAP})$, is small. Therefore, the largest probability of integration is expected for some mid-range SOA values. Although $P(I_{FAP})$ is unobservable, it should leave its mark on crossmodal interaction CI in Eq. 3 as a function of SOA because CI should have the same form as $P(I_{FAP})$, scaled only by some constant.

Moreover, if target and nontarget are presented in two distinct crossmodal conditions, one would expect parameter Δ to take on two different values. For example, for two spatial conditions, both stimuli presented either ipsilateral (i.e., in the same hemifield) or contralateral (in different hemifields), the values could be Δ_i and Δ_c say. Subtracting the corresponding crossmodal interaction terms then gives (cf. Eq. 3)

$$\mathrm{CI}_i - \mathrm{CI}_c = P(I_{FAP}) \cdot (\Delta_i - \Delta_c), \tag{4}$$

an expression that should again yield the same qualitative behavior, as a function of SOA, as $P(I_{FAP})$.

These, and a host of other predictions, have been tested in a series of experiments providing evidence for the principal assumptions of TWIN (cf. references above).

Determining Optimal Window Width

An infinitely large time window will lead to mandatory integration, a zero-width time window will rule out integration entirely. From a decision-making point of view, however, neither case is likely to be optimal in the long run. In a noisy, complex, and potentially dangerous driving environment, with multiple sources of nearly simultaneous sensory stimulation, the issue of whether or not two given stimuli of different modality arise from a common source, i.e., are due to one and the same event, may be critical for successful driving performance. For example, for an audiovisual warning signal to be effective, both modality components must be recognized as belonging to the signal. On the other hand, interpreting any occurrence of crossmodal information as relating to a common event (in particular, a warning signal) may result in a depletion of attentional resources and inadequate reactions.

Recently, we have suggested an approach to computing an optimal window width within a Bayesian framework [4]. An optimal window can be determined under the expectation–maximization rule as a function of (i) the prior probability of a common event, (ii) the likelihood function of arrival time differences under a common vs. separate events, and (iii) the payoff values for correct and incorrect decisions. Figure 1 illustrates the dependence of optimal window width on the prior probability, for different parameter values of the likelihood functions. Recent empirical evidence for an important role of such effects on orienting response time (human head saccades to a visual target) has been found by [23].

Concluding Remarks

One contribution of the TWIN modeling framework is to provide an estimate of the multisensory integration effect that is 'contaminated' neither by a specific stimulus onset asynchrony nor by intramodal stimulus properties like intensity. While the functional dependence of $P(I)$ on stimulus onset asynchrony and on stimulus parameters, like intensity, is made explicit in the rules governing the opening and closing of the time window, the TWIN model framework as such does not stipulate a specific mechanism for determining the actual amount of interaction, Δ. Nevertheless, TWIN has been demonstrated to afford a number of empirically testable predictions like the effect of varying the intensity of target or nontarget stimuli and the effect of increasing the number of sensory modalities. Furthermore, a number of predictions concerning top-down processing effects, like the prior probability of joint crossmodal events or the likelihood of specific

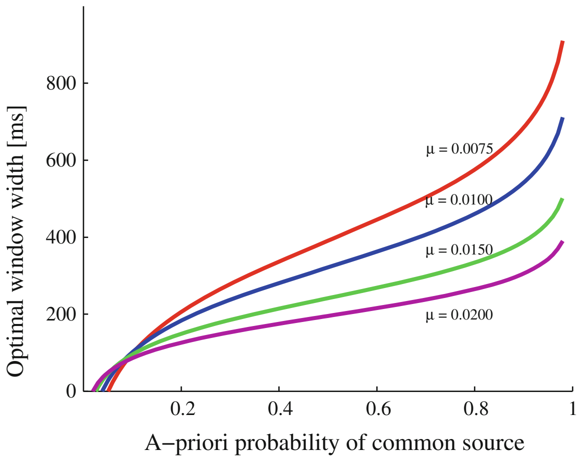

Fig. 1 Optimal window width increases as a function of the a priori probability of a common event. The increase becomes less steep by increasing the (exponential) likelihood of an arrival time difference of zero (μ)

temporal contiguities among stimuli from different modalities, can be made via hypotheses about the modulation of the time window width. It will remain a task for future research to implement these features of TWIN into the design of multisensory warning signals and to check to what degree the predictions of the model framework will be confirmed in the complex driving situation.

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Part IV
Cultural Aspects in Design

Culture Implications on Future Work Design—New Technologies and Collaborations for Controllers and Pilots

Pernilla Ulfvengren, Lena Mårtensson and Fredrik Barchéus

Abstract Future air traffic management is facing major changes that will bring pilots and controllers, two professional cultures, closer with new technologies and collaboration. Earlier research on safety culture and organisational change such as mergers and implementing new system designs have been rewieved to identify applicable implications for the future work design of the air-ground joint system. The HILAS project has developed relevant tools for both intra- and inter-organisational processes for maintenance and flight operations and may function as a role model. It is concluded that preventive measures for facilitating successful future system operations is to develop similar integrating tools for knowledge management, process modeling, training modules for cross-learning, reporting, risk models as well as performance measures and indicators.

Keywords Safety culture · ATC · Flight operations · Work design

Introduction

We know that many major organisational changes fail. We know that merger between different organizations may have effect on many work performance related aspects. We know that implementing new technologies bring unanticipated surprises and will need continuous adjustments and improvements. We also know that the future air traffic management (ATM) is facing major changes that will merge two professional cultures closer with new technologies and collaborations. Current harmonisation work such as the European Single Sky initiative in Europe is

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resulting in that new technology is gradually being introduced in order to meet challenges for system capacity limits, due to traffic increase [8]. The future system change means pilots and air-traffic controllers will have new roles, responsibilities and ways of collaboration [4]. Changing technology will also change routines and work content that may affect the system performance. An example is increased shared information which may or may not improve decision making. Enabled by Automatic Dependent Surveillance-Broadcast (ADS-B) traffic information will be available in the cockpit. This will in theory allow for pilots to control separation of aircraft. The currently very clear division of labour between pilots and controllers may be changed with the introduction of Cockpit Displays of Traffic Information, CDT. The provision of information to the flight crew means that pilots can question controller decisions based on their own traffic picture. This may in turn interfere with controller intentions and might result in increased workload and stress for controllers [5]. The future data link communication using Controller Pilot Data Link Communication (CPDLC) is new technology for communication. In present ATC, communication between pilots and controllers is managed using analogue radio technology, thus radio transferred speech is the main mean of communication today. It is effortless in input and flexibility. Previous research has shown that much of the communication is not acknowledged properly [15], mainly because of language deficiencies and sound quality. Despite this, the shared radio frequencies enable pilots to create a situational model based on communication between other parties in the vicinity, generally referred to as Party Line Information [14].

One Human Factors (HF) area of relevance to new system design is human-centered design and cognitive systems engineering [16]. Here HF still needs to have impact to carefully consider work design as well as design of organisational changes. This also include being able to effectively monitor and evaluate system performance. It is essential that the real system is understood in order to design effective preventive measures in terms of procedures and training or indicators at various levels. Rasmussen already argued for an information system that interrelates decision support throughout the organisation. HF need to include what has separately been going on in engineering, human factors and organisational science. This idea was implemented [12] in the HILAS project (Human Integration into the Lifecycle of Aviation Systems).

The context for pilots and controllers work is very different, yet they are complementary actors in a common system with overlapping functional causal system. Air traffic controllers and pilots are completely dependent on each other in their daily work, minute by minute. It may be considered as a joint cognitive system [10]. Technology development for the new system has been going on for years. Still, very little has been done between the two. When changing allocation of authority between the two professions, pilots are made more autonomous and require more coordination [3]. Just as in automation [6] and the classical Fitt's list from 1951on MABA–MABA (men are better at–machines are better at) perhaps it is time to start thinking in terms of PABA–CABA (pilots are better at–controllers are better at) and better support their collaborations.

This paper is a contribution to for research considering flight deck and ground stations together and the objective is to discuss cultural implications for future design of work, new technologies and collaborations for controllers and pilots. This discussion will be based on research on cultural aspects, organisational changes as well as the HILAS system on the one hand and briefly describing flight operations (FO) and air traffic control (ATC) as two work domains and professional cultures in a common system on the other. Our group at KTH is a multidisciplinary Human Factors specialist group with engineers, psychologist and pilots with broad experience and domain knowledge from aviation. We have participated in the HILAS project as well as conducted research in ATM/ATC. Our research is based on work with pilots, controllers and personnel in airlines and air traffic management organizations at all levels. The overall goal with our research is to increase overall system performance and human well-being without compromising safety.

Cultural Aspects

Today the importance of organisational culture is clearly acknowledged in regulation by researchers and by practitioners such as airlines, maintenance organizations and air traffic controllers. In this paper a broad approach is taken. Culture may be described as peoples' reflection on the real system they encounter, meaning that they make sense of their whole situation they are in [12]. ICAO discusses national, organisational and professional culture. They merely consider culture as "a means to achieve an essential safety management prerequisite of effective safety reporting" [11]. Reason [17] discuss safety culture being an informed culture. For this here needs to be a good reporting culture which requires a just, flexible and learning culture. Safety culture may also be seen as the oil lubricating work with safety management systems, including continuous improvement of the SMS itself [1]. Organisational aspects that safety culture surveys typically shed light on are for example; communication, personal engagement and individual responsibility [2]. These aspects are central for any safe and innovative organisation [19]. Safety culture surveys are common and considered as a part of proactive safety management in many organisations. SAS in their annual report 2009 give examples on key aspects for their positive safety culture; communication based on mutual trust, a common view on the importance and role of safety work, having confidence in effectiveness in proactive measures taken and a well-functioning reporting routine.

Cultural aspects have been studied in a merger of two airlines [20] which is an organizational change including two different and strong professional cultures in a new common context. Within the newly developed airline, management acknowledged the importance of considering the culture from the two airlines as well as the feeling of uncertainty among the staff. Seminars were held and courses given in order to create a joint culture focusing on similarities between the two companies. Results suggest that *management should communicate the goals of the merger* to all employees and create opportunities to brain storm the different processes in the airline with the personnel well in advance. They are encouraged to *involve personnel and the trade unions* in the planning and to have the *operations manuals and the procedures ready* before the merger. This is mandatory by regulation but it also gives a smoother process. Last but not least they are recommended to have the *agreements between management and the trade unions on salaries, pensions, holidays and working conditions ready before the merger*. If that is not the case too much time will be spent on fighting each other. The great number of trade unions, 14, as it was in this case, makes this process a delicate matter. This merger is successful today and shows that it is possible to learn from each other's although adequate time has to be given for the process.

Díaz-Cabrera et al. [7] identifies requirements for successful implementation of a major organisational change. The change is implementation of a socially-based or people driven knowledge management system (KMS). Díaz-Cabrera et al. reports that many times socio-cultural aspects of evaluation processes and organisational change are often overlooked and fall mainly on technological aspects. A KMS is described to focus on improving knowledge creation among individuals in a group as well as at organisational level. It is stated that the success of an implementation of a KMS depends on the existence of an organisational culture that facilitates intra-and inter-organisational coordination and information and communication processes. The research identifies organisational culture enablers and barriers and develops a HILAS Organisational Cultural Scale (H-OCS). The identified relevant cultural dimensions are (ibid.): (1) Organisational values (*information permeability, approachability of management)*; (2) Organisational Practices and Policies (*two-way vertical interaction, participation*); (3) Individual and Group Perceptions (*shared values of work, organisation and change process*); (4) Trust in management and organisation (*credibility, justice*); (5) Climate (*foster motivation, job satisfaction*). Examples of underlying issues are given in parenthesis. Except for taking into account these dimensions when implementing organisational changes recommendations are also given (ibid.) to plan the change process by developing a: Dissemination plan; Organisational plan; Training program about KMS implementation; Change process success evaluation.

Human Integration into the Lifecycle of Aviation Systems

The Aviation Psychology Research Group at Trinity College in Ireland has for many years conducted excellent human factors research in the maintenance domain in the ADAMS, AMPOS, AITRAM and ADAMS-2 projects. A summary that accounts of much of this evidence can be found in McDonald, 1999, 2001; McDonald et al., 2000, as cited in McDonald [12]. This research has identified some main phenomena which are not possible to explain by common theory or HF models: *Double standard* describing the gap between strategic management views of operations and the real "normal" operations as performed by operators, *WIPIDO* meaning Well Intended People In Dysfunctional Organisations and describes how operators do their best to overcome an actual or perceived lack of support in operations, a strong *professional culture* seams to compensate for weaknesses in the organisation and *cycles of stability* describes that even after failures organizations do not easily learn and change. It is believed that effects of these phenomena are haltering change and improvement of system. As an answer to this research a New Human Factors model has been suggested [12] combining four key theoretical themes; *system, action, sense-making* and *culture.* "It is proposed that these terms represents or refer to different aspects of the same underlying reality…" (Mc Donald [12]) necessary to explain the phenomena mentioned above. This led their research to acknowledging the importance of the operational processes enabling and supporting change and creating the necessary understanding of what needs to change and provide new channels of action to achieve that change. With this "research call", the HILAS project [9, 13] was launched and run successfully together with 40 other partners, for 4 years.

The *HILAS system* [13] is developed as an integrated management system and the project's results include organisational and technical tools for processes for managing change, performance, risk and learning (task support, intelligent planning, risk analysis, performance indicators, SMS support and a knowledge management system). This overall process framework have strategic, tactical and operational management in mind. For example, in design of reporting tools it meant having both top-down as well as bottom-up requirements for information and feedback as well as related change processes to prove reporting effective and meaningful. The HILAS system also considers individuals as well as system input and feedback on risk- and performance management, which is balancing support and control. HILAS created and developed a new process for knowledge transformation which includes process modeling and analysis of the "real process". An essential tool for this is the OPM/KSM which consists of an Operational Process Model and a Knowledge Space Model. These tools and knowledge transformation process facilitate creating a common view of the system processes as well as cross-learning between groups in an organisation, between professions and between organisations.

Pilot and Controller Work Domains and Contexts

Both controllers and pilots have highly specialized tasks. These two groups share an awareness of the great responsibility involved in their high risk work. Working with risk increases the need for timely and relevant information and support both for planning and real-time operations. They work shift with irregular working hours with varying sleeping patterns.

Air traffic controllers maintain the safe and orderly movement of several airplanes along air routes at control centres and around airport at approach. The aerodrome controllers guide landing and taxing to the terminal. Controllers give pilots instructions and advice as to height, speed and course.

Pilots maintain the safe and orderly movement of aircraft and its passengers by flying along one air route. They have several phases such as pre-flight, flight execution and post flight. Every time an airplane enters a new sector the pilot has to manually change radio frequency to transfer to the new controller.

The general opinion on the cooperation between controllers and pilots is that it is overall good and that there is trust between the two groups today [5]. Pilots are responsible for keeping flight costs down and want to land without delays. The controller has to create a steady flow of traffic, and may occasionally have to take decisions that are not optimal for single airplanes. Controllers have stated that they would agree to hand over the responsibility for separation, but will not take it back since they no longer have the full picture. "It is still us and them. The pilots only have their aircraft. We have everything" (ibid.).

In commercial airplanes there is one captain and one co-pilot in the cockpit team. The flying crew works with the cabin crew as well. Pilots seldom work with the same pilot or cabin crew since the team varies from flight to flight. An airline like SAS has around 2000 pilots. Overall face to face communication is rare among a large group of pilots or with their managers.

In the ATC team there are two controllers for each sector, one executive and one planner. The executive is working with the current air traffic flow and the planner has supervision over the traffic entering the sector and plans the work in order to facilitate for the executive (Eurocat 2000E, as cited in [2]). Controllers interact with colleagues on a daily or weekly basis in both towers and at control centers. For example Arlanda ATCC has around 250 persons.

Both controllers and pilots follow standard operations procedures (SOP). The aviation community uses a strict phraseology in order to increase intelligibility over noisy radio frequencies [5] but also for communication between pilots and controllers, or within individual teams in their routine work. Pilots have periods of lower work load, which may give opportunity to casual conversations. Controllers are normally scheduled with 1 h on duty followed by 30 min break with opportunities for casual interaction.

Reporting is part of a standard routine in case of events which may have effect on safety. Results from both ATC [2] and FO [18] research show that operators still think it is too difficult or inconvenient to file reports. The main reasons for not reporting in flight operations have been found [18] to be due to organisational issues such as lack of relevant feedback, lack of change initiatives accordingly and environmental factors such as access to tools, time and effort to file reports. The reporting tools needs to be easily accessible and user-friendly.

Discussion

A summary of the earlier research is that several of the organisational aspects are reoccurring in the various contexts of safety culture, mergers, and implementing major organisational change. The list include the need for mutual trust, credibility and justice, shared values of work, a common view, well-functioning communication and reporting within an organisation, job satisfaction and motivation, strategic goals need to be communicated in advance and concerned stakeholders need to be invited to participate and to have personal engagement.

Considering differences and commonalities between pilots and controllers work domains it is assumed here that it is possible to identify implications for their separate work as well as their common system in relation to these other contexts. Trying to achieve the organisational aspects listed above among pilots and controllers it is necessary to ascribe both intra-organisational as well as inter-organisational structure to the system. Bringing two different professional cultures closer together applies to organisational mergers. The new technology and related changes will affect air and ground separately as well as jointly on a two-way "horizontal" level.

HILAS processes already support intra and inter-organisational processes for managing change, risk, performance and learning and has developed both organisational and technical tools for task support, intelligent planning and risk analysis, performance indicators and knowledge management. The Operational Process Model is central for the purpose to facilitate a common view of system processes and cross-learning between groups, professions or organizations.

In conclusion there is a need for preventive measures for potential future mismatch between air and ground, due to the natural fact that they make sense of different contexts and work. If understanding of the functionality of the system differs between groups, this logically will make effective change more difficult. Tools and methods for the joint air-ground system are required to acquire human factors related information from operations, and to facilitate communication processes for information handling and reporting. Resources, structures and tools must fit the real operations as well as management throughout the organisation.

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Cultural Variation of Views on Effective Crew Resource Management Skills

Hans-Juergen Hoermann

Abstract While it is generally agreed in the aviation community, that effective crew resource management (CRM) skills are an indispensable condition for a safe and efficient flight operation, there seems to be a wider range of views on what behaviors constitute effective crew performance. Within a European project an evaluation tool for CRM skills called NOTECHS was developed with four categories: Co-operation, Leadership and Managerial Skills, Situation Awareness and Decision Making. In a study to examine its suitability as a standard for CRM skills in different European regions the cultural robustness of the method was tested. 105 instructor pilots from 15 different airlines representing 12 European countries participated. The participants evaluated crew behaviors in eight video scenarios with the NOTECHS method. According to variance analytical results, regional differences in Europe seem to affect the ratings of CRM-skills only to a small degree. Cultural differences are confounded with other background variables, such as English language proficiency, work experience, instructor experience and attitudes. These background variables seem to have stronger effects on views of effective CRM behaviors than culture per se. Results of the analyses are discussed with respect to cultural robustness of the NOTECHS method.

Keywords Culture · CRM · CRM-skills assessment · Pilots · NOTECHS

Introduction

In aviation culture is described as '*the norms, attitudes, values, and practices that members of a nation, organization, profession, or other group of people share*' (FAA HF [4]). Since cultural values are interwoven in all sorts of social

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interaction, they are as well important elements in Crew Resources Management (CRM) behaviors of flight crew members. For example, culture as 'the way we do things around here' [13] can influence how crewmembers communicate, how they delegate tasks and accept orders, how procedures are adhered, how risks are evaluated and decisions are found. Culture can be understood as integral part of the contextual conditions, which contribute to the meaning of specific behavior patterns. With respect to aviation, ICAO distinguishes four relevant contextual layers in which (national and organizational) culture is embedded: (1) the economical and political, (2) the geographical and physical, (3) the social, and (4) the airline operational contextual layer. On all four layers direct and indirect influences on flight crews' behavior can be imagined. Within our own cultural boundaries we normally behave intuitively adequate because the common set of values and norms enables us to anticipate more correctly what other people expect and vice versa. If we cross cultural boundaries however, then the same behavior pattern can have a completely different degree of adequacy.

From this point of view it does not seem very likely that good CRM behaviors would be evaluated equally across different cultural contexts. On the other side, the aviation industry as well as public international media accelerated the buildup of the *global village,* where frequent international travel beyond cultural boundaries became very common and created a better understanding and exchange of values and habits [13]. In addition the pilot community seems to be a quite homogenous population which is marked by a very strong professional culture that contributes to a wide set of common standards. This study examines the question whether CRM behavior effectiveness can be assessed across Europe by the same set of standards or by culturally diverse qualities.

The entire concept of CRM was formed primarily by human factors teams in the US and other Western regions based on thorough investigations of many safety-related events. Crew behavior patterns have repeatedly been identified as effective or ineffective in accidents and incidents, regardless of where these events occurred. However, the acceptance of the earlier generations of CRM trainings when being transferred into non-Western cultural regions was weak. A search for more universally valid CRM goals by the University of Texas Human Factors Research group has led recently to the Threat and Error Management (TEM) model with a wider range of applicability [8].

In Europe, the issue of CRM-skills evaluation became increasingly important in the light of the Joint Aviation Authorities' (JAA) efforts to harmonize legislation for its member states. Based on a thorough review of existing behavioral marker systems in the industry, a consortium of four human factors research centers came up in the late 1990s, with a schematic framework called NOTECHS [1, 5]. Since NOTECHS was supposed to have sufficient generality to work in different language contexts as well as in different size companies it was designed on a rather low level of complexity with CRM-skills decomposed into four categories and 16 behavioral elements as shown in Fig. 1. Two of the categories, Co-operation (CO) and Leadership and Managerial skills (LM), reflect social skills. Two others, Situation Awareness (SA) and Decision Making (DM), are cognitive skills.

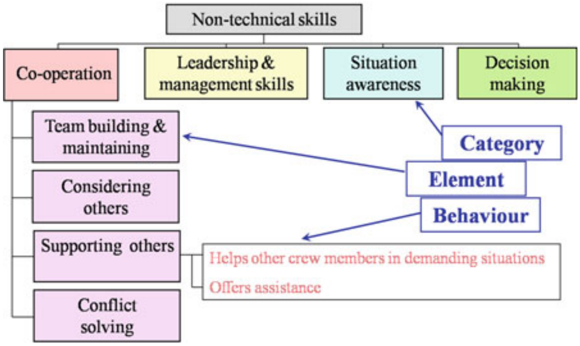

Fig. 1 The NOTECHS descriptive framework consists of Categories, Elements and behavioural examples [5]

Along with other actions of the crew, communication behavior is an important source of information for the examiner or instructor to observe social and infer cognitive skills of the pilots. From what is reported in the relevant literature, it seems quite likely that the way in which this information is judged, in relation to positive CRM behavior and flight safety, will be subject to cultural variation especially for the social skills. Table 1 shows the set of elements that define the four NOTECHS categories.

EASA [3] has accepted the NOTECHS system as a method to assess CRM-skills of flight crews during line-checks and recurrent training for the purposes of (a) providing feedback to the crew and the individual, (b) identifying retraining where needed, and (c) improving the CRM training system.

Approach

Our approach to study cultural variation of views on good CRM practice started with a review of influential international surveys on the comparison of working values of employees from different regions in the world [7, 9, 15]. It was shown that the complexity of cultural differences can be described by variations on four general dimensions. We expect that three of these dimensions tap the social as well as the operational context layers and that they also reflect on flight crew behaviors in multi-pilot aircraft:

- *Individualism–Collectivism* (ID) is the tendency to favor personal choices and achievements over the continuing membership to a specific group to which one is attached,
- *Power Distance* (PD) is the extent to which the less powerful members of an organized group expect and accept that power is distributed unequally,
- *Uncertainty Avoidance* (UA) is the extent to which members of a culture tend to feel threatened by uncertain or ambiguous situations.

European cultures were grouped for the purposes of this study on the data of these surveys into five clusters, each with a distinct pattern of values on these three

Table 1 Categories and elements in the NOTECHS system [5]

Categories	Elements
Co-operation (CO)	Team building and maintaining
	Considering others
	Supporting others
	Conflict solving
Leadership and Managerial Skills (LM)	Use of authority and assertiveness
	Providing and maintaining standards
	Planning and co-ordination
	Workload management
Situation Awareness (SA)	Awareness of aircraft system
	Awareness of external environment
	Awareness of time
Decision Making (DM)	Problem definition and diagnosis
	Option generation
	Risk assessment and option selection
	Outcome review

dimensions. To examine the cultural robustness of NOTECHS, N = 105 instructor pilots were recruited and trained by the JAR-TEL consortium to assess flight crews' CRM-skills in eight different video scenarios. The distribution of the instructor pilots across Europe is shown in Table 2. The video scenarios were taped in a Boeing B757 simulator with professional flight crews:

1. Descent—First Officer (FO) is flying. A passenger problem is reported by the cabin crew. The action centers on the Captain allowing himself to be distracted by secondary events and not monitoring the FO's actions. The altitude bust that

Table 2 Cluster approach to European cultures based on Hofstede's dimensions of Power Distance (PD), Individualism (ID) and Uncertainty Avoidance (UA). Distribution of participants in the JAR-TEL study [10, 12]

Cluster	Number of Pilots	Nationalities
Scandinavia	19	12 Danish
high ID		1 Norwegian
low PD, UA		6 Swedish
Northwest	21	10 British
high ID		11 German
medium PD, UA		
Southcentral	30	13 French
high PD, UA		17 Italian
medium ID		
Southperipheral	16	6 Portuguese
high PD, UA		10 Slovenian
low ID		
East	19	12 Hungarian
high ID, PD		5 Latvian
		2 Russian

concludes the sequence is the direct technical consequence of the FO missetting the cleared flight level but the Captain's behavior precipitates the error.

2. In cruise over Brussels—170 miles to destination London Heathrow. After suffering an engine fire, the Captain decides to continue to destination against the good advice of the FO.
3. Crew carrying out pre-departure checks. The FO is unfamiliar with the airfield and receives little or no support from the Captain.
4. Top of descent—an electrical failure occurs. Problem well handled by both pilots working as a team.
5. Approach in very gusty conditions. The Captain is very supportive of the under-confident FO and achieves a very positive result after good training input.
6. A night approach in the mountains. Captain decides to carry out a visual approach through high terrain and triggers a GPWS warning. FO takes control and prevents an accident.
7. An automatic approach in CAT III conditions. Very good standard operation. An example of a typical everyday flight deck activity with both pilots contributing to a safe outcome.
8. Joining the holding-pattern awaiting snow-clearance. The Captain persuades the FO that they should carry out a visual approach with an illegally excessive tailwind for commercial reasons. The FO points out to the Captain that he disagrees with his decision.

For the NOTECHS method to be robust the results of a statistical comparison should show that CRM-skills assessments for the same scenarios and same NOTECHS categories do not vary systematically across the five different clusters. With multivariate analyses of variance (MANOVA) we compared the assessments of the 105 instructor pilots with the cultural clusters as an independent factor.

Findings

An initial qualitative check has revealed that the degree of agreement with the suggested decomposition of CRM-skills into categories and elements showed no significant variation across the five European regions. This finding provides evidence that pilots across Europe do have a good degree of common understanding on the concepts of CRM and which qualities it addresses.

In quantitative analyses of the individual CRM assessments a number of significant differences between the cultural clusters was found. Stronger effects were found for Captains than for FOs. CO, LM and SA of the Captains were affected by the cultural clusters and SA and DM for the FOs. However, it could be shown that the majority of these differences can be explained by different levels of English language proficiency of the instructor pilots [10]. In 2-factorial MANOVAs with (self-rated) English Proficiency as another independent factor, most of the significances of the cultural factor disappeared.

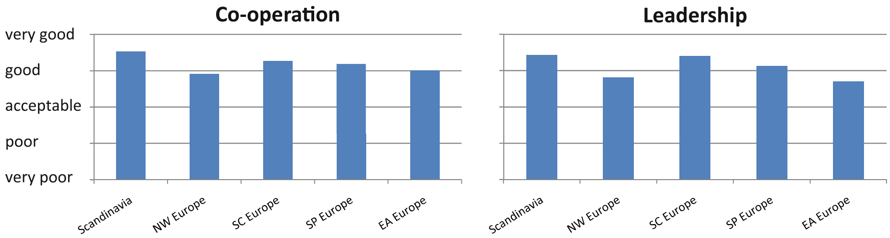

Fig. 2 Average assessments of CRM-skills for Captains in scenario 5

The remaining differences that obviously are rooted in cultural factors concentrated in the category LM for the Captains as well as SA and DM for the FOs. The only multivariate F-Test which became significant is for scenario 5 of the Captains ($F(16,372) = 2{,}37$, $p < 0.01$). Some univariate F-Tests for single categories were significant as well: LM (scenario 5 and 7), SA (scenario 7) and DM (scenario 5) for the Captains. For the FOs the significant univariate F-Tests are for DM (scenario 3 and 5), SA (scenario 2) and CO (scenario 4). However, the effect sizes are rather small and did not traverse the critical threshold of pass and fail. We identified stronger cultural differences for positive CRM behaviors than for negative. On the five-point scales ratings often varied between acceptable, good and very good and not between pass/fail. Two examples of cultural differences are shown in Figs. 2 and 3.

The distributions of average CRM assessments shown in Figs. 2 and 3 do not exactly reflect differences on the Hofstede scales underlying the European cultural clusters (see Table 1). Nevertheless, for the FO assessments some significant negative correlations with the FMAQ-scale Command Responsibility [7] were found. Command Responsibility is related to Hofstede's dimension of Power Distance. Correlations were with Co-operation—.22 ($p = 0{,}04$), Leadership—.24 ($p = 0{,}05$), Situation Awareness—.33 ($p = 0.00$), Decision Making—.25 ($p = .07$). In other words instructor pilots who prefer lower authority gradients in the cockpit tended to

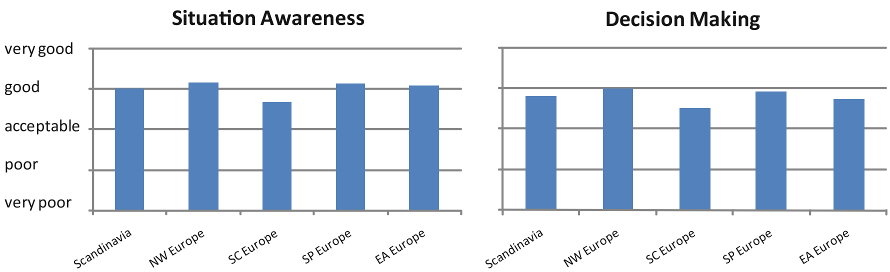

Fig. 3 Average assessments of CRM-skills for FOs in scenario 2

assess the FOs CRM-skills slightly higher than those who belonged to higher Power Distance groups.

Conclusions

This investigation into the cultural robustness of NOTECHS has shown that the system in fact covers some quasi-universal CRM concepts at least for the European region. On the qualitative level it seems to provide appropriate orientation towards the kind of behavioral skills which should be observed in a CRM assessment. Related to the proposed cultural clusters, a few quantitative differences could be identified. While instructors across Europe had no disagreement about the nature of bad CRM practice, there seems to be more cultural diversity in views about excellent CRM performance especially for Captains. The agreement was higher for the cognitive skills (SA, DM) of Captains than for their social skills (CO, LM). For FOs agreement was higher on their social skills.

Some but not all of the cultural difference can be attributed to effects of English language proficiency. In this context it is interesting to note the recent requirement by ICAO [11] for language proficiency of pilots and air traffic controllers, which intends to prevent communication problems due to lack of English. In the long run, this requirement could also improve the common understanding of the CRM terminology. Another factor contributing to the cultural variation in views about CRM skills is PD. Instructors who prefer higher authority gradients in the cockpit tended to judge FOs' CRM skills stricter.

NOTECHS can be seen as an example of a *dominant model* in aviation [13]. Even though it was derived from a thorough literature review of a variety of other models, it reflects values for effective crew co-operation with preference for lower levels of Power Distance and higher degrees of Individualism. These assumptions may be challenged by some contextual conditions, which limit their generality. Therefore, its implementation in any airline's operational context requires some amount of adaptation work. If under different local conditions management would simply prescribe to emulate the dominant model, this could lead to just *cosmetic compliance* with the danger to collapse under stressful operational conditions. The only way to develop accurate and efficient solutions in regions that do not share the same economic and cultural features inherent in the dominant model, is to consider culturally calibrated modifications of the model. Regulators and international organizations should mediate in this respect. Some practical experiences about implementation of NOTECHS in the operational context of airlines in Europe and the Middle East are reported in the literature (e.g. [2, 6, 12, 14].

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