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Musicality of Human Brain through Fractal Analytics

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Dedicated
to
myriad-minded person
Rabindranath Tagore

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Contents

Prologue

Can music be defined? "*You are the music while the music lasts*"—music is so defined by T.S. Eliot. Music is one of the oldest entities of human culture, played a very important role in the evolutionary process. There is no culture which has no language; there is no culture which has no music; this book intends to explore this universal nature of music. Tagore in his famous conversation with Einstein says "In India, the measure of a singer's freedom is in his own creative personality. He can sing the composer's song as his own, if he has the power creatively to assert himself in his interpretation of the general law of the melody which he is given to interpret". The conversation which took place almost a century ago is still very much relevant in the present context. Still today, most people in the Indian subcontinent see music as a thing of art and craft, something in diametrically opposite poles to Science. It is only from the last two decades of the twentieth century that scientists began to understand the huge potential of systematic research that Indian Classical Music has to offer in the advancement of cognitive science as well as psychological research. The aim of any dramatic performance is to emote in the minds of audience a particular kind of aesthetic experience, which is described as "Rasa". The concept of "Rasa" or emotion is said to be the most important and significant contribution of the Indian mind to aesthetics. The ardor to obtain insights into these complex musical structures and their cognitive counterparts led to the foundation of this book. This book tries to seam together these two parallel domains of art and science with the help of another fascinating concept of the last century—the Chaos. The Chaos theory is said to be the new link between human and nature; where apparently random, disordered processes are characterized with some inherent order. The fractal techniques—which are essentially an offshoot of the chaos theory act essentially as a mathematical microscope delving into the depths of complex acoustic and EEG signal with such a high resolution that is not achievable by other methods. With the fractal tools, apparently random chaotic nonlinear signals reveal themselves in such a simple form in front of the readers. There lies the beauty of the technique which is so complicated in technical details, yet yields so simple outputs.

Starting from a unique insight into the modalities of Indian classical music, this book takes the readers to an idiosyncratic journey where they learn about how the emotions prevail in human mind even after they have stopped listening to the song to an objective method for capturing "improvisational" cues in Hindustani Music (HM). Improvisation, which is one of the forte of HM makes it separate from its Western counterpart, which mostly relies on written compositions has been dealt with objectively for the first time in this book. The readers also have novel insights into the neural mechanisms of a Hindustani classical musician when he is imagining or performing a *raga*; whether he is visualizing something or there is something else. A recent neuro-imaging based fMRI study published in *Nature Scientific Reports* says "creativity cannot be fully explained in terms of the activation or deactivation of a fixed network of brain regions; rather, when creative acts engage brain areas involved in emotional expression, activity in these regions strongly influences which parts of the brain's creativity network are activated, and to what extent". This prompted the need of a robust correlation based study to identify which regions of the brain are involved during a creative act which has been elaborately dealt with in this book. The book also shows how the simplest of acoustical stimuli, a tanpura drone has the ability to regulate and change brain state. Gestalt phenomenon in music is also dealt with in this book, where the question of nonrecognition of music is addressed with the help of different scaling methods by clipping certain frequency ranges. HM is known throughout the world because of its ability to convey emotions (or *rasas* as it is called in India) to its listeners, and that the emotions are often ambiguous, i.e., consists of more than one emotions. This eccentric feature is addressed in this book with an attempt to categorize and objectify emotional appraisals both from acoustic as well as neuro-scientific perspective. Finally, the book signs off with a number of new EEG signal processing techniques which have the ability to monitor single EEG frequency and has great potential in feature extraction as well as in the ambitious single neuron monitoring project. This is the first of its kind study with such a high resolution to look into the real-time EEG data.

The wide spectra of topics covered in this book will help the readers in better understanding of the intimate relationship between music and the emotional experience and its neuro-cognitive significance which in turn can guide to use proper music as an effective therapeutic agent, which is the ultimate long-term goal for conducting this kind of research work. Application of derived knowledge from the work may be utilized in different physiological counseling centers, chronic physiological ailing persons and in school education.

The authors hope that this compilation of the original research work on the analysis on musicality and brain through fractal analysis will definitely provide a platform and a direction for inquisitive students and researchers of music, psychologists, and neuro-scientists to think objectively on the premises. The authors also feel that this work will stimulate more exhaustive research in different genres of music for its enrichment.

We are really happy that the leading publisher Springer Nature has accepted the book for publication. The authors sincerely thank editors and all the other staffs of Springer Nature for their continual help, support, and suggestions to enrich the book. We thank all the musicians whose recordings have been used for analysis in the book. We conclude with the words of the great maestro, Tagore:

On this harp of finitude. You play the tune of Infinite, O Boundless!

Kolkata, India

Dipak Ghosh
Ranjan Sengupta
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Chapter 1
Introduction

Neuroscience can't tell you what beauty is,
but if you find it beautiful the medial orbito-frontal cortex
is likely to be involved; you can find beauty in anything
—Semir Zeki

1.1 Music and Science

Music is one of the oldest forms of art that has survived the perks of globalization and evolved in new forms. It has been integrated with the cultural activities of mankind from time immemorial. Probably because of the integral relationship between music and culture, it sparked interest among early philosophers in every civilization and India is no exception. The recorded evidence of musical activities in India dates back to more than 2000 years. There have been attempts to a sort of metaphysical rationalization in music in early days followed by attempts, at times, to formalize music including structures in some domains of it. A definite direction in the paradigm of music analysis seemed to emerge universally which was mainly attributed to the perception of pitch. The other cognitive phenomena of attention, among others, were loudness, timbre and rhythm. Pitch began to be conceived not as a continuum but a repetitive set of discrete intervals. Notably this discretization of continuum has striking similarity in terms of numbers, measures and repeatability in the music of completely different origin in different parts of the world. As the development of music continued, number of intervals grew and ultimately stabilized in a reasonably small numbers. The big intervals later on began to be divided into smaller sub-intervals because of the need to understand finer aesthetic perception. In Indian musical structures, swaras (intervals) and shrutis (microtonal intervals) emerged some 2000 years back. The ancient period witnessed intense debate and theorization by different philosophers of music. The basic premise on which these debates relied is the acute sense of perception simply because of the absence of appropriate tools for objective measurement of the related matters. Modern scientific research aims to understand everything about music: it's basic structure; it's biological, emotional and psychological effect on humans and the

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brain; its healing abilities; and its function in the evolutionary process. Why can a person relate to music without learning it first? Why does music evoke such an emotional response? Why does some music evoke a strong response in some and not in others? How did music come to be? With the development of robust scientific tools for analysis of music, we have seen a great interest among experts in the fields of neuroscience, psychology, biology, physiology, physics and education who are working alongside musicians to unravel the mysteries of music. A comprehensive scientific approach therefore needs to address the physical reality of acoustics and the mental realities of semiotics. In Indian music, this approach needs to have a dimension somewhat different from that obtainable for western music as Indian classical music (ICM) focuses more on melody created using a sequence of notes while in Western Classical music (WCM) apart from melody, there is stress on harmony too i.e. different notes are played together instead of in a sequence. Thus, ICM is mainly monophonic while in WCM the stress lies to a great extent in polyphonic composition. Datta et al. (2017) in their recent book has discussed a comprehensive overview of the basics of Hindustani music and the associated signal analysis and technological development.

To our mind, it is this ultimate reality, where matter and mind play equal roles, the science of music should and must graze. The formation of a linkage between the natural processes of progress from sensory perception to concept formation inherent in human mind is to be included in the scheme of science. It is useful to recollect here the caution given by Pauli (Schuster 1995) "…. pure logic is fundamentally incapable of constructing such a linkage. The most satisfactory course, it seems, is to introduce at this point a postulate of an order …., the relation between sense perception and Idea remains a congruence of the fact that both the soul and what is known as perception are subject to an order objectively conceived." This order is to be born and this is the real challenge of science in music.

The study of music cognition is drawing an increasing amount of research interest as there is an increasing understanding among scientists that music is a universal human trait, which plays crucial roles in everyday life and at different stages of life. Also, from the perspective of studying the human mind, the cognitive processing of music simultaneously engages most of the perceptual, cognitive, and emotional processes. Like language, music is a human universal involving perceptual discrete elements organized into hierarchically structured sequences. Music can thus provide the study of brain mechanisms, underlying complex sound processing, and also can provide novel insights into the functional and neural architecture of brain functions. The change in the structure and form of music might bring a change in the neural dynamics which can be studied in detail using the modern tools of neuroscience. Thus, the study of music cognition in general is important for studying the structural patterns of music in general as well as to gain novel insight into the complex neural dynamics.

From a physical point of view, musical signals are approximately periodic in micro and macro forms. In this approach, musical signals seem to have a deterministic behavior but this is not really the case, as music would then be a deterministic issue of rational human thought (Baroni et al. 1999). On the other hand, there is a widespread opinion (in linguistic, aesthetic and cognitive philosophy) that music is a complex, and multidimensional nonlinear system (Frova 1999). A number of earlier studies are based on rhythmic and harmonic structure of the musical notes, while frequency analysis may fail to decipher the real dynamics in case of polyphonic recordings. A few studies have been done to correlate complex actions coordinated by people with complex rhythmic musical sequence (Large 2000; Loehr et al. 2011). One such study says (Large 2000) that as people listen to rhythmic structure of music; a stable multi-periodicity pattern arises psychologically, which is a manifestation of the temporal structure of the rhythm. Non-linear dynamical modeling for source clearly indicates the relevance of non-deterministic / chaotic approaches in understanding the speech/music signals (Hsü and Hsü 1990; Datta et.al. 2008; Sengupta et.al. 2001, 2010, 2010b; Bigrelle and Iost 2000). In this context, fractal analysis of the signal which reveals the complex geometry embedded in signal assumes significance. The Electroencephalography (EEG) on the other hand is a neuro-scientific bio-sensor which gives plentiful information about the complex neuronal interactions happening in different locations of the brain in the form of scalp potentials. The complex EEG signals arising from different lobes of brain has been assessed with a number of methods of which non-linear techniques have been found to be most appropriate due to the presence of inherent spikes in EEG data. In this book, we look forward to study mainly various ways in which music (with special emphasis given on Hindustani Classical Music) conveys emotions and the associated brain correlates involved in emotion processing by fractal analysis of both the music signals and EEG signals.

1.2 Music and Emotion: Looking into Historical Perspective

Music has existed in one way or another for over thirty thousand years. Archeologists discovered that early Neanderthals were able to create simple flutes. However, early humans most likely did not have the ability to do much with music since they were hunters and gatherers. As a result, early humans were probably much too concerned with making sure that they did not wake up one morning and discover that the herds of wild game that they had been hunting had moved on. Not until much later in history did humans begin to connect music with the ability to heal. Ancient Egyptians thought that their gods gave them music so they could heal and purify their souls. The ancient Greeks connected music with the power to heal the body. Yet, music was not explored in greater detail with regard to its healing abilities until about thirty years ago. Since then, people have dedicated more time and money into researching the physical effects of music on the mind and body. Since World War II, the health benefits of music have become more recognized in mainstream medicine. Today, no human culture is known that does not have music.

"Music medicine" has only begun to receive serious scientific consideration, with rigorous medical research beginning to build up in the late 1980s.

The ability of music to activate "pleasure centers" (Blood and Zatorre 2001) and induce a wide range of emotions has been well established in the last decade or so (Juslin and Sloboda 2001; Scherer 2005). Listening to music and appreciating it is a complex process that involves memory, learning and emotions, Music is remarkable for its ability to manipulate emotions in listeners. However, the exact way in which the brain processes music is still a mystery. What are the specific features of music which induce emotional responses, and how do they induce? Can certain specific features of music only trigger emotional responses? If so, what are they? Till date there is no single unified theory of music and emotion to which everyone agrees. A number of theories have been proposed to address such questions and include influential discussions by Aristotle, Charles Darwin, Suzanne Langer, Leonard Meyer, Peter Kivy, and many others but the fundamental question still remains: Do music convey emotional arousal directly or are there certain cognitive processes and motor neurons involved which mediate the link?

A wide range of human response based psychological studies were conducted over the last century to know the exact modality in which emotional appraisal takes place due to various features of music. These studies revealed that specific features of music such as intensity (loudness), tempo, dissonance, and pitch, are strongly associated with emotional expressions. A small change in any of these features results in considerable change of emotional expressions (Ilie and Thompson 2006) and affective experience (Husain et al. 2002; Ilie and Thompson 2011).

In Hindustani Music (HM), the study of emotions has gained momentum only from the last decade of 20th century, though HM is known to convey a wide range of emotional experiences as briefed in Bharata' *Natyashastra* (Martinez 2001). A number of works tried to harvest this immense potential by studying objectively the emotional experiences attributed to the different *ragas* of Hindustani classical music (Balkwill and Thompson 1999; Balkwill et al. 2004; Wieczorkowska et al. 2010; Sengupta et al. 2012; Mathur et al. 2015), but all the studies deal with the psychological aspects of music induced emotion. We will first discuss a number of studies in the psychological domain which deal with the emotional appraisal of music and then we continue on to how the same can be done from a neuro-scientific approach.

1.3 Psychological Analysis of Emotion

The psychological studies of music induced emotions mostly believe that affective experience can be explained on the basis of two continuous dimensions—arousal and valence (Russell 1999, 2003). These dimensions of the circumplex model supposed to be orthogonal, where in any emotion can be characterized by its coordinates in a two-dimensional space. The 2-D emotion model has been used extensively in a number of earlier studies (for e.g., Krumhansl 1997; Schmidt and Trainor 2001; Husain et al. 2002; Kreutz et al. 2008; Vieillard et al. 2008). In one study, multidimensional scaling was used to examine the underlying structure of emotional responses to music (Bigand et al. 2005). Listeners were asked to group pieces on the basis of their similarity in emotional meaning. Dimensional models assume that positive and negative valence lie on opposite ends of a bipolar dimension (Russell 1991; Fontaine et al. 2007); hence it was assumed that positive and negative emotions are mutually exclusive and cannot be felt simultaneously (Russell and Carroll 1999). But the beauty of any music, especially Hindustani Music lies in its ambiguous nature i.e. the ability to convey multiple emotions which has also been supported by a few studies (Hunter et al. 2008; Larsen et al. 2009). In both of these experiments, listeners recorded higher levels of simultaneous happy and sad feelings when the tempo and mode cues were mixed compared to when they were consistent. Another interesting finding was that sad-sounding music elicited higher levels of mixed feelings compared to happy-sounding music.

There are a number of methods employed by the researchers to assess the emotional rating from the listeners. Mostly, listeners are asked to rate the emotion to the extent they feel the or perceive the effect of a particular emotion (e.g., Gagnon and Peretz 2003; Hunter et al. 2008). Another method is to present listeners with a list of possible emotions and ask them to indicate which one (or ones) they hear (e.g., Gundlach 1935). A third approach is to require participants to rate pieces on a number of dimensions (often arousal and valence; e.g., Schmidt and Trainor 2001; Vieillard et al. 2008). Though a number of studies in this domain, there is still a lot of debate regarding what emotions they measure, felt or perceived emotions. A number of studies report that perceived and felt musical emotions are associated (Evans and Schubert 2008; Hunter et al. 2010), i.e. when listeners feel sad after listening to sad music (Garrido and Schubert 2013, 2015). In general, however, emotions are perceived more strongly than experienced (Evans and Schubert 2008; Gabrielsson and Lindström 2010; Hunter et al. 2010). For example, a recent study report that participants feel happy while listening to sad music (Garrido and Schubert 2013), there is also a theory of time dilation while listening to pleasant music (Ghosh et al. 2016) or negative emotions when listening to pieces they like (and presumably find aesthetically pleasing; Schubert 2013).

But, there is a dearth in literature when it comes to the use of robust scientific methods being applied for categorization and quantification of emotions perceived from music. In the next section, we will explain in brief about the details about the advent of chaos theory and its implications in assessment of musical emotions using fractal techniques.

1.4 Chaos Theory: Small Fluctuations Large Outcome

Chaos is said to be the science of surprises, of the nonlinear and the unpredictable. It teaches us to expect the unexpected. While most traditional science deals with supposedly predictable phenomena like gravity, electricity, or chemical reactions, Chaos Theory deals with nonlinear things of the Universe, that are effectively impossible to predict or control, like turbulence, weather, the stock market, our brain states, internet traffic, seismic data, so on and so forth. The chaos theory can be best explained on the basis of "Butterfly Effect" developed by Edward Lorenz during his tenure as meteorologist at the Massachusetts Institute of Technology. The main essence of this theory was that small perturbations in the initial state lead to large fluctuations in the future which were beautifully substantiated with the help of following statement: "e.g. a butterfly flapping its wings in South America can affect the weather in Central Park". Unpredictability also plays an important role in defining the state of a complex system as we are never aware fully of the initial state of the system. These phenomena are often described by fractal mathematics, which captures the infinite complexity of nature. Fractals are said to be human's immediate link with nature. Benoit Mandelbrot developed the field of fractal geometry (Mandelbrot 1977) which played a key role in the emergence of chaos theory. Chaos is not simply disorder but explores the transitions between order and disorder, which often occur in surprising ways. Many natural objects exhibit fractal properties, including landscapes, clouds, trees, organs, rivers etc., and many of the systems in which we live exhibit complex, chaotic behavior. Recognizing the chaotic, fractal nature of our world can give us new insight, power, and wisdom. In his pioneer work Poincaré (1914, 2013) says: "If we knew exactly the law of nature and the situation of the universe at the initial moment, we could predict exactly the situation of that same universe at a succeeding moment. But even if it were the case that the natural laws had no longer any secret for us, we could still only know the initial situation approximately. If it enabled us to predict the succeeding situation with the same approximation, that is all we require, and we should say that the phenomenon had been predicted, that it is governed by laws. But it is not always so: it may happen that small differences in the initial conditions produce very great ones in the final phenomena. A small error in the former will produce an enormous error in the latter. Prediction becomes impossible, and we have the fortuitous phenomenon". Thus, in case of deterministic chaos, measurements made on the state of a system at a given time may not allow us to predict the future situation, despite the fact that the governing equations are exactly known. By definition, these equations are named chaotic and that they predict a deterministic chaos. But with the advent of mathematics and technology, it has now become possible to perform numerical calculations of the time evolution of the properties of systems sensitive to initial conditions. It is also known that deterministic chaos is always associated with nonlinear systems; and nonlinearity is a necessary condition for chaos but not a sufficient one. In this regard, the use of fractal and multifractal techniques to assess a number of nonlinear physiological and biological systems assumes great importance. This techniques form the main forte of this book and has been discussed in the next section elaborately.

1.5 Fractals and Multifractals: A New Dialogue Between Human and Nature

A fractal is a rough or fragmented geometrical object that can be subdivided in parts, each of which is (at least approximately) a reduced-size copy of the whole. Fractals are generally self-similar and independent of scale (fractal dimension)—the degree of roughness or brokenness or irregularity in an object. They are created by repeating a simple process over and over in an ongoing feedback loop. A fundamental characteristic of fractal objects is that their measured metric properties, such as length or area, are a function of the scale of measurement. A classical example to illustrate this property is the "length" of a coastline (Mandelbrot 1967). When measured at a given spatial scale d, the total length of a crooked coastline L(d) is estimated as a set of N straight line segments of length d. Since the small intricate details of the coastline are not measured in lower resolution, the length L(d) of the coastline keeps on increasing with the increase of measurement scale of 'd'.

Figure 1.1 objectively gives an assessment about how the length of the British coastline changes when the scale of measurement is varied and made as small as possible.

As one looks closer we observe that the large triangle is composed of three smaller triangles half the size (side length) of the original, which in turn are composed of three smaller triangles, and so on, and so on. On all scales the Sierpenski triangle is an exactly self-similar object. In this regard, a fractal tool acts as a mathematical microscope zooming its way into the intricate complex details of an otherwise random object/signal/image (Fig. 1.2).

Fig. 1.1 The coastline of Britain in different scales *Source* http://www.duke.edu/~mjd/chaos/chaos.html

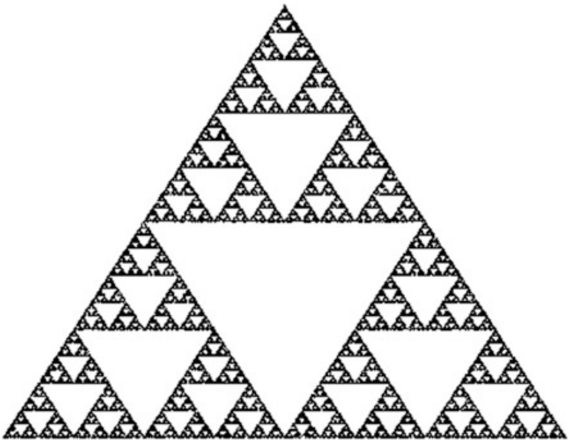

Fig. 1.2 The Sierpenski triangle: A common example of fractal image *Source* https://en.wikipedia.org/wiki/Sierpinski_triangle

Fractal geometry allows bounded curves of infinite length, and closed surfaces with infinite area. It even allows curves with positive volume, and arbitrarily large groups of shapes with exactly the same boundary. This is exactly how our lungs manage to maximize their surface area. Our lungs cram the area of a tennis court into the area of just a few tennis balls. The kidneys, the liver, the pancreas are all organs constructed along self-similar fractal rules (Figs. 1.3, 1.4, 1.5, and 1.6).

On the other hand, a multifractal is a set of intertwined fractals. Self-similarity of multifractals is scale dependent (spectrum of dimensions). It is well-established experience that naturally evolving geometries and phenomena are rarely characterized by a single scaling ratio; different parts of a system may be scaling differently. That is, the clustering pattern is not uniform over the whole system. Such a system is better characterized as 'multifractal' (Lopes and Bertouni 2009). A multifractal can be loosely thought of as an interwoven set constructed from sub-sets with different local fractal dimensions. Real world systems are mostly multifractal in nature. Nowadays, fractal geometry is used to describe many

Fig. 1.3 Influenza Virus *Source* www.sciencephoto.com

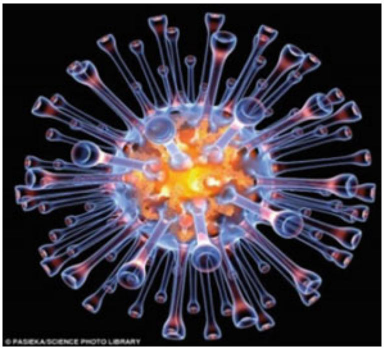

Fig. 1.4 Swine Flu Virus *Source* www.sciencephoto.com

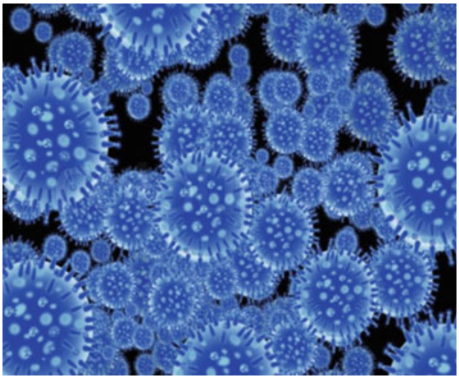

Fig. 1.5 Bacteria *Source* www.sciencephoto.com

Fig. 1.6 Blood vessels *Source* www.sciencephoto.com

complex phenomena. Fractals help us understand turbulence, not just how it arises, but the motion of the turbulence itself. Blood vessels can also be considered as fractals, as they can be divided down into smaller and smaller sections. They perform what has been described as “dimensional magic”, squeezing a large surface area into a limited volume. So are earthquakes. The distribution of earthquakes was known to fit a mathematical pattern. This pattern was picked up by geologists and found to be fractal. The fractal dimensions of a metal’s surface also tell us a lot about its strength. Since it was proposed MFDFA has been applied in diverse fields starting from turbulence analysis (Telesca and Lovallo 2011), traffic movements (Shang et al. 2008), faults and joint systems (Lin and Chen 2013), geological time series (Hajian and Movahed 2010), blood flow oscillations (Liao and Jan 2011) to stock exchange (Yuan et al. 2009; Gu et al. 2010), words in literature (Marcussen 2014), radar pulses (Hu et al. 2006) and even for the prognosis of diseases (Dutta et al. 2013; Ghosh et al. 2014). In the domain of music induced emotion, a number of recent works by the authors (Banerjee et al. 2016, 2017; Sanyal et al. 2016a, 2016b; Maity et al. 2015) deal with the discrimination of neural state under the influence of two different sets of emotional music. A number of chapters in this book also deals with these features. The next section of this book gives an introduction to how different musical clips affect our brain states and how, emotions can be quantified with the help of robust fractal techniques.

1.6 How Music Affects Our Brain: From a Neuro-Physical Approach to Fractal Analysis Techniques

Music engages much of the brain, and coordinates a wide range of processing mechanisms. This naturally invites consideration of how music cognition might relate to other complex cognitive abilities. The tremendous ability that music has to affect and manipulate emotions and the brain is undeniable, and yet largely inexplicable. Very little serious research had gone into the mechanism behind music’s ability to physically influence the brain and even now the knowledge about the neurological effects of music is scarce.

The human brain is said to be the complex organ in the Universe and what’s more fascinating is that it is organized by chaos. The organizational geometry of human cortical grey matter was the subject of study for Zhong (2008). The analysis on all spatial sizes shows fractality up to the measurement of 2.5 mm depending on cortex thickness. Also, the folding of the brain shows fractality for the largest spatial scales. As a whole, it can be said that fractality exists in both area and volume of the brain. Thus, human brain functional networks demonstrate a fractal small-world architecture which supports critical dynamics and task-related spatial reconfiguration while preserving global topological parameters. It involves billions of interacting physiological and chemical processes that give rise to experimentally observed neuro-electrical activity, which is called an electroencephalogram (EEG).

Music can be regarded as input to the brain system which influences the human mentality along with time. Since music cognition has many emotional aspects, it is expected that EEG recorded during music listening may reflect the electrical activities of brain regions related to those emotional aspects. The results might reflect the level of consciousness and the brain's activated area during music listening. It is anticipated that this approach will provide a new perspective on cognitive musicology.

Music is widely accepted to produce changes in affective (emotional) states in the listener. However, the exact nature of the emotional response to music is an open question and it is not immediately clear that induced emotional responses to music would have the same neural correlates as those observed in response to emotions induced by other modalities. Although there is an emerging picture of the relationship between induced emotions and brain activity, there is a need for further refinement and exploration of neural correlates of emotional responses induced by music. Cognitive musicology was envisaged by Seifert (1993) and Leman (1994) to be composed from diverse disciplines such as brain research and artificial intelligence striving for a more scientific understanding of the phenomenon of music. In recent years, computational neuroscience has attracted great aspirations, exemplified by the silicon retina (Chow et al. 2004) and the ambitious Blue Brain Project that aims at revolutionizing computers by replacing their microcircuits by models of neocortical columns (Markram 2006). Research activity in auditory neuroscience, applied to music in particular, is catching up with the scientific advances in vision research. Shamma et al. (2001) proposed that the same neural processing takes place for the visual as well as for the auditory domain. Other researchers suggested biologically inspired models specific to the auditory domain; e.g., Smith and Lewicki (2006) decomposed musical signals into gammatone functions that resemble the impulse response of the basilar membrane measured in cats.

Brain imaging grants access to music-related brain processes directly rather than circuitously via psychological experiments and verbal feedback by the subjects. A lot of experimental work in auditory neuroscience has been performed, in particular exploring the innate components of music abilities. In developmental studies of music, magnetoencephalograms have been used to study fetal music perception (Eswaran et al. 2002). Mismatch negativity in newborns has shown how babies discriminate pitch, timbre, and rhythm (Stefanics et al. 2007). A summary of electroencephalogram research in music leads Koelsch and Siebel (2005) to a physiologically inspired model composed of modules, e.g., for gestalt formation and structure building where the special features of the model are the feedback connections enabling structural reanalysis and repair. EEG has been used in cognitive neuroscience to investigate the regulation and processing of emotion for the past decades. Linear signal analysis methods such as Power Spectral Density (PSD) of alpha, theta and gamma EEG frequency rhythms have been used as an indicator to assess musical emotions (Schmidt and Trainor 2001). Asymmetry in alpha or theta power among the different regions of brain has been used in a number of studies as an emotion identification algorithm (Lin et al. 2010; Sammler et al. 2007; Schimdt and Hanslmayr 2009). Though the frontal lobe has been proven to the most vital when it comes to the processing of musical emotions in healthy as well as depressed individuals, there are other lobes also which has been identified to be associated with emotional responses. In (Sarlo et al. 2005) it was shown that the alpha-power changes at right parietal lobe, while the theta-power changes at right parietal lobe (Aftansas et al. 2004), pleasant music produces an increase in the frontal midline (Fm) theta power (Sammler et al. 2007), while degrees of the gamma band synchrony over distributed cortical areas were found to be significantly higher in musicians than non musicians (Bhattacharya and Petsche 2001). Human being interacts with music both consciously and unconsciously at behavioral, emotional and physiological level. Listening to music and appreciating it is a complex process that involves memory, learning and emotions. To this end, Bhattacharya and Petsche (2005) have presented a phase synchrony analysis of EEG in five standard frequency bands: delta (< 4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (> 30 Hz). The analysis was done using indices like coherence and correlation in two groups of musicians and non musicians. They observed a higher degree of gamma band synchrony in musicians. Frequency distribution analysis and the independent component analysis (ICA) were used to analyze the EEG responses of subjects for different musical stimuli. It was shown that some of these EEG features were unique for different musical signal stimuli (Bhattacharya and Petsche 2001). Lin et al. (2014) used independent component analysis (ICA) to systematically assess spatio-spectral EEG dynamics associated with the changes of musical mode and tempo. The results showed that music with major mode augmented delta-band activity over the right sensorimotor cortex, suppressed theta activity over the superior parietal cortex, and moderately suppressed beta activity over the medial frontal cortex, compared to minor-mode music, whereas fast-tempo music engaged significant alpha suppression over the right sensorimotor cortex.

The scalp EEG arises from the interactions of a large number of neurons whose interactions generally nonlinear and thus they can generate fluctuations that are not best described by linear decomposition. On the other hand, the classical nonlinear dynamics method such as correlation dimension and Lyapunov exponents are very sensitive to noise and require the stationary condition, while EEG signals often are highly non-stationary. But, the use of non linear parameters to determine the music induced emotional states from EEG data is very scarce in literature. Natarajan et al. (2004) used nonlinear parameters like Correlation Dimension (CD), Largest Lyapunov Exponent (LLE), Hurst Exponent (H) and Approximate Entropy (ApEn) are evaluated from the EEG signals under different mental states. The results obtained show that EEG to become less complex relative to the normal state with a confidence level of more than 85% due to stimulation. It is found that the measures are significantly lower when the subjects are under sound or reflexologic stimulation as compared to the normal state. The dimension increases with the degree of the cognitive activity. This suggests that when the subjects are under sound or reflexologic stimuli, the number of parallel functional processes active in the brain is less and the brain goes to a more relaxed state. Gao et.al. (2007) was the first to apply the scaling technique called Detrended Fluctuation Analysis (DFA) on EEG signals to assess the emotional intensity induced by different musical clips. In this study two scaling exponents' β1 and β2 was obtained corresponding to high and low alpha band. It was concluded that emotional intensity was inversely proportional to β1 and directly proportional to β2.

1.7 Study of Effects of Music on Brain: An Indian Perspective

Music in India has great potential in this study because Indian music is melodic and has somewhat different pitch perception mechanisms. Western classical music which is based on harmonic relation (Martinez 2001) between notes versus the melodic mode (*raga*) structures in the Hindustani classical music system (HCM) within the rhythmic cycle music may demand qualitatively different cognitive engagement. The analysis of EEG data to determine the relation between the brain state condition in the presence of HCM and its absence would therefore be an interesting study. How rhythm, pitch, loudness etc. interrelate to influence our appreciation of the emotional content of music might be another important area of study. This might decipher a technique to monitor the course of activation in the time domain in a three-dimensional state space, revealing patterns of global dynamical states of the brain. It might also be interesting to see whether the arousal activities remain after removal of music stimuli.

Despite the world's diversity of musical cultures, the majority of research in cognitive psychology and the cognitive neuroscience of music have been conducted on subjects and stimuli from Western music cultures. From the standpoint of cognitive neuroscience, identification of fundamental cognitive and neurological processes associated with music requires ascertaining that such processes are demonstrated by listeners from various cultural backgrounds and music across cultural traditions. It is unlikely that individuals from different cultural backgrounds employ different cognitive systems in the processing of musical information. It is more likely that different systems of music make different cognitive demands.

Western classical music which is based on harmonic relation between notes versus the melodic mode (*raga*) structures in the Indian classical music system (ICM) within the rhythmic cycle music may demand qualitatively different cognitive engagement. To elaborate this point further, ICM music is monophonic or quasi monophonic. Unlike the western classical system, there is no special notation system for music. Instead letters from the colloquial languages are used to write music. For instance notations of the ICM such as 'Sa, Re, Ga' may be written in Hindi, Kannada or Tamil where as the Western classical system music includes a unique visuo-spatial representation. It emphasizes on reading the exact position of symbol indicating a whole tone or a semitone on the treble or a bass clef. The scale systems (*Raga*s) are quite elaborate and complex provides a strict framework within which the artist is expected bring out maximum creativity. Although specific emotion (rasa) is associated with particular *raga*, it is well known that the same *raga* may evoke more than one emotion. Well trained artists are able to highlight a particular rasa by altering the structures of musical presentations such as stressing on specific notes, accents, slurs, gamakas or taans varying in tempo etc. Musicians as well as ardent connoisseurs of music would agree that every single note has the ability to convey an emotion. Many experience a 'chill' or 'shiver down the spine' when a musician touches certain note or sustains of a note. The meter system is again quite complex. Indian rhythm and metre system is one of the most complex systems compared to other meters used in world music. Film music, which has been influenced by music from all over the world, is much more popular in the current times. Therefore implicit of knowledge of the Western chord system is perhaps present in our population. ICM is chiefly an oral tradition with importance given on memorizing compositions and *raga* structures and differences exist in the methods of training even within the two traditional systems of ICM. Semantics of Indian music would differ from that of the western classical music system or other forms of musical system. More often than not music in Indian culture is intimately associated with religious and spiritual practices. Hypothetically these differences in the musical systems perhaps makes qualitatively different demand on the cognitive functions involved and thereby qualitatively varying degree of involvement of the specialized neural networks implicated in musical processing. Research endeavours are yet to be carried out in this direction.

In India research in the area of Music Cognition is still in its infancy. The effect of Indian classical music and rock music on brain activity (EEG) was studied using Detrended fluctuation analysis (DFA) algorithm, and Multi-scale entropy (MSE) method (Karthick et al. 2006). This study concluded that the entropy were high for both the music and the complexity of the EEG increases when the brain processes music. Another work in the linear paradigm (Geethanjali et al. 2012) analyses the effect of music (carnatic, hard rock and jazz) on brain activity during mental work load using electroencephalography (EEG). EEG signals were acquired while listening to music at three experimental condition (rest, music without mental task and music with mental task). The findings show that while listening to jazz music, the alpha and theta powers were significantly ($p < 0.05$) high for rest as compared to music with and without mental task in Cz. While listening to Carnatic music, the beta power was significantly ($p < 0.05$) high for with mental task as compared to rest and music without mental task at Cz and Fz location. It has been concluded from the study that attention based activities are enhanced while listening to jazz and Carnatic as compared to Hard rock during mental task. Chen et al. (2008) monitored the brain wave variation by changing the music type (techno and classical) and the results showed when the music was switched from classical to techno, there was a significant plunge of alpha band and from techno music to classical there was an increase in beta activity.

The presence of multifractality in tanpura, sitar, sarod and flute signals is studied through an examination of relationship between q and Dq and the functional relationship between Dqs (Datta et al. 2008; Sengupta et al. 2005, 2010a, b). Braeunig et al. (2012) describes a new conceptual framework of using tanpura drone for auditory stimulation in EEG. In a laboratory setting spontaneous brain electrical activity was observed during Tanpura drone stimulation and periods of silence. The brain-electrical response of the subject is analyzed with global descriptors, a way to monitor the course of activation in the time domain in a three-dimensional state space, revealing patterns of global dynamical states of the brain. Fractal technique has been applied to assess change of brain state when subjected to audio stimuli in the form of tanpura drone (Maity et al. 2015), studying hysteresis effects (Banerjee et al. 2016) and in a number of other studies. The EEG time series has been used to perform this study and the corresponding non-linear waveform of EEG was analyzed with the widely used DFA/MFDFA techniques. The following chapters give an elaborate account of all these studies performed at Sir C.V. Raman Centre for Physics and Music, Jadavpur University in the last decade or so. In this context, it is also worth mentioning that some excellent and rigorous research work in the area of music signal analysis was done at the ITC Sangeet Research Academy during the last three decades (Banerjee et al. 1983; Sengupta et al. 1983, 1989, 1995, 2000, 2001, 2005, 2007, 2010; Sengupta 1990; Banerjee and Nag 1991; Datta et al. 1997, 1998, 2006, 2007; Chakraborty et al. 2009).

The chapters in the book are intended to look objectively into various questions perturbing serious researchers of music and non linearity. It primarily contains the results of the exhaustive research done in the area at Sir C V Raman Centre for Physics and Music, Jadavpur University, India. The book arises out of the need to consolidate this scattered knowledge in a structured and comprehensive manner. The authors also feel that there is a need for awareness about the immense potential of combining experimental and experiential approach in this kind of unique research in the subcontinent. While consolidating these scattered results, each of the experiments was thoroughly and critically examined and whenever necessary the experiments were redone including review of the data. We hope that the book may be useful to musicologists in general and those interested in the area of music cognition and music therapy. This may also be of interest to people who want to know about different application of non linear dynamics. It is also hoped that the book will go a long way in narrowing the gap between musicians and scientists. The book may give the scientific mind a new field to play with.

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Chapter 2
Non Linear Techniques for Studying Complex Systems

Clouds are not spheres, mountains are not cones,
coastlines are not circles,
and bark is not smooth,
nor does lightning travel in a straight line

—Benoit Mandelbrot

2.1 Introduction

In the words of Mendelbrot, a fractal is defined as a "A rough or fragmented geometric shape that can be subdivided in parts, each of which is (at least approximately) a reduced/size copy of the whole." In the last two or three decades much research has gone into the research of chaos theory which mainly deals with the dynamics of different complex systems that are found in nature. Chaos can be found everywhere, from nature's most intimate considerations to art of any kind. Chaos theory is the study of how systems that follow simple, straightforward, deterministic laws can exhibit very complicated and seemingly random long term behavior. With the advent of chaos theory we now have a number of robust tools which can deal with a variety of complex signals like DNA sequence, earthquake, turbulent water flows, weather changes, financial time series, faults in bone and most importantly human bio-signals. The use of fractal dimension has opened a whole new plethora of studies dealing with complex dynamics of these signals. This chapter is essentially a detailed description of the different algorithms used in various sections of this book. We start off with conventional Fourier decomposition methods which were used to compare with the non-linear methods and then continue with the various non-linear methods which have been used for assessment of various EEG and music signal data.

Most frequently used techniques of EEG analysis such as Fourier decomposition are essentially linear, but the human brain is the most complex nonlinear system. The scalp EEG arises from a large number of neurons, whose interactions with the neighboring neurons as well as with remote neurons are ought to be nonlinear and thus they can generate fluctuations that are not best described by linear

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decomposition. Hence, it is important to analyze these signals with the help of techniques which are robust against non-stationarities inherent in these signals as well as the spikes present. Classical methods of signal analysis work well mostly on stationary signals, so we need a new solution—new methods. Non-linear dynamical analysis has emerged as a novel method for the study of complex systems in the past few decades. The non-linear analysis method is effectively applied to electroencephalogram (EEG) data to study the dynamics of the complex underlying behavior. The growth of this method as a tool for mental health evaluation mainly rests on the non-invasive nature of EEG. The approach is based on the principles of non-linear dynamics and deterministic chaos that involves the characterization of the system attractors with its invariant parameters.

For a neuronal network such as the brain, nonlinearity is introduced even on the cellular level, since the dynamical behavior of individual neurons is governed by threshold and saturation phenomena. Moreover, the hypothesis of an entirely stochastic brain can be rejected due to its ability to perform sophisticated cognitive tasks. For these reasons, the electroencephalogram (EEG) appears to be an appropriate area for nonlinear time series analysis techniques, the practical spin-off from the theory of deterministic chaos.

Nonlinear dynamics (more precisely in this case—chaos theory) provides many new ways of analyzing signals, such as fractal methods. Some of these methods determine the scaling exponent of the signal which indicates the presence or absence of fractal properties (self-similarity). The FD of a waveform represents a powerful tool for transient detection. This feature has been used in the analysis of ECG and EEG to identify and distinguish specific states of physiological function. The fractal tool thus can essentially be compared with a mathematical microscope zooming its way into the inherent complex patterns of the signal and deducing a complex scaling exponent from the apparent random pattern. Many robust algorithms are available to determine the FD of the waveform. There are different methodological approaches and their respective statistical parameters to capture fractality namely Correlation dimension, Lyapunov exponent, Box counting method etc. These are very sensitive to noise and require the stationary condition while EEG signals are highly non stationary. For this reasons, we use a nonlinear method named Detrended Fluctuation Analysis (DFA) followed by Multifractal Detrended Fluctuation Analysis (MFDFA) which has the ability to capture scale varying nature of different naturally occurring time-series signals. To further elucidate how the internal dynamics of one signal affects the other, or in other words what is the degree of cross-correlation among the two, we take the help of Multifractal Detrended Cross Correlation analysis (MFDXA) which gives the cross-correlation coefficient as an output. Other unique and new methods used for feature extraction from EEG signals like neural jitter/neural shimmer and pitch extraction have also been discussed in detail in this chapter.

Music signals are far more complex in their dynamics as compared to the EEG signals due to the superposition of a large number of frequency components and hence their treatment with conventional power spectrum techniques is not justifiable. The MFDFA technique is much more accurate than the conventional DFA technique especially in case of music signals because of the fact that there are segments with extremely large variation as well as segments with very small variation (i.e. they are multifractals) therefore, the normal distribution considering second order RMS variation cannot be applied and all the q-order moments need to be considered. This method is very useful in the analysis of various non-stationary time series and it also gives information regarding the multifractal scaling behaviour of non-stationary signals. The music signals were initially processed with music analysis software Wavesurfer (Sjölander and Beskow 2000) and Cool Edit (Johnston 1999) before being used for listening test and EEG data acquisition.

The raw EEG signal is generally contaminated by various types of external artifacts such as eye blinks, muscular movement etc. Eye blinks and eye movements are characterized by frequency of less than 4 Hz and high amplitude. So, it is essential to get an EEG data which are free from these artifacts, which may induce considerable error in the final results. We propose a novel data-driven noise removal technique called Empirical Mode Decomposition (EMD) which helps in generation of noise/artifact-free EEG data in a few steps.

The Wavelet Transform Technique (WT) have also been utilized as a superior alternative to conventional Fourier Transform (FT) technique which decomposes the complete EEG signal into its five characteristic frequency bands viz. Delta (δ): 0–4 Hz (2) Theta (θ): 4–8 Hz (3) Alpha (α) 8–13 Hz (4) Beta (β): 13–30 Hz (5) Gamma (γ): 30–50 Hz. As most of the previous works in the domain of EEG signal processing uses the spectral power from these bands as a feature for distinguishing one brain state from another, we felt the need to compare the results obtained from non-linear analysis of these very spectral bands. Hence the WT technique has been applied in a number of studies elaborated later in this book. In the next sections, we present algorithms of the various techniques utilized later in this book, some of which have been used widely while some are entirely new based on our research in this subject. Firstly, the novel EMD technique utilized for removing the artifacts from raw EEG signal.

2.2 Empirical Mode Decomposition (EMD)

EMD is a decomposition method for non-stationary and nonlinear signals (Huang et al. 1998). The EMD technique decomposes a signal into a number of intrinsic mode functions (IMFs) that represent fast to slow oscillations. An IMF is a function that satisfies two conditions:

(1) the number of extrema and the number of zero crossings must either be equal or differ by at most one; and (2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. To obtain an IMF from the original signal x, a sifting process is performed (Huang et al. 1998) as follows:

First, all extrema of the original signal x need to be identified. All local maximum points are connected by a cubic spline line to form the upper envelope e_u. All local minima points are connected likewise to form the lower envelope e_l. The mean of e_u and e_l, a_1, is calculated as:

$$a_1 = \frac{(e_u + e_l)}{2} \tag{2.1}$$

The difference between the original signal and the mean is defined as the first component h_1:

$$h_1 = x - a_1 \tag{2.2}$$

In the next sifting process, h_1 is treated as the signal, and the mean a_{11} of its local maxima and local minima is found. Thus, we have:

$$h_{11} = h_1 - a_{11} \tag{2.3}$$

Subsequently, we can repeat this sifting procedure k times until h_{1k} is an IMF, with:

$$h_{1k} = h_{1(k-1)} - a_{1k} \tag{2.4}$$

Therefore, the first IMF component derived from the original signal is designated as:

$$c_1 = h_{1k} \tag{2.5}$$

The sifting process has been stopped when an IMF has been established by limiting the size of the standard deviation (SD), calculated from the two consecutive sifting sequences as below:

$$SD = \sum_{t=0}^{T} \frac{\left[h_{1(k-1)}(t) - h_{1k}(t)\right]^2}{h_{1(k-1)}^2(t)} \tag{2.6}$$

A typical value for SD can be set between 0.2 and 0.3 (Huang et al. 1998). In our case the value was set to 0.25. To extract the 2nd IMF component, we remove c1 from the original signal x:

$$r_1 = x - c_1 \tag{2.7}$$

The residual r_1 is treated as a new signal, and the same sifting process is applied to obtain the 2nd IMF component c_2 and the residual:

$$r_2 = r_1 - c_2 \tag{2.8}$$

This procedure is repeated on the subsequent residuals r_j's, until the final residual r_J no longer contains any oscillation information,

$$r_j = r_{j-1} - c_j \tag{2.9}$$

By summing up Eqs. (2.7)–(2.9), we can obtain:

$$x = \sum_{j=0}^{J} c_j + r_j. \tag{2.10}$$

Thus, original signal x is decomposed into J empirical modes c_j's and a residue r_J.

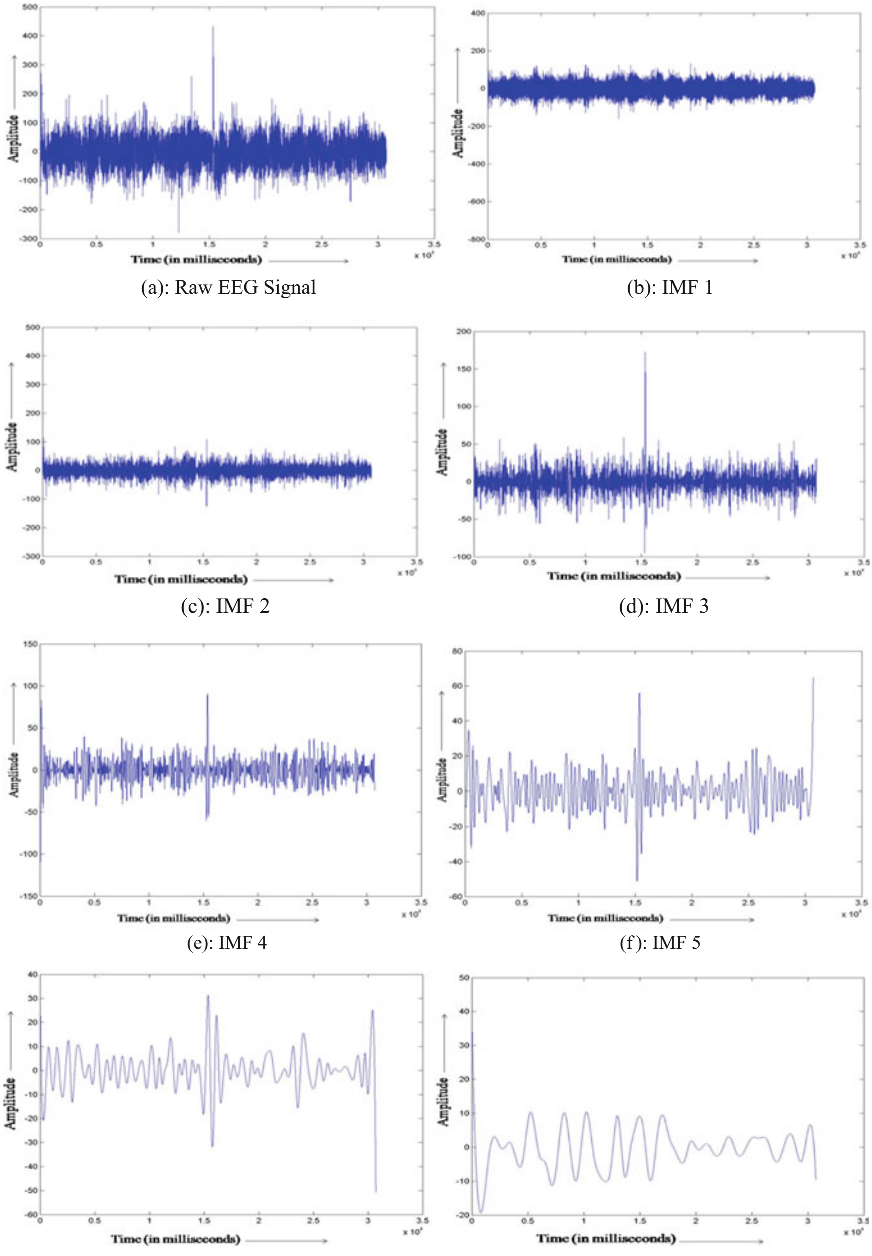
Since, the artifacts lies in the low frequency regions (<3.5 Hz) (Bizopoulos et al. 2013; Jung and Saikiran 2016), the IMFs that appear in this band are rejected. Thus, the filtered signal is the sum of the remaining IMFs and more specifically, only the first few IMFs including the residue were kept (Bizopoulos et al. 2013). We have obtained noise free EEG data for all the electrodes using the EMD technique and used this data for further analysis and classification of acoustic stimuli induced EEG features.

Figure 2.1a–k shows a representative figure of the F3 electrode in 10 s duration which was subjected to EMD technique and the noise-free EEG data. The sifting process was continued until the final residue is a constant, a monotonic function, i.e. a function with only one maxima or minima from which no more IMF's can be derived. We have set the value of SD to be 0.25 after which the sifting process has been stopped.

The noise-free signal obtained after the removal of muscular and blink artifacts has been used as the input for the wavelet transformation technique (Fig. 2.2).

2.3 Wavelet Transform

Wavelet transform forms a general mathematical tool for signal processing with many applications in EEG data analysis (Selesnick et al. 2005; Dimoulas et al. 2007; Hazarika et al. 1997). Its basic use includes time-scale signal analysis and decomposition of EEG signal. We have used WT technique to decompose the noise cleaned EEG signal obtained from the previous step into various frequency bands i.e. alpha (9–13 Hz), delta (1–3 Hz), theta (4–8 Hz), beta (14–30 Hz). The DWT (Akin et al. 2001) analyzes the signal at different frequency bands with different resolutions by decomposing the signal into a coarse approximation and obtains detailed information. DWT generally employs two sets of functions, called the scaling functions and wavelet functions, associated with low pass and high pass filters, respectively. The decomposition of the noise free signal into different frequency bands is done by successive high pass and low pass filtering of the time domain signal. The original signal x[n] is first passed through a half band high pass



(a): Raw EEG Signal

(b): IMF 1

(c): IMF 2

(d): IMF 3

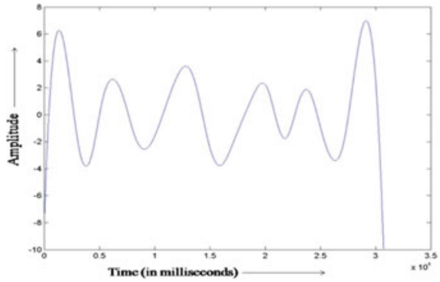
(e): IMF 4

(f): IMF 5

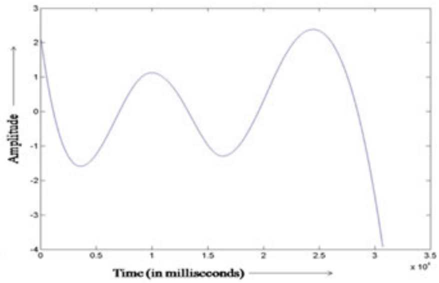
(g): IMF 6

(h): IMF 17

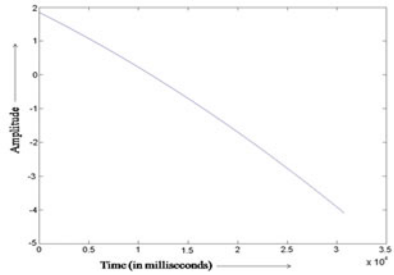
Fig. 2.1 Empirical Mode decomposition of a 10 s ‘with drone’ EEG signal of F3 electrode



(i): IMF 8



(j): IMF 9



(k): Residue

Fig. 2.1 (continued)

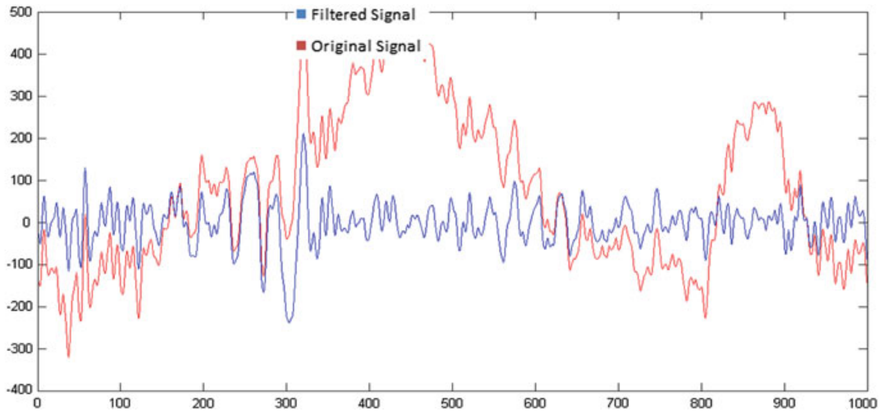


Fig. 2.2 Raw EEG signal and Artifact free EEG signal of 10 s

filter g[n] and a low pass filter h[n]. This constitutes one level of decomposition and can mathematically be expressed as follows:

$$y_{high}[k] = \sum x[n].g[2k - n] \tag{2.11}$$

$$y_{low}[k] = \sum x[n].h[2k - n] \tag{2.12}$$

where $y_{high}[k]$ and $y_{low}[k]$ are the outputs of the high pass and low pass filters respectively, after sub sampling by 2. This decomposition halves the time resolution since only half the number of samples now characterizes the entire signal. However, this operation doubles the frequency resolution, since the frequency band of the signal now spans only half the previous frequency band, effectively reducing the uncertainty in the frequency by half. The above procedure, which is also known as the sub band coding, can be repeated for further decomposition (Sivanandam and Deepa 2006; Mehrotra et al. 1997). Using the DWT technique we have extracted the amplitude envelope as well as the time series data corresponding to the two different experimental conditions for all the frontal electrodes.

The amplitude envelope of alpha and theta frequency ranges have been obtained for all the frontal electrodes in "before drone" and "with drone" conditions. The time series data for the alpha and theta frequency ranges have also been obtained. Figures 2.3 and 2.4 are representative figures which demonstrate the change of alpha and theta frequency rhythms under the application of drone music (Maity et al. 2015). The figure shows a 10 s EEG alpha and theta rhythm for F3 electrode in the two experimental conditions. A definite response is reflected in both the low frequency ranges under the application of drone.

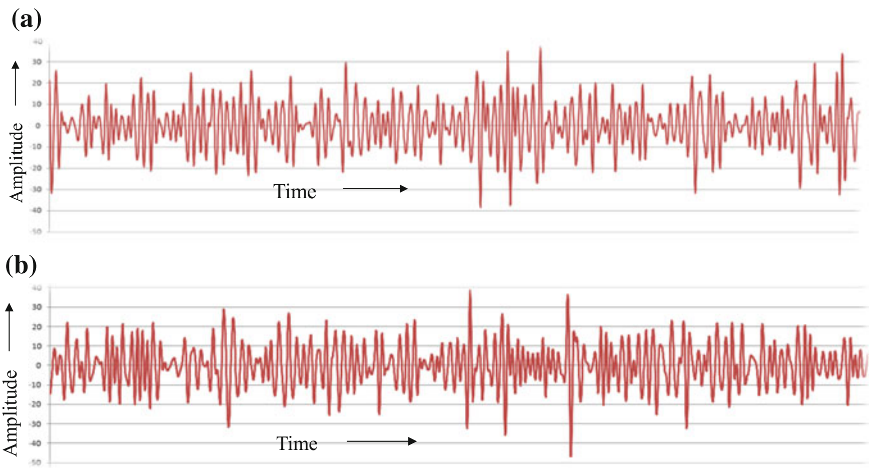


Fig. 2.3 10 s alpha frequency range data for **a** "before drone" and **b** "with drone" condition

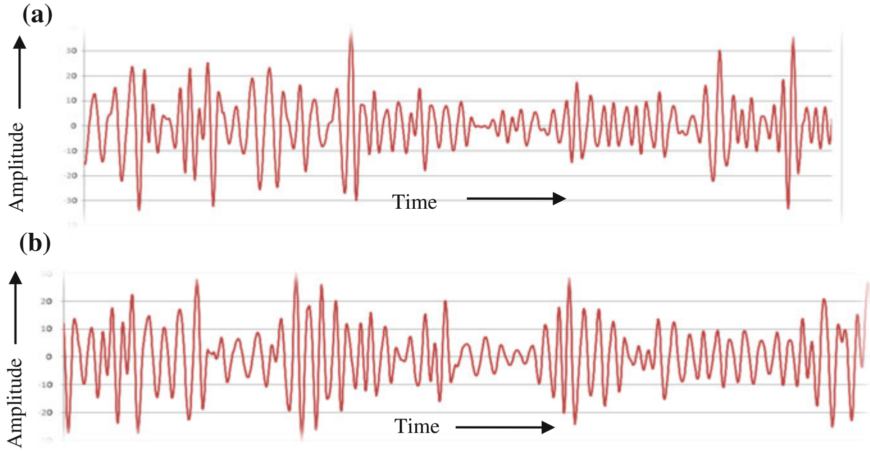


Fig. 2.4 10 s theta frequency range data for **a** "before drone" and **b** "with drone" condition

The obtained data from WT technique is subjected to DFA/MFDFA/MFDXA methods while sometimes the complete EEG signal has also been subjected to these techniques.

2.4 Detrended Fluctuation Analysis

Detrended Fluctuation Analysis (DFA) is used to analyze the long range temporal correlations (LRTC) of the observed fluctuations in EEG. In the realm of complex cognition, scaling analysis technique was used to confirm the presence of universality and scale invariance in spontaneous EEG signals (Linkenkaer-Hansen et al. 2001; Peng et al. 1994). In stochastic processes, chaos theory and time series analysis, DFA is a method for determining the statistical self-affinity of a signal. It is useful for analyzing time series that appear to be long-memory processes (diverging correlation time, e.g. power-law decaying autocorrelation function) or 1/f noise. The obtained exponent is similar to the Hurst exponent, except that DFA may also be applied to signals whose underlying statistics (such as mean and variance) or dynamics are non-stationary (changing with time). DFA method was applied in (Karkare et al. 2009) to show that scale-free long-range correlation properties of the brain electrical activity are modulated by a task of complex visual perception, and further, such modulations also occur during the mental imagery of the same task. In case of music induced emotions, DFA was applied to analyze the scaling pattern of EEG signals in emotional music (Gao et al. 2007) and particularly Indian music (Banerjee et al. 2016). The DFA of a time series $[x_1, x_2,\ldots,x_N]$ are as follows.

Step 1: Converting the noise like structure of the signal into a random walk like signal. It can be represented as:

$$\Upsilon(i) = \sum (x_k - \bar{x}) \tag{2.13}$$

where $\bar{x}$ is the mean value of the signal.

Step 2: The whole length of the signal is divided into Ns number of segments consisting of certain no. of samples. For s as sample size and N the total length of the signal the segments are

$$Ns = \mathrm{int}\left(\frac{N}{s}\right) \tag{2.14}$$

The original signal with the extracted trends has been shown in the Figs. 2.5 and 2.6 given at the end of this section.

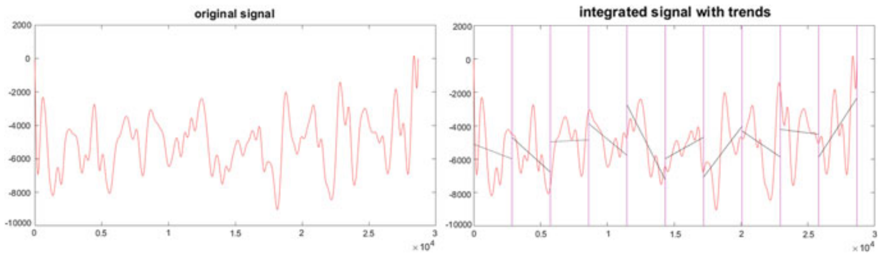


Fig. 2.5 Raw signal with the polyfit trends as found in Steps 1 and 2

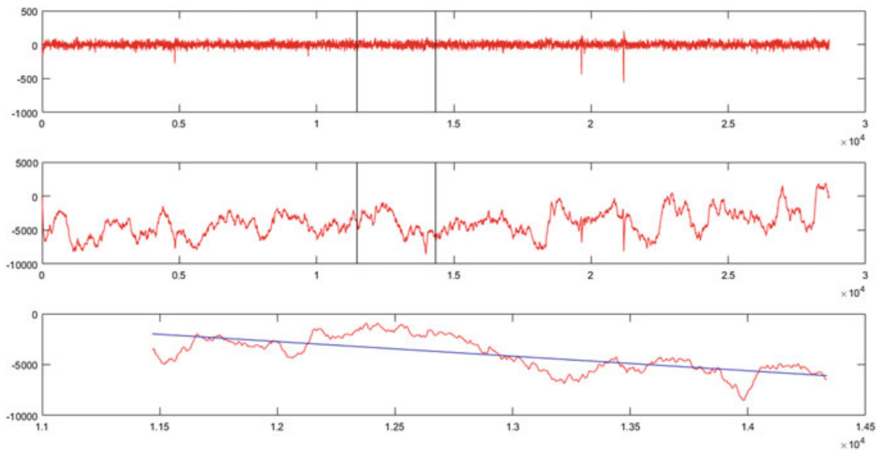


Fig. 2.6 Complete Signal with poly-fit trends

Step 3: The local RMS variation for any sample size s is the function $F(s, v)$. This function can be written as follows:

$$F^2(s, v) = \frac{1}{s}\sum_{i=1}^{s}\{Y[(v-1)s+i] - y_v(i)\}^2 \tag{2.15}$$

Step 4: The q-order overall RMS variation for various scale sizes can be obtained by the use of following equation

$$F_q(s) = \left\{\frac{1}{Ns}\sum_{\mathrm{v}=1}^{\mathrm{Ns}}\left[F^2(s, v)\right]^{\frac{q}{2}}\right\}^{\left(\frac{1}{q}\right)} \tag{2.16}$$

Step 5: The scaling behaviour of the fluctuation function is obtained by drawing the log-log plot of $F_q(s)$ versus s for each value of q.

$$F_q(s) \sim s^{h(q)} \tag{2.17}$$

where h(q) is called the generalized Hurst exponent expressed as the slope of a double logarithmic plot (Fig. 2.7). For q = 2, we obtain the monofractal scaling exponent or α. A monofractal time series is characterized by unique h(q) for all values of q. The parameter α (scaling exponent, autocorrelation exponent, self-similarity parameter etc.) represents the autocorrelation properties of the signal. DFA technique was applied following the NBT algorithm used in Hardstone et al. (2012). The scaling exponent provides a quantitative measure of long range temporal correlation (LRTC) that exists in the EEG. When the EEG is completely uncorrelated (Gaussian or non-Gaussian probability distribution), the calculation of the scaling exponent yields 0.5, also called “white noise”.

When applied to EEG data with LRTC, power-law behavior will generate scaling exponents with greater than 0.5 and less than 1. As the scaling exponent increases from 0.5 to 1, the LRTC in the EEG are more persistent (decaying more slowly with time). If a scaling exponent is greater than 1, the LRTC no longer exhibits power law behavior. Finally, if the scaling exponent = 1.5, this indicates Brownian noise, which is the integration of white noise. It can be converted into the Hurst exponent H = α − 1 and the estimated FD accordingly as

$$\mathrm{D_{DFA}} = 3 - \alpha. \tag{2.18}$$

The FD values were computed from Eq. (2.18) for all the frequency rhythms.

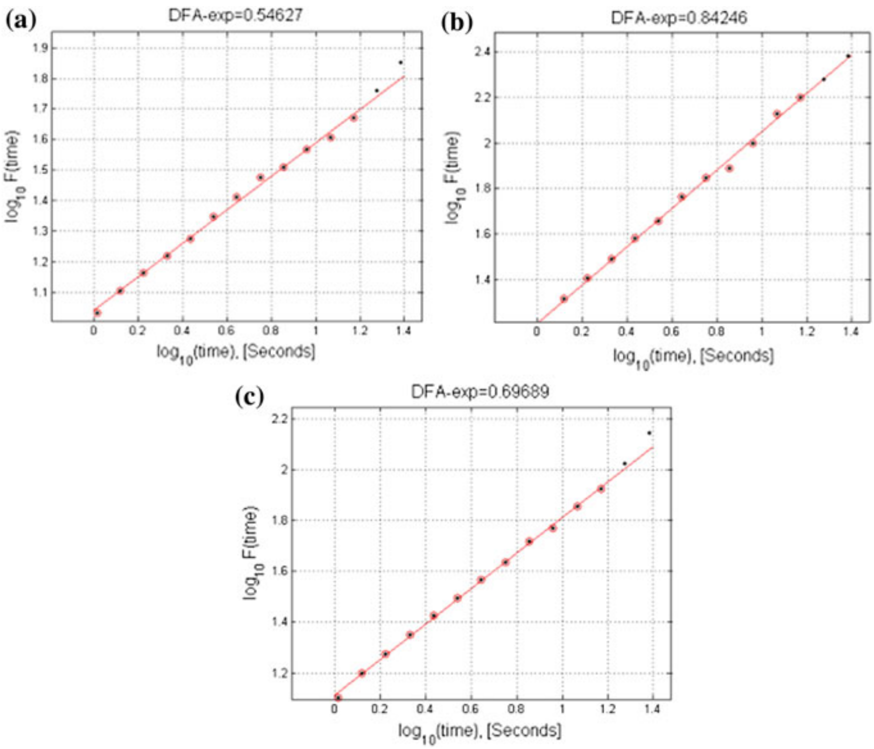


Fig. 2.7 a–c A sample log-log plot of alpha wave of an EEG signal in the three different experimental conditions

2.5 Multifractal Detrended Fluctuation Analysis (DFA)

The real-life fractal patterns that we see hardly scale according to a single scaling exponent, rather there should be multiple scaling laws to capture their growth or variation over time. These spatial and temporal scale variations indicate a multi-fractal structure of a particular signal that is defined by a multifractal spectrum of power law exponents. For these more practical cases, Kantelhardt et al. (2002) formulated the MFDFA algorithm which is essentially a generalization of the DFA algorithm as given before but takes into account different scaling ratios. For Eq. (2.17), putting q = 2, the standard DFA procedure is retrieved. We are interested in how the generalized q dependent fluctuation functions $F_q(s)$ depend on the time scale s for different values of q. Hence, we must repeat steps 2–4 for several time scales s. It is apparent that $F_q(s)$ will increase with increasing s. Of course, $F_q(s)$ depends on the DFA order m. By construction, $F_q(s)$ is only defined for $s \geq m + 2$. Again Step 5 is repeated with different values of q;

Step 5: Determination of the scaling behavior of the fluctuation functions by analyzing log-log plots $F_q(s)$ versus s for each value of q. If the series x_i are long-range power-law correlated, $F_q(s)$ increases, for large values of s, as a power-law,

$$F_q(s) \sim s^{h(q)} \tag{2.17}$$

In general, the exponent h(q) may depend on q. For stationary time series, h(2) is identical to the well-known Hurst exponent H. Thus, we will call the function h(q) generalized Hurst exponent.

The generalized Hurst exponent h(q) of MFDFA is related to the classical scaling exponent τ(q) by the relation

$$\tau(q) = qh(q) - 1 \tag{2.19}$$

A monofractal series with long range correlation is characterized by linearly dependent q order exponent τ(q) with a single Hurst exponent H. Multifractal signal on the other hand, possess multiple Hurst exponent and in this case, τ(q) depends non-linearly on q (Ashkenazy et al. 2003).

The singularity spectrum f(α) is related to h(q) by

$$\alpha = h(q) + qh'(q) \tag{2.20}$$

$$f(\alpha) = q[\alpha - h(q)] + 1 \tag{2.21}$$

where α denoting the singularity strength and *f*(α), the dimension of subset series that is characterized by α. The width of the multifractal spectrum essentially denotes the range of exponents. The spectra can be characterized quantitatively by fitting a quadratic function with the help of least square method (Figliola et al. 2007) in the neighbourhood of maximum,

$$f(\alpha) = A(\alpha - \alpha_0)^2 + B(\alpha - \alpha_0) + C \tag{2.22}$$

Here C is an additive constant $C = f(\alpha_0) = 1$ and B is a measure of asymmetry of the spectrum. So obviously it is zero for a perfectly symmetric spectrum. We can obtain the width of the spectrum very easily by extrapolating the fitted quadratic curve to zero.

Width W is defined as,

$$W = \alpha_1 - \alpha_2$$

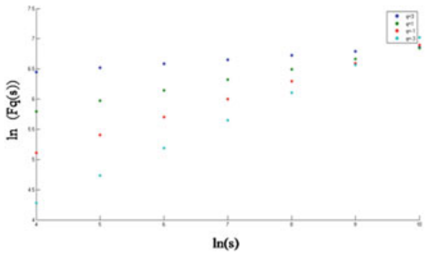
with

$$f(\alpha_1) = f(\alpha_2) = 0$$

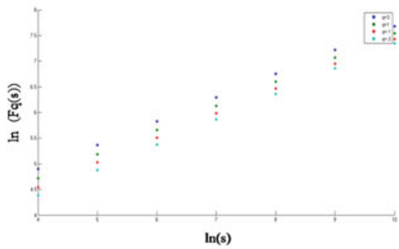
The width of the spectrum gives a measure of the multifractality of the spectrum. Greater is the value of the width W greater will be the multifractality of the spectrum. For a monofractal time series, the width will be zero as h(q) is independent of q.

The origin of multifractality in a EEG time series can be verified by randomly shuffling the original time series data (Figliola et al. 2007). In general, two different types of multifractality are present in a time series data: (i) Multifractality due to a broad probability density function for the values of the time series. Here, the multifractality of the time series cannot be removed by random shuffling and the shuffled data has the same variation of h(q) as the original data (ii) Multifractality due to a variety of long-range correlations due to the small and large fluctuations. In this case, the probability density function of the values can be a regular distribution with finite moments, for e.g. a Gaussian distribution. The corresponding shuffled series will exhibit non-multifractal scaling, since all long-range correlations are destroyed by the shuffling procedure. All long range correlations that existed in the original data are removed by this random shuffling and what remains is a totally uncorrelated sequence. Hence, if the multifractality of the original data was due to long range correlation, the shuffled data will show non-fractal scaling. If any series has multifractality both due to long range correlation as well as due to probability density function, then the shuffled series will have smaller width W and hence weaker multifractality than the original time series.

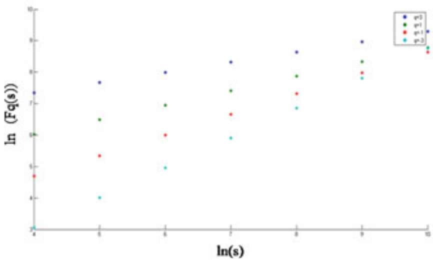
The qth order fluctuation function $Fq(s)$ for 10 points of q in between −5 and +5 was obtained. The time series values of both the waves have been randomly shuffled to destroy all the long range correlations present in the data, and what remained is a totally uncorrelated sequence. The regression plot of ln ($Fq(s)$) versus ln(s) averaged for different values of q (q = −3 to q = + 3 is shown in the plot for scales varying from 16 to 1024) for a sample electrode F3 is given in Fig. 2.8(a–d) for both alpha and theta waves. The slope of the best fit line thus obtained from ln ($Fq(s)$) versus ln(s) plot gives the values of $h(q)$. It is seen from Fig. 2.8 that the



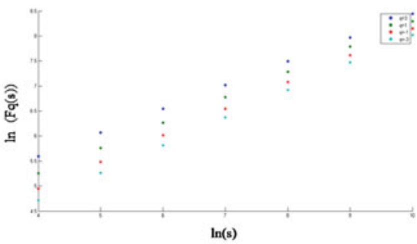
(a): ln(Fq(s)) vs. ln(s)for alpha



(b) ln(Fq(s)) vs. ln(s) for shuffled alpha



(c): ln(Fq(s)) vs. ln(s)for theta



(d) ln(Fq(s)) vs. ln(s) for shuffled theta

Fig. 2.8 a–d Plot of ln($Fq(s)$) versus ln(s) showing different h(q) corresponding to each q

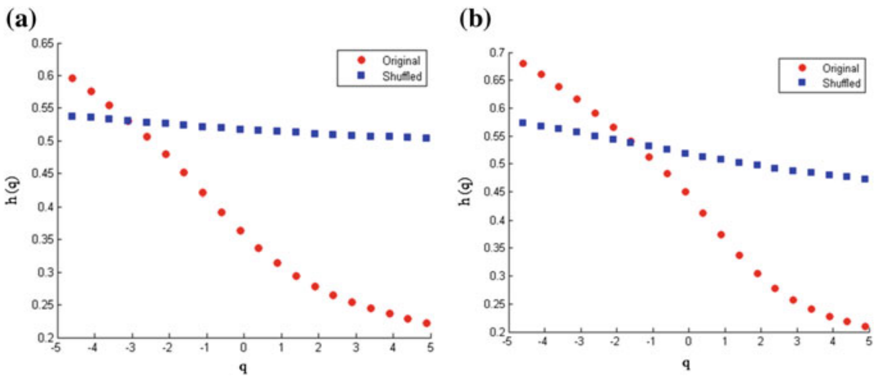


Fig. 2.9 Variation of h(q) with q for original and shuffled series

shuffled values of both alpha and theta do not change with the values of q, and thus has a fixed slope h(q) = H, which is the conventional Hurst exponent for monofractal time series.

For monofractal time series, h(q) is independent of q, since the scaling behavior of the variances $F^2(s, v)$ is identical for all segments v, and the averaging procedure in Eq. (2.18) will give just this identical scaling behavior for all values of q, only if small and large fluctuations scale differently, there will be a significant dependence of h(q) on q. For positive values of q, h(q) describes the scaling behavior of the segments with large fluctuations. Usually the large fluctuations are characterized by a smaller scaling exponent h(q) for multifractal series. On the contrary, for negative values of q, the segments v with small variance $F^2(s, v)$ will dominate the average Fq(s). Hence, for negative values of q, h(q) describes the scaling behavior of the segments with small fluctuations, which are usually characterized by a larger scaling exponent.

A representative figure for variation of *h*(*q*) with *q* for two different time-series is shown in Fig. 2.9a, b. It is clearly evident from the figures that the values of h(q) decreases with the increase of q, showing multifractal scaling in both the signals. For monofractal signals, a single value of Hurst exponent is obtained corresponding to different values of q, like the shuffled value of *h* (*q*) as seen in both the figures, where *h*(*q*) remains almost constant with the change of q. The amount of multifractality can be determined quantitatively in each of the windows of each signal from the width of the multifractal spectrum [f(α) vs. α]. The shuffled width obtained, is found to be always smaller than the original width of the signal (Fig. 2.10). This ascertains the fact that multifractality in the signals is both due to long range correlations as well as broad probability density function. In the ideal case, the shuffled data should behave as a monofractal signal with no multifractal scaling. Thus, in the plot of Hurst exponent, it is seen that the shuffled values of h(q) does not change in general with q, and in the f(α) versus α plot, the shuffled series will show a peak at α_0 close to 0.5. A representative figure (Fig. 2.11) shows the f(α) versus α plot for a single person in the alpha and theta frequency range for the two experimental conditions.

As a generalization of the DFA method, the detrended cross-correlation analysis (DCCA) is proposed to investigate the long-term cross-correlations between two

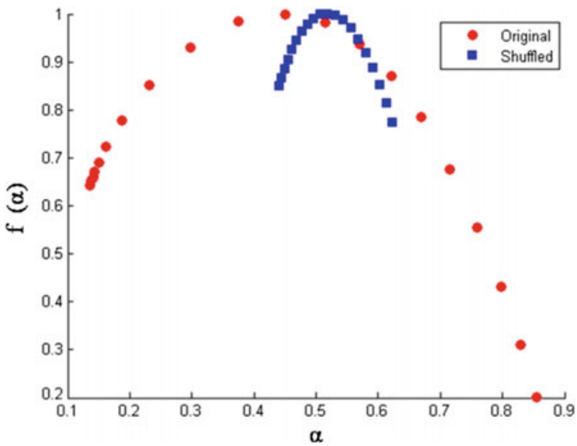


Fig. 2.10 f(α) versus α curve for original and shuffled series

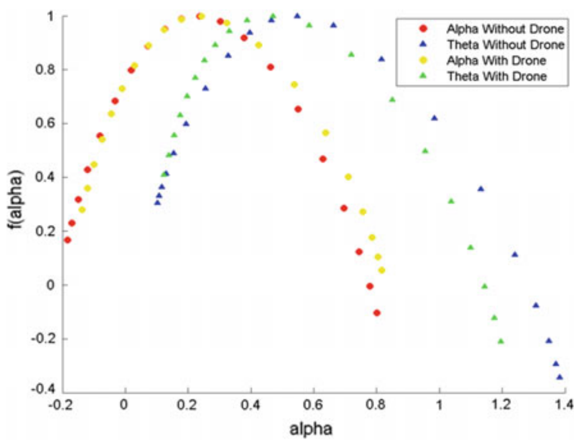


Fig. 2.11 Variation of spectral width in alpha and theta domain

non stationary time series (Podobnik et al. 2008, 2009; Podobnik and Stanley 2008; Xu et al. 2010), and Multifractal Detrended Cross-Correlation Analysis (MF-DXA) can unveil the multifractal features of two cross-correlated signals (He and Chen 2011; Jiang and Zhou 2011; Wang et al. 2013; Ghosh et al. 2014).

2.6 Multifractal Detrended Cross-Correlation Analysis (MFDXA)

MFDXA method was first used by Zhou (2008) and is an offshoot of the generalized MFDFA method. Here, we compute the profiles of the underlying data series x(i) and y(i) as

$$\begin{aligned} \mathrm{X(i)} &\equiv \left[\sum_{k=1}^{i} x(k) - \mathrm{x_{avg}}\right] \quad \text{for} \quad \mathrm{i} = 1\ldots\mathrm{N} \\ \mathrm{Y(i)} &\equiv \left[\sum_{k=1}^{i} x(k) - \mathrm{x_{avg}}\right] \quad \text{for} \quad \mathrm{i} = 1\ldots\mathrm{N} \end{aligned} \tag{2.23}$$

The next steps proceed in the same way as the MFDFA method, with the only difference being we have to take $2N_s$ bins here. The qth order detrended covariance Fq(s) is obtained after averaging over 2Ns bins.

$$\mathrm{F_q(s)} = \left\{ 1/2\ \mathrm{N_s} \sum_{v=1}^{2Ns} [F(s,v)]^{\mathrm{q}/2} \right\}^{\mathrm{q}/2} \tag{2.24}$$

where q is an index which can take all possible values except zero because in that case the factor 1/q blows up. The procedure can be repeated by varying the value of s. Fq(s) increases with increase in value of s. If the series is long range power correlated, then Fq(s) will show power law behavior

$$\mathrm{F_q(s)} \sim \mathrm{s}^{\lambda(\mathrm{q})}.$$

If such a scaling exists ln F_q will depend linearly on ln s, with λ(q) as the slope. Scaling exponent λ(q) represents the degree of the cross-correlation between the two time series. In general the exponent λ(q) depends on q. We cannot obtain the value of λ(0) directly because F_q blows up at q = 0. Fq cannot be obtained by the normal averaging procedure; instead a logarithmic averaging procedure is applied

$$\mathrm{F_0(s)} = \left\{ 1/2\ \mathrm{N_s} \sum_{v=1}^{2Ns} [F(s,v)] \right\} \sim \mathrm{s}^{\lambda(0)} \tag{2.25}$$

For q = 2 the method reduces to standard DCCA. If scaling exponent λ(q) is independent of q, the cross-correlations between two time series are monofractal. If scaling exponent λ(q) is dependent on q, the cross-correlations between two time series are multifractal. Furthermore, for positive q, λ(q) describes the scaling behavior of the segments with large fluctuations and for negative q, λ(q) describes the scaling behavior of the segments with small fluctuations. Scaling exponent λ(q) represents the degree of the cross-correlation between the two time series x(i) and y (i). The value λ(q) = 0.5 denotes the absence of cross-correlation. λ(q) > 0.5 indicates persistent long range cross-correlations where a large value in one variable is likely to be followed by a large value in another variable, while the value λ(q) < 0.5 indicates anti-persistent cross-correlations where a large value in one variable is likely to be followed by a small value in another variable, and vice versa (Movahed and Hermanis 2008).

Zhou (2008) found that for two time series constructed by binomial measure from p-model, there exists the following relationship:

$$\lambda(q = 2) \approx \left[h_x(q = 2) + h_y(q = 2)\right]/2 \tag{2.26}$$

Podobnik and Stanley have studied this relation when q = 2 for monofractal Autoregressive Fractional Moving Average (ARFIMA) signals and EEG time series (Podonik and Stanley 2008).

In case of two time series generated by using two uncoupled ARFIMA processes, each of both is autocorrelated, but there is no power-law cross correlation with a specific exponent (Movahed and Hermanis 2008). According to auto-correlation function given by:

$$C(\tau) = \langle[x(i+\tau) - \langle x\rangle][x(i) - \langle x\rangle]\rangle \sim \tau^{-\gamma} \tag{2.27}$$

The cross-correlation function can be written as

$$C_x(\tau) = \langle[x(i+\tau) - \langle x\rangle][y(i) - \langle y\rangle]\rangle \sim \tau_x^{-\gamma} \tag{2.28}$$

where γ and γ_x are the auto-correlation and cross-correlation exponents, respectively. Due to the non-stationarities and trends superimposed on the collected data, direct calculation of these exponents are usually not recommended; rather the reliable method to calculate auto-correlation exponent is the DFA method, namely $\gamma = 2 - 2h$ (q = 2) (Movahed and Hermanis 2008). Recently, Podobnik et al. (2011), have demonstrated the relation between cross-correlation exponent, γ_x and scaling exponent $\lambda(q)$ derived by Eq. (2.2) according to $\gamma_x = 2 - 2\lambda$ (q = 2). For uncorrelated data, γ_x has a value 1 and the lower the value of γ and γ_x more correlated is the data. In general, $\lambda(q)$ depends on q, indicating the presence of multifractality. In other words, we want to point out how two non-linear signals are cross-correlated in various time scales.

The qth order detrended covariance Fq(s) was obtained from relations 3 and 4 for values of q from −5 to +5 in steps of 1 just like the MFDFA part. Power law scaling of Fq(s) with s is observed for all values of q as is seen from Fig. 2.8a–d same as those found for MFDFA. We have also shown variation of h(q) with q for Part 1 of four clips by means of MF-DFA in Fig. 2.9. The plot depicts multifractal behavior of cross-correlations because for different q, there are different exponents; that is, for different q, there are different power-law cross-correlations. Further from the same figure we can see that the value of H(q) depends on q for all the four samples that we have taken in this study. We know that H(q) = 0.5 indicates that the series is an independent random process, and for H(q) < 0.5 it is characterized by long-range anti-correlations while for 0.5 < H(q) < 1, it is featured by long-term correlations. In this case the signal is stationary. The exponent H (q = 2) is equivalent with the well-known Hurst index. A representative figure (Fig. 2.12) reports the variation of cross correlation exponent λ(q) with q for two particular samples (Part 1 for Sample 1 and Sample 2), also the variation of h(q) with q for those two samples obtained from MFDFA technique are also shown in the same figure for comparison.

The variation of λ(q) with q for the two cross correlated signals (Part 1 for Sample 1 and Sample 2) show that they are multifractal in nature (Fig. 2.12). To illustrate further the presence of multifractality in the cross-correlated music signals, i.e. to have information about the distribution of degree of cross-correlation in various time scales, a representative multifractal spectrum was plotted for the two signals in Fig. 2.13. The way to characterize multifractality of cross correlation between two samples is to relate via a λ(q) Legendre Transform as in the case of

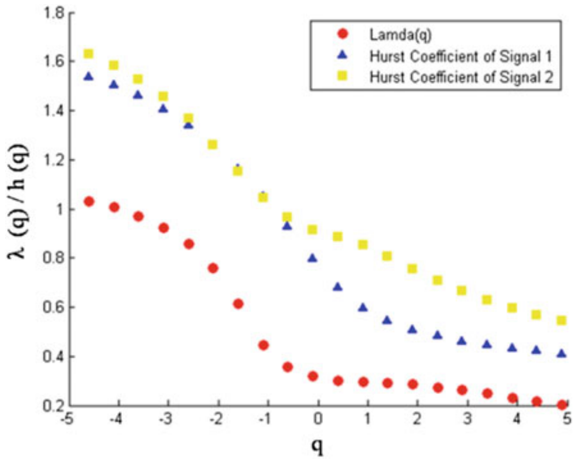


Fig. 2.12 Variation of λ(q) and h(q) for two sound signals

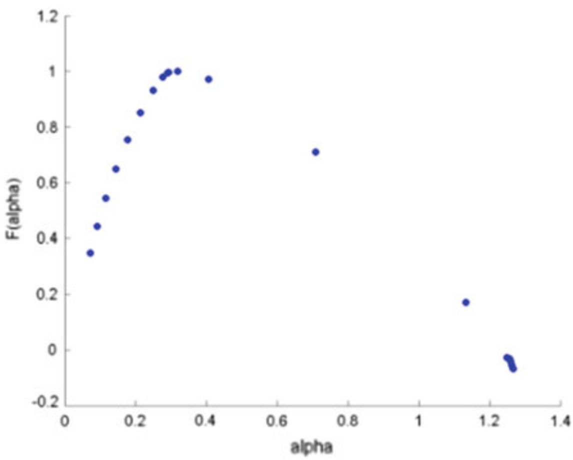


Fig. 2.13 Multifractal cross-correlated Spectrum of samples 1 and 2 (Part 1)

single series (Feder 2013). The growth of the width of f(α) or equivalently Δα shows the increase in degree of multifractality of the coupled signals. Again, it becomes evident from the spectrum that the cross correlated signals are multifractal in various time scales.

Jones and Kaul (1996) were the first to reveal a stable negative cross-correlation between oil prices and stock prices. The negative cross-correlations were also found in a number of previous works (Chen 2009; Berument et al. 2010; Reboredo et al. 2014). A negative value of cross correlation is an indication of strong cross-correlation between the two samples for which the cross correlation is being carried out. Using the MFDXA technique we have estimated the degree of cross-correlations between neuronal potentials originating from different lobes of human brain as well as parts of musical clip.

In the next section, we proceed to propose novel algorithms for feature extraction from raw EEG data which may open up new vistas in developing an automated emotion classification algorithm from music induced EEG signal analysis.

2.7 Estimation of Neural Jitter and Shimmer

Jitter conventionally refers to the variability of fundamental frequency while shimmer refers to the variability in the peak to peak amplitude (Farrús and Hernando 2009). These parameters have long been used by scientists working on speech and music signal processing for characterization of a speech/music signal. In speech signal processing, jitter/shimmer is a measure for vocal stability of a person. A jitter of less than 1% and a shimmer of less than 7% in frequency/amplitude is considered for a normal person, which increases/decreases in case of voice disorder. EEG signals possess almost the same properties in temporal domain like music/speech signal. Hence, applying the same concept to neural EEG domain, we have termed this factor as neural-jitter and neural-shimmer for EEG signals. These parameters are being calculated essentially to measure the perturbation index of a signal. We started off with calculation of neural jitter and shimmer percentage for different types of stimuli induced EEG signals and compared them with rest-state EEG signals. In this way we look to develop a threshold value/percentage like the one in speech signal which can objectively help in the assessment of mental state of a person. EEG signals (Fig. 2.14) are obtained in the temporal domain showing the variation of Extracellular Field Potentials (Buzsáki et al. 2012) with respect to time. Digital Signal processing methods allows converting between temporal domains to frequency domain. The transform is called Fourier Transform (Bracewell 1965) which generates Fourier coefficient for each frequency present in the temporal signal. The plot of the frequency domain, which shows the Fourier coefficients, is called frequency spectrum, (Fig. 2.15). The work is aimed to look into proposing a novel technique to calculate traditional Jitter/Shimmer in neural signals. The EEG signals were transformed into frequency domain double sided frequency spectrum

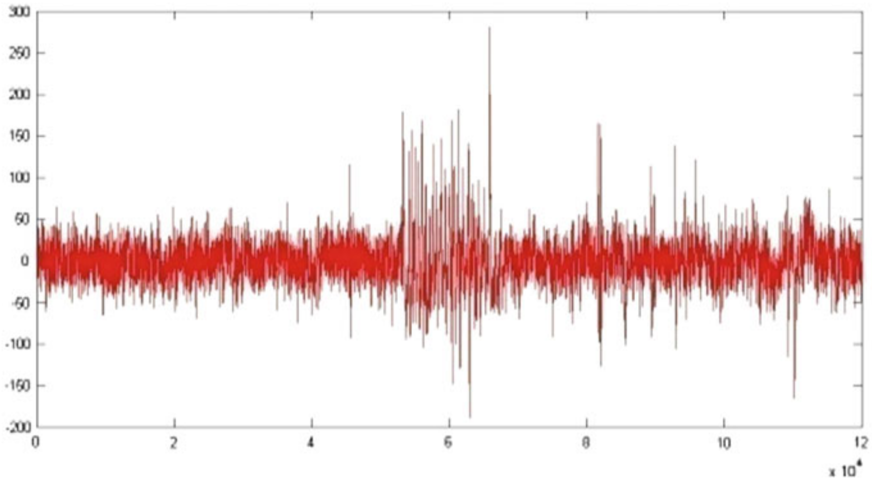


Fig. 2.14 Sample EEG signal plotted against y and x axes where y represents the values of the signal at different times ‘t’ and x represents the time ‘t’ axis

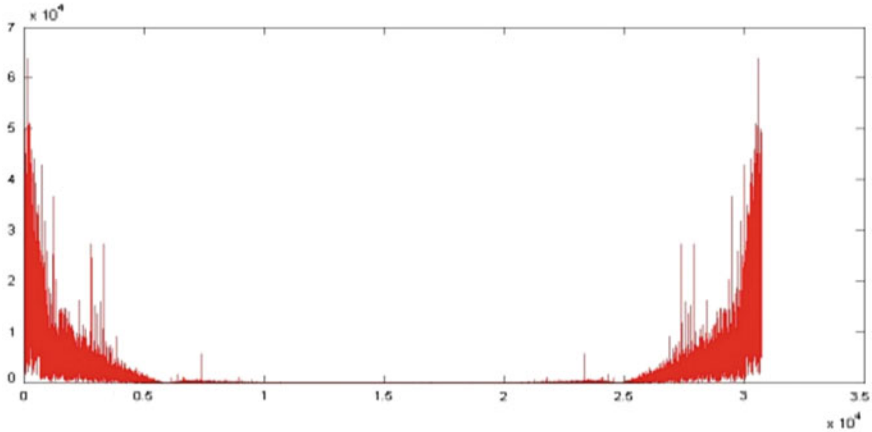


Fig. 2.15 Two-sided amplitude spectrum

(Fig. 2.16). The Fourier coefficients can be both real and complex. The plot and analysis was made with the absolute values of the coefficients. Single sided spectrum (Fig. 2.17) was used for analysis instead of double sided. An attempt to analyze the single sided frequency spectrum is made by considering only top 20% frequency coefficients. Threshold is 20% of (A_{max}) where is A_{max} the largest Fourier coefficients (Fig. 2.18). The Fourier coefficients above $A_{max}/5$ continue to posses

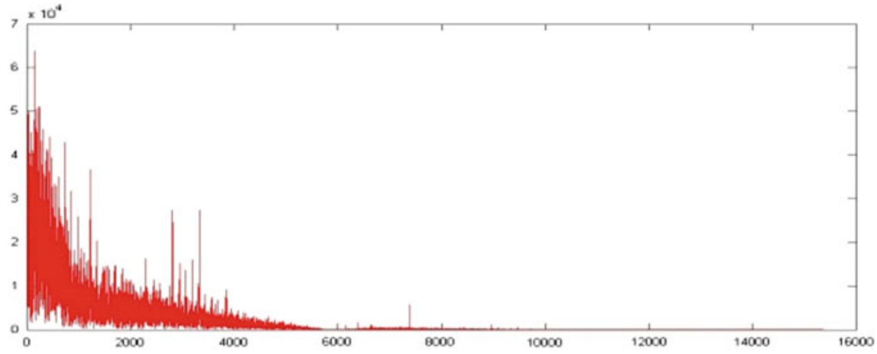


Fig. 2.16 Single-sided amplitude spectrums

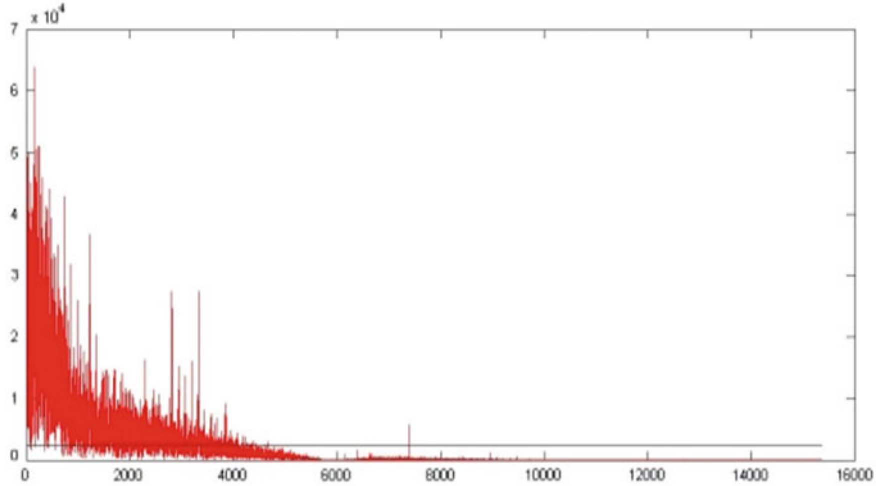


Fig. 2.17 Thresholding operations

its values and below $A_{max}/5$ becomes zero (Fig. 2.19). This transformation is expected to be good as values less than $A_{max}/5$ are literally less so losing those coefficient is expected not to cause much loss of information. A Frequency thresholding (*FT*) matrix is computed storing values of time periods $(2 * pi * \omega)$, ω are the frequencies with non zero Fourier coefficients in thresholding curve and the corresponding fourier coefficients. Figure 2.19 shows the plot with non-zero coefficients only. The time elements in *FT* matrix serve as T_i in calculating the jitter and the corresponding coefficient elements in *FT* matrix serve as A_i in the shimmer calculation.

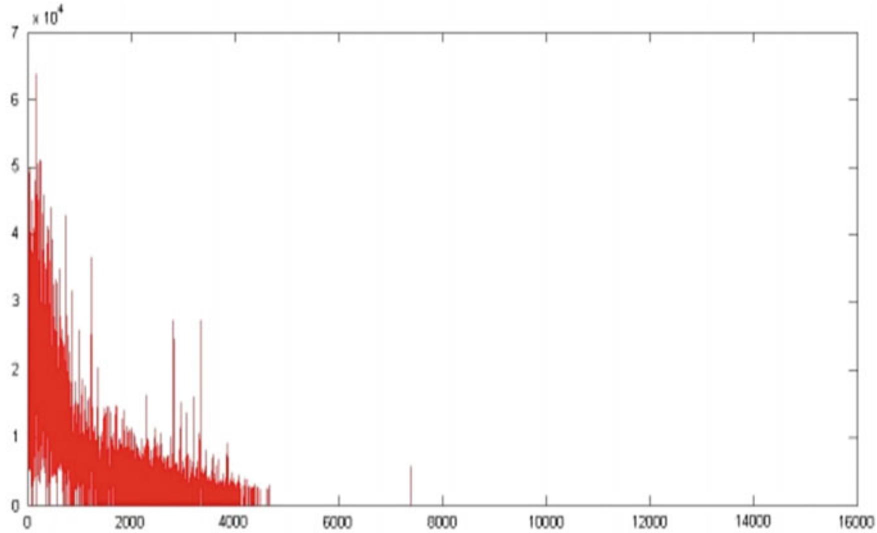


Fig. 2.18 Single-sided amplitude spectrums of the signal after thresholding with zero Fourier coefficients

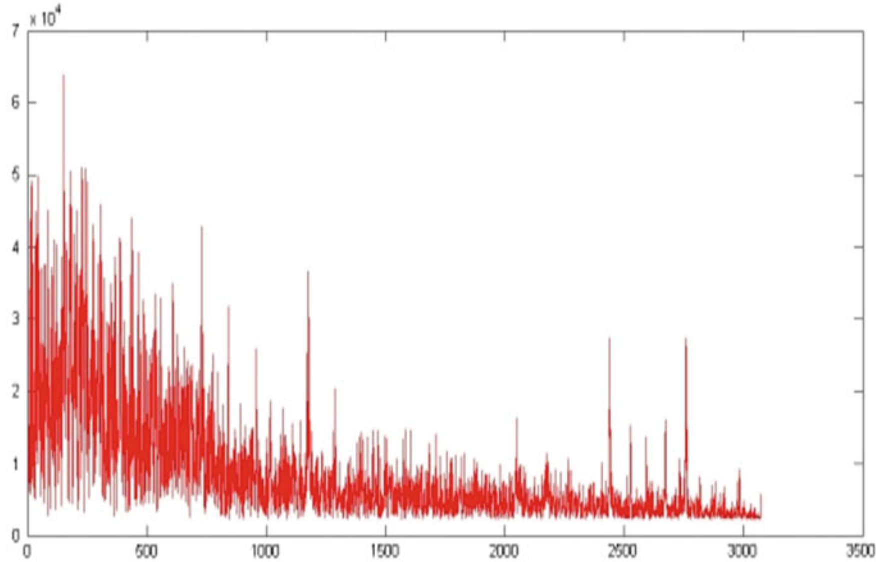


Fig. 2.19 Single-sided amplitude spectrums of the signal after thresholding with non-zero Fourier coefficients

Measurement of Neural Shimmer Values:

Shimmer is the variation of peak-to-peak amplitude. It is defined as the mean absolute difference between amplitudes of successive periods divided by the mean value of the amplitudes. Mathematically, given as

$$\frac{\frac{1}{N-1}\sum_{i=1}^{N-1}|A_i - A_{i+1}|}{\frac{1}{N}\sum_{i=1}^{N}A_i}$$

where N is the number of periods and A_i is the amplitude.

Measurement of Neural Jitter Values:

Jitter is the perturbation of fundamental frequency. It can also be defined as the deviation from true periodicity of an apparently periodic signal, given as the mean absolute difference between successive periods divided by the mean value of the periods. Mathematically, given as

$$\frac{\frac{1}{N-1}\sum_{i=1}^{N-1}|T_i - T_{i+1}|}{\frac{1}{N}\sum_{i=1}^{N}T_i}$$

where N is the number of periods and T_i is the duration (in seconds) of the *i*th period.

The jitter and shimmer values essentially gives an estimate of the perturbations in the amplitude/frequency of the EEG signals. These perturbations when computed as a function of time will give a time series which is essentially record of the fluctuation of the fluctuations. Non-linear scaling methods detailed above can be used for scaling the fluctuation property of jitter/shimmer time series.

2.8 Estimation of Pitch of EEG Signal from Zero-Crossings

EEG signal comprises of a number of spectral components. The lower and upper cut-offs of the frequency range of an EEG signal is indistinguishable, essentially ranging from of 0.5 to 30 Hz. As has been iterated before, EEG rhythms are categorized as follows: Delta (0–4 Hz), Theta (4–7 Hz), Alpha (8–13 Hz), Beta (14–30 Hz) and Gamma (30–50 Hz). We use the DWT algorithm explained in this chapter for decomposing an EEG signal into these frequency bands first. The EEG sampling frequency being 256 Hz in our case. We considered 3 signals containing respectively the 3 frequency bands, namely, Alpha, Theta and Gamma obtained from wavelet decomposition of a particular EEG signal. Suppose '*X*' denotes the signal containing frequencies in the Alpha band. The recorded time of each signal was 2 min, i.e., 120 s. So, we attempt to divide '*X*' into intervals of length 1 s, the total number of segments being 120. In each of these segments we calculated the number of zero-crossings, that is, the number of times the curve cuts the time axis. We denote the number of zero-crossings for each interval '*i*' as Z_{i}, since the value changes with the interval number. The number of zero crossing or the zero crossing rate (ZCR) is an indirect way of measuring the fundamental frequency which has been used in a number of studies (Kedeem 1986; Scheirer and Slaney 1997; Roads 1996) in the acoustic domain. Using the same technique, we sought to have an idea of the neural pitch of an EEG signal. For a particular signal (say F4 electrode, Alpha band signal for Subject 1 in resting state) we have a *Pitch* matrix denoted as '*P*' which essentially contains each of Z_{i} for each interval i where i ranges from 1 to 120. The size of this P matrix is 1×120 (a row matrix containing the number of columns = number of segments as mentioned previously). For a particular electrode for 3 frequency band signals we concatenate the matrix P which now becomes 3×120. Using MATLAB we show scatter plots of Z_{i} as a function of i. Figure 2.20a–c denotes the variation of ZCR in F3 electrode under the effect of a pair of music of contrast emotion. While Fig. 2.20a shows the distribution in rest condition, Fig. 2.20b, c denote the distribution of zero crossing under the effect of happy and sad music clip respectively.

A simple glance to the figures reveal that the distribution pattern significantly changes under the effect of two different categories of music clips. The probability distribution plot of different fundamental frequencies is expected to reveal unique information about the processing of different emotions in human brain. The same has been repeated for theta and gamma frequency ranges and analyzed rigorously to

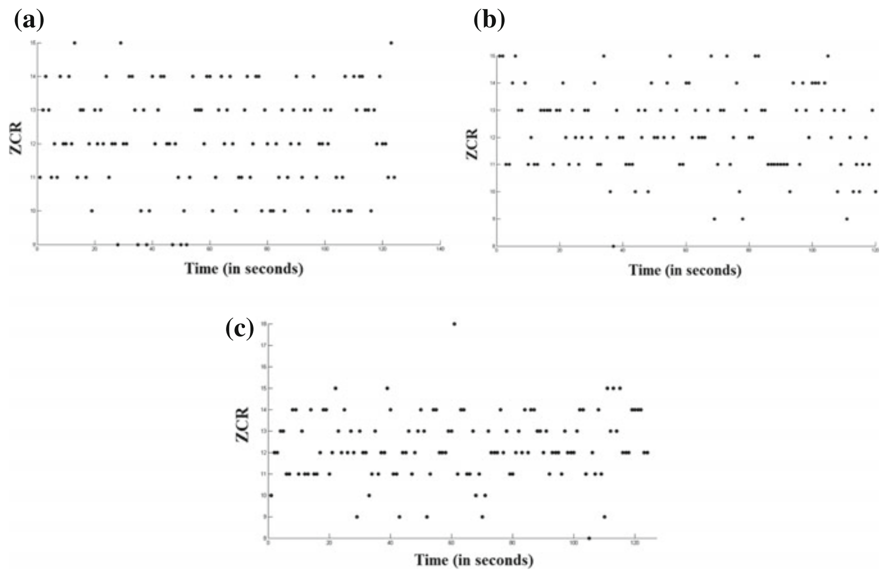


Fig. 2.20 **a** ZCR in rest condition, **b** ZCR in happy music, **c** ZCR in sad music

find the existence of a preferred fundamental under the influence of a certain group of music clips. The ‘preferred fundamental’ is the one whose probability is the maximum under the effect of a certain music and has been coined with a new terminology “neural pitch”. The “neural pitch” of an EEG signal is actually the most basic and simplest feature of all other which have been used till date. The probability distribution curves obtained from the values of ZCR is essentially the void probability distribution calculated over time. The neural pitch analysis can thus be extended in the form of DFA/MFDFA analysis to study the fluctuation pattern of the void probability distribution. This will enable us to have an estimate of the fractal/multifractal scaling pattern (if any) of the probability distribution of voids. We sincerely believe that this feature has immense potential in categorization and classification of different EEG brain states. The new features in the domain of EEG signal processing viz. neural jitter, shimmer and pitch have been discussed at length in Chap. 10 of this book.

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Chapter 3
Emotions from Hindustani Classical Music: An EEG based study including Neural Hysteresis

Memory believes before knowing remembers.
Believes longer than recollects,
longer than knowing even wonders

—William Faulkner

3.1 Introduction

3.1.1 Background

The ability of human brain to perceive and respond to emotional music has long been a subject of interest for musicologists and psychologists. But, the neuro-cognitive aspects of this arousal based activities have captured the interest of the neuro-scientists only in the last decade. Music like speech is also a mode of communication between human beings. The communicator endeavors to communicate certain messages, be it mood, feelings, expression and the like. Through this he creates a story, a sort of ambience for the audience. A scientific understanding of music must begin by taking into account how minds act in the ambience of music. In a sense music appears to be a more fundamental and universal phenomena than speech. In speech communication the listener has to know the language of the speaker to get the message. In creating music an artist produces an objective material called sound which along with lyrics contribute to communication. It is possible for a listener to identify with the mood of the artist irrespective of the knowledge of the lyrics by merely feeling the senses of music. Herein lies the importance of a study which involves different type of emotional clips and their respective differential response in the particular lobes of human brain.

Music cognition has become a very interesting interdisciplinary subject of research since emotions elicited by music are complex processes comprising of several interacting parameters which are very difficult to assess objectively. None the less modeling of emotion is also a challenging problem. With the development of robust neuro-biosensors like EEG, fMRI, PET, one can modestly attempt to identify correlates relevant to different specific emotions. The development of

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robust tools to analyze the intricate EEG waveform has also given a good window to study the neural attributes corresponding to songs of different emotions. Listening to music regularly helps to keep the neurons and synapses more active. Depending on the way sound waves are listened or pronounced, they have an impact in the way neurological (brain and nerve) system work in the human body. Neurological studies have identified that music is a valuable tool for evaluating the brain system (Peretz and Zatorre 2005). It is also observed that while listening to music, different parts of the brain are involved in processing music, this include the auditory cortex, frontal cortex and even the motor cortex (Kristeva et al. 2003). Research findings indicate some of the cognitive tests are more influenced by exposure to music (Schellenberg et al. 2007).

3.1.2 What Is Hysteresis?

In terms of physics, "Hysteresis" means the dependence of a system on its history, or in other words, the amount of "memory" retained by the system of its previous state. This phenomenon is observed in magnets, where a lagging in the values of resulting magnetization in a magnetic material (as iron) is observed due to a changing magnetizing force. Whether the hysteresis effect is present in the case of neurons triggered by musical stimuli has not yet received the attention of cognitive neuroscientists. Hysteresis is usually investigated using designs comprising of "ascending" and "descending" sequences, that is, sequences ordered in terms of a certain physical parameter (Miura et al. 2013). In this case we used a positive emotional clip as an ascending sequence while another clip conveying negative emotion consisted of the descending one. In the middle, "no music" or rest conditions comprised of the neutral states which we considered as the baseline or the threshold value. In case of music induced emotions, it would be interesting to know which emotions stay longer in the human brain and whether it has any relationship to the type and genre of music. We attempt here the study with Hindustani music utilizing a rigorous non-linear approach as elaborated later.

3.1.3 Neural Plasticity and Hysteresis

A number of previous reports deal with neural plasticity—i.e. the ability of human brain to reorganize itself by forming new neural connections throughout their life. But, all these reports mainly deal with long-term memory affects which gradually decline with ageing, i.e. the brain is said to lose its plasticity with age. We are mainly concerned with short term memory and arousal based effects which can be recorded instantaneously with the application of musical stimulus. Works in perceptual hysteresis show that the content of one's perception at time t depends on the recent history of the perceptual system (Kleinschmidt et al. 2002). In the visual domain, Sacharin et al. (2012) showed that when subjects are presented with certain facial emotional expressions evolving over time from a particular emotion to another, they persist in perceiving the original emotion. In this paper, we wanted to test whether hysteresis-like effects are present in brain response to emotional musical stimuli. To test our prediction, we used a protocol which reveals the time duration for which the neuronal activation persists even after the removal of the musical stimuli.

3.1.4 Hindustani Classical Music and Emotions

Music in the Indian subcontinent has been a source of aesthetic delight from time immemorial. From the time of Bharata's Natyashastra (Ghosh 2002), there have been a number of treatises which speak in favor of the various *rasas* (emotional experiences) that are conveyed by the different forms of musical performances. The aim of any dramatic performance is to emote in the minds of audience a particular kind of aesthetic experience, which is described as "Rasa". The concept of "Rasa" is said to be the most important and significant contribution of the Indian mind to aesthetics. The study of aesthetics deals with the realization of beauty in art, its relish or enjoyment, and the awareness of joy that accompanies an experience of beauty; but till date science had nothing to do with the aesthetic experiences corresponding to a particular performance and was kept as a separate entity.

It is only from the last two decades of the 20th century that scientists began to understand the huge potential of systematic research that Hindustani Music (HM) has to offer in the advancement of cognitive science as well as psychological research. A number of works tried to harvest this immense potential by studying objectively the emotional experiences attributed to the different *ragas* of Hindustani classical music (Balkwill and Thompson 1999; Martinez 2001; Wieczorkowska et al. 2010). The *raga* is a sequence of musical notes and the play of sound which delights the hearts of people. The word Raga is derived from the Sanskrit word "Ranj" which literally means to delight or please and gratify (Brahaspati 2002). Although there are a number of definitions attributed to a Raga, it is basically a tonal multifarious module. In HM the existing phrases are stretched or compressed, and the same may happen to motives from the phrases; further motives may be prefixed, infixed and suffixed. Phrases may be broken up or telescoped with others, and motives or phrases may be sequenced through different registers (Neuman 1990). Thus, during a performance, a singer steadily loosens the strangle hold of the rules of music in a subtle way. He does not flout them, he merely interprets them in a new way, which is the beauty of Hindustani classical music and there comes the wisdom that *Raga* and its grammar are only means and not ends in themselves.

3.1.5 EEG and Musical Emotions

Each type of music has its own frequency, which can either resonate or be in conflict with the body's rhythms (heart rate). Studying EEG dynamics typically relies on the calculation of temporal and/or spectral dynamics from signals recorded directly from the scalp. Due to volume conduction, EEG data recorded at the scalp are linear mixtures of electrical potentials projected from multiple distinct cortical domains and non-brain artifacts arising from eye blinking, lateral eye movement, muscle tension, etc. (Onton and Makeig 2006). Each frequency band of the EEG rhythm relates to specific functions of the brain. EEG rhythms are classified into five basic types: i) delta (δ) 0.5-4Hz, (ii) Theta (θ) 4–8 Hz,(iii) alpha (α) 8-13Hz, (iv) beta (β) 13-30 Hz and (v) gamma (γ) 30-50 Hz.

It has been observed that pleasant music produces a decrease in the alpha power at the left frontal lobe and unpleasant music produces decrease in the alpha power at the right frontal lobe (Tsang et al. 2001; Schimdt and Trainor 2001; Sammler et al. 2007). Also, activity in the alpha frequency band has been found to be negatively related to the activity of the cortex, such that larger alpha frequency values are related to lower activity in the cortical areas of the brain, while lower alpha frequencies are associated with higher activity in the cortical areas (Davidson 1988; Mizuki et al. 1992). Davidson (1988) have shown that disgust cause less alpha frequency in the right frontal region than happiness while, happiness cause less alpha power in the left frontal region. Frontal midline (Fm) theta has been mostly related to heightened mental effort and sustained attention during various functions. The Fm theta power was positively correlated not only with scores of internalized attention but also with subjective scores of the pleasantness of the emotional experience. Furthermore, two studies on the relationship between Fm theta and anxiety reported negative correlations between Fm theta during mental tasks and anxiety measures (Mizuki et al. 1992; Suetsugi et al. 2000). It has also been shown that pleasant music would elicit an increase of Fm theta power (Sakharov et al. 2005). Recent researches have demonstrated that the modulation of gamma band activity (GBA) in time windows between 200 and 400 ms following the onset of a stimulus is associated with perception of coherent visual objects (Müller et al. 1999), and may be a signature of active memory. GBA has also been found sensitive to emotional vs non emotional stimuli and more specifically it was related to the arousal effect: GBA was enhanced in response to aversive or highly arousing stimuli compared to neutral picture (Balconi and Lucchiari 2008). While listening to music, degrees of the gamma band synchrony over distributed cortical areas were found to be significantly higher in musicians than non musicians (Bhattacharya and Petsche 2001a; Bhattacharya et al, 2001). Another study reports higher order inter-frequency phase synchrony between delta oscillations in anterior and gamma oscillations in posterior region for musicians. Also, consistent left hemispheric dominance, in terms of the strength of phase synchrony, was observed in musicians while listening to music, whereas right hemispheric dominance was observed in non-musicians (Bhattacharya and Petsche 2005). The gamma band EEG distributed over different areas of brain while listening to music can be represented by a universal scaling which is reduced during resting condition as well as when listening to texts. (Bhattacharya and Petsche, 2001b). Specifically, (Summerfield et al, 2002) have found that gamma activity increases after subjects had been made aware of the stimulus. So, we envisaged to study the response of all three bands in emotion elicited by Hindustani music stimuli.

3.1.6 *Use of DFA to Assess Emotions and also Neural Hysteresis*

There have been a few studies which assess the emotion elicited by different ragas of Hindustani music (Balkwill and Thompson 1999; Chordia and Rae 2007; Wieczorkowska et al. 2010; Patranabis et al. 2013; Mathur et al. 2015). In the study made by Balkwill and Thompson (1999), Western listeners were asked to rate the expression of emotions by 12 different ragas. The study made by Wieczorkowska et al. (2010) also studied the Raga-Rasa relationship and on a cross-cultural paradigm where listeners from both India as well as from West participated. A recent study by Mathur et al. (2015) with 122 participants across the globe revealed that not only a particular raga is capable of eliciting emotion, but the emotional content varies across different portions of the rendition of raga—namely *alaap* and *gat*. All these are human response studies which strengthen the assumption that Hindustani ragas are powerful elicitor of emotion and robust analysis techniques are required to quantitatively assess the emotional arousal from a particular musical clip. To estimate the hysteresis effects, we used a positive emotional clip as an ascending sequence while another clip conveying negative emotion consisted of the descending one. In the middle, “no music” or rest conditions comprised of the neutral states which we considered as the baseline or the threshold value. In case of music induced emotions, it would be interesting to know which emotions stay longer in the human brain and whether it has any relationship to the type and genre of music. We attempt here the study with Hindustani music utilizing a rigorous non-linear approach as elaborated next.

We used a scaling analysis technique called Detrended Fluctuation Analysis (DFA) to analyze the long range temporal correlations (LRTC) of the observed fluctuations in EEG. In the realm of complex cognition, scaling analysis technique was used to confirm the presence of universality and scale invariance in spontaneous EEG signals (Bhattacharya 2009). In stochastic processes, chaos theory and time series analysis, DFA is a method for determining the statistical self-affinity of a signal. It is useful for analyzing time series that appear to be long-memory processes (diverging correlation time, e.g. power-law decaying autocorrelation function) or 1/f noise. The obtained exponent is similar to the Hurst exponent, except that DFA may also be applied to signals whose underlying statistics (such as mean and variance) or dynamics are non-stationary (changing with time). DFA method was applied in (Karkare et al. 2009) to show that scale-free long-range correlation properties of the brain electrical activity are modulated by a task of complex visual perception, and further, such modulations also occur during the mental imagery of the same task. In case of music induced emotions, DFA was applied to analyze the scaling pattern of EEG signals in emotional music (Gao et al. 2007) and particularly Indian music (Karthick et al. 2006). The advantage of using this model is that we can define arousal and valence levels of emotions with the calculated FD values. For example, the increase in arousal level corresponds to the increase of FD values (Olga et al. 2012). Fractal dimension (FD) values of EEG could reveal geometric complexity of the signals. It has been shown that FD could be applied in real-time EEG signal processing to identify different brain states (Accardo et al. 1997; Sourina et al. 2011; Liu et al. 2010). Applications of fractal dimension in EEG analysis were given in (Sourina et al. 2008, 2009) where music was used to elicit emotions. In (Sourina et al. 2011; Wang et al. 2010) concentration levels of the subjects were recognized from EEG, and FD values were used as the classification features.

3.1.7 Overview of Our Work

The objective of this study is to analyze the effect of Hindustani music on brain activity during the normal relaxing condition, using electroencephalography (EEG). Four (4) different Hindustani music raga clips of contrasting emotion (romantic/sorrow) were used in the study. EEG was performed on ten (10) subjects while they listened to the two pair of clips conventionally known to portray contrast emotions. The subjects were made to listen to the 3 min 40 s clip of happy emotion (*Chayanat/ Bahar*) first followed by the 3 min 40 s clips which convey sad emotion (*Darbari Kanada/ Mian ki Malhar*). Each period of listening was separated from the other by a resting period of 3 min 40 s which was maintained to see how long the arousal based activities persisted in human brain after the removal of stimulus. Two different experiments were conducted to assess the emotional response from *Chayanat/ Darbari Kanada* and *Bahar/Mian ki Malhar*. While the objective of the first experiment is to study the hysteresis like phenomenon in human brain while the second study mainly focuses on the categorization and quantification of emotional cues from Hindustani classical music. The brain response corresponding to the frontal electrodes were only taken in consideration throughout this chapter as the frontal lobe proves to be the most important when it comes to higher order cognitive processing. Also, In this context, we studied the valence lateralization theory in human brain which proposes that a particular emotion is processed in a particular direction of the brain.

DFA technique was used to quantify how the scaling pattern of EEG frequency rhythms changed as the emotional appraisal from a certain music clip changed. The findings show that alpha and theta frequency ranges showed consistent arousal based activities as is evident from their respective rise of DFA scaling exponents while the subjects were listening to the music clips. The arousal based activities persisted for quite some time even after the stimulus were removed. The gamma frequency ranges were also studied in this context, but failed to provide any conclusive results in this direction which may possibly due to the limitations of EEG system. It was also observed that when the music stimuli were removed, significant alpha brain rhythms persisted, showing residual arousal activities. This is analogous to the conventional 'Hysteresis' loop where the system retains some 'memory' of the former state, but in case of emotions induced by musical stimuli.

3.2 Experimental Details

3.2.1 Subjects Summary

Ten (10) (Male-6, Female-4) healthy right handed volunteers participated in this study. The ages of participants were in the range of 20–45 years (average age = 26 years and SD = 7.39 years) and average body weight was 65 kg. They had no formal musical training and could thus all be considered as non-musicians. All experiments were performed at the Sir C.V. Raman Centre for Physics and Music, Jadavpur University, Kolkata. The experiment was conducted in the afternoon with a normal diet in a normally conditioned room sitting on a comfortable chair and performed as per the guidelines of the Institutional Ethics Committee of SSN College for Human volunteer research. All subjects gave written consent before participating in the study, approved by the Ethics Committee of Jadavpur University, Kolkata.

3.2.2 Choice of **Ragas: Chayanat and Darbari Kanada/Bahar and Mian Ki Malhar**

The two pair ragas chosen for our analysis were "Chayanat"/"Bahar" (romantic/joy) and "Darbari Kannada"/ "Mian ki Malhar" (pathos/sorrow). Variations in the timbre were avoided by making the same artist play the two ragas with the same sitar. Both the signals were normalized to within 0 dB and hence intensity or loudness and attack cue are not being considered. Each of these sound signals was digitized at the sample rate of 44.1 kHz, 16 bit resolution and in a mono channel. From the complete playing of the ragas, segments of about 3 min and 40 s were cut out for analysis of each Raga. Help was taken of some experienced musicians for identifying the emotional phrases in the music signal along with their time intervals, based on their feelings. A sound system (Logitech R_Z-4 speakers) with high S/N ratio was used in the measurement room for giving music input to the subjects. The EEG experiment was conducted in the afternoon (around 2 p.m.) in a room with the subjects sitting in a comfortable chair. There were two round of experiments with the two sets of music clip of contrast emotion.

3.2.3 Experimental Protocol

Since the objective of this study was to analyze the effect of Hindustani music on brain activity during the normal relaxing condition, the frontal lobes were selected for the study. EEG was done to record the brain-electrical response of ten male subjects. Each subject was prepared with an EEG recording cap with 19 electrodes (Ag/AgCl sintered ring electrodes) placed in the international 10/20 system. Another experiment was also conducted with *Bahar/ Mian ki Malhar* as the two set of clips which conveyed contrast emotion with 10 more participants using the same methodology as in this experiment.

Figure 3.1 (obtained from Recorders and Medicare EEG Systems manual) depicts the positions of the electrodes. Impedances were checked below 5 kΩ. The ear electrodes A1 and A2 linked together have been used as the reference electrodes. The same reference electrode is used for all the channels. The forehead electrode, FPz has been used as the ground electrode. The EEG recording system (Recorders and Medicare Systems) was operated at 256 samples/s recording on customized software of RMS. The data was band-pass-filtered between 0 and 50 Hz to remove DC drifts. Each subject was seated comfortably in a relaxed condition in a chair in a shielded measurement cabin. They were also asked to close their eyes. Since the subjects were not instructed to gaze at a fixation cross presented on a screen and to simultaneously rate the music during the recording, closing eyes helped them to attentively yet comfortably listen to music in the long experiment. The subjects were not instructed to identify any specific musical structures.

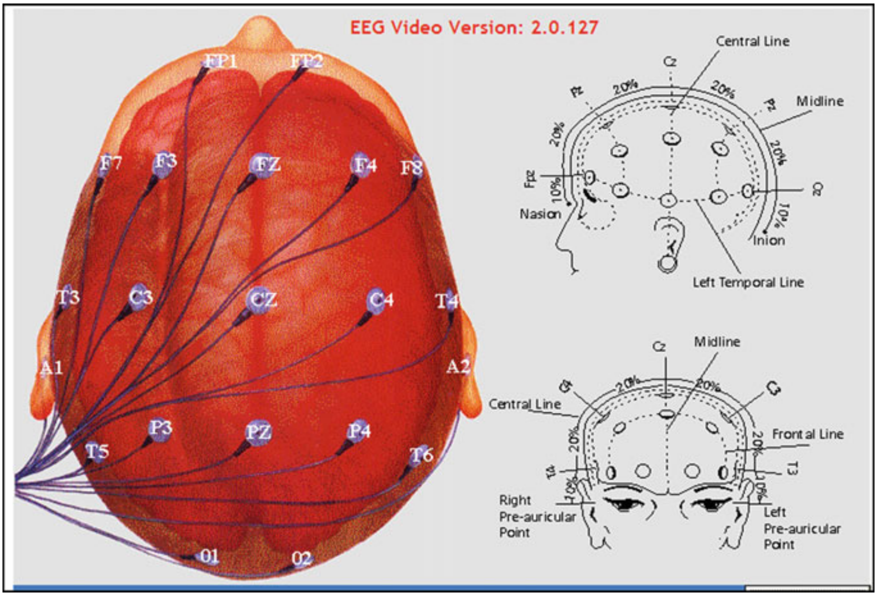


Fig. 3.1 The position of electrodes on the head are depicted

A sound system (Logitech R_Z-4 speakers) with high S/N ratio was set up in the measurement room that received input from outside the cabin. After initialization, a 17 min 40 s recording period was started, and the following protocol was followed:

1. Three Minutes No Music
2. 3 min 40 s With Music (Chayanat)
3. 3 min 40 s No Music
4. Sequence 2–3 was repeated With Music (Darbari Kannada)

Each signal length was 3 min 40 s. Markers were set at start, signal onset/offset, and at the end of the recording. On the second day, the same protocol was followed, only Music 1 and Music 2 have been replaced by “Bahar” and “Mian Ki Malhar” respectively.

3.3 Methodology

In order to eliminate all frequencies outside the range of interest, data was filtered within a range of 0.5–50 Hz using a finite impulse response (FIR) filter. The filter order for the FIR filter is set to two cycles of the lower frequency limit of that particular band, in order to accurately detect the oscillations while also limiting the temporal integration caused by the filter. Thus, in case of alpha band (8–13 Hz), the filter order is set to be two cycles of 8 Hz each, similar procedure was used for the other frequency bands. The amplitude envelope of the alpha (8–13 Hz), theta (4–7 Hz) and gamma (30–50 Hz) frequency range was obtained using wavelet transform technique. DFA was performed on the obtained amplitude envelope to quantify the scaling exponent, α for the different experimental conditions following the procedure given in Linkenkaer-Hansen et al. (2001).

3.3.1 *Empirical Mode Decomposition (EMD)*

EMD is a decomposition method for non-stationary and nonlinear signals (Huang 1998). The EMD technique decomposes a signal into a number of intrinsic mode functions (IMFs) that represent fast to slow oscillations. The EMD technique has been elaborated in the Methodology Chapter (Chap. 2) of this book. We have obtained noise free EEG data for all the electrodes using the EMD technique and used this data for further analysis and classification of acoustic stimuli induced EEG features.

3.3.2 *Wavelet Transform*

Wavelet transform (WT) forms a general mathematical tool for signal processing with many applications in EEG data analysis (Selesnick et al. 2005; Dimoulas et al.

2007; Hazarika et al. 1997a, b). The amplitude envelope of the different frequency rhythms were obtained using the above technique for ‘before music’, ‘with music’ as well as ‘without music’ conditions in the two different frontal lobes i.e. F3 (left) for Chayanat and F4 (right) for Darbari.

3.3.3 Detrended Fluctuation Analysis (DFA)

Earlier work has shown the importance of frontal electrodes in case of processing of emotions. So, we chose to study the variation of scaling exponent corresponding to various frequency rhythms in the two frontal electrodes while listening to music of contrast emotions. It has now been known that the human brain is obviously a complex nonlinear system (Hwa and Ferree 2002; Ferree and Hwa 2003; Lee et al. 2002; Peng et al. 1995). The scalp EEG arises from a large number of neurons whose interactions are generally nonlinear (Linkenkaer-Hansen et al. 2001) and thus they can generate fluctuations that are not best described by linear decomposition (Ferree and Hwa 2002). On the other hand, the classical nonlinear dynamics method such as correlation dimension and Lyapunov exponents are very sensitive to noise and require the stationary condition, while EEG signals often are highly non-stationary (Lee et al. 2002). Chaos analysis based on the assumption of low-dimensional attractors has also been applied to qualify the nonlinear behavior of the EEG, but in fact, the underlying neural populations are unlikely to obey entirely low-dimensional dynamics (Ferree and Hwa 2002). In our study, DFA technique has been applied to discuss the scaling behavior of the fluctuations in the amplitude envelope of alpha, theta and gamma frequencies while listening to emotional music.

DFA has been developed for quantifying correlation properties in non-stationary signals (Peng et al. 1995), e.g., in physiological time series, because long-range correlations can also come from the artifacts of the time series data. The amplitude envelope of the different frequency rhythms obtained from DWT technique elaborated above has been used to compute the scaling exponent using DFA. DFA technique was applied following the NBT algorithm used in Hardstone et al. (2012). The procedure to compute DFA has been elaborated in chapter 2 of this book. The FD values were computed from $D_{DFA} = 3 - \alpha$ for all the frequency rhythms in F3 and F4 electrodes in all the experimental conditions.

3.4 Results and Discussion

The amplitude envelope of alpha frequency rhythm corresponding to F3 electrode for the three experimental conditions has been shown in a representative Fig. 3.2 for a particular subject.

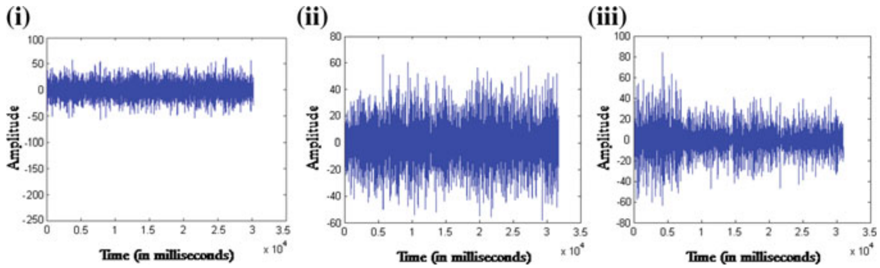


Fig. 3.2 Amplitude envelope of alpha wave in F3 for (i) before music (ii) with Chayanat and (iii) after Chayanat

DFA was applied on the extracted amplitude envelopes on a moving window basis with a window size of 22s taking an overlap of 50% between the windows. A single scaling exponent α was obtained corresponding to each window of 22 s. The total duration of the musical clip was 220 s; hence the window size of 22s was chosen to facilitate ten values of scaling exponents within the total recording period of “with music” and “after music” conditions.

A representative scaling plot computed from the amplitude envelope of alpha frequency rhythm shown for the electrodes F3 and F4, has been shown in Figs. 3.3 and 3.4 for all the experimental conditions.

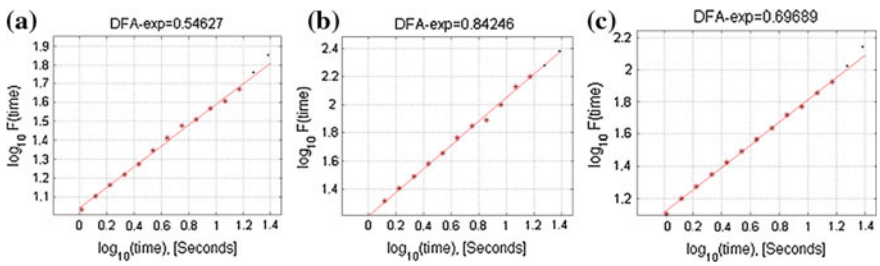


Fig. 3.3 **a–c**: Scaling plot of alpha wave of F3 electrode in the three experimental conditions

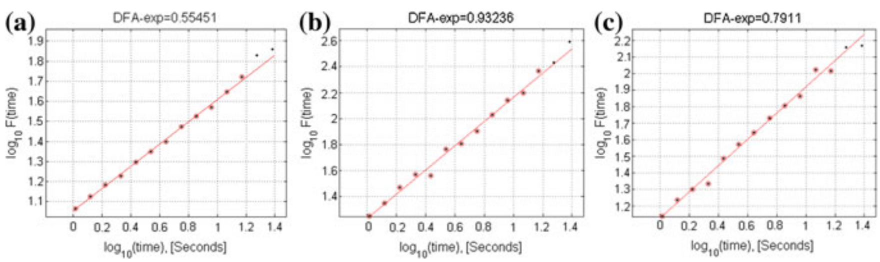
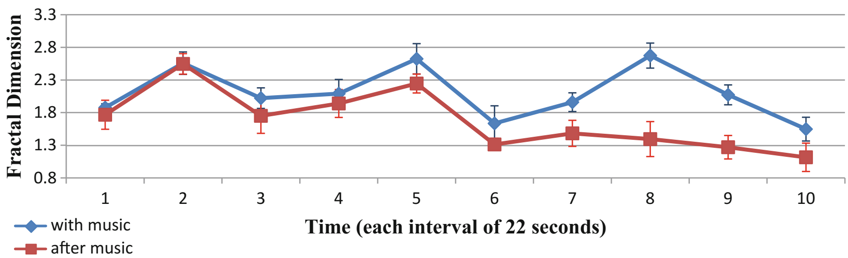


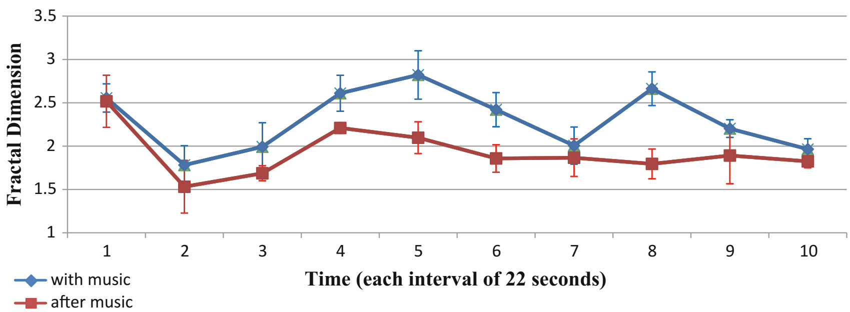
Fig. 3.4 **a–c**: Scaling plot of alpha wave of F4 electrode in the three experimental conditions

Fractal dimension was computed against the EEG channels F3 and F4 for alpha, theta and gamma frequency rhythms using Eq. (4). We have observed earlier (Sanyal et al. 2013) that the alpha frequency in the frontal electrodes was low in the odd electrodes for raga Chayanat (happy) and low in the even electrodes for raga Darbari (sad). The FD values of the 'after the withdrawal of music' tend to be lower than the 'with music' condition. Due to multivariable data, two EEG channels were selected from the left and right hemispheres to simplify further investigation. Left and right FD values, which revealed significant patterns, are shown in Figs. 3.5, 3.6 and 3.7 for both 'with music' and 'after the withdrawal of music' conditions in case of alpha, theta and gamma frequency rhythms. The plot for the variation of the FD in the latter case was done for 220 s in the 'without music' condition. For comparison they are drawn in the same time scale. The figures depict the FD values of the alpha, theta and gamma rhythms in time intervals of 22 s. Since both the music specimens are of 220 s duration, EEG was continued for another 220 s after the withdrawal of music. The error bars in all the plots represent the SD values computed for different time windows in each experimental condition.

The sole objective was to see how long the memory of the former state (i.e. that particular music) remains after its withdrawal. It is observed that in Chayanat, FD of the alpha at F3 shows high complexity in the neural processing in different time regions, depicting high arousal for happy music. After its withdrawal, in the next

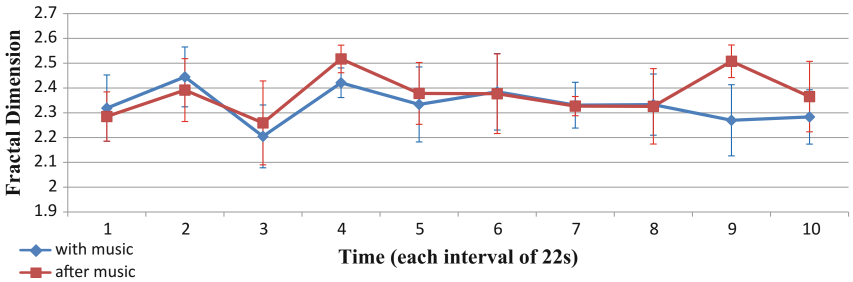


(a) Variation of FD with time of alpha frequencies of F3 for Chayanat and after its removal

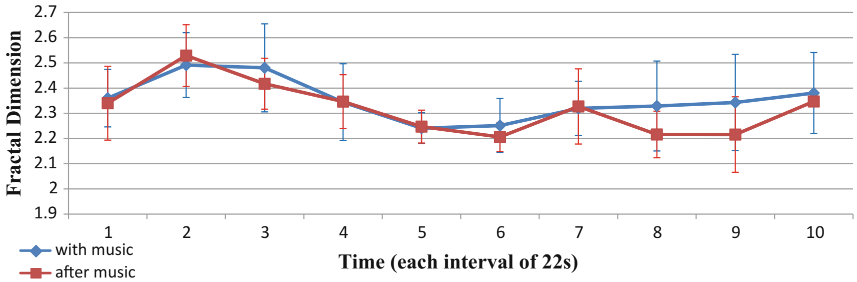


(b) Variation of FD with time of alpha frequencies of F4 for Darbari and after its removal

Fig. 3.5 **a** Variation of FD with time of alpha frequencies of F3 for Chayanat and after its removal. **b** Variation of FD with time of alpha frequencies of F4 for Darbari and after its removal



(a) Variations of FD with time of theta frequencies of F3 for Chayanat and after its removal

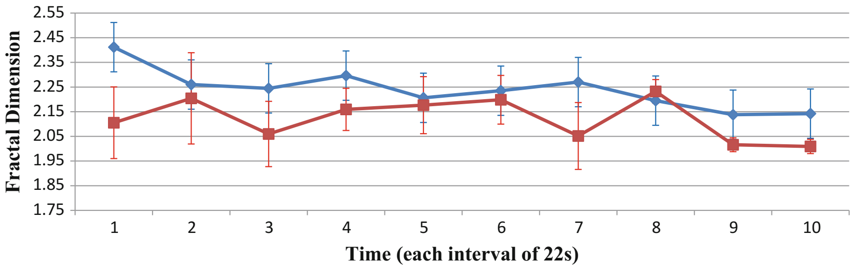


(b) Variation of FD with time of theta frequencies of F4 for Darbari and after its removal

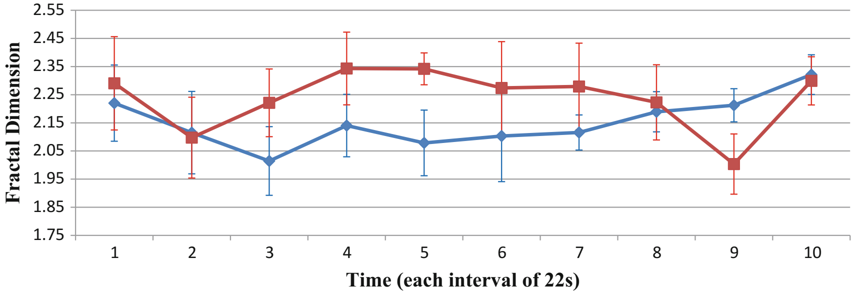
Fig. 3.6 **a** Variations of FD with time of theta frequencies of F3 for Chayanat and after its removal. **b** Variation of FD with time of theta frequencies of F4 for Darbari and after its removal

220 s, the FD of alpha remains high up to 120 s and then falls, thereby showing retention of the emotion of Chayanat for 120 s. In the case of Darbari also, FD of the alpha at F4 shows high complexity in the neural processing in different time regions depicting high arousal for sad music. After its withdrawal, in the next 220 s, the FD of alpha remains high up to 77 s and then falls, thereby depicting retention of the emotion of Darbari for 77 s. In case of theta frequency rhythms, the arousal effects are not so much prominent, though the left frontal lobe i.e. F3 shows high complexity till 77 s for Chayanat and then decays. But in F4, neural complexity of theta rhythm decreases roughly 33s after the removal of Darbari. In case of gamma frequency rhythm, we failed to find any such residual arousal effects as is evident from Fig. 3.7. The variation of FD values after the removal of Chayanat and Darbari corresponding to gamma frequency rhythm in both the left and right hemisphere is absolutely random and is unable to decipher any conclusive result.

Rigorous analysis of the FD and alpha frequency data obtained from our experiment for both the music clips in ‘with music’ and ‘without music’ condition reveals that the Fractal Dimension (FD) values of alpha frequency increase and hence complexity increases in “with music” condition (for both clips) and decreases in “after music” condition. The average FD value of alpha for ‘after music’ (Darbari) is greater than that of Chayanat as shown in Table 3.1. This clearly indicates retention of the previous state of brain and eventually leads to some



(a) Variation of FD with time of gamma frequencies of F3 for Chayanat and after its removal



(b) Variation of FD with time of gamma frequencies of F4 for Darbari and after its removal

Fig. 3.7 **a** Variation of FD with time of gamma frequencies of F3 for Chayanat and after its removal. **b** Variation of FD with time of gamma frequencies of F4 for Darbari and after its removal

Table 3.1 The average FD and the SD value of alpha wave for different conditions

Alpha wave	Before Music	With Chayanat	After Chayanat	With Darbari	After Darbari
mean FD	1.3884	2.1059	1.6828	2.3018	1.9278
SD	0.2024	0.3958	0.4585	0.3575	0.2805
Theta wave					
mean FD	2.2257	2.332	2.3734	2.3546	2.3193
SD	0.1359	0.0715	0.0846	0.0823	0.1028
Gamma wave					
mean FD	2.2232	2.240	2.1212	2.1510	2.2372
SD	0.0464	0.0797	0.0831	0.0868	0.1088

evidence of hysteresis. In case of theta and gamma waves the change of FD value was insignificant as is evident from the values given in Table 3.1. ANOVA (Miller 2004) tests were performed in the three frequency domains for the three experimental conditions i.e. 'before music', 'with music' and 'after music' for both the electrodes. Table 3.2 reports the ANOVA parameters for the two electrodes corresponding to alpha, theta and gamma waves. The significant value was set to

Table 3.2 ANOVA values for the different experimental conditions

F4 electrode (for Darbari)		Gamma wave				Theta wave				Alpha wave			
Source	df	SS	MS	F	*p*	SS	MS	F	*p*	SS	MS	F	*p*
Treatment (between experimental conditions)	2	0.049	0.024	2.75	0.08	0.122	0.061	5.94	0.39	1.194	0.597	8.53	0.001
Residual (within experimental conditions)	27	0.239	0.009			0.277	0.010			1.889	0.699		
Total	29	0.288				0.399				3.082			
F3 electrode (for Chayanat)		Gamma wave				Theta wave				Alpha wave			
Source	df	SS	MS	F	*p*	SS	MS	F	*p*	SS	MS	F	*p*
Treatment (between experimental conditions)	2	0.082	0.041	8.03	0.58	0.122	0.061	5.94	0.07	2.602	1.301	9.6	0.007
Residual (within experimental conditions)	27	0.139	0.005			0.277	0.010			3.672	0.136		
Total	29	0.221				0.399				6.273			

SS Sum of squares
df Degrees of freedom
MS Mean squares
F = (MStreatment/MSresidual)

$p = 0.05$ in One Way ANOVA performed here. The ANOVA results are found to be significant only for alpha frequency rhythms for both the electrodes. For gamma and theta frequencies, ANOVA tests yielded a value of $p > 0.05$ which can be considered as insignificant, hence the average graph is plotted only for alpha frequency range. Also, the variation among the means in case of alpha rhythm was found to be significantly greater than what is expected by chance, even at 95% confidence level. All tests for ANOVA were performed in the SPSS software package for Windows (Coakes and Steed 2009).

Post hoc analysis test in the form of Tukey-Kramer multiple comparison test was performed for the alpha frequency domain which yielded a significant value of $p < 0.05$. The results for F3 and F4 electrode are given below in Table 3.3. We see that in the odd electrode, F3, significance level is maximum for comparison between 'before Chayanat' and 'with Chayanat' condition and is minimum for both the without music condition. In the even electrode F4, maximum significance is found in the 'with Darbari' and 'after Darbari' condition. Although the ANOVA results indicate that in case of F3 electrode, the values of "Before Music" and "After Music" are not significant, we may mention the fact that our study concerns with retention of emotion only after withdrawal, which we emphasize as our primary goal.

The fractal dimension analysis of alpha frequency rhythms might provide a simple summary of the complex dynamics across physiologically meaningful time scales. This is manifested in Fig. 3.8, from where we can see that after removal of both types of stimuli; FD values remain high for a certain time duration and then decays off. Using nonlinear methods such as DFA can lead to additionally useful information such as a hysteresis effect in the case of neurons triggered by audio stimuli, viz. emotive music. The change of average FD values obtained from theta and gamma frequencies was not very much significant as compared to alpha frequency range.

Table 3.3 Tukey-Kramer multiple comparison test results

Comparison	Mean difference	q	*p*-value	
F3 electrode (alpha waves)				
Before Music vs With Chayanat	−0.7175	6.153	Highly significant	$p < 0.001$
Before Music versus After Chayanat	−0.2944	2.525	Not significant	$p > 0.05$
With Chayanat versus After Chayanat	0.4231	3.628	Significant	$p < 0.05$
F4 electrode (alpha waves)				
Before Music versus With Darbari	0.0854	1.022	Not significant	$p > 0.05$
Before Music versus After Darbari	0.4594	5.492	Significant	$p < 0.05$
With Darbari versus After Darbari	0.3739	4.471	Highly Significant	$p < 0.01$

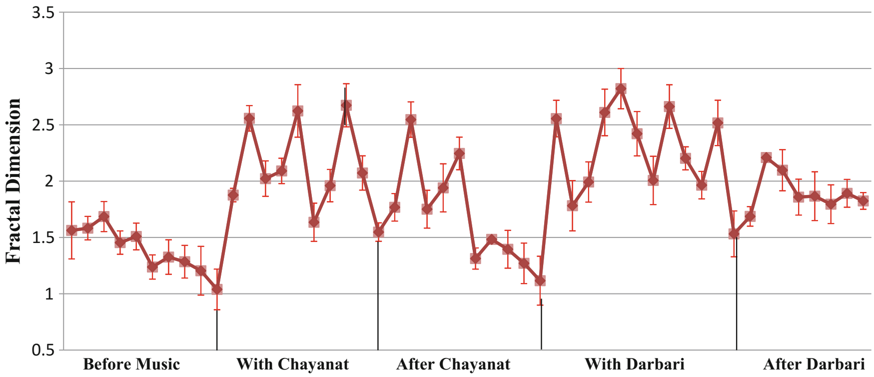


Fig. 3.8 Variation of average FD of alpha waves in different stages viz. 'no music', music (Chayanat), after Chayanat, music (Darbari), after Darbari conditions

The second experiment mainly focuses on the quantification and categorization of emotions from Hindustani music and hence we studied the response to music clips over the five electrodes namely F3, F4, F7, F8 and Fz.

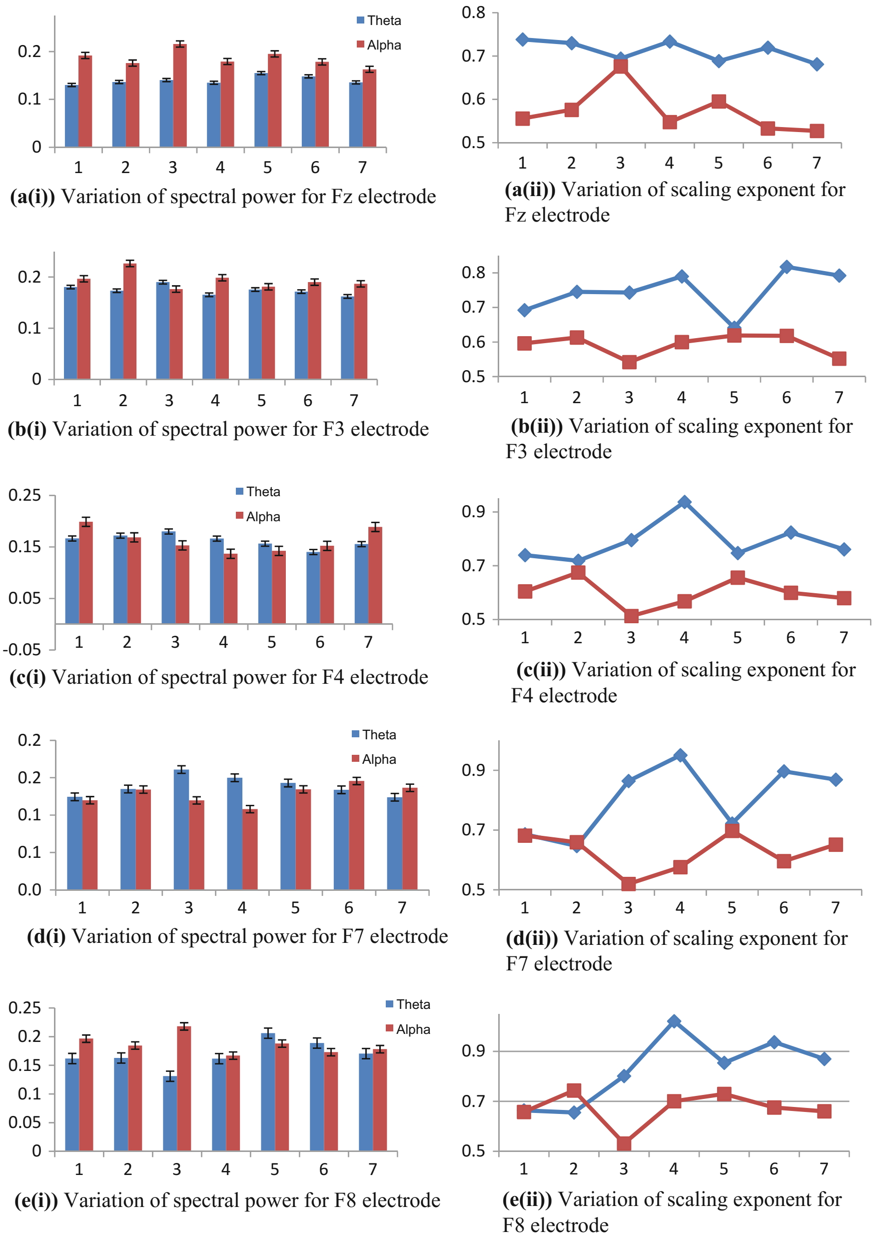
The following table (Table 3.4) gives the DFA scaling exponent values for *Bahar and Mian ki Malhar.*

The following Fig. 3.9 shows the variation in alpha and theta spectral power values as well as the scaling exponents in the 2nd experiment for the five frontal electrodes.

The alpha power as well as the alpha scaling exponent decreases for the 1st music (i.e. Bahar or happy music) in the odd electrodes F3 and F7. This goes in line with our previous knowledge (Banerjee et al. 2016), which says that the processing of happy emotion takes place in the left hemisphere of the brain. As is found in previous studies decrease in alpha power corresponds to higher arousal based activities, we have also found here that the dip in alpha power corresponds to a dip in complexity of neural activities. In case of the 2nd music (i.e. Mia ki Malhar or sad music), there is also a dip in spectral alpha power but the dip is not as significant as in the case of 1st music. But the scaling exponent or the complexity shows a rise corresponding to 2nd music. Interestingly, the even electrodes F4 and F8 follow almost the same pattern as the odd ones, with the alpha scaling exponents showing a sharp dip corresponding to the 1st music, while it rises for the 2nd music. It may be inferred loosely that the emotional content or the emotion eliciting capacity of the 2nd music may not be as strong as that of the 1st music. But the alpha spectral power values form a prominent dip for the 2nd music as compared to the 1st music for the even electrodes. In this case the behavior of the alpha spectral power values goes in opposition to the scaling exponent values. In the frontal midline electrode, i.e. Fz, the alpha power dips for both the music and again increases after the removal of music. The alpha scaling exponent does not vary significantly in the Fz electrode throughout the experimental period. The theta spectral power increases more for the 2nd music, also the dip in theta scaling exponent is more in case of the 2nd music.

Table 3.4 Scaling exponent α computed for the 2nd experiment

		Without music	With Drone	With Bahar	After Bahar	With Mia ki Malhar	After Music 1	After Music 1
F3	Theta	0.64 ± 0.04	0.70 ± 0.03	0.69 ± 0.02	0.74 ± 0.06	0.59 ± 0.04	0.77 ± 0.02	0.74 ± 0.01
	Alpha	0.55 ± 0.02	0.56 ± 0.02	0.49 ± 0.04	0.55 ± 0.03	0.57 ± 0.01	0.57 ± 0.04	0.50 ± 0.04
F4	Theta	0.69 ± 0.04	0.67 ± 0.04	0.75 ± 0.02	0.89 ± 0.03	0.70 ± 0.01	0.77 ± 0.04	0.71 ± 0.03
	Alpha	0.55 ± 0.01	0.62 ± 0.04	0.46 ± 0.02	0.52 ± 0.06	0.61 ± 0.03	0.55 ± 0.04	0.53 ± 0.01
F7	Theta	0.64 ± 0.05	0.60 ± 0.04	0.81 ± 0.02	0.90 ± 0.03	0.67 ± 0.04	0.85 ± 0.02	0.82 ± 0.03
	Alpha	0.63 ± 0.02	0.61 ± 0.02	0.47 ± 0.04	0.53 ± 0.03	0.65 ± 0.04	0.55 ± 0.03	0.60 ± 0.05
F8	Theta	0.61 ± 0.03	0.61 ± 0.04	0.75 ± 0.06	0.97 ± 0.03	0.80 ± 0.02	0.89 ± 0.07	0.82 ± 0.04
	Alpha	0.61 ± 0.04	0.69 ± 0.04	0.48 ± 0.04	0.65 ± 0.02	0.68 ± 0.04	0.63 ± 0.04	0.61 ± 0.05
Fz	Theta	0.74 ± 0.04	0.73 ± 0.05	0.69 ± 0.02	0.73 ± 0.06	0.69 ± 0.04	0.72 ± 0.04	0.68 ± 0.04
	Alpha	0.56 ± 0.04	0.58 ± 0.04	0.58 ± 0.04	0.55 ± 0.02	0.52 ± 0.04	0.53 ± 0.04	0.53 ± 0.06



(a(i)) Variation of spectral power for Fz electrode

(a(ii)) Variation of scaling exponent for Fz electrode

(b(i) Variation of spectral power for F3 electrode

(b(ii)) Variation of scaling exponent for F3 electrode

(c(i) Variation of spectral power for F4 electrode

(c(ii)) Variation of scaling exponent for F4 electrode

(d(i) Variation of spectral power for F7 electrode

(d(ii)) Variation of scaling exponent for F7 electrode

(e(i)) Variation of spectral power for F8 electrode

(e(ii)) Variation of scaling exponent for F8 electrode

Fig. 3.9 **a (i)** Variation of spectral power for Fz electrode **a (ii)** Variation of scaling exponent for Fz electrode. **b (i)** Variation of spectral power for F3 electrode **b (ii)** Variation of scaling exponent for F3 electrode. **c (i)** Variation of spectral power for F4 electrode **c (ii)** Variation of scaling exponent for F4 electrode. **d (i)** Variation of spectral power for F7 electrode **d (ii)** Variation of scaling exponent for F7 electrode. **e (i)** Variation of spectral power for F8 electrode **e (ii)** Variation of scaling exponent for F8 electrode

In the odd electrodes F3 and F7, the theta spectral power again increases for both the music and then decreases after the removal of musical stimuli, while the theta scaling exponent shows a significant dip for the 2nd music while it increases to a small extent for the 1st music. This result is an interesting one, as the subjects may have found the 2nd music (conventionally a sad one) to be more pleasant than that of the 1st. In the even electrodes, F4 and F8, the theta spectral power again increases, to a greater extent for the 2nd music, to a smaller extent for the 2nd music. The theta scaling exponent shows a sharp dip for the 2nd music, while it increases a little for the 1st one. ANOVA test revealed significant value in the alpha frequency domain during Part 3 and 4 (p = 0.048811), for the 2nd music also in Part 5 and Part 6 (p = 0.0319). All tests were performed in SPSS Package for Windows.

To summarize, in this work we have described how the DFA method can be applied to reveal the complexity in the alpha, theta and gamma frequency rhythms extracted from EEG data while listening to emotional music and after the withdrawal of music. The work presents new data regarding neuro-cognitive functioning of the brain in the alpha and theta frequency domain in response to musical stimuli. Most works in this genre have made the use of linear techniques and are focused mainly in the alpha and theta frequency domains. The linear techniques fail to decipher the finer level of information embedded in the data that non-linear methods succeed to. The use of a robust non linear technique like DFA has helped us to identify the finer intricate details of complex EEG data both with and without music. We have tried to compare the data obtained from two sets of Hindustani Raga music which are conventionally known to elicit two contrasting emotions (happy/joy and sorrow/pathos). Our study indicates that using nonlinear methods such as DFA can lead to additionally useful information such as a hysteresis effect in the case of neurons triggered by audio stimuli, viz. emotive music.

3.5 Conclusion

In this work, for the first time rigorous non-linear EEG signal processing approach has been taken to estimate the emotional arousal based responses to different *ragas* of Hindustani Classical music. That Hindustani music is an elicitor of a variety of emotional responses is well known—even a single *raga* doesn't always convey a single emotion but a variety of emotional responses during the course of rendition of the *raga*. The neural response to Hindustani *raga* music poses to be an interesting piece of study as the way in which the brain interprets this genre music is still a mysterious affair and this work, for the first time tries to get an overview of the response. The overall conclusions from this study have been listed as under:

1. Fractal dimension (DFA) analysis of the alpha frequency rhythm, which is the manifestation of complexity in the neuron activity show that arousal activities were enhanced for some time ($\sim$120 s for Chayanat *raga* while $\sim$77 s in case of Darbari *raga*) in both the left and right frontal lobes corresponding to happy and sad music respectively.

2. The variation of degree of complexity shows a clear retention of that particular emotion even after the withdrawal of music. The left frontal lobe being more active in case of *raga* C*hayanat* and the right frontal lobe being more active in case of *raga Darbari* may point in the direction of valence lateralization of emotional appraisal even in case of Hindustani music.
3. A hysteresis-like phenomenon was observed in case of emotions induced by Hindustani music stimuli. The alpha complexity remained higher both in case of odd and even electrode for some time, even after the music stimuli was removed and the participants were in resting state.
4. The obvious fluctuation in the brain arousal states (indicated by sudden dips and spikes in FD values) may be an indication that Hindustani classical music is ambiguous in nature: i.e. there is no fixed emotion and that the emotional content varies even during the course of a particular rendition. This may cause the periodic fluctuations of alpha/theta FD values when the listeners were listening to the two *ragas* of contrast emotion.
5. In case of sad music (*raga Mian ki Malhar*), the results show considerable ambiguity in respect to conventional wisdom and the results that we obtained. This inspires us to revisit and redefine the concept of sadness again.
6. Fractal analysis of the alpha frequency band further hints that in case of pathos/sad emotion, retention time is more as is evident from the FD values. This data is new and is of extreme importance in the context of recent research interest on enhancement of memory with music.
7. Further, the FD values corresponding to "during music" and "after music" conditions are highly significant as supported by one way ANOVA test and subsequent post hoc analysis. This observation speaks in favor of the fact that hysteresis like effect may be present in case of music induced emotions.

The present investigation and its findings demand that more rigorous analysis of large samples of EEG data with different types of music needs to be done to frame a robust algorithm for acquiring a thorough knowledge of music processing in the brain, particularly the neuro-dynamical behavior of memory retention. With this cue, we move on to the next Chapter which deals with the creativity and perception associated when a professional artist imagines as well as listens to a *raga*.

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Chapter 4
Musical Perception and Visual Imagery: Do Musicians visualize while Performing?

Melody and harmony are like lines and colors in pictures.
—Rabindranath Tagore

4.1 Introduction

Music and human brain are two of the most beautiful creations found in this nature. Music has its power to evoke many shades of different emotions in the human brain. For the past few decades, researchers are trying to gather in depth knowledge about how an external music stimulus is perceived in brain and then emotions are elicited as a result. Due to the advancement of modern technology and high speed computing, this area of research has taken a new dimension. After the development of neuro bio-sensors like EEG, fMRI, detailed quantitative study of the brain state change has been possible while the subjects listened to various types of music stimuli. Now, if we look at the other face of the coin, the first question that comes to our mind is "What about the musicians who create/compose that music we listen to everyday?" This thought eventually evokes a number of questions. The most fascinating one among all of them is: What does a musician think at the precise moment when he/she creates a particular music? People are striving to get an answer to this question for years, but until the discoveries of neuro sensors, there was no scientific way which could reveal the picture inside the human brain in the exact moment of creating something artistic.

Issues of artistic creativity might involve too many variable parameters such as personality, inherent artistic ability, mood etc. and it becomes very difficult to tackle all these parameters simultaneously. But, with the onset of neurocognitive science we have robust neuro-imaging techniques with which we look forward to have an accurate insight of brain response while an artist is mentally creating as well as listening to a particular musical composition (*raga* in our case). Simply put, a *raga* in Hindustani Classical music is a musical theme created by choosing a specific set of notes from within an octave. Different sets of notes evoke different moods and inspire different feelings (Balkwill and Thompson 1999). The literature regarding perception and imagination of a musical stimuli involving Hindustani *raga* music is

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quite scarce, though it is quite rich and diverse when it comes to the variety of emotions induced by it (Wieczorkowska et al. 2010; Mathur et al. 2015; Banerjee et al. 2016). The Electroencephalography (EEG) is a neuro scientific tool which gives precise measurement of the timing of the response because of its high temporal resolution, which is an advantage of EEG over PET (Positron Emission Tomography) or fMRI (functional Magnetic Resonance Imaging). A number of EEG studies have been conducted with the help of power spectral analysis to assess musical emotions (Bhattacharya and Petsche 2001; Schmidt and Trainor 2001; Sammler et al. 2007; Davidson 1988). These studies mostly speak in favor of the lateralization theory when it comes to the processing of positive and negative emotions. Most of the power spectral studies show that activity in the alpha frequency band is negatively related to the activity of the cortex, such that larger alpha frequency values are related to lower activity in the cortical areas of the brain, while lower alpha frequencies are associated with higher activity in the cortical areas (Schmidt and Trainor 2001; Davidson 1988). It has also been shown that pleasant music would elicit an increase of Fm theta power (Sammler et al. 2007). Most of the earlier works make use of coherence properties between the lobes using linear power spectral analysis in various frequency ranges to assess the amount of interdependence. Coherence, a parameter obtained from spectral analysis of the EEG, is the normalized cross-spectrum of two signals and reflects the correlation between them with respect to frequency. Applied to EEG analysis, the value of coherence lies in its providing data on the relationships between the electric oscillations recorded from two locations on the skull (Petsche et al. 1993). While listening to music, degrees of the gamma band synchrony over distributed cortical areas were found to be significantly higher in musicians than non-musicians (Bhattacharya and Petsche 2001). Musical training can have strong effects on the structural and cognitive development of brain (Pinho et al. 2014; Schneider et al. 2002; Bengtsson et al. 2005; Kleber et al. 2010; Pantev and Herholz 2011; Hyde et al. 2009; Schlaug et al. 2005).

In this work, we endeavored to study the neuro-dynamical effect of mentally composing as well as listening to a '*raga*' taking the help from two experienced performers of Hindustani classical music. No previous study, to the best of our knowledge, has rigorously analyzed the non-linear aspects of EEG signal to study creative musical imagery on trained musicians with auditory stimuli (in our case—a sample of Hindustani *raga* music).

4.1.1 Creativity in Musical Performances: Brain Response

Creativity in musical performances is gaining rapid importance as a field of research in recent years; the primary question being how to assess creative correlates during a performance. The primary hitch in these approaches being the proper definition of creativity. A general definition is given by Stein (1953) which says creativity is the production of something both novel and useful. The literature on musical creativity is quite large with its facets ranging from musicology (Richardson and Saffle 1983), psychology (Simonton 2000; Byrne et al. 2003), cognitive science (Dietrich 2004) and art history (Sloboda 1988); but it is the cognitive modalities of creative improvisation during a performance that is currently drawing huge interest.

Musical improvisation is by far the most challenging task that an artist has to undertake, requiring the real-time generation and production of novel melodic and rhythmic sequences in line with an ongoing musical performance. Thus, understanding musical improvisation is crucial to understand how in general creative processes are conducted in human being.

Assessment of creative thinking using EEG based studies has been one of the predominant issues of neuroscience that provided contradictory results in the past. A group of researchers in favor of the lateral dominance have, come to the conclusion that the right hemisphere and its regions are specialized for creative tasking (Bhattacharya and Petsche 2005; Bowden and Jung-Beeman 2003; Mihov et al. 2010), while a number of studies have come up with contradictory evidence (Martindale et al. 1984; Razumnikova and Bryzgalov 2006). Although, it seems a bit impractical to assume that only the right hemisphere is involved in the process of creative thinking as there is stupendous amount of correlation among the hemispheres involved in different perceptual and cognitive tasks (Chiarello and Maxfield 1996). A recent neuro-imaging study (Bashwiner et al. 2016) reports increased surface area for subjects reporting high levels of musical creativity which suggests that domain-specific musical expertise, default-mode cognitive processing style, and intensity of emotional experience might all coordinate to motivate and facilitate the drive to create music. Earlier brain-imaging studies pointed the importance of Pre-Frontal cortex (PFC) in case of creative thinking (Jung et al. 2013; Beaty et al. 2014), while a study on Jazz musicians (Limb and Braun 2008) reveals that improvisation (compared to production of over-learned musical sequences) was consistently characterized by a dissociated pattern of activity in the prefrontal cortex.

4.1.2 Improvisation in Hindustani Music

As we focus our work mainly around the genre of Indian classical music, we need to know what is usually meant by “musical improvisation” in Hindustani music (HM). Till date, no study tries to harvest the immense potential that a Hindustani musician has to offer when it comes to the study of creativity in musical performances. In contrast to western music, our HM imposes no hard and fast restriction of composed melodies on the performers while performing a “*Raga*”. This genre of music offers the musicians an infinite canvas for improvising within the structured framework of a *raga,* hence every musician in this genre is a composer as well as a performer simultaneously. A musician while performing expresses the *raga* according to his mood. Thus even if one particular artist sings or plays the same *Raga* and same *Bandish* twice, certainly there will be some dissimilarities in between the two renditions. These differences which make the two renditions of the same *raga* unique in their own way are generally termed as improvisations. Unlike symphony or a concerto, *Raga* is unpredictable; it is eternally blooming, blossoming out into new and vivid forms during each and every performance which is the essence of "improvisation" (McNeil 2007).

4.1.3 Musicians and Visual Imagery: Claims and Beliefs

The images which we see not through our eyes, but through our mind are what we call "visual imagery". A person who is having a visual imagery is believed to process certain information in his brain as though he perceives some stimuli like sight, sound, smell etc. when none of these stimuli are actually present. Study of this visual imagery is drawing attention from researchers of various disciplines like psychology, cognitive science and recently neuroscience. This visual imagery is closely linked with music creation and perception too.

Over the years the performers of Hindustani raga music insist that while performing or composing a musical piece, they have a visual imagery of that particular composition/*raga* in their mind which helps them to improvise and reach to the audience better. According to claims these images can vary from an artist to another for a particular raga or composition. Also the nature of imagery may vary for an artist over time but, there is one certainty that some sort of visual imagery is always present in their mind. These claims can now be verified scientifically after the invention of bio-sensors like EEG, fMRI etc. Not much scientific studies have been found till date which could reflect some lights in this domain.

4.1.4 Musical Imagination and the Role of Occipital Lobe

From previous knowledge, it is now a well accepted fact that the frontal lobe of our brain is usually associated with reasoning, cognitive processing and expressive language; the temporal lobe is important for interpreting sounds and the language we hear while the occipital lobe is important for interpreting visual stimuli and information processing (Mellet et al. 1995, 1996, 1998; Kosslyn 1996). Generally, there is strong evidence that perception and imagination of music share common processes in the brain. In his recent review of the literature on auditory imagery, Hubbard (2010) concludes that "auditory imagery preserves many structural and temporal properties of auditory stimuli" and "involves many of the same brain areas as auditory perception." The same is also found by Schaefer (2011) whose "most important conclusion is that there is a substantial amount of overlap between the two tasks (music perception and imagery), and that internally creating a perceptual experience uses functionalities of normal perception." A number of studies dealing with verbal instructions also provide report that the so-called dorsal route known to process visuospatial features can be recruited even by auditory verbal stimuli (Mellet et al. 1996, 1998, 2000). Also, in addition to higher order visual areas, mental imagery shares common brain areas with other major cognitive functions, such as language, memory and it reflects the high degree of interaction between mental imagery and other cognitive functions (Mellet et al. 1998). The precise route and nature of visual imagery remains to be determined though it has been suggested by previous researchers that musical stimuli may be more effective in generating visual imagery.

4.1.5 Use of MFDFA and MFDXA to Study Musical Imagination

The brain is said to be the most complex structure found in human body and the EEG signals generated from brain are essentially non-stationery and scale varying in nature (Chen et al. 2002). There has been increasing evidence that spontaneous brain responses, as recorded from single neuron to millions of neurons, is not necessarily random; on the contrary, it could be better characterized by persistent long-range temporal correlations and scale-free dynamics (Kantelhardt et al. 2001). Different scaling exponents can be revealed for many interwoven fractal subsets of the time series. So, a multifractal analysis of the data would be more appropriate than a single scaling exponent as is obtained from Detrended Fluctuation Analysis (DFA) (Peng et al. 1995).

As mentioned in Sect. 3.1.4, we identified three different lobes of the brain namely frontal, temporal and occipital whose functions mostly concur with our work. We therefore chose one pair of electrodes from each of these lobes (F3/F4 from frontal, T3/T4 from temporal O1/O2 from occipital) to study the brain electrical response of the artist while he is creating as well as listening to a raga of his choice. The non stationary time signals of EEG generated from different electrodes are best analyzed with the MFDFA technique (Maity et al. 2015). Multifractal Detrended Fluctuation Analysis of EEG time series helps us to quantify the arousal based effects in each of the chosen lobes during musical imagery and perception. Next, the signals from the two different groups of electrodes are analyzed with the help of MFDXA technique to assess the inter lobe as well as intra lobe cross correlation from EEG recordings of the same person during creating and perceiving music. Then using Wavelet Transform (Akin et al. 2001) technique, the EEG signals obtained from two different lobes of brain were separated into alpha and theta frequency rhythms and again analyzed with the help of MFDXA technique. This analysis can unveil the higher-dimensional multifractal measures of two cross-correlated signals and can provide a quantitative parameter depicting ‘degree of cross-correlation’. The resultant cross correlation exponent gives the degree or the amount by which the two signals are correlated. It is worth mentioning here, that though a number of previous works referred here rely on fMRI or PET data, robust non-linear techniques such as MFDFA and MFDXA can only be applied on EEG time series data obtained from different electrodes in the brain.

When a musician is listening and also imaging a certain raga in their mind, they claim that the role of musical expectancy as well as the memory of the just listened phrases and the possible connection to this with immediately following expected musical events is higher. This may lead to strong correlations among specific frequency bands in the specific lobes where the processing of musical imagery and perception takes place. The complexity of the EEG time series obtained from these particular lobes may also be suitably affected when the processing of musical imagery or perception is taking place. This was the main objective behind this work, where we quantitatively analyze the arousal based effects in each lobe during creative composition as well as perception of a musical piece, and also analyze the degree of cross-correlation between different lobes of the brain during these experimental conditions. What we look forward to in this paper is to conjure a paradigm in which we can identify the lobes of brain mostly involved during perception and mental improvisation (or imagination) of a *raga* piece.

4.2 Experimental Details

4.2.1 Subjects Summary

Two male professional performers of Hindustani music (age between 45 and 50 years, average body weight ~60 kg) voluntarily participated in the study. One of them is a renowned vocalist and the other an eminent *sitar* player, both of them performing in stage for more than 30 years. The two performers were chosen keeping in mind their difference in musical pedagogy which means their mode of musical training is different, so we can assume that their mode of expression and creative improvisation is different. Both the subjects are researchers associated with Sir C.V. Raman Centre for Physics and Music, Jadavpur University, Kolkata, India. Non musicians were not involved in this study as creative imagery of a Hindustani *raga* can only be perceived by an experienced musician. The experiments were performed at the Sir C.V. Raman Centre for Physics and Music, Jadavpur University, Kolkata. The experiment was conducted in the afternoon with a normal diet in a normally conditioned room sitting on a comfortable chair and performed as per the guidelines of the Institutional Ethics Committee. All subjects gave written consent before participating in the study, approved by the Ethics Committee of Jadavpur University, Kolkata.

4.2.2 Choice of **Raga: Jayjayanti**

Both the musicians (henceforth referred to as Subject 1 and Subject 2) were asked to choose a common *raga* and the instruction for them was to imagine the *alaap* or introductory part of the chosen *raga* as they would have done during any performance. Both of the participants chose *raga Jayjayanti* for this particular study. *Raga Jayjayanti* follows the characteristics of "*Khamaj Thaat*" and conventionally said to evoke a happy mood in listeners as well as performers. Following the prescription of the performers, both of them were asked to bring a 3 min recording of their own recital of the same music sample (a 3 min *alaap* of *raga Jayjayanti*). The *alaap* portion of each raga was chosen as the inherent form of the entire *raga* is essentially established and identified in this part. The *alaap* part gradually reveals the mood of the raga using all the notes used in that particular raga and allowed transitions between them with proper distribution over time. It reflects the temperament, creativity and uniqueness of musical training of a musician.

4.2.3 Experimental Protocol

Each of the chosen sound signals was digitized at the sample rate of 44.1 kHz, 16 bit resolution and in a mono channel. Both the signals were normalized to within 0 dB and hence intensity or loudness and attack cue are not being considered. A sound system (Logitech R_Z-4 speakers) with high S/N ratio was used in the measurement room for giving music input to the subjects. Then, each subject was prepared with an EEG recording cap with 19 electrodes (Ag/AgCl sintered ring electrodes) placed in the international 10/20 system.

Figure 4.1 depicts the positions of the electrodes. Impedances were checked below 5 kΩ. The ear electrodes A1 and A2 linked together have been used as the reference electrodes. The same reference electrode is used for all the channels. The forehead electrode, FPZ has been used as the ground electrode. The EEG recording system (Recorders and Medicare Systems) was operated at 256 samples/s recording on customized software of RMS. The data was band-pass-filtered between 0 and 50 Hz to remove DC drifts. Each subject was seated comfortably in a relaxed

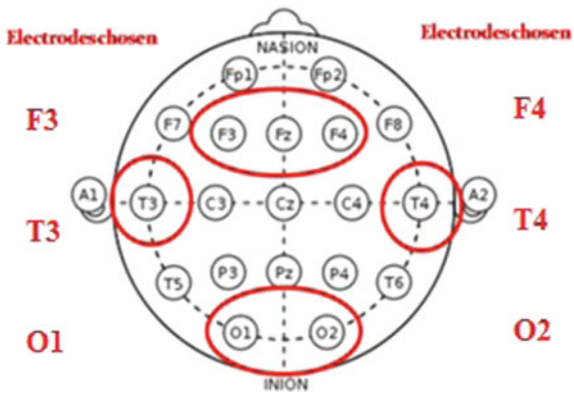


Fig. 4.1 The lobes and electrodes chosen for our analysis

condition in a chair in a shielded measurement cabin. They were also asked to close their eyes. A sound system (Logitech R_Z-4 speakers) with high S/N ratio was set up in the measurement room that received input from outside the cabin. After initialization, a 20 min recording period was started, and the following protocol was followed:

1. 2 min 30 s “Before think”
2. 2 min 30 s “While thinking raga *Jayjayanti*”
3. 2 min 30 s “After think”
4. 5 min resting period
5. 2 min 30 s “Before Listen”
6. 2 min 30 s “With listen *raga Jayjayanti*”
7. 2 min 30 s “After Listen”

4.3 Methodology

Noise free EEG data were obtained for all the electrodes using the EMD technique as described in Chap. 2 and these data were used for further analysis and classification of acoustic stimuli induced EEG features. In order to eliminate all frequencies outside the range of interest, data was filtered within a range of 0.5–50 Hz using a FIR filter. The amplitude envelope of the alpha (8–13 Hz), theta (4–7 Hz) and gamma (30–50 Hz) frequency range was obtained using wavelet transform technique. Data was extracted for these electrodes according to the time period given in the Experimental protocol section i.e. for Experimental conditions 1–7.

MFDFA was performed on the obtained amplitude envelope to calculate the Multifractal spectral width (W) for the different experimental conditions as well as MF-DXA technique was applied to analyze the degree of cross-correlation between different lobes of the brain during these experimental conditions.

4.4 Results and Discussion

The EEG data extracted from each electrode was filtered with the help of EMD technique. The entire analysis was done in two steps. In the first part, multifractal analysis was performed on the noise reduced time series data obtained for the chosen six electrodes following the methodology mentioned above. The qth order fluctuation function $Fq(s)$ for 10 points of q in between −5 to +5 was obtained. The time series values of both the waves have been randomly shuffled to destroy all the long range correlations present in the data, and what remained is a totally uncorrelated sequence. The regression plot of ln ($Fq(s)$) versus ln(s) averaged for different values of q (q = −3 to q = +3 is shown in the plot for scales varying from 16 to 1024) for a sample electrode F3 is given in Fig. 4.2a–b for the different experimental conditions. The slope of the best fit line thus obtained from $\ln(Fq(s))$ versus $\ln(s)$ plot gives the values of $h(q)$. It is seen from Fig. 4.2 that the shuffled values of the EEG time series data do not change with the values of q, and thus has a fixed slope h(q) = H, which is the conventional Hurst exponent for monofractal time series.

A representative figure for variation of $h\ (q)$ with q of a person corresponding to "imagination" and "listening" part has been shown in Fig. 4.3. It is clearly evident from the figures that the values of h (q) decreases with the increase of q, showing multifractal scaling in all the EEG time signals. For monofractal signals, a single value of Hurst exponent is obtained corresponding to different values of q, like the shuffled value of $h\ (q)$ as seen from the figures, where $h(q)$ remains almost constant with the change of q. The amount of multifractality can be determined quantitatively in each of the windows of each signal from the width of the multifractal spectrum [f(α) vs α]. The shuffled width obtained, is found to be always smaller than the original width of the signal (Fig. 4.4). This ascertains the fact that

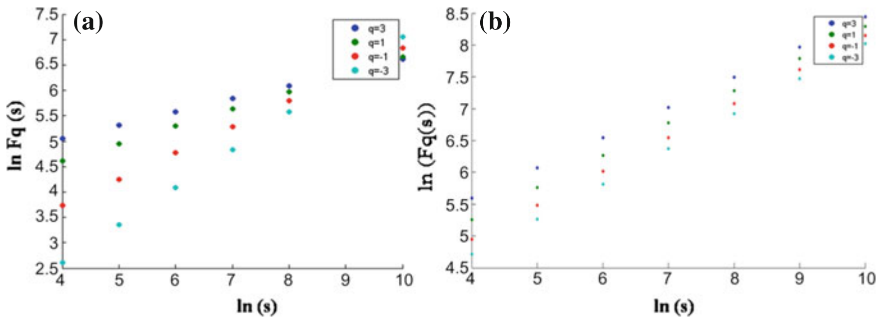


Fig. 4.2 **a** ln(Fq(s)) versus ln(s) for F3 **b** ln(Fq(s)) versus ln(s) for shuffled F3

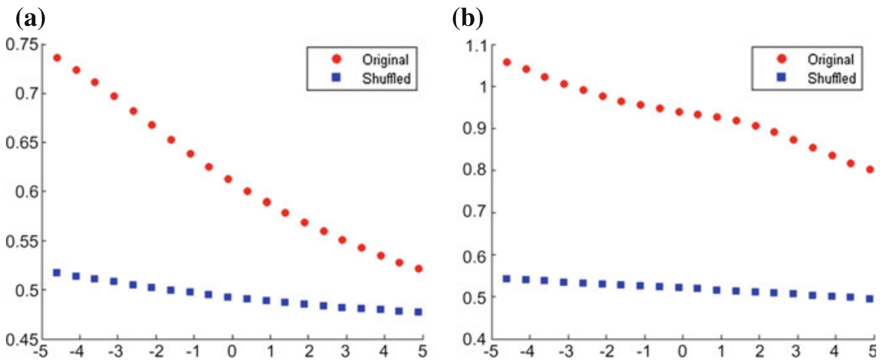


Fig. 4.3 **a** Variation of h(q) versus q for "imagination" in F3 electrode. **b** Variation of h(q) versus q for "listening" in F3 electrode

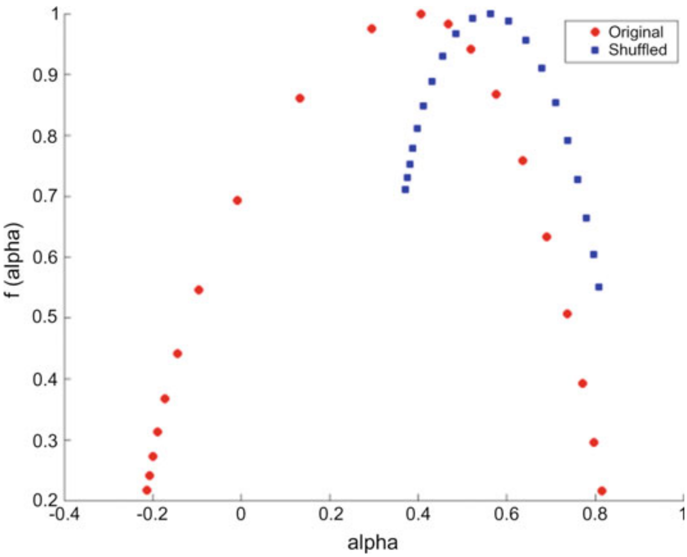


Fig. 4.4 Original and shuffled multifractal width in F3 electrode

multifractality in EEG waves is both due to long range correlations as well as broad probability density function. In the ideal case, the shuffled data should behave as a monofractal signal with no multifractal scaling. Thus, in the plot of Hurst exponent, it is seen that the shuffled values of h (q) does not change in general with q, and in the f(α) vs. α plot, the shuffled series will show a peak at α_0 close to 0.5. For the sake of comparison, the multifractal spectrum for a single person in the three experimental conditions ("before", "during" and "after thinking") corresponding to F3 electrode has been plotted in Fig. 4.5.

Tables 4.1, 4.2, 4.3 and 4.4 give the averaged multifractal spectral width values computed for Subject 1 and 2 while "imagining" and "listening" to the same *raga*. Table 4.1 gives the averaged multifractal spectral width while Subject 1 is thinking the raga '*Jay Jayanti*' for a period of 2 min 30 s while Table 4.2 denotes the values when the subject is listening to the same raga '*Jay Jayanti*'. Each recording period was divided into three windows of 45 s each taking an overlap of 50% within each window; the spectral width was computed for each window. From the values obtained in the three windows, we obtained a weighted average of spectral width corresponding to each experimental condition for our analysis and studied the variation of spectral width corresponding to each condition shown in the following tables. Tables 4.3 and 4.4 represent the same for Subject 2. The SD values computed for each condition have also been shown in the following tables which give the variation of complexity values in the six different electrodes while 'imagining' and 'listening' to the *raga*.

Figures 4.6, 4.7, 4.8 and 4.9 shows graphically the variation of spectral width for the two musicians while imagining and listening of the *raga Jay Jayanti.* The error

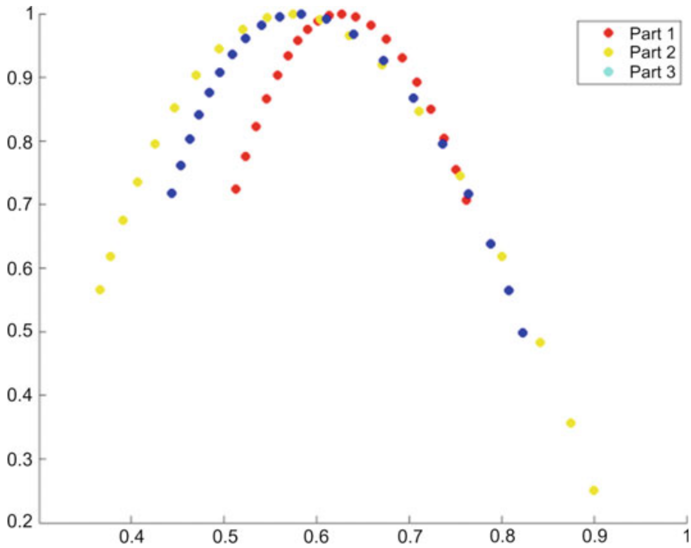


Fig. 4.5 Variation of multifractal width in F3 electrode for three different conditions

Table 4.1 Variation of multifractal width while imagining raga '*Jay Jayanti*' for Subject 1

Electrodes	Before imagination (BI)	During imagination (DI)	After imagination (AI)
F3	0.445 ± 0.04	0.705 ± 0.09	0.553 ± 0.07
F4	0.417 ± 0.06	0.626 ± 0.02	0.501 ± 0.04
O1	0.443 ± 0.03	0.693 ± 0.04	0.607 ± 0.03
O2	0.429 ± 0.07	0.625 ± 0.06	0.556 ± 0.05
T3	0.423 ± 0.02	0.418 ± 0.07	0.429 ± 0.06
T4	0.405 ± 0.05	0.410 ± 0.08	0.429 ± 0.05

Table 4.2 Variation of multifractal width while listening to raga '*Jay Jayanti*' for Subject 1

Electrodes	Before listening (BL)	During listening (DL)	After listening (AL)
F3	0.422 ± 0.05	0.672 ± 0.04	0.570 ± 0.03
F4	0.359 ± 0.06	0.608 ± 0.07	0.513 ± 0.08
O1	0.457 ± 0.08	0.672 ± 0.11	0.531 ± 0.04
O2	0.418 ± 0.07	0.570 ± 0.09	0.492 ± 0.02
T3	0.396 ± 0.03	0.641 ± 0.06	0.461 ± 0.06
T4	0.398 ± 0.02	0.622 ± 0.04	0.451 ± 0.05

Table 4.3 Variation of multifractal width while imagining raga '*Jay Jayanti*' for Subject 2

Electrodes	Before imagination (BI)	During imagination (DI)	After imagination (AI)
F3	0.406 ± 0.04	0.704 ± 0.05	0.430 ± 0.02
F4	0.395 ± 0.02	0.595 ± 0.08	0.404 ± 0.03
O1	0.488 ± 0.03	0.671 ± 0.06	0.499 ± 0.03
O2	0.449 ± 0.03	0.621 ± 0.04	0.488 ± 0.03
T3	0.409 ± 0.04	0.410 ± 0.04	0.388 ± 0.04
T4	0.435 ± 0.07	0.435 ± 0.06	0.408 ± 0.04

Table 4.4 Variation of multifractal width while listening to raga '*Jay Jayanti*' for Subject 2

Electrodes	Before listening (BL)	During listening (DL)	After listening (AL)
F3	0.537 ± 0.04	0.881 ± 0.12	0.633 ± 0.04
F4	0.535 ± 0.11	0.753 ± 0.04	0.627 ± 0.03
O1	0.442 ± 0.02	0.646 ± 0.06	0.562 ± 0.03
O2	0.439 ± 0.04	0.632 ± 0.04	0.552 ± 0.02
T3	0.465 ± 0.04	0.770 ± 0.09	0.555 ± 0.04
T4	0.492 ± 0.04	0.703 ± 0.05	0.527 ± 0.03

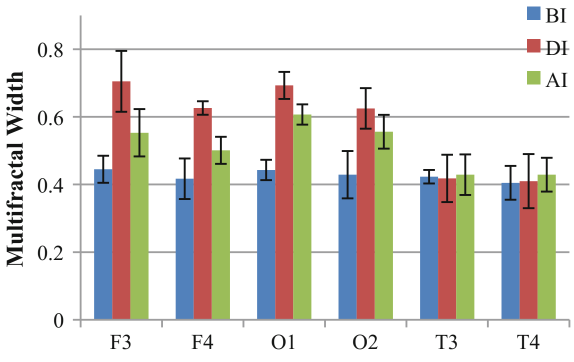


Fig. 4.6 Variation of multifractal width while imagining raga '*Jay Jayanti*' for Subject 1

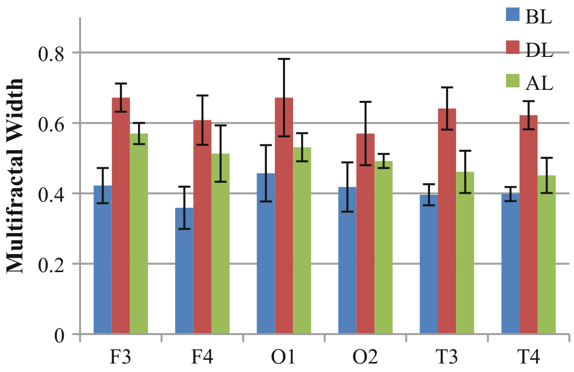


Fig. 4.7 Variation of multifractal width while listening to raga '*Jay Jayanti*' for Subject 1

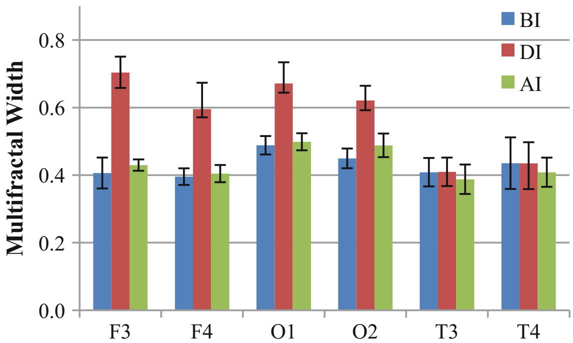


Fig. 4.8 Variation of multifractal width while imagining raga '*Jay Jayanti*' for Subject 2

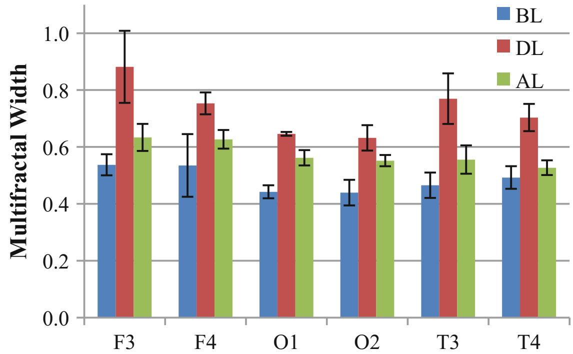


Fig. 4.9 Variation of multifractal width while listening to raga '*Jay Jayanti*' for Subject 2

bars in all the figures denote the SD values computed for that particular experimental condition. The response of each subject was studied individually keeping in mind personality specific traits which are supposed to be very much predominant in this study due to differences in school of musical training of the two subjects chosen here.

A careful investigation of the figures leads to the following interesting observations. The values of multifractality in general increase for all the electrodes while imaging the *raga Jay Jayanti* except for the T3 and T4 electrode, where the spectral width remains almost the same for both the subjects. This can be attributed to the fact that temporal lobe is mostly involved in processing of auditory stimuli, since there is no auditory stimulus involved while the subjects are mentally recreating the imagery; the temporal electrodes may have remained inert. In contrast, during the "listening part" we see that both the temporal electrodes (T3 and T4) are strongly simulated as the complexity increases to a large extent in both the subjects. Another interesting observation is that the two electrodes in the occipital lobe. i.e. O1 and O2 show considerable response in both the experimental conditions for the two performers. Though the increase in complexity is more pronounced in the "during imagination" part, but the response in "during listening" part is also quite significant especially for Subject 1. This is quite a gripping observation considering the fact that occipital lobe is primarily known to process visual stimuli (Mellet et al. 1995; Kosslyn 1996). This result may offer a passive support to the claim made by a section of musicians that while performing (or listening to) a *raga*, they have a visual picture of the *raga* in their mind. This "visual imagery" may be the cause for increase of complexity of occipital electrodes during the "imagination" and "listening" period as found here. The odd electrodes F3, T3 and O1 show much greater response compared to the even electrodes in both "imagination" and "listening" part of the *raga*. This may be due to the fact that *raga Jay Jayanti* is conventionally assigned to the positive hemisphere of emotional model (Martinez 2001); and a number of earlier studies which speak in favor of hemispheric dominance (Schmidt and Trainor 2001; Sammler et al. 2007; Trainor and Schmidt 2003; de Manzano and Ullén 2012; Sato and Aoki 2006) claim that left hemisphere is involved in processing of positive emotions. In the "after imagination" as well as "after listening" part, the complexity decreases to a large extent for all the electrodes but does not return to the initial value. This observation is evidence on "hysteresis" of brain (Banerjee et al. 2016)—the brain has a unique property of retaining musical memory even after the removal of stimulus. The frontal electrodes have been known to be associated mainly with cognition in a number of previous experiments; our results also show that the two frontal electrodes respond significantly both during musical imagery and listening. But the interesting fact is that no previous study has focused on the occipital lobe, which has reported remarkable results here. Both the electrodes O1 and O2 have shown sharp increase in complexity for both the experimental conditions, also the retention of musical memory is much higher in these two electrodes.

Next, the cross correlation coefficient is evaluated for all possible combinations of electrodes during the two experimental conditions. All the data sets were first transformed to reduce noise in the data. The integrated time series were then divided to Ns bins where Ns = int (N/s), N is the length of the series. The qth order detrended covariance Fq(s) was obtained for values of q from −5 to +5 in steps of 1. Power law scaling of Fq(s) with s is observed for all values of q. Figure 4.10 is a representative figure which shows the variation of scaling exponent, $\lambda(q)$ with q for two frontal electrodes F3 and F4 in the "listening" period is displayed. For comparison, we have also shown variation of H(q) with q individually for the same two electrodes F3 and F4 by means of MF-DFA in the same figure. If the scaling exponent is a constant, the series is monofractal, otherwise it is multifractal. The plot depicts multifractal behavior of cross-correlated time series as for q = 2 the cross-correlation scaling exponent $\lambda(q)$ is greater than 0.5 which is an indication of persistence long-range cross-correlation between the two electrodes. In the same way, $\lambda(q)$ was evaluated for all the possible combinations. The q-dependence of the classical multifractal scaling exponent $\tau(q)$ is depicted in Fig. 4.11 for the electrodes F3 and F4. From Fig. 4.11 we can see $\tau(q)$ is nonlinearly dependent on q, which is yet another evidence of multifractality. We also plotted the multifractal width of the cross correlated signals of F3 and F4 in Fig. 4.12. The presence of spectral width of cross correlated EEG signals confirms the presence of multifractality.

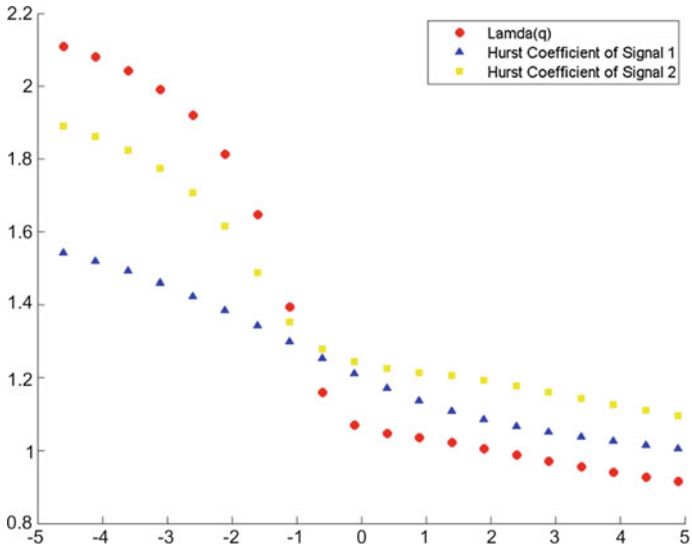


Fig. 4.10 Variation of λ(q) versus q for F3 and F4 electrode

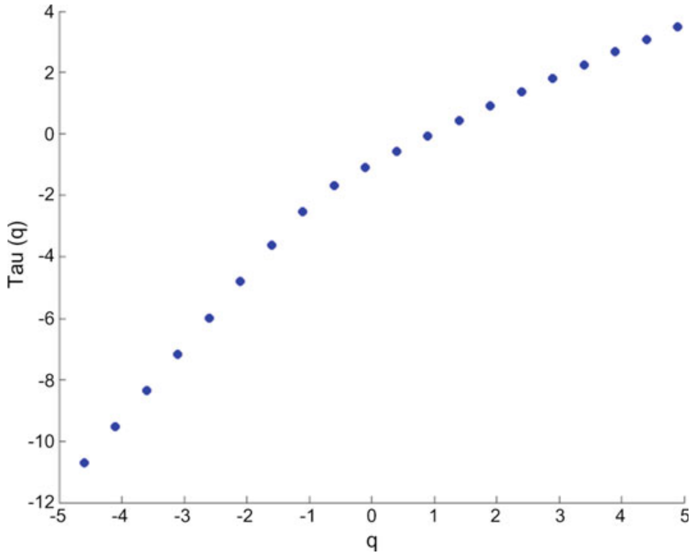


Fig. 4.11 Variation of τ(q) versus q for F3 and F4 electrode

The averaged cross correlation coefficient γ_x for q = 2 corresponding to the different experimental conditions along with their SD values for the various combination of electrodes are given in Tables 4.5, 4.6, 4.7 and 4.8 for the two subjects. As already said, negative values of γ_x correspond to strong cross correlation

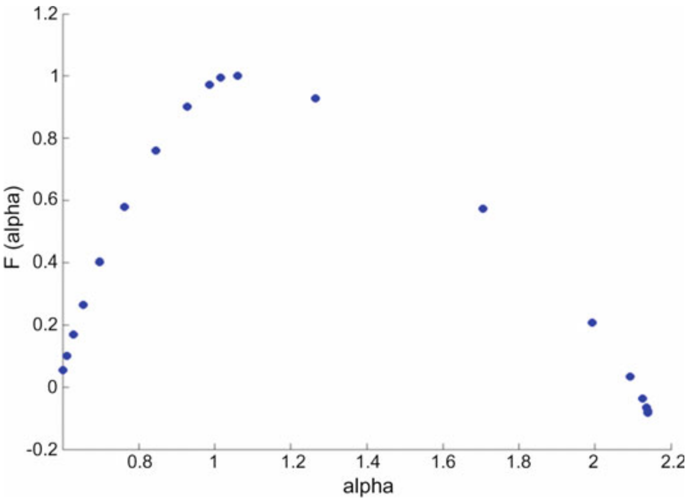


Fig. 4.12 Multifractal spectral width for cross correlated F3 and F4 electrode

between the two non-linear signals; we report the variation of cross-correlation coefficients in the different lobes while the performers "imagine" and "listen" to the raga *Jay Jayanti*. The figures that follow (Figs. 4.13, 4.14, 4.15 and 4.16) show a quantitative measure of how the cross-correlations between different lobes are affected while musical imagery and listening is constituted in a performer's brain. Figures 4.17, 4.18, 4.19 and 4.20 show how the same combination of lobes behaves when after the removal of the stimuli.

These studies indicate that the cross correlation between the two frontal electrodes, F3 and F4 significantly increases in both the experimental conditions which in turn supports the conventional wisdom that the role of frontal lobe is very significant when it comes to higher level cognitive processing. The recreation of the imagery of a particular *raga* involves higher order cognitive processing in the performer's brain, hence the strong correlation between the two frontal electrodes become eminent. The correlation between the temporal electrodes and other electrodes becomes sufficiently enhanced during the "listening" period of the *raga* as compared to the "imagination" period. As is seen from the figures, for both the subjects, degree of cross correlation rises considerably for F3-T3, F3-T4, O1-T3 and O1-T4 for the "listening" period, while the enhancement is not so pronounced during the "imagination" period. This may be due to the simultaneous involvement of cognitive as well as auditory skills of the performer which is manifested in the enhancement of cross-correlation between the particular lobes. The correlation between frontal and occipital lobes (F3-O1, F3-O2) has been found to significantly increase both during "imagination" and "listening" of the *raga*. The degree of cross correlation between F4-O2 and F4-O1 increased to a great extent during "imagination" part of the *raga*, but decreases during "listening" part. This result implies in the direction of simultaneous processing of cognitive and visual information in the

Table 4.5 Variation of cross correlation coefficient (γ_x) during "imagination" of *Raga* (*Subject 1*)

Combination of electrodes	Before imagination (BI)	During imagination (DI)	After imagination (AI)	Change in cross-correlation (BI-DI)	Change in cross-correlation (DI-AI)
F3-F4	−1.032 ± 0.04	−1.918 ± 0.06	−1.574 ± 0.02	0.886	−0.344
F3-O1	−1.949 ± 0.03	−2.272 ± 0.05	−2.010 ± 0.04	0.324	−0.263
F3-O2	−2.382 ± 0.06	−2.723 ± 0.04	−2.691 ± 0.07	0.341	−0.032
F3-T3	−1.590 ± 0.07	−1.799 ± 0.07	−1.714 ± 0.05	0.209	−0.085
F3-T4	−1.449 ± 0.04	−1.439 ± 0.11	−1.426 ± 0.06	−0.010	−0.013
F4-O1	−1.273 ± 0.05	−2.134 ± 0.10	−1.113 ± 0.08	0.861	−1.021
F4-O2	−2.231 ± 0.06	−3.356 ± 0.06	−2.400 ± 0.13	1.125	−0.956
F4-T3	−2.644 ± 0.05	−2.690 ± 0.04	−2.521 ± 0.07	0.046	−0.169
F4-T4	−1.856 ± 0.07	−1.903 ± 0.03	−1.898 ± 0.08	0.047	−0.005
O1-O2	−1.320 ± 0.04	−3.226 ± 0.05	−2.210 ± 0.06	1.906	−1.016
O1-T3	−1.618 ± 0.06	−1.629 ± 0.06	−1.631 ± 0.04	0.011	0.003
O1-T4	−2.122 ± 0.08	−2.360 ± 0.05	−2.167 ± 0.05	0.238	−0.192
O2-T3	−2.004 ± 0.07	−2.094 ± 0.04	−1.843 ± 0.07	0.090	−0.252
O2-T4	−1.810 ± 0.06	−1.978 ± 0.03	−1.657 ± 0.03	0.168	−0.322
T3-T4	−1.921 ± 0.03	−2.041 ± 0.05	−1.974 ± 0.02	0.119	−0.067

Table 4.6 Variation of cross correlation coefficient (γ_x) during "listening" of *Raga* (*Subject 1*)

Combination of electrodes	Before listening (BL)	During listening (DL)	After listening (AL)	Change in cross-correlation (BL-DL)	Change in cross-correlation (DI-AL)
F3-F4	−1.873 ± 0.05	−2.640 ± 0.07	−1.927 ± 0.05	0.767	−0.713
F3-O1	−1.015 ± 0.06	−1.617 ± 0.04	−1.188 ± 0.06	0.602	−0.429
F3-O2	−1.232 ± 0.08	−2.117 ± 0.05	−1.414 ± 0.07	0.885	−0.703
F3-T3	−1.283 ± 0.09	−2.328 ± 0.08	−1.437 ± 0.04	1.045	−0.891
F3-T4	−1.782 ± 0.07	−2.383 ± 0.06	−1.265 ± 0.08	0.601	−1.118
F4-O1	−1.553 ± 0.05	−1.485 ± 0.05	−1.562 ± 0.05	−0.067	0.077
F4-O2	−1.662 ± 0.04	−1.444 ± 0.07	−1.248 ± 0.03	−0.219	−0.196
F4-T3	−2.334 ± 0.03	−3.129 ± 0.06	−2.246 ± 0.04	0.795	−0.882
F4-T4	−2.497 ± 0.09	−2.585 ± 0.09	−2.228 ± 0.06	0.088	−0.357
O1-O2	−1.575 ± 0.07	−3.135 ± 0.03	−2.346 ± 0.07	1.559	−0.788
O1-T3	−1.865 ± 0.05	−2.727 ± 0.04	−2.223 ± 0.05	0.861	−0.503
O1-T4	−2.792 ± 0.11	−3.224 ± 0.08	−2.292 ± 0.11	0.432	−0.932
O2-T3	−1.937 ± 0.07	−2.163 ± 0.07	−1.549 ± 0.09	0.226	−0.613
O2-T4	−1.323 ± 0.09	−2.063 ± 0.06	−1.504 ± 0.08	0.739	−0.559
T3-T4	−1.628 ± 0.06	−2.226 ± 0.05	−1.695 ± 0.07	0.598	−0.531

Table 4.7 Variation of cross correlation coefficient (γ_x) during "imagination" of *Raga* (*Subject 2*)

Combination of electrodes	Before imagination (BI)	During imagination (DI)	After imagination (AI)	Change in cross-correlation (BI-DI)	Change in cross-correlation (DI-AI)
F3-F4	−2.070 ± 0.07	−2.763 ± 0.05	−1.557 ± 0.07	0.693	−1.206
F3-O1	−1.969 ± 0.05	−2.168 ± 0.02	−1.630 ± 0.04	0.199	−0.538
F3-O2	−1.805 ± 0.03	−2.448 ± 0.07	−1.884 ± 0.03	0.643	−0.564
F3-T3	−1.643 ± 0.08	−2.149 ± 0.09	−1.585 ± 0.06	0.506	−0.564
F3-T4	−2.500 ± 0.07	−2.496 ± 0.08	−1.962 ± 0.08	−0.004	−0.534
F4-O1	−1.261 ± 0.04	−2.038 ± 0.11	−1.334 ± 0.05	0.777	−0.705
F4-O2	−1.818 ± 0.09	−2.240 ± 0.07	−1.678 ± 0.06	0.422	−0.562
F4-T3	−2.174 ± 0.05	−2.072 ± 0.05	−1.819 ± 0.05	−0.103	−0.252
F4-T4	−2.617 ± 0.06	−2.630 ± 0.03	−2.781 ± 0.09	0.013	0.151
O1-O2	−1.339 ± 0.03	−2.853 ± 0.09	−2.720 ± 0.12	1.514	−0.133
O1-T3	−2.352 ± 0.09	−2.436 ± 0.08	−2.397 ± 0.08	0.084	−0.038
O1-T4	−1.613 ± 0.07	−1.704 ± 0.07	−1.982 ± 0.06	0.091	0.278
O2-T3	−1.660 ± 0.02	−1.702 ± 0.05	−1.684 ± 0.08	0.042	−0.018
O2-T4	−2.556 ± 0.05	−2.712 ± 0.06	−2.802 ± 0.05	0.156	0.091
T3-T4	−2.338 ± 0.03	−2.378 ± 0.05	−2.383 ± 0.06	0.040	0.005

Table 4.8 Variation of cross correlation coefficient (γ_x) during "listening" of *Raga* (*Subject 2*)

Combination of electrodes	Before listening (BL)	During listening (DL)	After listening (AL)	Change in cross-correlation (BL-DL)	Change in cross-correlation (DI-AL)
F3-F4	−2.304 ± 0.05	−3.107 ± 0.09	−3.091 ± 0.08	0.804	−0.016
F3-O1	−1.527 ± 0.06	−2.062 ± 0.07	−1.922 ± 0.05	0.535	−0.141
F3-O2	−2.916 ± 0.12	−3.121 ± 0.06	−1.931 ± 0.11	0.205	−1.189
F3-T3	−2.203 ± 0.06	−3.172 ± 0.03	−2.806 ± 0.06	0.969	−0.366
F3-T4	−1.642 ± 0.07	−1.997 ± 0.05	−2.255 ± 0.08	0.355	0.258
F4-O1	−2.539 ± 0.09	−1.985 ± 0.08	−2.024 ± 0.03	−0.554	0.039
F4-O2	−2.826 ± 0.03	−2.568 ± 0.15	−2.606 ± 0.07	−0.258	0.038
F4-T3	−2.537 ± 0.06	−2.952 ± 0.12	−1.432 ± 0.05	0.415	−1.520
F4-T4	−2.260 ± 0.07	−2.033 ± 0.06	−1.991 ± 0.15	−0.226	−0.042
O1-O2	−1.267 ± 0.08	−4.138 ± 0.09	−2.559 ± 0.09	2.871	−1.579
O1-T3	−2.040 ± 0.09	−2.287 ± 0.07	−1.937 ± 0.06	0.248	−0.350
O1-T4	−1.939 ± 0.05	−2.846 ± 0.05	−2.316 ± 0.08	0.907	−0.530
O2-T3	−1.768 ± 0.03	−2.313 ± 0.06	−1.964 ± 0.06	0.545	−0.349
O2-T4	−2.633 ± 0.07	−2.733 ± 0.08	−2.365 ± 0.09	0.100	−0.368
T3-T4	−2.473 ± 0.11	−2.996 ± 0.09	−1.903 ± 0.07	0.524	−1.093

Fig. 4.13 Change in γ_x for different electrode combinations while Subject 1 imagines the *raga*

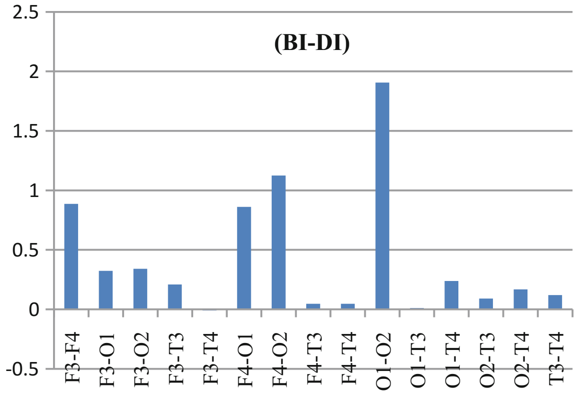


Fig. 4.14 Change in γ_x for different electrode combinations while Subject 2 imagines the *raga*

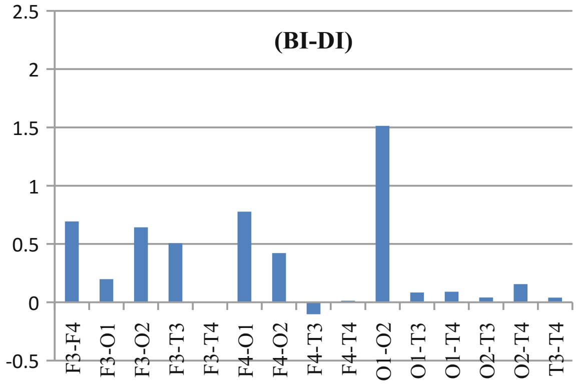
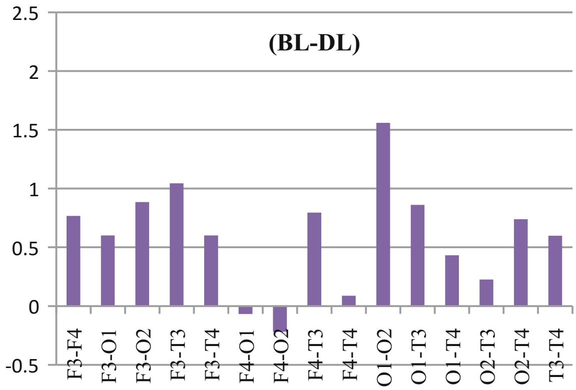


Fig. 4.15 Change in γ_x for different electrode combinations while Subject 1 listens the *raga*



performer's brain. The intra lobe cross-correlation between the temporal electrodes T3-T4 is also sufficiently enhanced during the "listening" of the *raga*, while the rise is negligible during the "imagination" part. Another curious observation is the

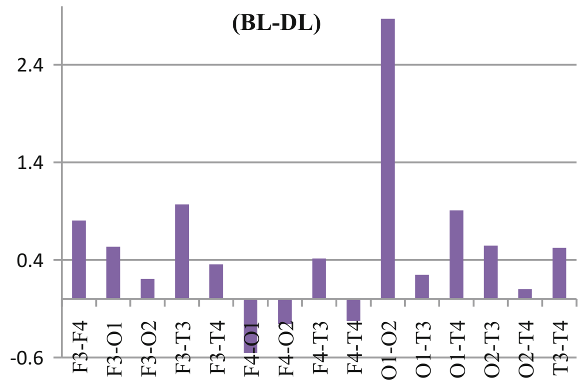


Fig. 4.16 Change in γ_x for different electrode combinations while Subject 2 listens the *raga*

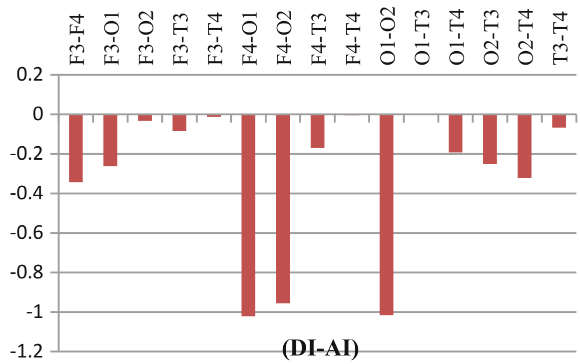


Fig. 4.17 Change in γ_x for different electrode combinations after imagination of *raga* by Subject 1

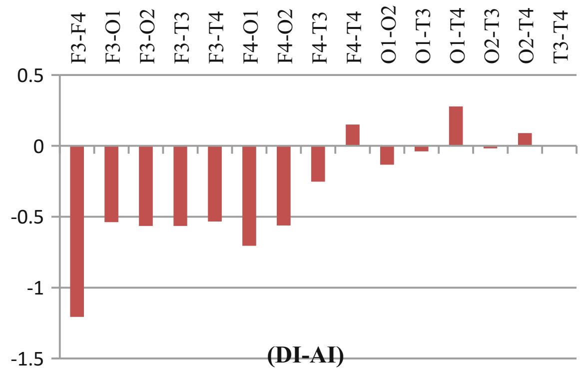


Fig. 4.18 Change in γ_x for different electrode combinations after imagination of *raga* by Subject 2

remarkable enhancement in the degree of cross correlation between the two occipital electrodes O1 and O2 for both the subjects. It has been found that the cross-correlation coefficient increases significantly both "during imagination" and "during listening" of the *raga*; though the subjects were sitting with their eyes closed while the EEG experiment was performed. In case of Subject 2, the increase

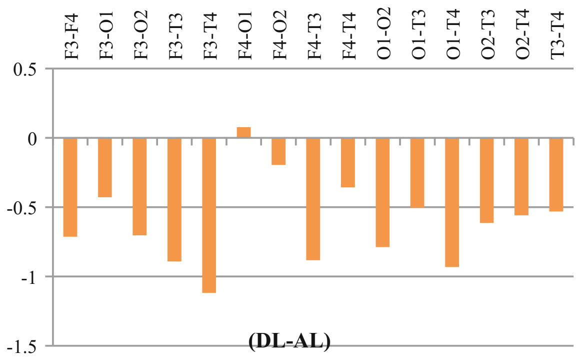


Fig. 4.19 Change in γ_x for different electrode combinations after listening of the *raga* by Subject 1

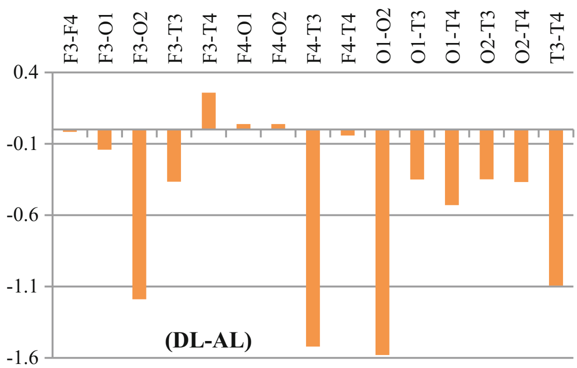


Fig. 4.20 Change in γ_x for different electrode combinations after listening of the *raga* by Subject 2

is much higher in the "listening" part. This result may have a far reaching conclusion, that when an artist is imagining a *raga* or listening to a *raga* performed by him, he is actually visualizing a picture of the *raga* in his mind, which eventually leads to higher degree of cross correlation manifested in the occipital lobe. After the removal of music stimulus, it is seen that the degree of cross-correlation decreases unanimously for all the electrodes to various extent; thus it can be said that music as a stimuli is able to enhance the correlation between different lobes of the brain to different extent, while the removal of the stimuli leads to decrease of cross correlation.

In the second part of our analysis, for more rigorous results we decided to observe the variations in the different frequency regions (viz. alpha, theta etc.) of EEG signal during "imagining" and "listening" to a *raga*. For this the amplitude envelope of the alpha (8–13 Hz) and theta (4–7 Hz) frequency ranges were obtained using wavelet transform technique. On the obtained EEG time series data of alpha and theta rhythms, MFDXA analysis was performed.

From these figures we observe that in the imagination stage, the predominance of alpha correlation is very strong; as we see strong increase in almost all the electrode combinations. The increase in alpha cross-correlations among the fronto-occipital electrode combinations are the strongest followed by the fronto-temporal electrodes and the occipital electrodes. The increase in cross-correlations among the fronto-occipital electrodes may be a signature of the simultaneous interplay of cognitive and visual domain processing in the performer's mind as he conjures up the entire *raga* from his musical memory. Also the intra-lobe cross correlation for both alpha and theta rhythms in frontal (F3-F4) and temporal (T3-T4) lobe show a decrement while imagining the *raga.* In the listening period, the cross correlation of theta frequency rhythms take a significant part for different electrode combinations along with alpha rhythms. The intra-lobe cross-correlation in frontal (F3-F4) and occipital electrodes (O1-O2) decrease significantly; while the intra lobe cross-correlation in temporal lobe (T3-T4) increases. The inter lobe correlation for F4-O2 electrodes increase consistently for both alpha and theta rhythms. Most significant changes are noticed in the fronto-temporal electrode combinations where F3-T3 and F3-T4 show a significant increase, while the other two register decrease in both the frequency rhythms, though theta is again predominant. In the occipital-temporal domain, the theta cross-correlation in O1-T3 increases significantly while for all other electrode combinations there is an average increase in both alpha and theta cross-correlations. The fronto-temporal and occipital-temporal increase in degree of correlation points in parallel processing of auditory and cognitive information as the artist is constantly relating the *raga* clip with his previous musical expertise and trying to conjure an image of the entire *raga*.

In the "after think" part, it is seen that the degree of cross-correlation for both alpha and theta rhythm decreases significantly for all the electrode combinations in different lobes of the performer's brain; with the highest decrease being registered in F4-O1 and O1-T4 combination. This leads to the general conclusion, that after the performer stops creating the *raga* picture in his brain, activity in different regions of the brain gets dilated which essentially leads to the decrease in the degree of cross-correlation in alpha and theta frequency rhythms. In the "after listen" part, even after the removal of stimulus, strong increase in theta and alpha cross-correlations are noticed in almost all the lobes; with the change being maximum in the fronto-temporal combinations as well as intra lobe occipital (O1-O2) and frontal (F3-F4) combinations. In the fronto-temporal combinations, the response is exactly reverse to what is seen in "with stimulus" condition, indicating the neuronal interactions returning to their basal state after the removal of stimulus; while the strong alpha correlations in the other electrode combinations like F4-T4 and O2-T4 indicates signifies the retention of musical auditory memory of the *raga* in the mind of the participants. This retention effect is more pronounced for theta rhythms in all electrode combinations of fronto-occipital and occipital-temporal domain. This retention is almost absent in case of thinking. This retention may have been caused as the subjects probably continued to think/imagine the *raga* even after removal of the auditory stimuli (Figs. 4.21 and 4.22).

The following figures (Figs. 4.23 and 4.24) show the same response in case of Artist 2:

In most cases, the observations are almost similar to the 1st subject, though a few minor deviations from the previous artist are noted. For Subject 2, in the thinking part, the theta cross-correlation also increases significantly for the same electrode

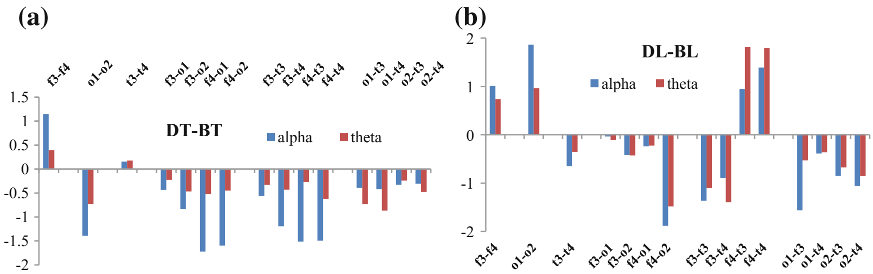


Fig. 4.21 Change in γ_x of alpha/theta when Subject 1 **a** imagines and **b** listens to *raga*

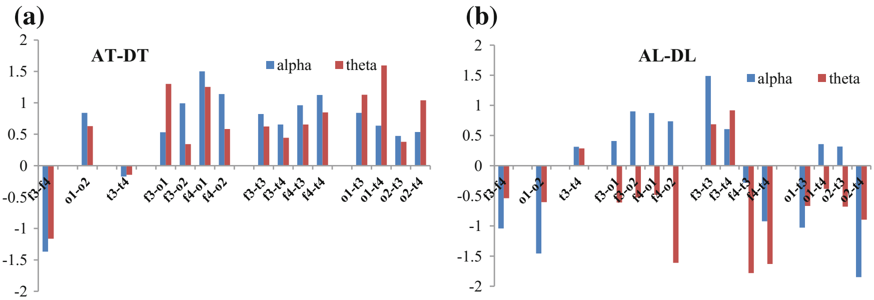


Fig. 4.22 Change in γ_x of alpha/theta after Subject 1 **a** imagines and **b** listens to *raga*

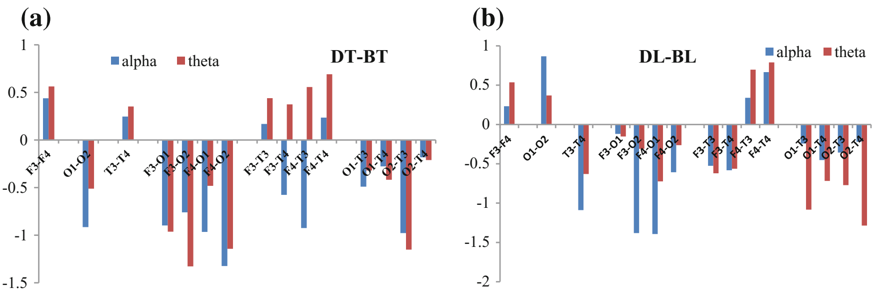


Fig. 4.23 Change in γ_x of alpha/theta for when Subject 2 **a** imagines and **b** listens to *raga*

combinations as in Subject 1 along with alpha rhythms. The occipital-temporal cross-correlations again show consistent increase; depicting again the simultaneous processing of cognitive and musical memory during the mental recreation of the *raga*. In the listening part, the observations are almost the same for the previous artist, with the theta cross-correlations being the most predominant; with significant increase in the occipital-temporal cross correlations. The enhancement in occipital-temporal correlations may be a signature of concurrence of auditory stimuli and musical cognition in the artist's brain. Here the intra lobe temporal

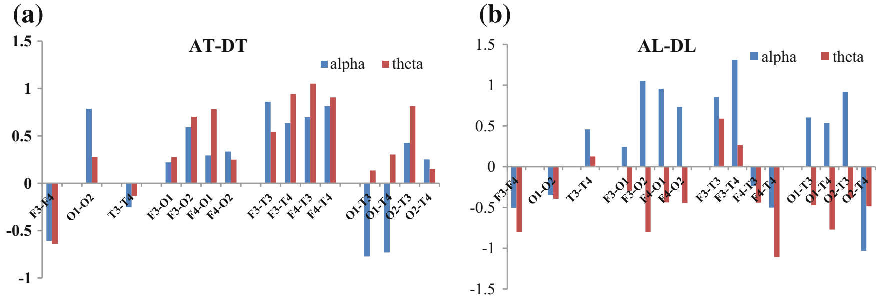


Fig. 4.24 Change in γ_x of alpha/theta after Subject 2 **a** imagines and **b** listens to *raga*

cross-correlations in alpha frequency domain also show an increase compared to the 1st artist. In the "after think" part, again the response is similar to 1st subject, with the alpha/theta cross-correlations decreasing in most of the cases; with the exception being alpha cross-correlation in O1-T3 and O1-T4 electrode where residual neuronal activities lead to further increase in cross-correlations. The frontal intra-lobe (F3-F4) alpha and theta correlation also increases further showing enhancement of neuronal interactions even after thinking. In the after listen part, the theta cross-correlation mostly bears the signs of retentive features in various lobes; with the degree of cross-correlation increasing further even after the stimulus is removed. Interestingly the intra-lobe occipital (O1-O2) and frontal (F3-F4) correlation increases for both alpha and theta frequency rhythms. The results have obvious ramifications in the form of differential musical processing and retention of musical memory by the two different performers belonging to different school of musical pedagogy.

These responses may vary for other musical pieces as with the change of the musical content of the piece, the emotion associated with it also changes. *Raga Jai jayanti* is conventionally known to evoke happy emotion in listeners. As both subjects were asked to imagine and listen to the same *raga* so, we can safely compare their results. Thus, with the help of this study we have reported for the first time, the effect on alpha and theta cross-correlations among different lobes of brain when an artist is performing creative tasks and improvising on a musical piece as well as when he is listening to the same musical composition sung by himself.

4.5 Conclusion

"*If a person can't read or write, you don't assume that this person is incapable of it, just that he or she hasn't learned how to do it. The same is true of creativity. When people say they're not creative, it's often because they don't know what's involved or how creativity works in practice*." wrote Sir Ken Robinson in his book *The Element* (2009). In this work, we have tried to visualize with the help of robust scientific methods, a general response of human brain while performing creative task. This work presents new data regarding neuro-cognitive basis of creative imagery and perception of a Hindustani *raga*. No previous study has been made using rigorous non-linear technique to assess quantitatively the degree of arousal and the variation of degree of cross-correlation between the different lobes of brain when a performer imagines and creates an imagery of the *raga*. The Multifractal Detrended Cross-Correlation Analysis (MFDXA) is a robust non-linear analysis technique developed recently which gives brilliant insight into the degree of cross-correlation existing in different lobes of human brain. The alpha and theta brain rhythms have been previously related to a number of modalities related to musical emotion processing in earlier studies, but this work for the first time, tries to quantify the correlations existing in alpha and theta rhythms to creative appraisal based task with the help of MFDXA technique.

The work presents the following interesting conclusions:

1. The multifractal spectral width, which is a measure of complexity increases for the frontal and occipital lobes during creative musical imagery by a performer. The temporal lobe also report significant increase in complexity along with the other two lobes during perception of auditory stimuli of the same musical piece. The strong activity of occipital lobe both during imagination and perception of musical piece is a fascinating outcome of this study. Interestingly, this observation persists for both the musicians studied.

The alpha cross correlation plays a significant role when the performer cogitates the *raga* in his mind; with the increment being most prominent in the fronto-occipital and fronto-temporal lobe. In case of musical appreciation, i.e. when an artist is listening to the *raga* sung/played by him, the theta cross-correlation is mostly affected in the fronto-temporal and occipital-temporal domain indicating simultaneous processing of cognitive and auditory data. This study also shows that inter-lobe cross-correlation is more affected during any creative processes compared to the intra-lobe correlation except in case of occipital lobe which is greatly affected during thinking for both subjects. The strong cross-correlation between the occipital electrodes both during imagination and perception of the musical piece probably supports the claim that when an artist is creating or listening to a *raga*, he is actually visualizing a picture of the *raga* in his mind. Musical creativity and improvisation thus mostly involves interplay between frontal, temporal and occipital lobes, since the correlation among these are the highest as is seen from our study.

2. In case of auditory stimulus, the cross-correlations of alpha as well as theta remain consistently high for some time in certain regions (viz. occipital-temporal domain, intra lobe temporal domain etc.) of the brain, even after the removal of stimuli, while in the "after thinking" period, the degree of cross-correlation decreases very quickly to its basal value in almost all regions. Thus a "hysteresis" like effect is evident in different electrodes which were elicited by musical stimuli, shows that the musical memory is retained in the brain for some time even after the removal of stimuli. This finding could have far-reaching effects if successfully applied to cognitive music therapy.

Although we analyzed the responses of two musicians (a vocalist and an instrumentalist) separately, expecting that each person can have different cognitive appraisals, we could not find any remarkable discrepancies in the results of the two. This may be due to the musical pedagogy of the two; both being trained in Hindustani classical music for many years, their imagination and improvisation of *raga Jay Jayanti* may be on similar lines.

Finally, we can conclude from what we have explored using EEG rhythms from different electrodes extracting features of functioning of different lobes, their intra and inter-correlation, that a straightforward jacketing of auditory-cognition route may be more empirical—the real scenario is a bit complicated, involving simultaneous processing of musical emotions in a number of different lobes. Some of the features of this interdependence, obtained from the degree of cross correlation of alpha/theta rhythms between two lobes, are revealed for the first time from our new data. Future works in this domain includes EEG data from a greater number of samples as well as a variety of musical cognitive tasks which may reveal higher degree of correlation between other lobes also. Also, comparing the data of musical appreciation of performers with that of naïve listeners is also an interesting piece of work; to see the difference in EEG response pattern of professionals and naïve listeners. A new model of emotion elicited by musical stimuli need to accommodate the findings of this investigation in regard to pronounced cross-correlation obtained in the occipital, frontal and temporal lobes. The obtained data may be of immense importance when it comes to studying the neuro-cognitive basis of creativity and alertness to a certain cognitive function. Taking help of this MFDFA technique, the next Chapter deals with how a simple acoustical stimulus like tanpura drone can change the brain state of an individual.

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Chapter 5
Tanpura Drone and Brain Response

Simplicity is the ultimate sophistication

—Leonardo da Vinci

5.1 Introduction

Musical research over the last century has become increasingly entwined with the scientific areas of acoustics and psychoacoustics (Fastl and Zwicker 2007). With the advent of neurocognitive techniques as well as novel non-linear dynamic chaos theory, it has become possible to study the effect of music on cognitive activity of brain quantitatively. Thus, it has become a topic of extreme research interest as new data is scarce, so it is difficult to arrive at a confident conclusion. Electroencephalography (EEG) is a very efficient technique to measure the non-linear fluctuations generating from different electrodes located in various lobes of the brain. It has been observed that different parts of the brain are activated in a different way on exposure to a variety of music. Earlier studies in the linear domain reported a dip in alpha frontal power in left frontal lobe for happy music while a sad music results in dip of alpha power in the right frontal lobe (Schmidt and Trainor 2001; Tsang et al. 2001). The frontal midline theta power was reported to increase while a pleasant music is played (Sakharov et al. 2005). But, very few studies have been conducted in the non linear domain, which reported the effect of musical stimuli on EEG brain waves (Gao et al. 2007; Karthick et al. 2006; Sourina et al. 2012). In view of this, in the present investigation, we have made an attempt to assess in-depth the effect of a simple musical stimuli played in Tanpura on the EEG pattern of human brain quantitatively using latest state-of-the-art nonlinear techniques. Tanpura is a plucked string instrument extensively used as a drone provider. The resounding twangs of the strings create the perfect ambience for Indian

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classical music. This work is essentially the report of new, quantitative data on the effect of Tanpura drone in human brain.

5.1.1 What Is Tanpura Drone?

The *Tanpura* (sometimes also spelled Tampura or Tambura) is an integral part of classical music in India. It is a fretless musical instrument. It consists of a large gourd and a long voluminous wooden neck which act as resonance bodies with four or five metal strings supported at the lower end by a meticulously curved bridge made of bone or ivory. The strings are plucked one after the other in cycles of few seconds generating a buzzing drone sound. The Tanpura drone primarily establishes the "Sa" or the scale in which the musical piece is going to be sung/played. One complete cycle of the drone sound usually comprises of Pa/Ma (middle octave)—Sa (upper octave)—Sa (upper octave)—Sa (middle octave) played in that order. The sounding of Tanpura drone acts as a canvas in Indian Raga Music and provides contrast to the tune and melody without introducing rhythmic content of its own. Its sound is considered very sweet and melodious and it stimulates both the musician and the audience. The peculiar sounding of Tanpura arises from the strings' grazing touch of the bridge in vertical direction, so they are clamped at different lengths, as has been observed and first described in the 1920s by the famous Indian physicist CV Raman (Raman 1921). This phenomenon is called *jvari* (pronounced jovari) in musical terms, which means "life giving" (Braeunig et al. 2012). The length where the string touches the ivory bridge is controlled by fine cotton threads that are carefully adjusted between the bridge and the strings during instrument tuning. The periodic change of length in the plucked string creates amplitude fluctuations in the higher harmonics so that the mechanical energy is spread out to very high frequencies (Bhattacharyya et al. 1956; Carterette et al. 1988, 1989; Houtsma and Burns 1982). The listener of Tanpura drone is captivated by its extremely rich harmonic structure. Later on a lot of study has been done on different aspects of Tanpura sound signals (Sengupta et al. 1983, 1989, 1995, 1996, 2002, 2003, 2004; Sengupta and Dey 1988; Ghosh et al. 2007). Even material characterization of Tanpura has been attempted by electron microscopic analysis (Mukhopadhyay et al. 1998). Acoustic Tanpura drones can be recreated using technical means like digitization of sound—although they fail to reproduce the important subtle imperfections of an acoustic Tanpura. Common substitutes for drone instruments are electronic sruti boxes, which are nowadays superseded by software generators and sampled sound. The latter are good for experimentation because the Electronic Substitute Tanpura (EST) allows a researcher to control its parameters in a reproducible manner.

5.1.2 How Does a Tanpura Drone Affect Brain Rhythm?

The drone signal has repetitive quasi-stable geometric forms characterized by varying complexity with prominent undulations of intensity of different harmonics. Thus, it will be quite interesting to study the response of brain to a simple drone sound using different linear and non-linear techniques. Because there is a felt resonance in perception, psycho-acoustics of Tanpura drone may provide a unique window into the human psyche and cognition. Traditionally, the human EEG power spectrum is divided into at least five frequency bands: delta, theta, alpha, beta, and gamma. (1) Delta (δ): 0–4 Hz; (2) Theta (θ): 4–8 Hz; (3) Alpha (α): 8–13 Hz; (4) Beta (β): 13–30 Hz; (5) Gamma (γ): 30–50 Hz. In the past decades, each frequency band has been related to specific functions. Now it is time to find out how each of these frequency bands in human brain is affected when the subject listens to a Tanpura drone in a particular pitch for some time.

Earlier "Fractal Analysis" technique has been used to study the non linear nature of the Tanpura signals (Sengupta et al. 2005). The drone environment is free of semantic content, such as melody or rhythm, similar to an acoustical Ganzfeld (Metzger 1930). From a complete waveform cycle of Tanpura drone, no sound objects with a distinct borderline can be recognized. In the Ganzfeld, cognitions arise spontaneously out of intrinsic activity (Pütz et al. 2006). The case is similar for cognition of Tanpura drone also. An earlier study which used non-linear DFA technique to analyze EEG data reported two distinct categories of subjects in response to drone sound, for one group the overall complexity increases in many major electrodes of frontal lobe while for the other group of subjects complexity decreases (Banerjee et al. 2014). Global Descriptors (GD) have also been used to identify the time course of activation in human brain in response to Tanpura drone (Braeunig et al. 2012).

5.1.3 Use of Tanpura Drone as a Baseline

The question of reference for baseline EEG in the resting condition where the subject has no task to perform is addressed in one of our works (Braeunig et al. 2012). We hypothesize that drone sounds are sufficiently neutral to the subject in that they are not popping into the fore of cognition, evoking reactions to the stimulus. This assumption is needed in order to define the resting condition where the subject has no task to perform (no-task resting frame). Drone can provide contrast but is not prompting a response. In a laboratory setting spontaneous brain electrical activity in the form of EEG response were observed during Tanpura drone stimulation and periods of silence. The sound stimulus was given by an electronic substitute Tanpura (EST) that allows controlling of its parameters. The timbral characteristics of the drone samples are given. The brain-electrical response of the subject is analyzed with global descriptors (GD), a way to monitor the course of activation in the time domain in a three-dimensional state space, revealing patterns of global dynamical states of the brain. Timbral characteristics such as tristimulus T1, T2, and T3 and the odd and even parameters have been chosen in view of the energy distribution in partials, whereas spectral brightness, irregularity and inharmonicity are descriptive of the harmonic content.

The EEG signals from 19 electrodes have been averaged in windows of 1 s width. With overlap of 50% the time resolution is 0.5 s. After removal of outliers the time series for the three global descriptors are displayed including the derived dimensions *E* and *I*. The first eye-catching features are the undulations during drone that show 3–4 drops of field strength (activity), which correlates with an increase in frequency and complexity. These undulations have a width of roughly 30 s (which is very slow). The simultaneous increase in Omega complexity can be interpreted as emergence of new cognitive modules (either by insertion or decay). Reduced activity is an indication that available energy is shared by more processes.

5.1.4 Use of MFDFA to Assess the Effect of Drone

In previous researches employing chaos theory it has been seen that biomedical signals like EEG possesses property of fractality i.e. they exhibits self similarity on different scales (Kantelhardt et al. 2002; Easwaramoorthy and Uthayakumar 2010). There are two type of fractality—multifractality and monofractality. Various investigations have employed Detrended Fluctuation Technique (DFA) to study the robustness of human EEG signals to non-stationarity (Lee et al. 2002; Peng et al. 1995). Though DFA has a wide spectrum of applications, many geophysical signals as well as medical patterns do not represent simple monofractal behavior which can be accounted for by a single scaling exponent (Kantelhardt et al. 2001; Hu et al. 2001), for e.g. if the signal consists of random spikes or a crossover timescale which separates regimes with different local behavior such as EEG signals. Thus different scaling exponents are required for different parts of the EEG time series indicating a time variation of the scaling behavior (Chen et al. 2002). In view of above facts, a multifractal analysis of EEG data would be more appropriate. Furthermore, the prerequisite of MFDF analysis i.e. large time series is also satisfied in our EEG data sample.

The main aim of this work is to study the different levels of neural activation in the human alpha and theta brain rhythms under the effect of simple acoustical stimuli using different EEG feature classification technique such as WT and MFDFA. The linear methods (such as power spectral density, FFT study etc.) miss out on the intricate details of the non-stationary EEG signals and rely on a coarse approximation for arriving at a conclusion. MFDFA is the most advanced non-linear tool found till date for studying non-linear, non-stationary EEG dynamics. The results show that there are significant changes in the complexity of alpha and theta brain rhythms corresponding to all the frontal electrodes even when a simple acoustic drone signal is played.

5.2 Experimental Details

5.2.1 Subjects Summary

10 young musically untrained right handed adults (6 male and 4 female) voluntarily participated in this study. Their ages were between 19 and 25 years (SD = 2.21 years). None of the participants reported any history of neurological or psychiatric diseases, nor were they receiving any psychiatric medicines or using a hearing aid. Informed consent was obtained from each subject according to the ethical guidelines of the Ethical Committee of Jadavpur University. All experiments were performed at the Sir C.V. Raman Centre for Physics and Music, Jadavpur University, Kolkata.

5.2.2 Processing of Tanpura Drone

The Tanpura stimuli given for our experiment was the sound generated using software 'Your Tanpura' in C# pitch and in Pa (middle octave)—Sa (upper octave)—Sa (upper octave)—Sa (middle octave) cycle/format. The signal was normalized to within 0 dB and thus the variation of intensity is not being taken into account. Time of each complete cycle was about 4.5 s. From the complete recorded signal a segment of about 2 min was cut out at the zero point crossing using open source software toolbox Wavesurfer (Sjölander and Beskow 2009). Variations in the timbre were avoided as same signal were given to all the participants. Figure 5.1 depicts a single cycle of Tanpura drone signal of 4.5 s duration that was given as an input stimulus to all the informants.

5.2.3 Experimental Protocol

The EEG experiments were conducted in the afternoon (around 2 PM) in an air conditioned room with the subjects sitting in a comfortable chair in a normal diet condition. All experiments were performed as per the guidelines of the Institutional Ethics Committee of Jadavpur University. Each subject was prepared with an EEG

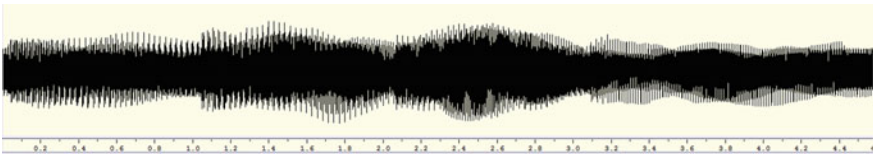

Fig. 5.1 Waveform of one complete cycle of Tanpura drone signal

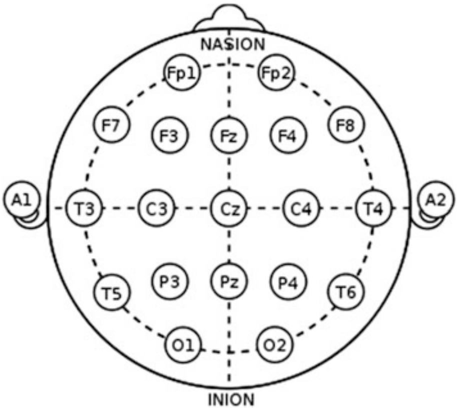

Fig. 5.2 The position of electrodes according to the 10–20 international system

recording cap with 19 electrodes (Ag/AgCl sintered ring electrodes) placed in the international 10/20 system. Figure 5.2 depicts the positions of the electrodes.

Impedances were checked below 50 kΩ. The EEG recording system (Recorders and Medicare Systems) was used to record the brain-electrical responses of the subjects at a rate of 256 samples/second with the customized software of RMS. The data was band-pass-filtered between 0.5 and 70 Hz to remove DC drifts and suppress the 50 Hz power line interference. A 6 min EEG recording was done as per the following protocol:

Part 1: 2 min No Music

Part 2: 2 min With Tanpura drone

Part 3: 2 min No Music

Markers were set at the onset and at the end of the experiment.

5.3 Methodology

The raw EEG signal is generally contaminated by various types of external artifacts such as eye blinks, muscular movement etc. Eye blinks and eye movements are characterized by frequency of less than 4 Hz and high amplitude. Thus, it is essential to identify these artifacts and to remove them from the raw EEG signal to get a noise free EEG data. A novel data driven technique called Empirical Mode Decomposition (EMD) was used to de-noise the EEG signal. Then different brain rhythms having different frequency regions were isolated with the help of widely used wavelet transform (WT) technique. For this the noise cleaned EEG signal was used as an input for the WT technique. The amplitude envelope of the alpha and theta frequency rhythms as well as their time series data were extracted for all the informants. Only the seven odd and even frontal electrodes (F3, F4, F7, F8, Fp1, Fp2 and Fz) were chosen for this study as earlier works have shown frontal electrodes play the most significant role during cognition of specific auditory musical stimuli. Now, using the MFDFA technique on the extracted alpha and theta brain rhythms, we have obtained the Hurst exponent for different values of q, Multifractal spectral width (W) of the two rhythms and then analyzed the change in multifractality in these signals when a constant repetitive music (here Tanpura drone) was played.

5.4 Results and Discussions

The multifractal analysis was performed on the amplitude envelope of alpha and theta wave obtained from the wavelet transform technique following the methodology mentioned above. The qth order fluctuation function $Fq(s)$ for 10 points of q in between −5 and +5 was obtained. The time series values of both the waves have been randomly shuffled to destroy all the long range correlations present in the data, and what remained is a totally uncorrelated sequence. The regression plots of ln $(Fq(s))$ versus $ln(s)$ averaged for different values of q ($q = -3$ to $q = +3$) were drawn for scales varying from 16 to 1024 for all the electrodes for both alpha and theta waves. $h(q)$ was determined from the slope of the best fit line of this $ln(Fq(s))$ versus $\ln(s)$ plot. From previous knowledge we know that the shuffled values of both alpha and theta do not change with the values of q, and thus has a fixed slope $h(q) = \mathrm{H}$, which is similar to the conventional Hurst exponent for monofractal time series. The statistical fit for the different values of $h(q)$ for different values of q were then calculated for the seven frontal electrodes both in "before drone" and "with drone" condition corresponding to alpha and theta frequency domain. The SD values are computed for each q taking into account the $h(q)$ values of 10 subjects. For positive values of q, $h(q)$ describes the scaling behavior of the segments with large fluctuations. Usually the large fluctuations are characterized by a smaller scaling exponent $h(q)$ for multifractal series. On the contrary, for negative values of q, the segments v with small variance $F^2(s, v)$ will dominate the average $Fq(s)$. Hence, for negative values of q, $h(q)$ describes the scaling behavior of the segments with small fluctuations, which are usually characterized by a larger scaling exponent. For both alpha and theta frequency ranges, we have found considerable variation of $h(q)$ with the change of q from −5 to +5, indicating the presence of strong multifractality in the waves. In the randomly shuffled series, where all the correlations have been destroyed, a non multifractal scaling $h_{shuf}(q) \sim 0.5$ is observed in most cases. The values of $h_{shuf}(q)$ remain almost unaffected by the change of q, showing monofractal behavior for the shuffled series. As for the original data, all the $h(q)$ values fall within the interval 0.5–1, indicating that both the alpha and theta time series have long range correlations in different scales as is evident from the variance of $h(q)$ values corresponding to different q's. Another interesting observation from the tables is that the generalized Hurst exponent values, in general increase for all q's as we move from "before drone" to "with drone" condition. The increase in h(q) values, though in different order, occurs uniformly for all the seven frontal electrodes.

A representative figure for variation of $h(q)$ with q of a single person corresponding to alpha and theta waves has been shown in Fig. 5.3. It is clearly evident from the figures that the values of $h(q)$ decreases with the increase of q, showing multifractal scaling in both alpha and theta frequency domain. For monofractal signals, a single value of Hurst exponent is obtained corresponding to different values of q, like the shuffled value of $h(q)$ as seen in Fig. 5.3, where $h(q)$ remains almost constant with the change of q. The amount of multifractality can be determined quantitatively in each of the windows of each signal from the width of the multifractal spectrum [f(α) versus α]. The shuffled width obtained, is found to be always smaller than the original width of the signal (Fig. 5.4). This ascertains the fact that multifractality in alpha and theta waves is present both due to long range correlations as well as broad probability density function. In the ideal case, the shuffled data should behave as a monofractal signal with no multifractal scaling.

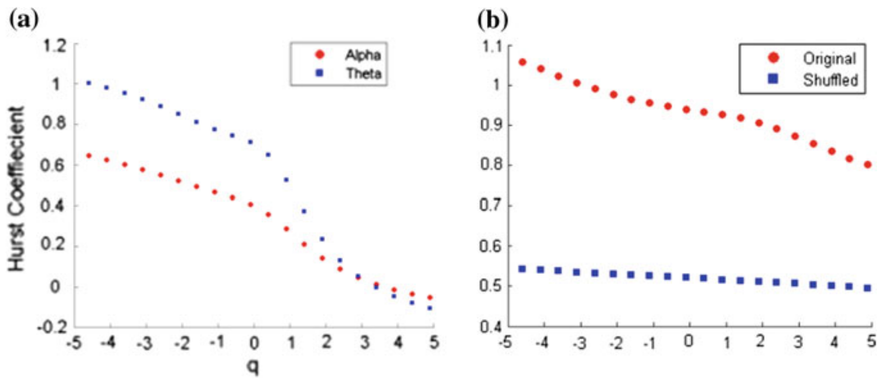

Fig. 5.3 **a** Variation of Hurst exponent h(q) with q for alpha and theta. **b** Original and shuffled values of Hurst exponent h(q)

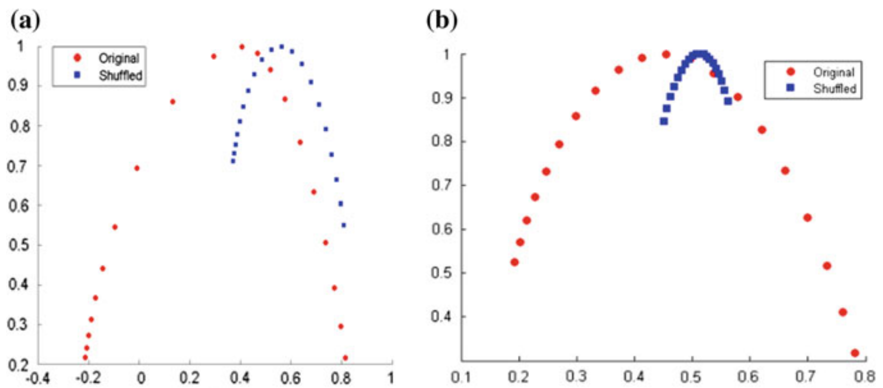

Fig. 5.4 f(α) versus α curve for **a** alpha and **b** theta waves

Thus, in the plot of Hurst exponent, it is seen that the shuffled values of $h(q)$ does not change in general with q, and in the $f(\alpha)$ versus α plot, the shuffled series will show a peak at α_0 close to 0.5. A representative figure (Fig. 5.4) shows the $f(\alpha)$ versus α plot including the original and shuffled width for a particular person corresponding to alpha and theta frequency domain in the frontal electrode F3.

For the sake of comparison, the multifractal spectrum for a single person in the alpha and theta frequency range for the two experimental conditions has been plotted in Fig. 5.5. The values of the spectral widths for all the persons were averaged for each of the electrode and the Standard Deviation values were computed corresponding to each electrode and frequency domain. These are given in Table 5.1.

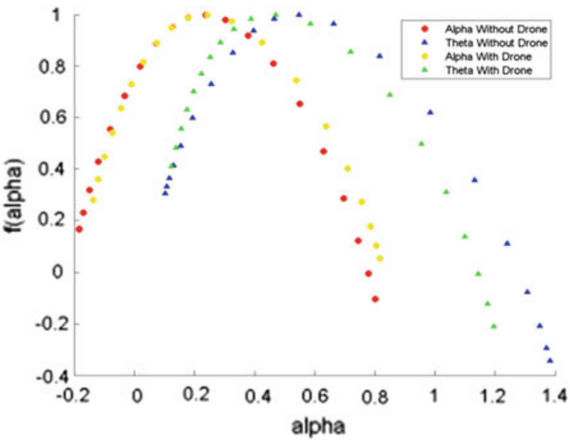

Fig. 5.5 Variation of spectral width in alpha and theta domain

Table 5.1 Alpha and theta multifractal spectral widths for the frontal electrodes

Electrode	Frequency rhythm	Before drone (multifractal width)	Shuffled width	With drone (multifractal width)	Shuffled width
F3	Alpha	0.787 ± 0.018	0.1326	1.147 ± 0.019	0.1241
	Theta	0.924 ± 0.118	0.1795	1.082 ± 0.057	0.1983
F4	Alpha	0.799 ± 0.016	0.1810	1.131 ± 0.017	0.1512
	Theta	0.922 ± 0.093	0.3396	1.273 ± 0.088	0.2671
F7	Alpha	0.951 ± 0.012	0.1972	1.200 ± 0.012	0.2084
	Theta	0.793 ± 0.019	0.3441	1.018 ± 0.116	0.2808
F8	Alpha	0.817 ± 0.020	0.0896	1.165 ± 0.015	0.1445
	Theta	0.898 ± 0.077	0.2160	1.093 ± 0.036	0.1948
Fp1	Alpha	0.860 ± 0.015	0.1720	1.225 ± 0.010	0.1419
	Theta	0.972 ± 0.027	0.1548	1.087 ± 0.052	0.2609
Fp2	Alpha	0.852 ± 0.016	0.1197	1.072 ± 0.013	0.1415
	Theta	0.708 ± 0.087	0.2736	1.212 ± 0.113	0.1722
Fz	Alpha	0.800 ± 0.015	0.1268	1.287 ± 0.016	0.1309
	Theta	0.927 ± 0.061	0.2078	1.173 ± 0.110	0.1139

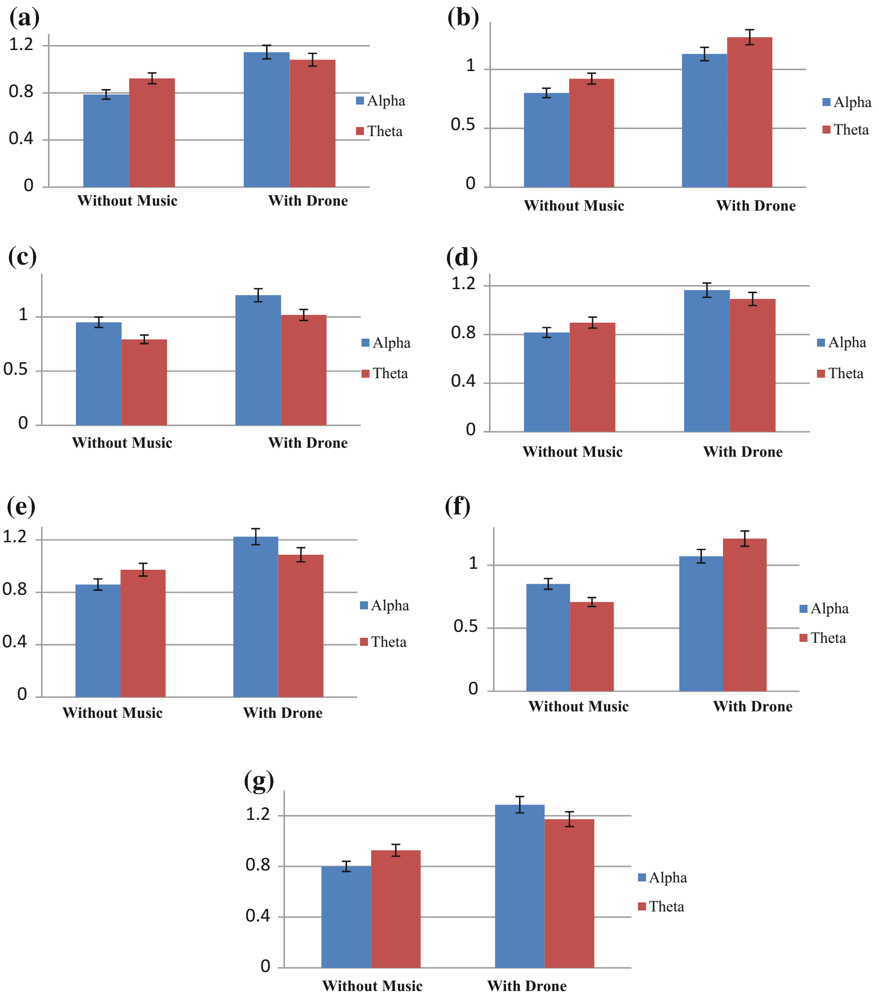

Fig. 5.6 **a** Alpha and theta spectral width in F3 electrode **b** Alpha and theta spectral width in F4 electrode **c** Alpha and theta spectral width in F7 electrode **d** Alpha and theta spectral width in F8 electrode **e** Alpha and theta spectral width in Fp1 electrode **f** Alpha and theta spectral width in Fp2 electrode **g** Alpha and theta spectral width in Fz electrode

The variation of multifractal width with respect to alpha and theta frequency domain under the application of drone for all the frontal electrodes has been shown in Figs. 5.6a–g. The Standard Deviation (SD) values computed from the multifractal analysis have been shown as error bars in all the figures.

From the figures it is evident that in all the frontal electrodes multifractality of alpha waves increase from “no music” to “with drone” condition. The frontal midline electrode reports maximum increase in multifractality of alpha waves, while F7 electrode reports minimum increase. In case of theta waves, the multifractality also show an increase for all the frontal electrodes. The even electrodes Fp2 and F4 report maximum increase in theta multifractality while all the other frontal electrodes exhibit a general increase in multifractal width. The increase in multifractal width is consistent with our previous finding for Hurst exponent, where the $h(q)$ values increase under the effect of drone in all the frontal electrodes. ANOVA (Freud and Miller 2004) tests were performed to test the statistical significance of the results. It was found that the averaged values were significantly different even at 95% confidence interval. This study presents a new data in the form that even a simple musical input like Tanpura drone produces an increase in complexity of alpha and theta waves in all the frontal electrodes. Thus, with the help of different non linear analysis techniques, we have shown that there is a considerable increase in alpha and theta spectral width and hence complexity of these particular brain waves when subjects listen to Tanpura drone. The increase in complexity of brain is related to more stable and accurate behavioral performance in humans (Lippé et al. 2009). Increase in brain complexity can thus be regarded as to be a measure for the brain reaching a healthier and active state. It is an interesting observation that with the help of a simple acoustical signal like Tanpura drone we have been able to achieve a state of brain in which the person can be said to be in a more pleasant and a relaxed state. This analysis could provide to be very fruitful in the context of cognitive music therapy.

5.5 Conclusion

The work presents a new data regarding neuro-cognitive activation human brain when presented with simple acoustical drone stimuli. Empirical Mode Decomposition (EMD) technique was used to neutralize the EEG data from spurious fluctuation patterns arising due to various artifacts. Then the resultant clean EEG data was decomposed into the alpha and theta frequency domain using Discrete Wavelet Transform (DWT) and they were analyzed with MFDFA technique. The analysis clearly reveals that even an input of simplest music significantly affects dynamics of brain functioning manifesting in different types of emotion.

The main findings of this work may be summarized as follows:-

1. From the values of generalized Hurst exponents $h(q)$s, it has been ascertained that both long range as well as short range fluctuations are present in the alpha as well as theta waves, and the presence of multifractality is ascertained in these waves.
2. One very interesting and new finding which deserves mentioning is that, the input of drone always enhances the theta as well as alpha complexity for all the frontal electrodes. The MFDFA method reveals the presence of multifractal scaling in case of both alpha and theta waves. This information is entirely new and has not hitherto been reported in literature. Previous studies dealt with linear

techniques like Fast Fourier Transform (FFT) to extract the alpha and theta power from various frontal electrodes, and related rise and fall of alpha and theta spectral power as a measure of elicitation of emotion. The linear techniques have a major drawback that they miss out on finer intricate details of the signal which sophisticated non-linear techniques like MFDFA can. In this case, multifractal spectral width corresponding to alpha and theta frequency domain for all the electrodes reported an increase from a very small value to a large value.

3. Furthermore, the Tanpura signal has a “buzzing” sound (drone) in which particular harmonics resonate with focused clarity. This ensures the perseverance of a tranquil atmosphere in the experiment room. This work is a pioneer in establishing the efficiency of non-linear analysis to study the ever-changing brain dynamics, and may be some day we will be able to consider the degree of complexity of brain waves as a measure of the well being of an individual. In this context, this study can have crucial application in the area of cognitive music therapy.

To conclude, this work presents sufficiently new and interesting findings which will be of extreme importance when it comes to music induced emotion identification and cognitive music therapy using EEG bio-signals. This study can be repeated with a variety of emotive music to see how the multifractality of alpha and theta waves vary under the application of these musical clips. This could be an important tool for specification of emotion digitally. The next chapter deals with the long-debated issue of universality of music taking the help of robust neuro-scientific tools.

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Chapter 6
Genesis of Universality of Music: Effect of Cross Cultural Instrumental Clips

I sing the body electric…
…in the depth of my soul there is a wordless song….
—Walt Whitman

6.1 Introduction

6.1.1 What Is Universality of Music?

Music is a common phenomenon that crosses all borders of nationality, race, and culture. A tool for arousing emotions and feelings, music is said to be far more powerful than language. An increased interest in how the brain processes musical emotion can be attributed to the way in which it is described as a "language of emotion" across cultures (Bukofzer 2013). More than any other stimulus, music has the ability to conjure up images and feelings that need not necessarily be directly reflected in memory. In the words of musicians, "music can communicate and transcend across cultural and linguistic boundaries in ways not possible by any other language". But what is meant by "universal" and "language"? Every culture has their own language, as well as their own form of music; which vary significantly from one culture to another. A number of studies have shown that listeners are able to identify two basic emotions from musical clips of unfamiliar genre—happy and sad. There are certain basic features of musical clips viz. pitch, tempo and rhythm, manipulating one or two of these is enough to change the emotional state of the listener. Higher pitch, more fluctuations in pitch and rhythm, and faster tempo convey happiness, while the opposite conveys sadness; and these features remain constant for music across all cultures, which might be the reasons why music is called a "universal language".

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6.1.2 Previous Research to Look for Universal Cues of Music

A number of studies in Western music culture deals with extraction of certain features of music perception which are universal and which are developed due to exposure to a certain culture (Balkwill and Thompson 1999; Trehub 2003; Hauser and McDermott 2003; Peretz 2006; Fritz 2009). In one of these studies (Fritz 2009) it is reported that native Africans (Mafa) population recognized three basic emotions (happy, sad, fear) from Western musical samples which led to the conclusion that these basic emotions in Western music can be recognized universally. There are only a few studies which make an effort to study musical cues which transcend cultural boundaries and are identifiable by people across all cultures (Balkwill and Thompson 1999; Balkwill et al. 2004; Gregory and Varney 1996). Most of these studies deal with psychological analysis of human response data for identification of musical cues across cultures like Westerners being made to listen to Hindustani music. The overall phenomenon in how music evokes emotion still contains a veil of mystery; the reasons behind the 'thrill' or 'chills' generated while listening to music are strongly tied in with various theories based on synesthesia (Loui 2013). Instrumental music is said to be brain's food. Earlier studies have found that listening and training in instrumental music has positive effects on cognitive development in children (Schlaug et al. 2005). Training in instrumental music results in greater growth in manual dexterity and music perception skills, significantly improved verbal and mathematical performance and more gray matter volume in the brain (Hyde et al. 2009; Hallam 2010; Wan and Schlaug 2010). People perform logic tasks better in the presence of instrumental music as opposed to vocal music, according to another study (Chamorro-Premuzic et al. 2009). Researchers found that those listening to classical music seemed more involved in the task, possibly brought on by the relaxing nature of the music (Phillips 2004). Those suffering from pain and/or depression should listen to instrumental music for relaxation and relief (Erkkilä 2008; Ozdemir and Akdemir 2009). Music therapy is instituted in many hospitals and hospices to relieve stress and provide comfort. Researchers have also found that playing slow instrumental music, including jazz, harp and piano music, reduced pain and anxiety in patients following open-heart surgery (Voss et al. 2004). Till date, there is no study which deals with the neuro-cognitive manifestation of universal cues associated with different genres of music.

6.1.3 Neuro-Cognition of Emotional Music Across Different Cultures

Music has the unique ability to evoke a wide variety of emotions involving valence (quality of a particular emotion) as well as arousal (quantity or bodily activation corresponding to a particular emotion) based affects (Russell 1980). Valence is a subjective feeling of pleasantness or unpleasantness while arousal is a subjective state of feeling activated or deactivated (Russell 1989). A number of studies have been conducted to test the validity of arousal-valence model in musical emotions, of which mostly are based on human response data (Scherer 2004; Juslin and Laukka 2004; Salimpoor et al. 2009), while a few studies use neuro-bio sensors (Schmidt and Trainor 2001; Kim and André 2008). Most of the studies related to emotional aspects of music are centered on Western music, while only a few studies deal with Hindustani music (Mathur et al. 2015; Wieczorkowska et al. 2010) and its neural correlates (Banerjee et al. 2016). A number of issues like universality, arousal-valence and its linkage with modularity or neural correlates have been baffling scientists for quite some time. This prompted us to use a wide variety of instrumental music originating from different parts of the globe and study their arousal and valence based effects in human brain using electroencephalography (EEG) using robust non-linear analysis techniques.

A number of previous studies speak in favor of the valence lateralization model, according to which positive emotions are associated with greater left frontal activity while the negative emotions are associated with increased right frontal activity (Schimdt and Trainor 2001; Trainor and Schmidt 2003; Sammler et al. 2007; Koelsch et al. 2006), although it seems a bit unrealistic to think that specific regions of the brain will be involved in processing a particular emotion, while others remain inert. A number of studies thus report against this lateralization theory claiming that a number of regions work together for the processing of musical emotions (Khalfa et al. 2005; Hamann and Mao 2002; Khalfa et al. 2008a, b) mainly happiness and sadness, as these are the most reliably induced musical emotions (Balkwill and Thompson 1999). A common feature of most of these studies is that they concentrate on the frontal lobe mainly during the perception and cognition of emotion, but a few studies have also reported the involvement of temporal lobe in the processing of musical emotions (Blood et al. 1999; Olson et al. 2007; Khalfa et al. 2008a, b), as well as occipital lobe in some cases (Kosslyn and Pylyshyn 1994; Mellet et al. 1995). Though the occipital lobe is mostly attributed to information and visual stimuli processing, the debate whether musical stimuli is able to produce mental imagery is well known. Thus, it would be interesting to see the response of occipital electrodes along with others when presented with musical stimulus conveying a palette of emotions. Most of the referred studies here use fMRI (functional Magnetic Resonance Imaging) or PET (Positron Emission Tomography) techniques which generally have high spatial resolution but lack in temporal precision. EEG data on the other hand have high temporal resolution in the form of time series data obtained from different corners of the brain which help in identifying specifically the regions which are more stimulated or activated in response to a particular emotional stimuli. A number of previous EEG studies based on linear analysis in the form of Power Spectral Density (PSD) have marked alpha activity as a mediator to identify emotional response (Schmidt and Trainor 2001; Trainor and Schmidt 2003; Sammler et al. 2007; Schmidt and Hanslmayr 2009) while a few also consider theta power (Sammler et al. 2007; Aftanas and Golocheikine 2001). Most of these studies speak in favor of asymmetric processing, where a decrease in left frontal alpha power is a mark of positive emotional processing, while a decrease in right frontal alpha power is a mark of negative emotion processing (Schmidt and Trainor 2001; Trainor and Schmidt 2003; Sammler et al. 2007). The rise in Frontal Midline (Fm) theta power was seen to be associated with processing of pleasant music (Sammler et al. 2007; Aftanas and Golocheikine 2001). But all these studies are based on linear Fourier Transform (FT) technique which has some obvious drawbacks as illustrated in (Conte et al. 2009; Klonowski 2009). The FT technique assumes the EEG signals to be linear and stationary, does not involve the inherent spikes in the time series, thus involving a major loss in data (Huang 1998).

6.1.4 Use of MFDFA on EEG to Assess Universality and Domain Specificity of Musical Emotion

EEG is a neuro-scientific bio-sensor which provides plentiful information about the complex human brain dynamics according to electrical activity in brain tissues (waves i.e. plot of voltage over time between electrodes by using the summation of many action potentials sent by neurons in brain) against human emotion elicited by music. The scalp EEG arises from the interactions of a large number of neurons whose interactions generally nonlinear and thus they can generate fluctuations that are not best described by linear decomposition. On the other hand, the classical nonlinear dynamics method such as correlation dimension and Lyapunov exponents are very sensitive to noise and require the stationary condition, while EEG signals often are highly non-stationary. In recent past, the DFA has become a very useful technique to determine the fractal scaling properties and long-range correlations in noisy, non-stationary time-series. It has been widely applied to diverse fields such as DNA sequences, heart rate dynamics, neuron spiking, human gait, and economic time-series and also to weather related and earthquake signals (Ossadnik et al. 1994; Peng et al. 1994; Blesić et al. 1999; Ashkenazy et al. 2001). DFA has also been applied to EEG signals to identify music induced emotions in a number of studies (Gao et al. 2007; Karthick et al. 2006; Banerjee et al. 2016). Gao et al. (2007) related emotional intensity with the scaling exponent, while a recent study (Banerjee et al. 2016) relate the variation of alpha scaling exponent generated from DFA technique with the retention of musical emotions—an evidence of hysteresis in human brain. But DFA has its own limitations. Many geophysical signals as well as bio-signals do not exhibit monofractal scaling behavior, which can be accounted for by a single scaling exponent (Hu et al. 2001; Kantelhardt et al. 2001), therefore different scaling exponents are required for different parts of the series (Chen et al. 2002). Consequently a multifractal analysis should be applied.

The Multifractal Detrended Fluctuation Analysis (MFDFA) technique was first conceived by Kantelhardt et al. (2001) as a generalization of the standard DFA. MFDFA has been applied successfully to study multifractal scaling behavior of various non-stationary time series (Sadegh Movahed et al. 2006; Telesca et al.

2004; Kantelhardt et al. 2003) as well as in detection or prognosis of diseases (Dutta et al. 2013, 2014), Figliola et al. 2007a, b). The multifractals are fundamentally more complex and inhomogeneous than monofractals (Stanley et al. 1999) and describe time series featured by very irregular dynamics, with sudden and intense bursts of high-frequency fluctuations (Davis et al. 1994). EEG signals are essentially multifractals as they consist of segments with large variations as well as segments with very small variations, hence when applied to the alpha and theta EEG rhythms, the multifractal spectral width will be an indicator of emotional arousal corresponding to particular clip. In case of music induced emotions, a recent study (Maity et al. 2015) used the multifractal spectral width as an indicator to assess emotional arousal corresponding to the simplest musical stimuli—a tanpura drone.

6.1.5 Overview of Our Work

The objective of this study is to analyze the effect of cross-cultural instrumental music signals on brain activity during the normal relaxing condition, using a robust non-linear analysis technique—MFDFA. It is well known that listening to music is a complex process for the brain, since it triggers a sequel of cognitive and emotional components. The choice of instrumental music was done so as to avoid any conflict that may arise due to cognition of language present in the musical clips. Our study therefore focuses on measuring the emotions elicited by the instrumental music stimuli in terms of neuron arousals. For this, we chose eight (8) 30 s instrumental clips originating from across different cultural attributes. The clips were chosen keeping in mind they convey a wide range of emotional arousal so that we can get a method to automatically identify the amount of arousal each clip causes. The clips were first standardized on the basis of a human response data of 100 respondents. The informants were asked to rate the clips in 2-dimensional emotional axes comprising of four basic emotions namely—joy, sorrow, anxiety and calmness in a 5 point scale. The clips which have maximum rating in the scale of 4/5 are those which have maximum arousal corresponding to a particular emotion. In this way, we can identify the clips which cause maximum arousal in the listeners. Next, EEG was conducted on 20 participants chosen arbitrarily from the 100 respondents who participated in the listening tests. The participants are made to listen to the 30 s clips in the same order in which they gave the listening test. The EEG signals were obtained from five frontal electrodes (F3, F4, F7, F8 and Fz), two temporal electrodes (T3/T4) and two occipital electrodes (O1/O2). The signals from each electrode were preprocessed with the well known EMD (Wu and Huang 2009) technique to make it free from blink/muscular artifacts (Looney et al. 2008; Chen et al. 2014). The artifact-free EEG signals were then subject to Wavelet Transform (WT) (Hazarika et al. 1997) technique to extract the theta and alpha time series data. Next the alpha and theta EEG brain rhythms were subject to the MFDF analysis which gives the alpha and theta multifractal spectral width corresponding to each musical clip. These neuronal arousals might be a manifestation of change of complexity as obtained from the variation of the multifractal width. The multifractal spectral width is known to be a measure of complexity of the EEG signal. The spectral width corresponding to the alpha and theta domain varies significantly from one clip to another and has unique manifestation in frontal, temporal and occipital lobe. This could be helpful as a parameter for emotion identification from music stimuli. Also, the arousal based effects from a musical clip can be localized with the help of this technique along with the identification of a parameter from which we can nullify or support the valence lateralization theory. Summing up, in this study, we provide a novel technique where, with the help of a single parameter (i.e. multifractal width) we can categorize, quantify musical emotion processing accomplished by different regions of human brain.

6.2 Experimental Details

6.2.1 Collection of Human Response Data

Participants were recruited through word of mouth and social media platforms. Since the study was conducted both on online and offline basis, participants from across the country participated in the study, but more than half the participants were from Kolkata. All the offline data were collected at the Sir C.V. Raman Centre for Physics and Music, Jadavpur University. In this study, ratings from 100 participants (F = 37, M = 63) were considered for analysis presented herewith. The subjects chosen had no formal musical training.

The subjects were asked to listen to eight (8) cross cultural instrumental musical clips of 30 s duration with a gap of 30 s between consecutive clips and mark their emotional arousal in a scale of 5. The clips were chosen in such a way that it covers the entire human emotional spectra. The markings on the emotional scale were based on a subject's perception of the meaning of "happy", "sad", "calm" or "anxious". There was no biasing imposed on the listener regarding the marking of clips. Corresponding to each musical clip, two pairs of emotion in a 5 point scale were given as shown:

An Instruction Sheet was given along with a Response form to each subject, and the subjects were asked to mark each clip on the emotional scale shown. If the subjects were not emoted by any clip, they were asked not to mark the scale. When a subject marked a emotional rating in 4/5, it implies high arousal corresponding to that particular musical clip. In this way, the average emotional grading corresponding to each musical clip is obtained, with which we compare the data obtained from EEG.

6.2.2 Processing of Music Signals

The following instrumental clips each of 30 s duration were chosen for our study (Table 6.1). Both the signals were normalized to within 0 dB and hence intensity or loudness and attack cue are not being considered. Each of these sound signals was digitized at the sample rate of 44.1 kHz, 16 bit resolution and in stereo channel.

6.2.3 Subjects Summary

20 (M = 14, F = 6) musically untrained adults chosen randomly from the pool created from listening test data who voluntarily participated in this study. The average age was 23 years (SD = 2.35 years) and average body weight was 65 kg. Each subject was made to sign a consent form prepared according to the guidelines of the Jadavpur University Ethics Committee. All experiments were performed at the Sir C.V. Raman Centre for Physics and Music, Jadavpur University, Kolkata. The experiment was conducted in the afternoon with a normal diet in a normally conditioned room sitting on a comfortable chair and performed as per the guidelines of the Institutional Ethics Committee of SSN College for Human volunteer research. The study was approved by the Jadavpur University Ethics Committee (Approval No.: 3/2013).

During the EEG acquisition period, the 20 subjects were made to listen to the same clips as in the listening test. Each experimental condition lasted for around 10 min. Each song clip of 30 s was followed by a resting period of 30 s during which no music was played. Subjects were asked to keep their eyes closed and to sit

Table 6.1 Details of the instrumental clips chosen for our study

Clip no.	Clip name	Artist	Instrument used
Clip 1	Amelie Road Crossing	Yann Tiersen	Accordion
Clip 2	Raga Bhairavi	Ustad Amjad Ali Khan	Sarod
Clip 3	Tocotta and Fugue in D' minor	J.S. Bach	Organ
Clip 4	Earthquake	Ustad Zakir Hussain	Tabla
Clip 5	Hachiko Soundtrack	Jan A.P. Kaczmarek	Piano
Clip 6	Raga Mishra gara	Pt. Nikhil Banerjee	Sitar
Clip 7	Raga Sudh Sarang	V.G. Jog	Violin
Clip 8	Water Dewdrops	Pt. Shivkumar Sharma	Santoor

calmly during each condition. First, the baseline (that is, a resting condition) was recorded for each subject before the start of the experiment with 2 min of 'no music' condition.

The music was presented with the computer-sound system (Logitech R _ Z-4 speakers) with very low S/N ratio was used in the measurement room for giving music input to the subjects ca. 120 cm behind the head of the subjects with a volume of 45–60 dB. The volume was adjusted individually within this range since the individually chosen pieces of music were typically listened at different sound volumes. For example, Hard-Rock is typically louder than classical music. The EEG experiment was conducted in the afternoon (around 2 PM) in a room with the volunteers sitting in a comfortable chair.

6.2.4 Experimental Protocol

Since the objective of this study was to analyze the effect of cross-cultural contemporary instrumental music on brain activity during the normal relaxing condition, the frontal, temporal and occipital lobes were selected for the study. EEG was done to record the brain-electrical response of 20 subjects. Each subject was prepared with an EEG recording cap with 19 electrodes (Ag/AgCl sintered ring electrodes) placed in the international 10/20 system. Figure 6.1 depicts the positions of the electrodes. Impedances were checked below 50 kΩ. The EEG recording system (Recorders and Medicare Systems) was operated at 256 samples/s recording on customized software of RMS. The data was band-pass-filtered between 0.5 and 35 Hz to remove DC drifts and suppress the 50 Hz power line interference. The ear electrodes A1 and A2 linked together have been used as the reference electrodes. The same reference electrode is used for all the channels. The forehead electrode, FPz has been used as the ground electrode. Each subject was seated comfortably in a relaxed condition in a chair in a shielded measurement cabin. They were also asked to close their eyes. After initialization, a 10 min recording period was started, and the following protocol was followed:

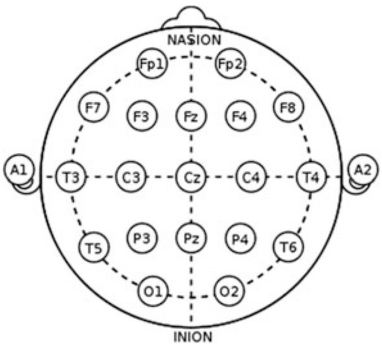


Fig. 6.1 The position of electrodes according to the 10–20 international system

1. 60 s No Music (Resting Condition)
2. 30 s Clip 1
3. 30 s No Music
4. 30 s Clip 2
5. 30 s No Music
6. 30 s Clip 3
7. 30 s No Music
8. 30 s Clip 4
9. 30 s No Music
10. 30 s Clip 5
11. 30 s No Music
12. 30 s Clip 6
13. 30 s No Music
14. 30 s Clip 7
15. 30 s No music
16. 30 s Clip 8
17. 60 s After Music

Markers were set at start, signal onset/offset, and at the end of the recording.

6.2.5 Methodology

6.2.5.1 Pre-processing of EEG Signals

We have obtained noise free EEG data for all the electrodes using the EMD technique as in Maity et al. (2015) and used this data for further analysis and classification of acoustic stimuli induced EEG features. The amplitude envelope of the alpha (8–13 Hz) and theta (4–7 Hz) frequency range was obtained using wavelet transform technique. Data was extracted for these electrodes according to the time period given in the Experimental protocol section i.e. for Experimental conditions 1–17.

6.2.5.2 Wavelet Transform

Wavelet transform (WT) forms a general mathematical tool for time-scale signal analysis and decomposition of EEG signal. We have used WT technique to decompose the EEG signal into various frequency bands i.e. alpha and theta. The DWT (Akin et al. 2001) analyzes the signal at different frequency bands with different resolutions by decomposing the signal into a coarse approximation and obtains detailed information. The time series data of alpha and theta waves were obtained corresponding to each experimental condition. On the obtained time series data, MFDFA analysis was performed.

6.2.5.3 Multifractal Analysis of EEG Signals

The analysis of the alpha and theta EEG signals are done using MATLAB (Ihlen 2012) and for each step an equivalent mathematical representation is given which is taken from the prescription of Kantelhardt et al (2002). The width of the spectrum gives a measure of the multifractality of the spectrum. Greater is the value of the width W greater will be the multifractality of the spectrum. For a monofractal time series, the width will be zero as h(q) is independent of q.

The origin of multifractality in a EEG time series can be verified by randomly shuffling the original time series data (Figliola et al. 2007a, b). All long range correlations that existed in the original data are removed by this random shuffling and what remains is a totally uncorrelated sequence. If any series has multifractality both due to long range correlation as well as due to probability density function, then the shuffled series will have smaller width W and hence weaker multifractality than the original time series. In this case we have seen that the original alpha and theta waves show multifractality values much higher than their corresponding shuffled values. This corroborates the findings of our previous work (Maity et al. 2015) where the origin of multifractality in alpha and theta waves is ascribed both due to long range correlation and probability distribution function.

6.3 Results and Discussions

The emotional ratings for each clip given by the respondents in the listening test are given in tabular form in Table 6.2. All the markings by the listeners from 1 to 5 corresponding to a particular emotion have been grouped under that emotion in the table.

On the basis of Table 6.2, the following radar plots are shown (Fig. 6.2a–h) which gives the level of arousal and valence of the listeners in response to each instrumental clip:

It is evident from the figures that Clips 1/8 and 2/7 have similar arousal but are of opposite valence, as Clips 1 and 8 have been rated to be joyful with almost 90% strength while Clips 2 and 7 have been rated to be sorrowful with almost 80%

Table 6.2 Strength of emotional response from listening test of 100 informants (in percentage)

	Joy	Anxiety	Sorrow	Calm
Clip 1	96	52	4	37
Clip 2	13	6	83	93
Clip 3	32	99	53	1
Clip 4	58	100	5	10
Clip 5	50	15	50	68
Clip 6	16	10	78	83
Clip 7	6	13	86	86
Clip 8	100	3	0	93

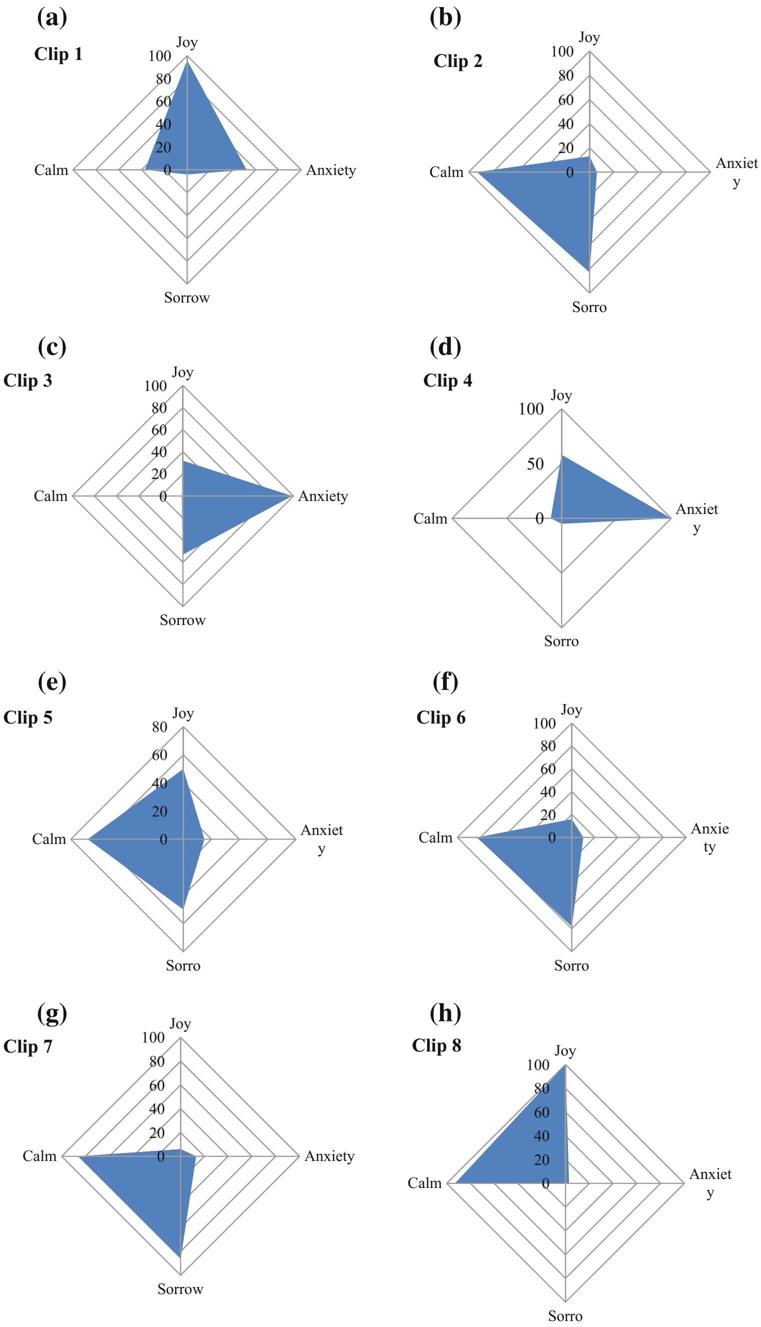


Fig. 6.2 **a** Emotional plot for Clip 1, **b** Emotional plot for Clip 2, **c** Emotional plot for Clip 3, **d** Emotional plot for Clip 4, **e** Emotional plot for Clip 5, **f** Emotional plot for Clip 6, **g** Emotional plot for Clip 7, **h** Emotional plot for Clip 8

strength. In a similar manner Clips 3/4 have been reported with 95% strength to convey anxiety while Clips 5/6 have been shown to be calm with 80 and 70% strength respectively. In this way, we have identified the arousal and valence corresponding to each instrumental clip and standardized the emotional appraisal pertaining to the clips. Next, the obtained EEG data for 20 participants for the same set of 8 cross cultural instrumental clips were analyzed with the help of well known MFDFA technique (Kantelhardt et al. 2002). Initially, the noise free EEG data was subjected to WT technique where from the amplitude envelope for alpha and theta waves were obtained for all the chosen electrodes. The time series data of the alpha and theta waves so obtained were analyzed with MFDFA method. The qth order fluctuation function $F_q(s)$ for 10 points of q in between −5 and +5 was obtained. The slope of the best fit line obtained from $\ln(Fq(s))$ versus $\ln(s)$ plot gives the values of $h(q)$. A representative figure for variation of $h(q)$ with q in response to Clip 1 for a particular electrode F3 (for a sample person) in both alpha and theta domain have been shown in Figs. 6.3 and 6.4. The shuffled values of h(q) has also been shown in the same figure (in blue dotted lines). The variation of $h(q)$ with q clearly indicates a multifractal behavior for both alpha and theta waves, as the shuffled values show remarkable difference from that of the original values. It is also evident from the figures that in most cases the values of $h(q)$ decreases with increasing q which as another evidence of multifractality in the time series. The shuffled values of the time series, on the other hand shows very little variation or sometimes no variation, showing monofractal behavior, since all the long range correlations are destroyed during random shuffling of the time series data.

The amount of multifractality can be determined quantitatively in each of the electrode from the width of the multifractal spectrum [**f(α) vs. α**]. A representative figure showing the multifractal spectrum for alpha and theta waves (both original and shuffled for a single person) before and after playing Clip 1 for electrode F3

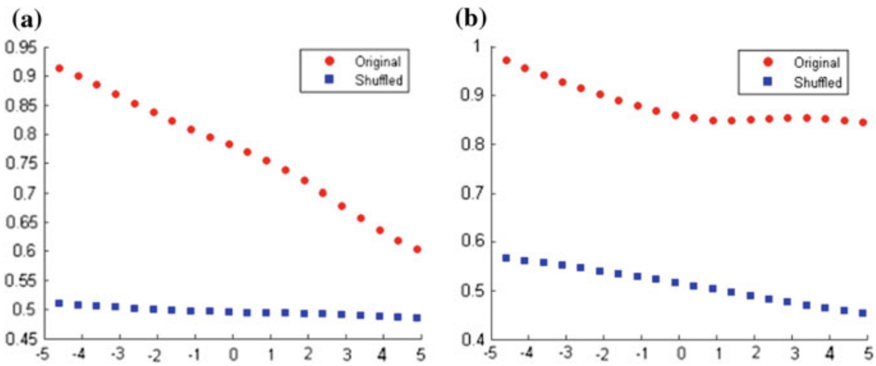


Fig. 6.3 Variation of original and shuffled values of h (q) vas q in F3 electrode for alpha waves. **a** Part 1 F3, **b** Part 2 F3

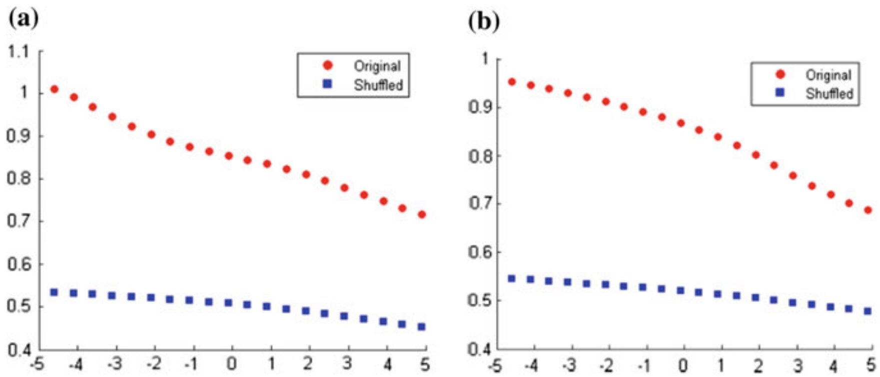


Fig. 6.4 Variation of original and shuffled values of h (q) vas q in F3 electrode for theta waves. **a** Part 1 F3, **b** Part 2 F3

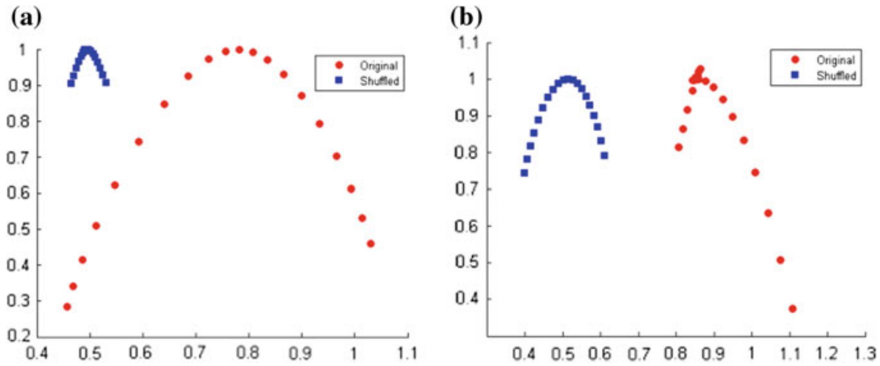


Fig. 6.5 Multifractal spectrum [f(α) vs. α] of alpha waves for a particular electrode F3. **a** Part 1 F3, **b** Part 2 F3

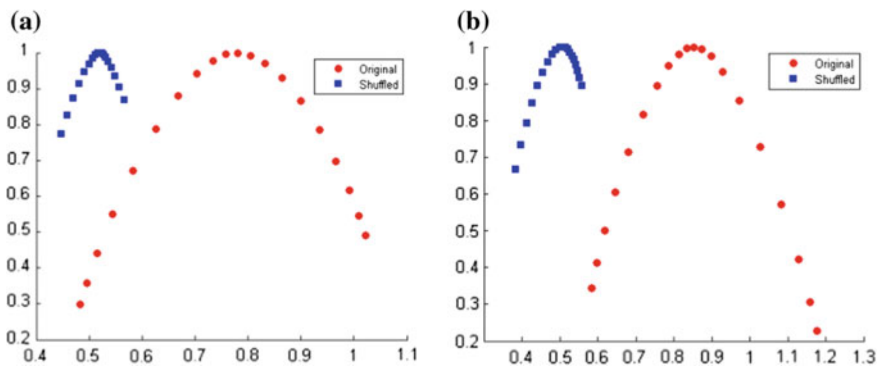


Fig. 6.6 Multifractal spectrum [f(α) vs. α] of theta waves for a particular electrode F3. **a** Part 1 F3, **b** Part 2 F3

have been shown in Figs. 6.5 and 6.6. As is evident from the figure the values of $W_{shuffled}$ are in general lower than the values of $W_{original}$. This indicates that the multifractality in the EEG signal is due to both broad probability distribution as well as long range correlation. But, multifractality due to long range correlation is more effective as the shuffled values show much less multifractalilty as compared to the original value in both the frequency domains. In case of shuffled values, the spectral width shows a peak value at around 0.5, which shows monofractal behavior for the shuffled signals. For the sake of comparison, in Fig. 6.7 we have shown the variation of multifractal width in both alpha and theta domain the response to Clip 1. It is evident that the spectral width is significantly different for the different experimental conditions ascribed to the emotional intensity of the clips and the arousal caused in different locations of the brain.

The values of spectral width were averaged for all the persons and the averaged values are presented in Table 6.3 along with the Standard deviation (SD) values computed for each experimental condition.

Table 6.3 shows the variation of multifractal width in different experimental conditions 1–17 for the different electrodes chosen in our study in both the frequency domains. We have computed the changes in multifractal widths for the four different categories of emotional arousal chosen. Thus, we have tried to see the changes in brain response when the valence is kept constant for two different clips. In this way, the following figures show the changes in multifractal spectral width of alpha and theta waves for the four emotional categories chosen (computed in percentage).

Figure 6.8 gives the change in multifractal width (in percentage) corresponding to alpha wave for the nine electrodes chosen.

The figures have the following interesting observations:

1. Clips 1 and 8 which were rated as ~90% joy in the listening test data have reported a decrease in spectral width unanimously across all the scalp electrodes

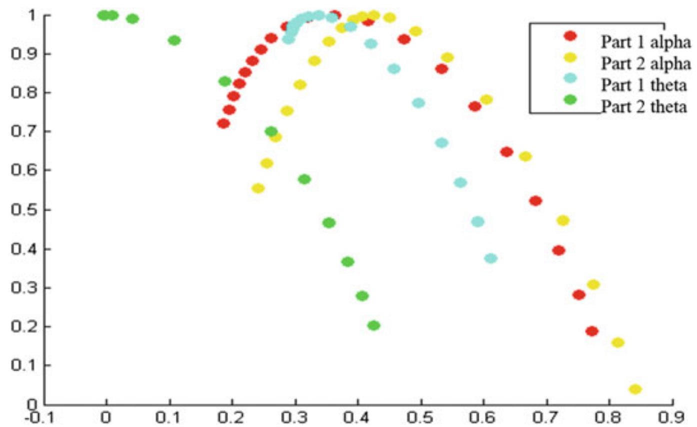


Fig. 6.7 Variation of multifractal width in alpha and theta domain for F3 electrode in response to Clip 1

Table 6.3 Variation of alpha and theta multifractality in different experimental conditions

	F3		F4		F7		F8		Fz	
	Alpha	Theta	Alpha	Theta	Alpha	Theta	Alpha	Theta	Alpha	Theta
Part 1	0.94 ± 0.05	1.21 ± 0.07	0.89 ± 0.06	1.08 ± 0.11	0.97 ± 0.07	1.19 ± 0.06	1.02 ± 0.08	1.22 ± 0.08	0.89 ± 0.07	1.15 ± 0.08
Part 2	0.83 ± 0.06	0.92 ± 0.05	0.84 ± 0.05	0.88 ± 0.12	0.83 ± 0.08	1.06 ± 0.05	0.94 ± 0.07	1.06 ± 0.13	0.78 ± 0.05	0.94 ± 0.07
Part 3	0.81 ± 0.08	1.01 ± 0.06	0.86 ± 0.07	1.14 ± 0.08	0.81 ± 0.03	1.04 ± 0.09	1.01 ± 0.06	1.06 ± 0.11	0.67 ± 0.06	1.07 ± 0.05
Part 4	0.86 ± 0.09	0.93 ± 0.04	0.79 ± 0.04	0.98 ± 0.06	0.85 ± 0.06	1.01 ± 0.08	0.88 ± 0.09	1.05 ± 0.04	0.78 ± 0.04	0.97 ± 0.06
Part 5	0.88 ± 0.07	1.14 ± 0.08	0.91 ± 0.08	1.06 ± 0.04	0.89 ± 0.05	1.12 ± 0.09	0.86 ± 0.05	1.02 ± 0.03	0.87 ± 0.08	0.97 ± 0.08
Part 6	0.72 ± 0.13	1.04 ± 0.05	1.01 ± 0.11	1.12 ± 0.03	0.8 ± 0.04	0.99 ± 0.04	0.69 ± 0.04	1.02 ± 0.05	0.78 ± 0.04	1.06 ± 0.11
Part 7	0.84 ± 0.11	0.94 ± 0.09	0.91 ± 0.09	1.01 ± 0.02	0.8 ± 0.06	1.04 ± 0.07	0.86 ± 0.03	1.02 ± 0.08	0.81 ± 0.09	0.94 ± 0.13
Part 8	0.67 ± 0.10	1.07 ± 0.11	0.98 ± 0.06	1.18 ± 0.10	0.73 ± 0.08	0.95 ± 0.05	0.78 ± 0.04	0.93 ± 0.07	0.73 ± 0.07	1.01 ± 0.07
Part 9	0.92 ± 0.07	0.96 ± 0.12	0.88 ± 0.07	0.97 ± 0.06	0.77 ± 0.07	1.08 ± 0.06	0.76 ± 0.06	1.04 ± 0.03	0.77 ± 0.06	0.98 ± 0.09
Part 10	0.82 ± 0.04	1.01 ± 0.14	0.84 ± 0.05	0.95 ± 0.07	0.78 ± 0.04	0.97 ± 0.08	0.94 ± 0.05	0.94 ± 0.08	0.78 ± 0.02	1.05 ± 0.04
Part 11	0.94 ± 0.08	1.04 ± 0.08	0.89 ± 0.06	0.94 ± 0.05	0.81 ± 0.06	1.12 ± 0.05	0.77 ± 0.04	0.91 ± 0.06	0.86 ± 0.07	0.93 ± 0.06
Part 12	0.88 ± 0.14	1.07 ± 0.06	0.78 ± 0.04	0.95 ± 0.04	0.8 ± 0.05	1.07 ± 0.09	0.76 ± 0.08	0.87 ± 0.06	0.92 ± 0.09	0.83 ± 0.08
Part 13	0.79 ± 0.13	0.99 ± 0.07	0.79 ± 0.05	1.12 ± 0.08	0.78 ± 0.07	1.04 ± 0.13	0.84 ± 0.06	1.08 ± 0.04	0.74 ± 0.12	0.91 ± 0.03
Part 14	0.87 ± 0.12	0.84 ± 0.09	0.72 ± 0.06	1.11 ± 0.09	0.82 ± 0.09	1.17 ± 0.014	0.79 ± 0.05	1.01 ± 0.03	0.9 ± 0.14	0.83 ± 0.04
Part 15	0.88 ± 0.16	1.1 ± 0.11	0.89 ± 0.05	1.06 ± 0.06	0.86 ± 0.06	1.05 ± 0.17	0.96 ± 0.03	0.95 ± 0.07	0.86 ± 0.17	1.09 ± 0.06
Part 16	0.72 ± 0.11	1.02 ± 0.09	0.77 ± 0.08	0.97 ± 0.05	0.73 ± 0.07	0.96 ± 0.09	0.84 ± 0.08	0.9 ± 0.06	0.8 ± 0.15	0.93 ± 0.07
Part 17	0.84 ± 0.09	1.18 ± 0.04	0.74 ± 0.07	0.93 ± 0.08	0.84 ± 0.05	1.14 ± 0.07	0.80 ± 0.09	1.22 ± 0.06	0.97 ± 0.11	1.05 ± 0.13

	O1		O2		T3		T4	
	Alpha	Theta	Alpha	Theta	Alpha	Theta	Alpha	Theta
Part 1	0.75 ± 0.08	1.06 ± 0.07	0.76 ± 0.08	1.06 ± 0.09	0.87 ± 0.10	1.02 ± 0.08	0.84 ± 0.09	1.11 ± 0.07
Part 2	0.64 ± 0.06	0.95 ± 0.04	0.68 ± 0.04	0.93 ± 0.11	0.73 ± 0.09	0.94 ± 0.06	0.76 ± 0.04	1.03 ± 0.06
Part 3	0.78 ± 0.17	1.03 ± 0.08	0.72 ± 0.07	1.01 ± 0.13	0.82 ± 0.13	0.9 ± 0.07	0.73 ± 0.06	0.92 ± 0.03
Part 4	0.87 ± 0.09	1.13 ± 0.05	0.66 ± 0.09	0.92 ± 0.09	0.73 ± 0.09	1.16 ± 0.05	0.77 ± 0.08	1.08 ± 0.11

(continued)

Table 6.3 (continued)

	O1		O2		T3		T4	
	Alpha	Theta	Alpha	Theta	Alpha	Theta	Alpha	Theta
Part 5	0.81 ± 0.07	0.98 ± 0.06	0.76 ± 0.08	0.91 ± 0.08	0.84 ± 0.11	0.91 ± 0.04	0.82 ± 0.04	1.01 ± 0.08
Part 6	0.67 ± 0.05	0.94 ± 0.04	0.69 ± 0.13	1.1 ± 0.08	0.77 ± 0.09	1.01 ± 0.06	0.76 ± 0.05	1.09 ± 0.07
Part 7	0.79 ± 0.04	0.95 ± 0.07	0.71 ± 0.09	1.08 ± 0.15	0.81 ± 0.06	0.97 ± 0.05	0.76 ± 0.06	0.91 ± 0.09
Part 8	0.64 ± 0.11	0.88 ± 0.05	0.67 ± 0.08	0.92 ± 0.06	0.73 ± 0.11	1.06 ± 0.04	0.72 ± 0.03	0.98 ± 0.11
Part 9	0.69 ± 0.08	1.02 ± 0.08	0.67 ± 0.06	1.26 ± 0.09	0.82 ± 0.08	1.01 ± 0.08	0.71 ± 0.08	1.03 ± 0.09
Part 10	0.68 ± 0.09	0.98 ± 0.11	0.73 ± 0.04	1.06 ± 0.07	0.79 ± 0.04	1.04 ± 0.07	0.78 ± 0.06	0.9 ± 0.06
Part 11	0.69 ± 0.06	0.88 ± 0.08	0.7 ± 0.05	0.95 ± 0.05	0.74 ± 0.06	1.01 ± 0.06	0.66 ± 0.08	1.01 ± 0.07
Part 12	0.61 ± 0.09	1.08 ± 0.06	0.78 ± 0.03	1.12 ± 0.12	0.72 ± 0.07	0.93 ± 0.04	0.73 ± 0.05	1.01 ± 0.05
Part 13	0.62 ± 0.07	1.05 ± 0.05	0.69 ± 0.06	0.95 ± 0.11	0.78 ± 0.05	0.97 ± 0.08	0.74 ± 0.09	0.91 ± 0.03
Part 14	0.67 ± 0.1	1.12 ± 0.04	0.73 ± 0.08	0.86 ± 0.09	0.68 ± 0.04	1.16 ± 0.07	0.71 ± 0.04	1.02 ± 0.11
Part 15	0.68 ± 0.06	0.99 ± 0.07	0.67 ± 0.06	1.02 ± 0.08	0.88 ± 0.05	0.88 ± 0.05	0.82 ± 0.05	1.17 ± 0.06
Part 16	0.58 ± 0.04	1.08 ± 0.03	0.61 ± 0.07	0.99 ± 0.03	0.8 ± 0.06	0.98 ± 0.09	0.72 ± 0.06	1.07 ± 0.02
Part 17	0.74 ± 0.08	0.90 ± 0.13	0.84 ± 0.08	1.30 ± 0.05	0.81 ± 0.07	1.04 ± 0.07	0.88 ± 0.09	1.0 ± 0.07

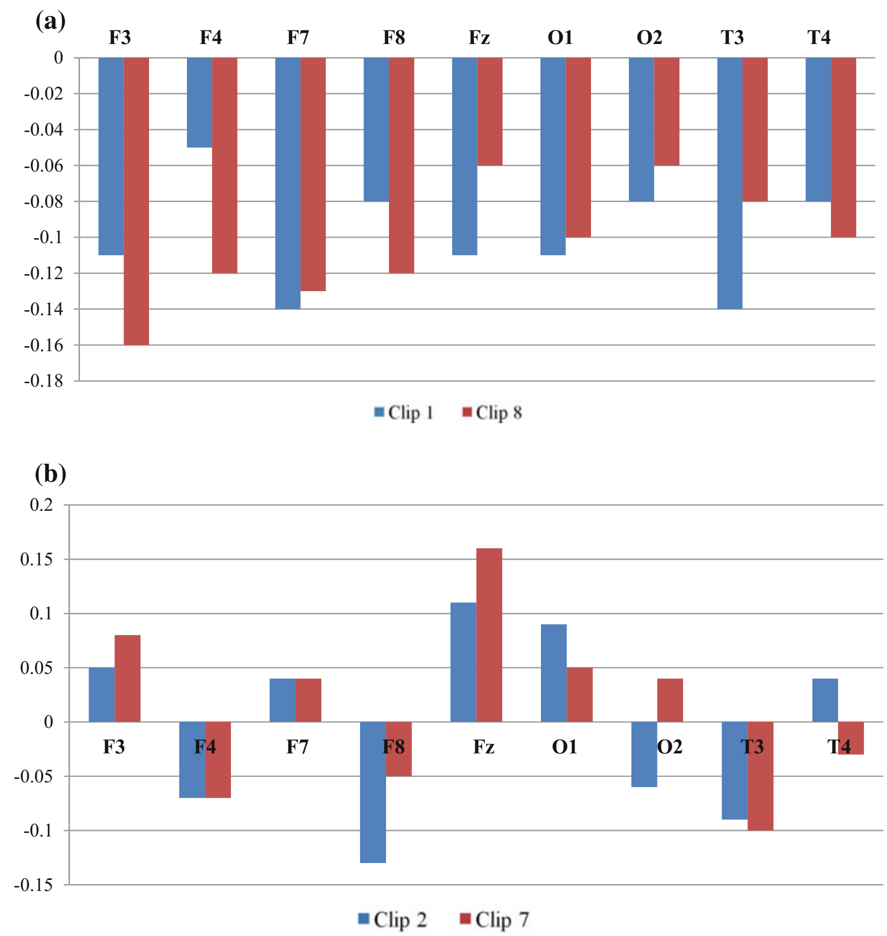
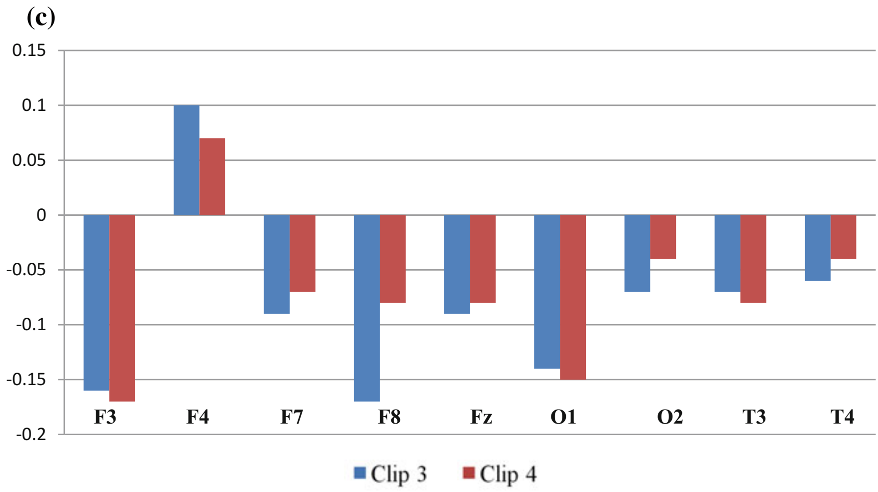


Fig. 6.8 **a** Change in alpha multifractal width for the two high joy clips, **b** Change in alpha multifractal width for the two high sorrow clips, **c** Change in alpha multifractal width for the two high anxiety clips, **d** Change in alpha multifractal width for the two high serenity clips

of the frontal, temporal and occipital lobes. The maximum dip, however are seen in the odd electrodes, i.e. F3, F7, O1 and T3 respectively, though the even electrodes have significant fall in spectral width as is evident from the figures. The simultaneous involvement of the different lobes of brain in the processing of joyful musical clips points in a direction opposite to the conventional valence lateralization theory, which says that only the left frontal lobe is involved in processing of joyful emotions. Here, we see that though the percentage of fall in complexity is higher in the left electrodes (of all the lobes), the complexity changes significantly for the even electrodes as well.



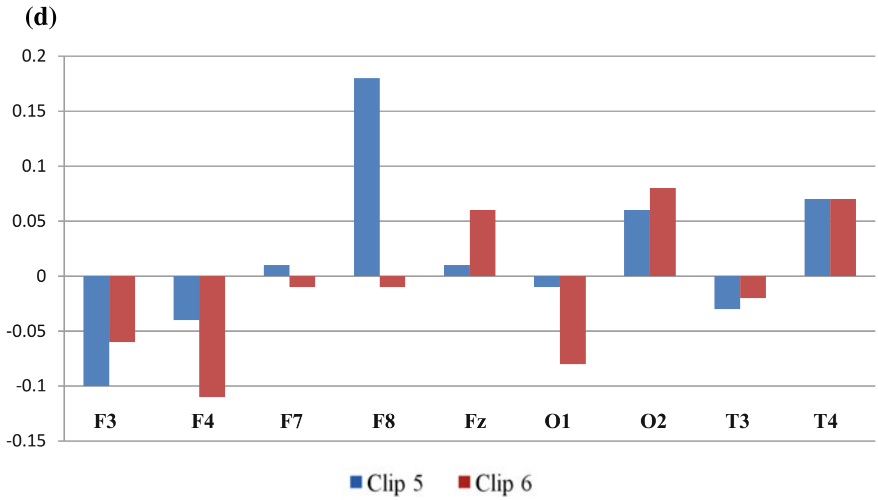


Fig. 6.8 (continued)

2. In case of Clips 2 and 7 rated as ∼80% sorrow, we see differential processing of the sad emotion in respect to left and right frontal electrodes. The left frontal electrodes F3 and F7, as well as the left occipital electrode O1 show an increase in complexity of alpha rhythms while, the right frontal electrodes F4 and F8 register a dip in complexity. The temporal electrodes show opposite phenomenon compared to the frontal one, with T3 showing a dip in complexity while in T4 complexity increases a little.

3. In case of valence anxiety, we again find unanimous response across all the scalp electrodes which show a dip in complexity, except for F4 where a rise in complexity is seen for both Clips 3 and 4. The arousal effects corresponding to alpha rhythms are more significant again for the frontal electrodes F3, F8 and an occipital electrode O1, while F4 demonstrates a considerable increase in alpha multifractality. We thus hypothesize that both anxiety (alias fear) and joy (alias happy) can be regarded as intense emotions which cause an arousal in almost all the lobes of the brain, manifested in a sharp dip in the multifractality of alpha rhythms generated from the respective lobes.
4. The emotion “serene” failed to generate any significant response from other electrodes except the frontal F3 and F4, which have registered a dip in the complexity. This can be attributed to the intensity of the valence “serene”. We have seen that emotions with high intensity have generated an uniform response in alpha rhythms across the electrodes, while the emotions with low intensity have generated lateralized or negligible response in the electrodes.
5. Another interesting observation is that, whatever be the valence of the musical clips, the frontal electrodes F3 and F4 have always shown significant increase or decrease of alpha multifractality. This corroborates the findings of previous works where the frontal lobe was attributed to be the main contributor for processing of musical emotions. Though, in these work we have seen electrodes from other regions getting aroused while processing of musical emotions.
6. The figures also provide a new knowledge regarding the age old debate of universality of music (Fritz et al. 2009). Here Clips 1 and 8 consists of instrumental clips of different cultures namely Western and Indian classical respectively, but the response obtained across the wide variety of subjects in listening test as well as in the EEG alpha rhythm analysis is strikingly uniform. In the same way Clips 3 and 4 are cross cultural clips which have shown to convey anxiety (or fear) valence in the listeners significantly. Also the response in the EEG alpha rhythm multifractality is consistent in all the electrodes. The clips 5 and 6 though cross-cultural and induce consistent amount of same valence (i.e. calm or serenity) in the listeners, report ambiguous response in the listening test. The arousal caused is more significant in Clip 6 (Indian Classical) as compared to Clip 5 (Western).

One way ANOVA (Miller 2004) tests were conducted separately for the clips belonging to the same valence. While the clips with valence joy and anxiety yielded 95% confidence in results, clips belonging to the valence sorrow and serene yielded 90 and 80% confidence in results respectively.

The following figures show the response of the same clips in theta domain. The difference in multifractal spectral width (in percentage) in response to each of the Clips is computed from Table 6.3 and plotted in Fig. 6.9a–d.

In case of theta domain, the responses of EEG data to the different cross cultural instrumental clips shows to have a certain level of inconsistency as compared to the values obtained in the alpha domain. Nevertheless, we have the following

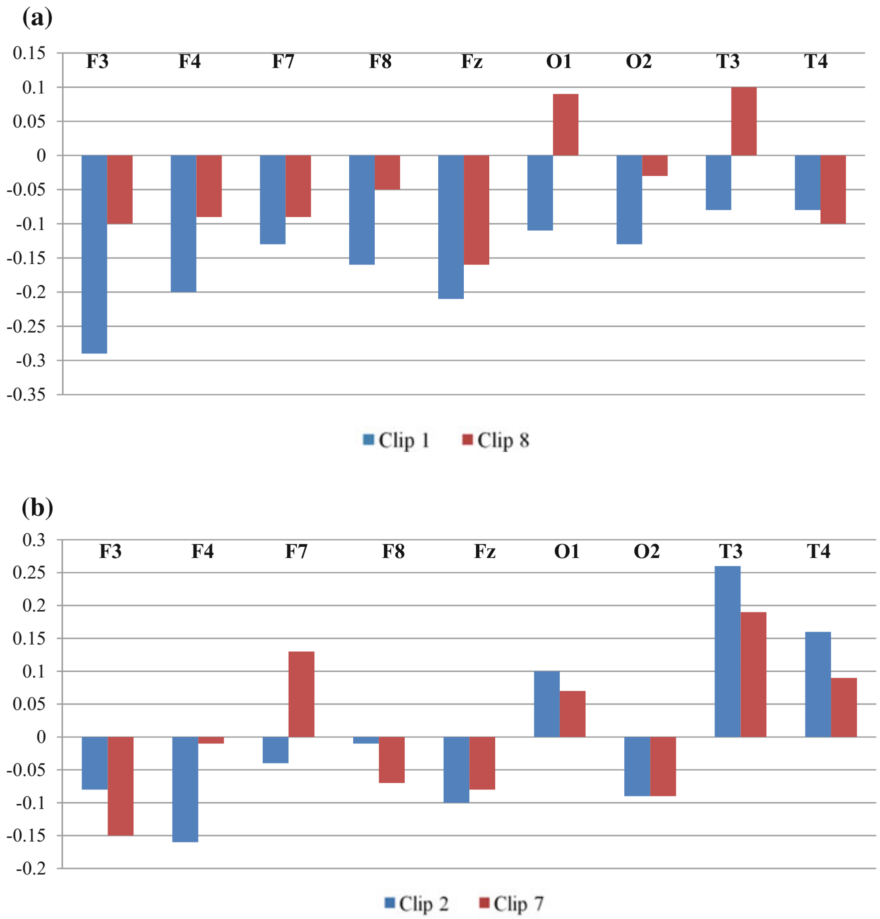


Fig. 6.9 **a** Change in theta multifractal width for the two high joy clips, **b** Change in theta multifractal width for the two high sorrow clips, **c** Change in theta multifractal width for the two high anxiety clips, **d** Change in theta multifractal width for the two high serenity clips

observations from the graphs of multifractal width obtained from analysis of theta frequency:

1. The two cross-cultural instrumental clip 1 and 8, having high joy content again show uniform dip in theta multifractal width throughout all the electrodes in general. All the frontal electrodes show significant dip in theta complexity along with the frontal midline electrode Fz, which has been earlier reported to play a significant role in theta domain to be a marker for pleasantness of a musical clip. An interesting point to be noted here is that Clip 8 i.e. the Hindustani instrument consistently has a lesser dip in spectral with compared to the 1st clip, the Western accordion. In electrodes O1 and T3, even an increase in theta

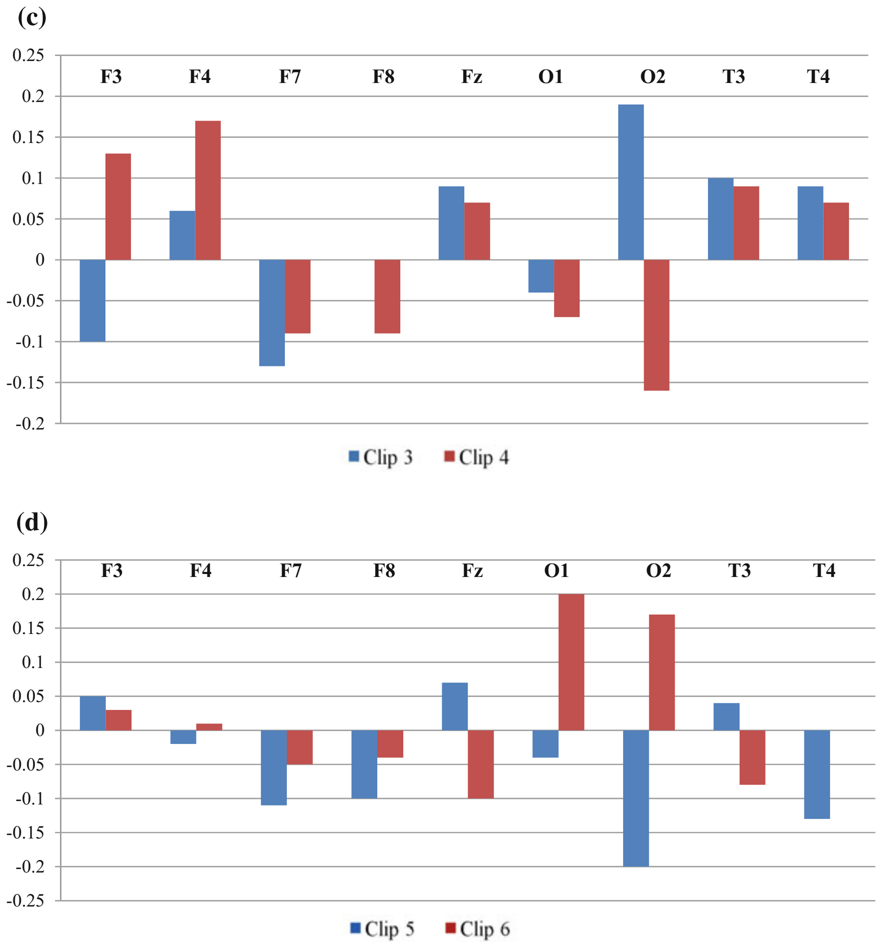


Fig. 6.9 (continued)

multifractality is manifested in Clip 8, which hints in the direction of differential cognitive engagement to some extent in the theta domain when it comes to processing of different types of music.

2. In case of the two sad clips, most of the electrodes remain inert to some extent except for the two temporal electrodes T3 and T4, where sufficient increase in theta multifractality is noted. The two occipital electrodes, O1 and O2, also shows differential processing of the sorrow clips, the multifractality in the odd electrode increase, while it decreases in the even ones. Clips 2 and 7, though instruments of Indian classical show different arousal in different positions of brain as is evident from the figures, thus in F3 we have sharp dip for Clip 7, while for Clip 2 we have sharp dip in F4 electrode. This can be attributed to the

differential arousal caused by the two same valence clips. Thus, in the theta domain we have identified the regions in which the valence, sorrow is processed from the arousal caused in the particular lobes manifested in the changes of theta complexity.

3. The two high anxiety cross-cultural clips show distinct ambiguity in the arousal activities corresponding to different electrodes. In the two temporal electrodes, consistent increase in theta multifractality is noted along with two frontal electrodes, F4 and Fz. Electrodes F3 and O1 show differential processing of the two cross-cultural high anxiety clips. While in F3, Clip 3 causes a dip in multifractality, in O1 we have significant increase for Clip 3, the reverse effect is seen for Clip 4 (Indian classical instrument). This may be the cause of different intensities of the valence anxiety induced by the Western classical instrument *Organ* and the Indian classical instrument, *Tabla.*
4. The two cross cultural clips conveying the valence calmness or serenity has given inconsistent results even in the theta domain, as in the alpha domain. In the valence, calm, the temporal lobes remain almost unaffected showing little or no change in most cases.The theta multifractality decreases for frontal electrodes F7 and F8, while differential arousal based activities are seen in O1 and O2. In both these occipital electrode, theta multifractality increases for Clip 5 (Western instrument, *piano*) while it increases considerably for Clip 6 (Indian classical instrument, *sitar*). The reverse effect is seen for the frontal midline electrode Fz. Again, this observation hints in the direction of different cognitive engagement for the musical clips of two different genres.

One way ANOVA (Miller 2004) gave 90% confidence in results for the happy clips. 80% for the sorrow and anxiety clips respectively, 70% for the serenity clips.

Thus, we have compared the clips belonging to the same valence but having different arousal intensity in the theta domain. The musical clips which have the same arousal and different valence can also be identified by their specific response in the different electrodes as briefed above. With these observations, we look forward to device an algorithm which can be applied as an automated one for the identification of musical emotions using latest state of the art non-linear techniques.

6.4 Conclusion

Music has been in the human civilization for eons. It has often been referred to as the universal language which is, and has been present in all human civilization known. A group of researchers even claim that music came much before speech. The effect of music on brain has been well documented in the past; one of them even goes to the extent to claim that individuals with Alzheimer's disease often recognize songs to the end of life. Recognizing and categorizing musical emotion thus remains a challenging problem primarily due to the inherent ambiguities of human emotions. The perception of emotion is particularly important in the musical domain because music appears to be primarily dedicated to evoking emotions. According to Yehudi Menuhin (http://www.menuhin.org/), a well known violinist "*Music creates order out of chaos: for rhythm imposes unanimity upon the divergent, melody imposes continuity upon the disjointed, and harmony imposes compatibility upon the incongruous*."

In this study, we envisaged to do the task of categorization and differentiation of four basic musical emotions with the help of robust non-linear MFDFA analysis and develop a parameter with which we can quantify and differentiate arousal and valence effects of cross cultural musical clips. The main findings of this work can be pointed as under:

1. The multifractal analysis of alpha frequency data points strongly in the direction of universality of music predominantly in the processing of two strong emotions (joy and anxiety) uniformly throughout the brain areas. The strong involvement of all the scalp electrodes in the processing of these two emotions is substantiated by the decrease in alpha complexity uniformly for the two instrumental clips of different origin. The decrease in alpha multifractal width can thus be a strong indicator of the valence of emotions and the amount of change can give a measure of arousal corresponding to that clip.
2. The other two emotions i.e. sorrow and calm give an indication of the lateralization processing of valence, leading to differential increase or decrease of alpha multifractality in odd-even (left/right) electrodes. Thus, we have an idea about electrode specificity also, regarding which emotion is processed by which electrodes, or whether all the electrodes take part simultaneously in the processing of valence.
3. In case of multifractal analysis on theta frequency, we have distinguishable response for Indian and Western instrumental clips of the same valence. Though the musical Clips for joy uniformly caused a decrease in multifractality across all the electrodes, but the arousal (measured from the amount of change of multifractality of theta) is significantly different for the two cross-cultural clips. This may be caused due to familiarity or other effects as the participants of the EEG test are all of Indian origin. Other clips gave electrode (alias lobe) specific arousal corresponding to a specific valence in the theta domain.

This work presents new and interesting data shedding light on universality of human brain functions as well as domain specificity of arousal valence in musical emotion. We have developed the multifractal spectral width (of alpha or theta EEG waves) as a parameter through which we can explore the arousal and valence based effects of different musical clips. The application of this work in the direction of cognitive music therapy on psychological patients utilizing a diverse variety of instrumental clips is immense. Investigating with more number and variety of clips and greater respondents in EEG study would lead to more robust and definite results. Finally, we can conclude that this work provides, for the first time, new data which may link the concept of arousal-valence based emotion with domain specific activity of the brain and shows a window to the comprehension of interactive brain function with the help of cross-cultural music. The next chapter deals with Gestalt phenomenon in musical signals, which frequencies we actually hear when we are listening to a song. MFDFA technique is used to assess the change in neural complexity when certain frequencies are clipped off from a song.

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Chapter 7
Gestalt Phenomenon in Music: Which Frequencies Do We Really Hear?

> *"...a piece of music which is initially too complex for an individual to like, may, with repeated playings, move down to a lower complexity level at which liking may begin to emerge".*
> —Paul Davies

7.1 Introduction

How does human being perceive and recognize a musical sound? Is there any specific frequency region of music which makes a particular song identifiable? If so, what is the corresponding brain response to that particular frequency band? In the domain of auditory signal processing, what is the manifestation of this change in perception of the particular song? These are a few questions which we try to venture with the help of this study.

7.1.1 What Is Gestalt Psychology?

Gestalt is a psychology term which means "unified whole". It refers to theories of visual perception developed by German psychologists in the 1920s. These theories attempt to describe how people tend to organize visual elements into groups or *unified wholes* when certain principles are applied (Koffka 2013). The various principles which make use of gestalt psychology are similarity, continuation, closure and proximity. A number of experiments in the visual domain try to explore the paradigm of gestalt psychology using ambiguous figures as visual stimuli. Ambiguous figures provide a fascinating exception from our normally stable visual world: On prolonged inspection, the "Necker cube" undergoes a sudden, unavoidable reversal of its perceived front-back orientation (Kornmeier and Bach 2004). This particular study tries to look into an Event Related Potential (ERP) correlate of endogenous reversal from ambiguity to disambiguity of a Necker 2D lattice: a negativity starting at about 160 ms with a first major deflection at

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250 ms after presentation of the ambiguous stimulus, and restricted to occipital and parietal locations. Such multistability in perception can arise from a variety of stimulus types, involving alterations in a pattern's perceived depth, direction of motion, or visibility (Necker 1832; Ramachandran and Anstis 1985; Rubin 1958; Dutour 1760), and have been used extensively in the visual sciences as a tool for investigating mechanisms of perceptual organization in a number of studies (Mori et al. 1982; Attneave 1971; Dune 1988).

7.1.2 Applications of Gestalt in Visual Domain

There is a group of research work which deals with the creative manifestations of gestalt therapy (Dune 1988; Brown 1969, 1970); which begin with the application of the principles of Gestalt theory, such as figure/ground, the principles of good Gestalt, Prägnanz and closure, as well as viewing perception as an active process. The reorganization of familiar, chronically poorly configured elements into something new and valuable and therefore beautiful reflects the embeddedness of Gestalt therapy in field theory.

According to a research at Cambridge University (Rayner et al. 2006), it doesn't matter in what order the letters in a word are, the only important thing is that the first and last letter be at the right place. The rest can be a total mess and you can still read it without problem. This is because the human mind does not read every letter by itself but the word as a whole. The whole idea of gestalt phenomenon in music originated from this experiment which is carried out mainly in the visual domain; we thought of reproducing the same type of experiment in the auditory domain which led us to developing the protocol of this particular experiment.

7.1.3 Gestalt in Auditory Domain

Although the main focus of gestalt theory has been on the visual domain, a number of works have been done in the auditory domain as well (Deliege 1987; Frankland and Cohen 2004; Todd and Werner 1999; Narmour 1989; Lerdahl and Jackendoff 1983), using the various principles of gestalt theory viz. proximity, similarity closure etc. If seen loosely, visual and auditory perceptions are poles apart from one another; one is spatial perception, the other temporal. However it is easy to see how each contains elements of the other—visual perception also changes over time, just like musical/auditory perception; when we look at moving or changing forms, even when we see a static image our eyes move across it in meaningful patterns. Further, our two ears allow us to detect distance and direction, and our musical sensibilities perceive movement in a space defined by such dimensions as timbre, pitch, duration, distortion, resonance and so on. Gjerdingen (1999) applies the Grossberg-Rudd neural model of apparent movement in vision to music and reveals definite similarities between visual and aural perception such as luminance/amplitude and colour/timbre. But yet the overall experience of seeing and hearing seem to be such different experiences. Gjerdingen (1999) offers a beautiful explanation for this, that while high-level cognition of vision and sound may be analogously weak, their low-level neural processes show striking similarities. That is, even though sound and light are very different mediums, the brain may process them in very similar ways. Western musical theory explores Gestalt principles in mainly two areas—grouping and expectation (Lerdahl and Jackendoff 1983); while groups vary from simple drum beats, a note to a complete musical piece; expectation is the influence of our previous perception on a recent event. No study, till date explores the scaling properties of music signals which have been doctored keeping in mind the principles of gestalt theory, as well as the brain response to that particular music signals.

7.1.4 Creativity and Gestalt Theory

Creativity in Gestalt theory means venturing beyond self-expression and entering the dynamics of the productive interchange within the therapeutic relationship, and thus creation of a space which is not ventured earlier. A formal definition for creative thinking, as ascertained by Guilford (1957) is "conceptual redefinition" or "the ability to redefine or reorganize objects of thought". The Gestalt Transformations test has shown very strong loadings on this factor (Kettner et al. 1959). The gestalt therapy system is truly integrative and includes affective, sensory, cognitive, interpersonal, and behavioral components where therapists and patients are encouraged to be creative in doing the awareness work. But all these works look into gestalt therapy mainly from the view of art and craft and not any scientific phenomenon. In this work, we envisaged to study gestalt-like phenomenon in a new light of sound scientific principles and the inherent brain dynamics associated with it.

7.1.5 Response of Brain to Certain Frequency Bands of Music Using Non-linear Techniques

Each type of music has its own frequency, which can either resonate or be in conflict with the body's rhythms (heart rate). Studying EEG dynamics typically relies on the calculation of temporal and/or spectral dynamics from signals recorded directly from the scalp. Each frequency band of the EEG rhythm relates to specific functions of the brain. EEG rhythms are classified into five basic types: (i) delta (δ) 0.5–4 Hz, (ii) Theta (θ) 4–8 Hz, (iii) alpha (α) 8–13 Hz, (iv) beta (β) 13–30 Hz and (v) gamma (γ) 30–50 Hz. It has been observed that pleasant music produces a decrease in the alpha power at the left frontal lobe and unpleasant music produces decrease in the alpha power at the right frontal lobe (Tsang et al. 2001; Schimdt and Trainor 2001; Sammler et al. 2007). Also, activity in the alpha frequency band has been found to be negatively related to the activity of the cortex, such that larger alpha frequency values are related to lower activity in the cortical areas of the brain, while lower alpha frequencies are associated with higher activity in the cortical areas (Davidson 1988; Mizuki et al. 1992). Davidson (1988) have shown that disgust cause less alpha power in the right frontal region than happiness while, happiness cause less alpha power in the left frontal region. The Frontal midline (Fm) theta power was positively correlated not only with scores of internalized attention but also with subjective scores of the pleasantness of the emotional experience. Furthermore, two studies on the relationship between Fm theta and anxiety reported negative correlations between Fm theta during mental tasks and anxiety measures (Mizuki et al. 1992; Suetsugi 2000). It has also been shown that pleasant music would elicit an increase of Fm theta power (Sakharov et al. 2005). Recent researches have demonstrated that the modulation of gamma band activity (GBA) in time windows between 200 and 400 ms following the onset of a stimulus is associated with perception of coherent visual objects (Muller et al. 1999), and may be a signature of active memory. While listening to music, degrees of the gamma band synchrony over distributed cortical areas were found to be significantly higher in musicians than non musicians (Bhattacharya et al.2001; Bhattacharya and Petsche 2001a).The gamma band EEG distributed over different areas of brain while listening to music can be represented by a universal scaling which is reduced during resting condition as well as when listening to texts (Bhattacharya and Petsche 2001b).

The scalp EEG arises from the interactions of a large number of neurons whose interactions generally nonlinear (Linkenkaer-Hansen et al. 2001) and thus they can generate fluctuations that are not best described by linear decomposition (Hwa and Ferree 2002). On the other hand, the classical nonlinear dynamics method such as correlation dimension and Lyapunov exponents are very sensitive to noise and require the stationary condition, while EEG signals often are highly non-stationary (Lee et al. 2002). Chaos analysis based on the assumption of low-dimensional attractors has also been applied to qualify the nonlinear behavior of the EEG, but in fact, the underlying neural populations are unlikely to obey entirely low-dimensional dynamics (Hwa and Ferree 2002).

In recent past, the Detrended Fluctuation Analysis (DFA) (Peng et al. 1994) has become a very useful technique to determine the fractal scaling properties and long-range correlations in noisy, non-stationary time-series (Hardstone et al. 2012). DFA is a scaling analysis method used to quantify long-range power-law correlations in signals—with the help of a scaling exponent, α, to represent the correlation properties of a signal. In the realm of complex cognition, scaling analysis technique was used to confirm the presence of universality and scale invariance in spontaneous EEG signals (Bhattacharya 2009). In case of music induced emotions, DFA was applied to analyze the scaling pattern of EEG signals in emotional music and particularly Indian music (Banerjee et al. 2016). But DFA has its own limitations. Many geophysical signals as well as biosignals do not exhibit monofractal scaling behavior, which can be accounted for by a single scaling exponent (Hu et al. 2001; Kantelhardt et al. 2001), therefore different scaling exponents are required for different parts of the series (Chen et al. 2002). Consequently a multifractal analysis should be applied.

The Multifractal Detrended Fluctuation Analysis (MFDFA) technique was first conceived by (Kantelhardt et al. 2002) as a generalization of the standard DFA. MFDFA has been applied successfully to study multifractal scaling behavior of various non-stationary time series (Kantelhardt et al. 2003; Sadegh et al. 2006; Telesca et al. 2004) as well as in detection or prognosis of diseases (Dutta et al. 2013). The multifractals are fundamentally more complex and inhomogeneous than monofractals (Stanley et al. 1999) and describe time series featured by very irregular dynamics, with sudden and intense bursts of high-frequency fluctuations (Davis et al. 1994). EEG signals are essentially multifractals as they consist of segments with large variations as well as segments with very small variations, hence when applied to the alpha and theta EEG rhythms, the multifractal spectral width will be an indicator of emotional arousal corresponding to particular clip. In case of music induced emotions, a recent study (Maity et al. 2015) used the multifractal spectral width as an indicator to assess emotional arousal corresponding to the simplest musical stimuli—a tanpura drone.

7.1.6 *Doctoring of Clips from Tagore Songs*

We chose to study brain response to different frequency bands of 4 musical clips—i.e. 4 pre-recorded Tagore songs, sung by a renowned artist without any accompaniment. Music in general is polytonic, i.e. a number of pure tones mixed together in such a way that it sounds harmonius; musical sound produced by human voice in this way is also periodic albeit highly complex in nature. The different frequency bands were also analyzed with the same techniques as used for the analysis of EEG signals. To avoid any variation arising due to the change of timbral parameters, recordings from the same singer were taken for our experiment. From the complete recording, approximately 20 s clips were clipped and segregated into five frequency bands viz. Band 1 (50–1 kHz), Band 2 (1–2 kHz), Band 3 (2–3 kHz), Band 4 (3–4 kHz) and Band 5 (4 kHz and above) using Fast Fourier Transform (FFT) techniques.

7.1.7 *Overview of Our Work*

This work is first of its kind which looks to find brain response corresponding to various frequency bands of music. The response corresponding to each frequency band may shed new light about how human brain perceives and recognizes a known musical clip. For this, 4 different clips of Tagore songs were doctored into 5 different frequency bands as explained in the previous section. Next a human response data was collected from about 100 participants, where the respondents were asked to mark the band in which they could not identify the song. The clips were played in a jumbled manner with the original clip being always played initially, so that the respondents are aware of what song they are listening to. From the resulting human response data, it was seen that maximum non-recognition is being seen in the 4th and 5th band, while in spite of the removal of fundamental frequency and two/three higher harmonics, the respondents can clearly recognize the song in the 2nd and 3rd band. From this observation it is clear that human mind can recognize musical timbre till around 3 kHz even without the presence of fundamental frequency, while a switch occurs above that, which leads to its non-recognition. With this cue, we sought to understand the EEG brain response of this switch, where the human mind is unable to process the frequency bands. For this, a pool of 20 subjects was randomly chosen from the pool of 100 respondents who participated in the human response study and EEG experiment was performed on them using the same protocol in which psychological response was taken. Next, 10 electrodes were chosen (F3, F4, F7, F8, T3, T4, T5, T6, O1 and O2) from different locations of the brain whose modalities match with our work, and time series data were extracted from each one of them. The time series data obtained from each of the 10 electrodes were separated into alpha, theta and gamma frequency rhythms for each of the experimental condition and analyzed with the help of MFDFA technique. The multifractal spectral width obtained for each of the experimental condition acts as a parameter with which we can identify the arousal based activities in different lobes of brain. From the results obtained we see there is a definite switch in the alpha, theta and gamma complexities in different lobes in response to 4th and 5th band (where there is non-recognition), with the response most significant in the temporal lobe and gamma band. With this work, we try to venture into a hitherto unexplored domain of human brain response to different frequency bands of music, which may be a cue to study the gestalt principles in the auditory domain. Also, the application of robust state of art non-linear methods to assess EEG data makes the study a crucial one in the field of auditory cognitive neuroscience. The results and implications are discussed in detail in the following sections.

7.2 Experimental Details

7.2.1 Collection and Analysis of Human Response Data

Participants for psychological data were recruited mostly through word of mouth and social media platforms. All the listening test data were collected at the Sir C.V.

Raman Centre for Physics and Music, Jadavpur University over a period of 2 months. In this study, response from 100 participants ($F = 46$, $M = 54$) were considered for analysis presented herewith, who participated voluntarily. The subjects chosen had no formal musical training.

For the listening test, a template like the one given in Fig. 7.1 were made for each of the sample and presented to the respondents. The template consists of the clips in the following order:

Original Clip => Band 3 (2–3 kHz) (Part 1) => Band 2 (1–2 kHz) (Part 2) => Band 5 (4–5 kHz) (Part 3) => Band 4 (3–4 kHz) (Part 4) => Band 1 (50–1 kHz) (Part 5).

A resting time of about 5 s were given between each successive clip. All the clips were normalized to keep the amplitude constant.

Approximately 20 s clips from four popular Tagore songs sung by a renowned singer (without any accompaniment) were taken for our analysis, with the original clip being played first, followed by the jumbled order of clips. An Instruction Sheet along with a response form like the one given below (Fig. 7.2) was given to the respondents where they were asked to mark the parts where they could not recognize the song.

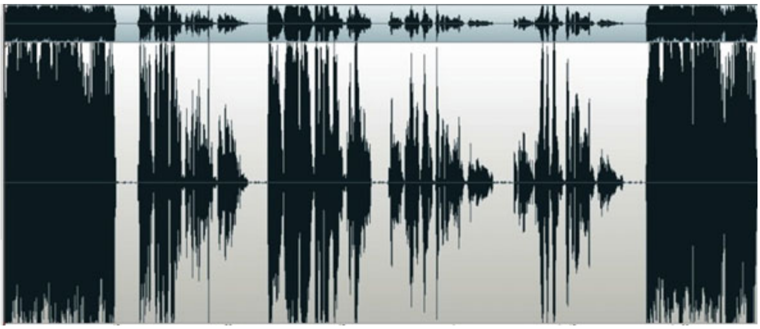


Fig. 7.1 The template of music clip containing different frequency bands played randomly

	Part 1	Part 2	Part 3	Part 4	Part 5
Clip 1					
Clip 2					
Clip 3					
Clip 4					

Fig. 7.2 Response sheet to identify the non-recognition of each song

7.2.2 Subjects Summary

20 (M = 13, F = 7) musically untrained adults chosen randomly from the pool created from listening test data who voluntarily participated in this study. The average age was 23 years (SD = 2.35 years) and average body weight was 60 kg. Informed consent was obtained from each subject according to the guidelines of the Ethical Committee of Jadavpur University. All experiments were performed at the Sir C.V. Raman Centre for Physics and Music, Jadavpur University, Kolkata. The experiment was conducted in the afternoon with a normal diet in a normally conditioned room sitting on a comfortable chair and performed as per the guidelines of the Institutional Ethics Committee of SSN College for Human volunteer research.

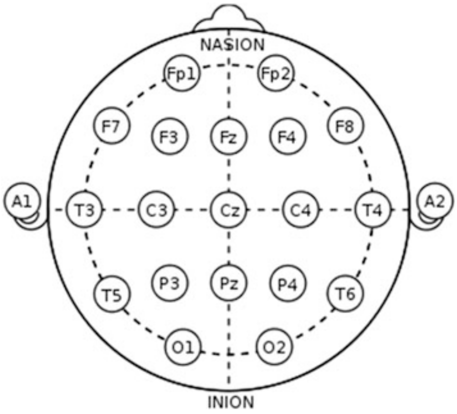
7.2.3 Experimental Protocol

During the EEG acquisition period, the 20 subjects were made to listen to the same clips in the same order as in the listening test. Each experimental condition lasted for around 12 min. Each song clip of 20 s was followed by a resting period of 5 s during which no music was played. Subjects were asked to keep their eyes closed and to sit calmly during each condition. First, the baseline (i.e. a resting condition) was recorded for each subject before the start of the experiment with 1 min of 'no music' condition.

The music was presented with the computer-sound system (Logitech R _ Z-4 speakers) with very high S/N ratio was used in the measurement room for giving music input to the subjects ca. 120 cm behind the head of the subjects with a volume of 45–60 dB. The EEG experiment was conducted in the afternoon (around 2 PM) in a room with the volunteers sitting in a comfortable chair.

Since the objective of this study was to analyze the effect of different frequency bands of music on brain activity during normal relaxing conditions, the frontal, temporal and occipital lobes were selected for the study. EEG was done to record the brain-electrical response of 20 subjects. Each subject was prepared with an EEG recording cap with 19 electrodes (Ag/AgCl sintered ring electrodes) placed in the international 10/20 system. Figure 7.3 depicts the positions of the electrodes. Impedances were checked below 50 kΩ. The EEG recording system (Recorders and Medicare Systems) was operated at 256 samples/s recording on customized software of RMS. The data was band-pass-filtered between 0.5 and 35 Hz to remove DC drifts and suppress the 50 Hz power line interference. The ear electrodes A1 and A2 linked together have been used as the reference electrodes. The forehead electrode, FPz has been used as the ground electrode. Each subject was seated comfortably in a relaxed condition in a chair in a shielded measurement cabin. They were also asked to close their eyes. After initialization, a 10 min recording period was started, and the following protocol was followed:

Fig. 7.3 The position of electrodes according to the 10–20 international system



1. 60 s No Music (Resting Condition)
2. 20 s Clip 1 (Original)
3. 5 s No Music
4. 20 s Clip 1 Band 3 (Part 1)
5. 5 s No Music
6. 20 s Clip 1 Band 2 (Part 2)
7. 5 s No Music
8. 20 s Clip 1 Band 5 (Part 3)
9. 5 s No Music
10. 20 s Clip 1 Band 4 (Part 4)
11. 5 s No Music
12. 20 s Clip 1 Band 1 (Part 1)
13. 30 s Resting period

The same protocol was repeated for Clips 2, 3 and 4 with a 30 s resting period in between each clip. Markers were set at start, signal onset/offset, and at the end of the recording.

7.3 Methodology

We have obtained noise free EEG data for all the electrodes using the EMD technique as in Maity et al. (2015) and used this data for further analysis and classification of acoustic stimuli induced EEG features. The amplitude envelope of the alpha (8–13 Hz), theta (4–7 Hz) and gamma (14–30 Hz) frequency range was obtained using wavelet transform technique. Data was extracted for these electrodes according to the time period given in the Experimental protocol section i.e. for Experimental conditions 1–13.

The Wavelet Transform technique (Akin et al. 2001) was used to extract the alpha, theta and gamma band EEG signals as elaborated in the methodology chapter. On the obtained time series data, MFDFA analysis was performed.

The alpha, theta and gamma band EEG signals were subjected to multifractal analysisis using MATLAB (Ihlen 2012) and for each step, an equivalent mathematical representation is given following Kantelhardt et al. (2002). The width of the obtained spectrum gives a measure of the multifractality of the spectrum. Greater is the value of the width W greater will be the multifractality of the spectrum. For a monofractal time series, the width will be zero as h(q) is independent of q.

7.4 Results and Discussions

From the results of listening test data, a percentage response chart like the one given in Table 7.1 is plotted:

It is seen for most of the clips, there is a definite switch in human perception above Band 3 i.e. above 3 kHz frequency; the human ear is not able to recognize the song from somewhere above this frequency range; which follows that in Band 5 (which contains frequencies from 4 kHz and above) almost all the participants were unable to recognize the song. In the following sections we will try to discuss the brain correlates associated with this switch in perception. From the human response study, we get an important cue that up to 3 kHz frequency human brain follows the principle of closure and is able to perceive the entire song even when the fundamental along with a few more harmonics have been cut off. But above that, mostly there is non-recognition for that particular song except for certain percentage of listeners who are able to perceive the song even above that from the melodic cues attached to a specific song.

The amount of multifractality and hence the complexity can be determined quantitatively in each of the electrode from the width of the multifractal spectrum [**f(α) vs α**]. The values of multifractal widths have been averaged for the 20 persons and the variation of complexities from the resting (no music condition) have been computed for all the experimental conditions. In the following figures the variation in alpha, theta and gamma complexities in response to the various frequency bands of 4 music clips have been shown graphically for each of the 10 electrodes we chose to study Fig. 7.4(a–d):

Table 7.1 Amount of Non-Recognition of Song from a listening test of 100 informants (in percentage)

	Band 1	Band 2	Band 3	Band 4	Band 5
Clip 1	0	0	20	78	100
Clip 2	0	0	13	89	95
Clip 3	0	0	15	86	100
Clip 4	0	0	16	89	97

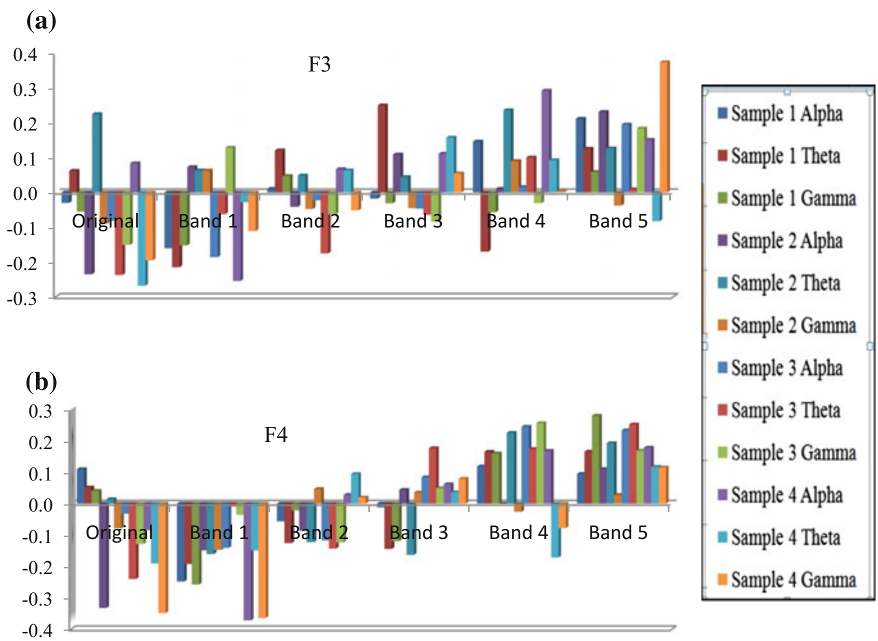


Fig. 7.4 **a** Variation of multifractal width of F3 electrode for alpha, theta gamma **b** Variation of multifractal width of F4 electrode for alpha, theta and gamma **c** Variation of multifractal width for frontal F7 electrode for alpha, theta gamma frequency ranges **d** Variation of multifractal width for frontal F8 electrode for alpha, theta and gamma frequency ranges

A general glance into the figures help us to identify that there is a characteristic switch from Band 3 to Band 4, in the complexities corresponding to each of the frequency band in all the frontal electrodes. While for all the frequency bands up to 3, there is a general decrease in alpha, theta and gamma complexities, a sudden spike in the complexities is seen corresponding to Band 4 and Band 5, which are the regions of non-recognition as is verified from the psychological test data. The sudden increase in complexity is very prominent in the alpha and gamma frequency range of right frontal electrodes F4 and F8. The theta frequency range gives somewhat ambiguous results wherein any specific pattern is not observed for the various frequency bands of music given as input. For some songs, specifically 3 and 4, however we find that the alpha and theta complexities taking ajump from Band 3 only; which may be a cue that the respondents had some confusion in perceiving the song from this frequency band also. The variation in multifractal widths for the four temporal electrodes is given in Fig. 7.5(a–d):

For the temporal electrodes, the switch from recognition to non-recognition shows the same signature as in the case of frontal electrodes, but since the temporal lobes are generally associated with auditory processing, the manifestation of change is also very strong here. In this case, however we find the response is strongest in the T5 and T6 electrodes, whereby a definite rise in alpha and gamma complexity is

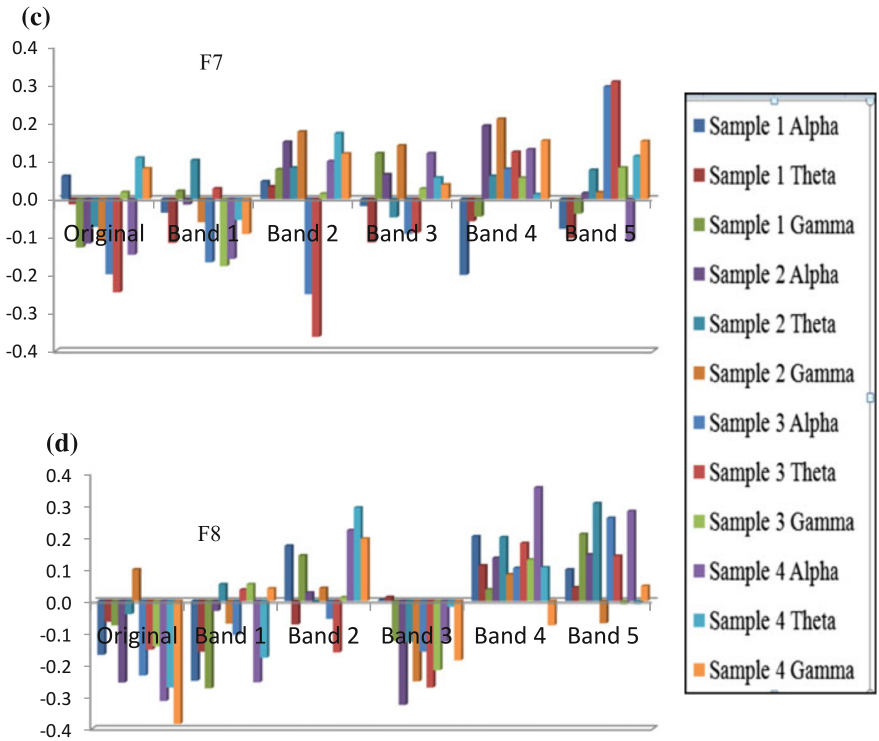


Fig. 7.4 (continued)

seen in Band 4 and Band 5 as compared to their fall in other frequency bands of music. An interesting observation here is that for Sample 4, the alpha complexity decreases for all the temporal electrodes which may be a symbol of recognition of this particular music clip, although theta and gamma complexity registers an increase. For Sample 1, the theta and gamma complexity reports a decrease under the effect of Frquency Band 4 for all the electrodes, which may be a signature of the respondents being able to recognize the song, while in Band 5 their sudden increase may be due to complete non-recognition. In general, for the first two low frequency bands of music, there is a decrease in complexity for all the EEG frequency bands; while for the last two high frequency bands there is a general increase in complexity for most of the EEG frequency bands in case of the temporal electrodes. The Fig. 7.6 (a and b) show the change in complexities for the two occipital electrodes O1 and O2.

Although, occipital electrodes are associated with processing of visual imagery, any musical piece is associated with some sort of visual imprint in the minds of the listener and hence, the response of occipital electrodes in the perception of different sections of a musical piece is very important. For both the electrodes, we find that the signature for onset of non recognition, i.e. a sudden increase in alpha, theta and

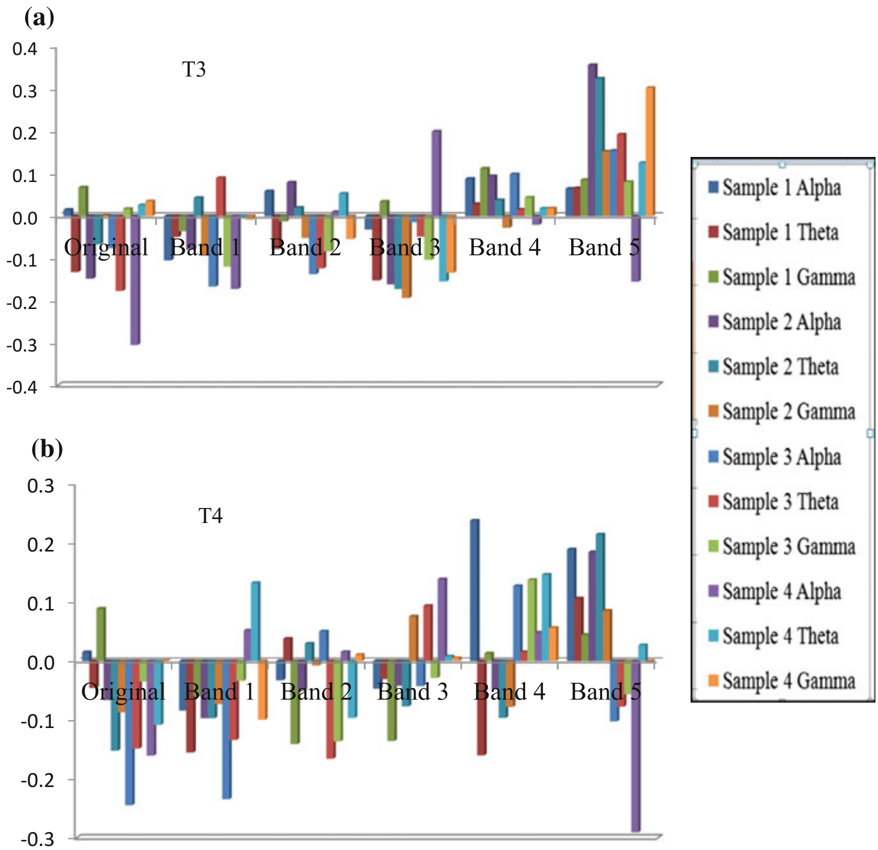


Fig. 7.5 **a** Variation of multifractal width for temporal T3 electrode for alpha, theta and gamma frequency ranges **b** Variation of multifractal width for temporal T3 electrode for alpha, theta and gamma frequency ranges **c** Variation of multifractal width for temporal T5 electrode for alpha, theta and gamma frequency ranges **d** Variation of multifractal width for temporal T5 electrode for alpha, theta and gamma frequency ranges

gamma multifractal width comes at Band 2 for Sample 4, while for Sample 1 it comes at Band 3. The other two samples behave in a similar manner as is found in the temporal and frontal electrodes, with the onset of non-recognition coming at Band 4. For the occipital electrodes, theta band also plays an important role as a marker to detect the switch from recognition to non-recognition of musical frequency bands.

We find the strongest response for all the EEG frequency ranges in the 1st band of music, i.e. which contains the fundamental frequency as well as 2/3 higher harmonics. This is fairly reasonable as this part contains all the signature of the original song; hence it is easy for the respondents to form a mental imagery for that particular song, which eventually leads to strong arousal in the occipital electrodes

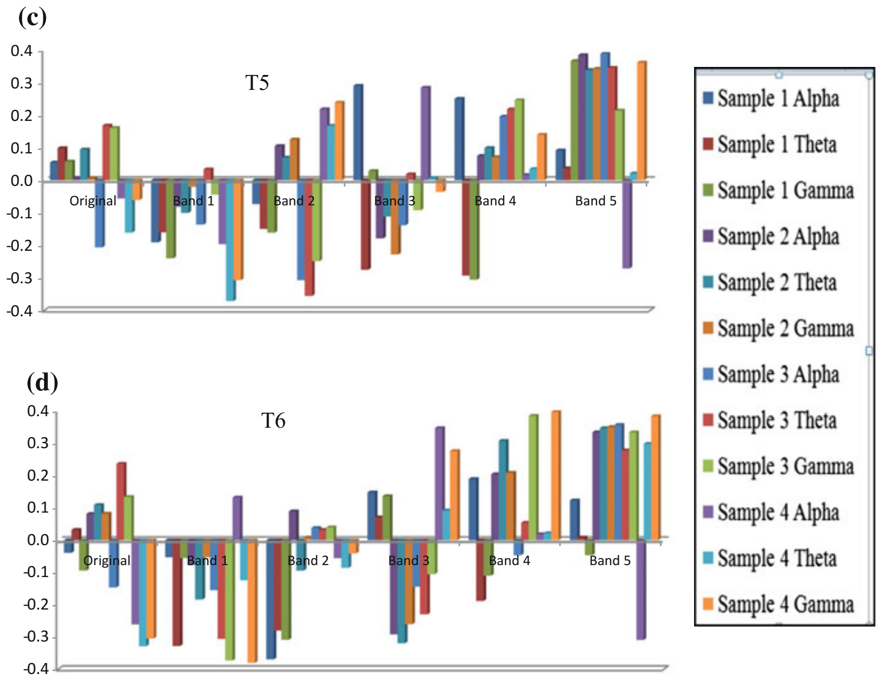


Fig. 7.5 (continued)

for that particular song. Eventually as more and more frequency bands are cut-off from the musical clips, the occipital lobe fails to perceive the original music and hence we see a decreasing arousal based response in Band 2 and a sudden jump in Band 3/Band 4 where there is complete non-recognition and hence no corresponding visual imagery.

Thus, with the help of this study we have tried to establish a threshold for gestalt phenomenon in music, whereby brain fails to perceive a musical piece above a particular resonant frequency, i.e. the cue for recognition of that particular musical piece is lost, and hence the closure property of gestalt principle fails.

7.5 Conclusion

With this work, we tried to venture an unknown horizon of gestalt principle—i.e. is there a cut-off frequency beyond which human mind cannot recognize even a known piece of music. We used a robust non-linear technique for the analysis of EEG data—MFDFA to identify the brain response if there exists such a cut-off frequency for musical piece. The study yields the following interesting conclusions:

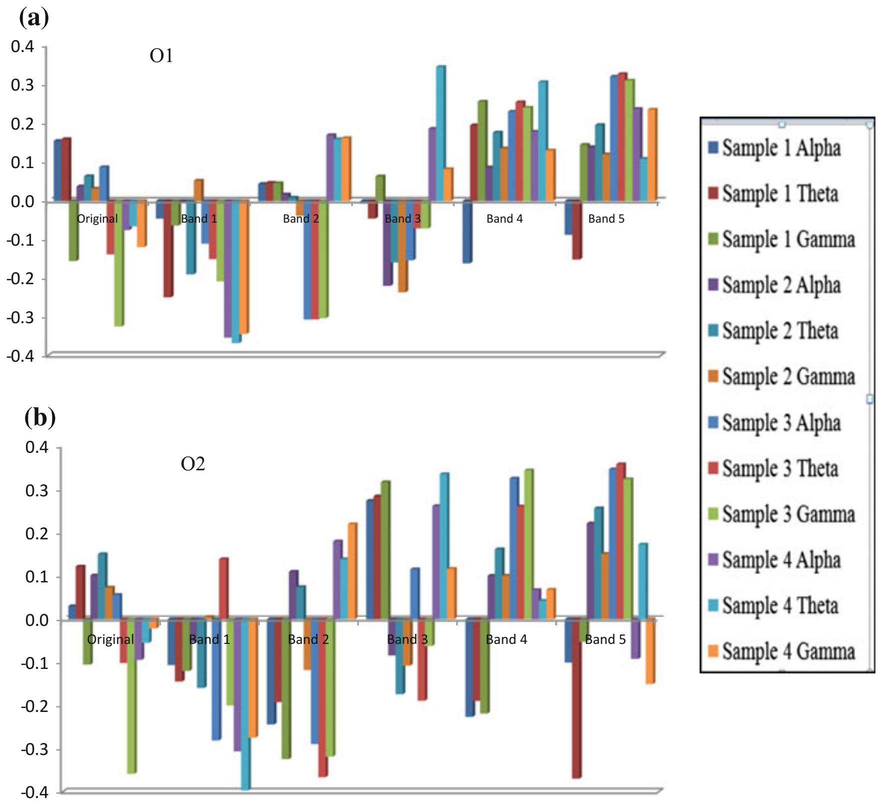


Fig. 7.6 a–b: Variation of multifractal width for occipital O1 and O2 electrodes

1. From the psychological data, it is seen that human brain is unable to perceive a musical frequency above a frequency of 3 kHz in general, although there are certain exceptions; but we can safely assume 3 kHz as the switch over frequency while above 4 kHz there is complete non-recognition, i.e. there are almost no musical element left above 4 kHz which will help the human mind to identify the song. The frequency bands below 3 kHz however are easily identified by the participants as the original song, though the fundamental frequency and a number of overtones have been removed from the piece.
2. To find the EEG correlates for the switch, alpha, theta and gamma complexity were studied for 10 electrodes in frontal temporal and occipital region. Statistical analysis showed the arousal based effects were most strong in the right frontal electrodes, F4 and F8 as well as right temporal electrodes T4 and T6; which leads us to the conclusion that perception and recognition based activities are mostly performed in the right frontal and temporal lobe; with the response in T6 and F4 being the strongest in all.

3. We studied the complexity values corresponding to the three frequency ranges of EEG data, with the conclusion that alpha and gamma are the most important markers of gestalt principle in music. The complexity values for both these frequency ranges decrease when the human brain is able to identify a known musical piece, and increase suddenly whenever there is non-recognition of a particular piece. Mostly, we see that switch comes in Band 4 (i.e. for music signals above 3 kHz), and in some exceptional cases, in Band 2 (i.e. between 2 kHz and 3 kHz) also. The theta frequency range however plays a significant role in case of the occipital electrodes, where it can be safely used as a marker to distinguish between the two states.

To conclude, in this work, we have proposed a novel algorithm with which one can categorize between two states of human mind in response to a well known doctored musical clip which is devoid of certain frequency values. We see that up to a certain frequency band, it can easily perceive the musical piece, while above that range, it becomes unrecognizable. To know the exact value of this cut-off, experiments are going on by fine tuning the Band 4 into smaller and smaller groups to yield the exact/range of threshold value(s) where this switch from recognition to non-recognition occurs. The use of robust algorithm like MFDFA leads to new and interesting results in the domain of neuro-cognition of musical pieces. Although we obtained certain variations from Sample to Sample, but those small variations can be neglected as statistical fluctuations, and hence a definite threshold is obtained above which the closure principle of gestalt fails. This study has the potential to impact applications like generation of humanized clips from machines, audio editing as well as researchers of creativity who look for unique behaviors of human brain. Ambiguity—the most important facet of Hindustani classical music is analyzed with the help of robust non-linear techniques in the next Chapter. Acoustical as well as EEG signals have been analyzed to categorize and quantify different emotional clips.

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Chapter 8
Emotion and Ambiguity: A Study

Learning to live with ambiguity is learning to live with how life really is, full of complexities and strange surprises
—James Hollis

8.1 Introduction

8.1.1 Emotions in Hindustani Music and the Importance of Ambiguity

In North Indian Classical Music, *raga* forms the basic structure over which individual improvisations is performed by an artist based on his/her creativity. The *raga* is a sequence of musical notes and the play of sound which delights the hearts of people (Raja 2005). The word Raga is derived from the Sanskrit word "Ranj" which literally means to delight or please and gratify. The listener has to listen to several pieces of the Raga in order to recognize the Raga. The goal of a performer of Hindustani music is to convey the musical structure and expression so that the audience gets pleasantness (Jairazbhoy 1995; Martinez 2001). The presentation of a Raga is started with *Alap*. The *Alap* is the opening section of a typical Hindustani Music (HM) performance. In the *alap* part, the *raga* is introduced and the paths of its development are revealed using all the notes used in that particular *raga* and allowed transitions between them with proper distribution over time. In India, music (*geet*) has been a subject of aesthetic and intellectual discourse since the times of *Vedas (samaveda)*. *Rasa* was examined critically as an essential part of the theory of art by Bharata in Natya Sastra, (200 century BC). The *rasa* is considered as a state of enhanced emotional perception produced by the presence of musical energy. Although unique, one can distinguish several flavors according to the emotion that colors it. Several emotional flavors are listed, namely erotic love (*sringara*), pathetic (*karuna*), devotional (*bhakti*), comic (*hasya*), horrific (*bhayanaka*), repugnant (*bibhatsa*), heroic (*vira*), fantastic, furious (*roudra*), peaceful (*shanta*). Italics represent the corresponding emotion given in the Indian treatises.

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Although there have been a number of studies to decipher emotions elicited by Western Classical music using various brain-computer interaction techniques (Kim et al. 2010; Eerola and Vuoskoski 2011; Wieczorkowska et al. 2006; Hunter and Schellenberg 2010; Koelsch et al. 2006), there has been a dearth of such studies when it comes to Hindustani Classical music. Few studies (Ross and Rao 2012; Belle et al. 2009; Datta et al. 2012) look to identify a particular *raga* with the help of computer-aided techniques while some look to detect emotional appraisal from various *ragas* of Hindustani music (Balkwill and Thompson 1999; Wieczorkowska et al. 2010; Sengupta et al. 2012; Mathur et al. 2015). The detection of emotional cues from Hindustani Classical music is a demanding task due to the inherent ambiguity present in the different *ragas*, which makes it difficult to identify any particular emotion from a certain *raga.* Also, no two performances in Hindustani music are identical as opposed to Western music culture, as there is ample scope for improvisation within melodic framework of a particular *raga* (Slawek 1998; Rahaim 2012; Sanyal et al. 2004; Banerjee et al. 2016). Every performer of this genre is essentially a composer as well as an artist as while performing a Raga the way the notes are approached and rendered in musical phrases and the mood they convey are more important than the notes themselves. Hence, it requires a very high resolution mathematical microscope to procure information about the inherent complexities and time series fluctuations that constitute an acoustic signal (Sanyal et al. 2016).

8.1.2 Non Linear Source Modeling of Musical Instruments

Musical instruments are often thought of as linear harmonic systems, and a first-order description of their operation can indeed be given on this basis. The term ‘linear’ implies that an increase in the input simply increases the output proportionally, and the effects of different inputs are only additive in nature. The term ‘harmonic’ implies that the sound can be described in terms of components with frequencies that are integral multiples of some fundamental frequency, which is essentially an approximation and the reality is quite different. Most of the musical instruments have resonators that are only approximately harmonic in nature, and their operation and harmonic sound spectrum both rely upon the extreme nonlinearity of their driving mechanisms. Such instruments might be described as ‘essentially nonlinear’ (Fletcher 1999).

The three instruments chosen for our analysis are *sitar, sarod and flute.* All of them have been phenomenal for the growth and spread of Hindustani classical music over the years. The first two are plucked string instruments having a non-linear bridge structure, which is what gives them a very distinct characteristic buzzing timbre. It has been shown in earlier studies that the mode frequencies of a real string are not exactly harmonic, but relatively stretched because of stiffness

(Morse 1948), and that the mode frequencies of even simple cylindrical pipes are very appreciably inharmonic because of variation of the end correction with frequency; hence a non linear treatment of the musical signals generated from these instruments become invincible. Non-linear fractal analysis/physical modeling of North Indian musical instruments were done in a few earlier works (Fletcher 1999; Burridge et al. 1982; Datta et al. 2008; Siddiq 2012; Das and Das 2006; Sengupta et al. 2010a, b, Sengupta et.al. 2005) but using them to quantify and categorize emotional appraisal has never been done before. That music has its effect in triggering a multitude of reactions on the human brain is no secret. However, there has been little scientific investigation in the Indian context (Balkwill and Thompson 1999; Wieczorkowska et al. 2010; Mathur et al. 2015; Slawek 1998; Rahaim 2012; Sanyal et al. 2004; Sengupta et al. 2012; Banerjee et al. 2016; Sanyal et al. 2016) on whether different moods are indeed elicited by different *ragas* and how they depend on the underlying structure of the *raga*.

8.1.3 Neural Response to Emotional Stimuli

The exact way in which different emotions are processed in the human brain has been the subject of a number of psychological studies (Hariri et al. 2002; Vuilleumier et al. 2002; Buhle et al. 2014) in the last few decades, most of which involved the use of visual stimuli to evoke emotion in human mind. However, in case of music induced emotions, whether the induced emotional response is similar to the other modalities or whether there is significant difference between them is an open question. In a number of EEG studies, it has been found that pleasantness of music has been reported to be positively correlated with power spectral density (PSD) in the theta band (4–7 Hz) over the prefrontal cortex (Sammler et al. 2007) while the reported valence (pleasantness/unpleasantness) and arousal (intensity/energy) of musical stimuli have been reported to correlate with frontal alpha (8–13 Hz) asymmetry (Schmidt and Trainor 2001). A number of studies posit on the inter-connectivity of brain lobes (Daly et al. 2014; Koelsch 2014) during a variety of cognitive processing motor control (Daly et al. 2012), emotional responses to audio-visual stimuli (Costa et al. 2006), and perception of music (Bhattacharya et al. 2001). Most of these apply the coherence features to assess connectivity features between different lobes, which successfully discriminate between two or more groups of music-induced emotions. But, these measures are mostly linear and lead to huge data loss in the form of inherent spikes of EEG data which are averaged in the form of square wave approximation. The non-linear techniques take into account these inherent spikes of EEG data and hence are much more accurate than the conventional linear techniques and may shed new light on the neural assembly networks of human brain in regard to emotion processing.

8.1.4 Use of MFDFA to Assess Acoustical/Human Response

The human brain response to a pair of *ragas* which portray contrast emotion has been elaborately studied in Chap. 3. In this chapter, the main focus is to make use of the acoustic features of different musical instruments to classify the emotional manifestations of different *ragas* as well as to see the corresponding brain correlates. Whether there exists a certain threshold beyond which the emotional context of a particular *raga* changes to other in respect of acoustic parameters. In this context, the ambiguous clips also play an important factor acting as a bridge between two clips of contrast emotions and hence the parameter extracted from them will be an interesting one in the quest for quantification of music induced emotions. We chose 3 min *alap* portion of six conventional *ragas* of Hindustani classical music namely, "*Darbari Kanada", "Yaman", "Mian ki malhar", "Durga", "Jayjayanti" and "Hamsadhwani*" played in three different musical instruments. The first three *ragas* correspond to the negative dimension of the Russell's emotional sphere (Posner et al. 2005; Russell 1991), while the last three belong to the positive dimension (conventionally). The music signals were analyzed with the help of latest non linear analysis technique called Multifractal Detrended Fluctuation Analysis (MFDFA) which determines the complexity parameters associated with each *raga* clips. The MFDFA technique is superior to other conventional techniques due to the fact that it accounts both the small and large variations present in the music signal by varying the q-order moments. This technique has been successfully applied in the past to detect complexity parameters associated with music clips (Jafari et al. 2007; Telesca and Lovallo 2011; Banerjee et al. 2017; Bhaduri and Ghosh 2016; Sanyal et al. 2016) and further to classify music clips based on this parameter. With the help of this technique, we have computed the multifractal spectral width (or the complexity) associated with each *raga* clip and further to classify them on the basis of their emotional attribute. The complexity values give clear indication in the direction of categorization of emotions attributed to Hindustani classical music. It is observed that the *ragas* which belong to the positive valence normally possess lower values of complexity, while those belonging to the negative valence have comparatively higher values of complexity. Also, specific cues are obtained for each of the musical instruments used in this study, which makes each of the inherent ambiguities present in the *ragas* of Hindustani classical music beautifully reflected in the results. The complexity value corresponding to different parts of a particular raga becomes almost similar to the values corresponding to parts of a different *raga.* This implies acoustic similarities in these parts and hence the emotional attributes of these parts are bound to be similar. Furthermore, EEG was done on a sample pool of participants using the same music clips to see if any correlation can be obtained between the acoustic and neural complexities. The frontal, temporal and occipital electrodes were analyzed in this regard and interesting observations were found in regard to categorization of emotions as well as specification of instrumental characteristics' using this technique. In this way, we have tried to develop automated algorithm with which we can classify and quantify emotional arousal corresponding to different *ragas* of Hindustani music. The study can be developed further with a wide variety of signals including vocal music which will lead to the generation of an automated algorithm with which we can conclusively identify and quantify emotional cues corresponding to a particular music clip originating from a characteristic source.

8.2 Experimental Details

8.2.1 Choice of Three Pairs of Ragas

Six different *raga* clips of Hindustani Classical music played in traditional flute, *sitar* and *sarod* were taken for our analysis. The *ragas* were chosen by an experienced musician such that they belong to the positive and negative valence of the 2D emotional sphere illustrated in Fig. 8.1 (Russell 1991).

The three pairs of *ragas* were chosen in a way that half of them belong to the positive valence while the other three belong to the negative valence as corroborated from a listening test conducted beforehand and also in ancient treatises (Ghosh 2002) of Hindustani music. In this way we want to have an acoustic as well as neuro-cognitive categorization of emotional appraisal from *ragas* of Hindustani music. We chose 3 min *alap* portion of six conventional *ragas* of Hindustani classical music namely, "*Darbari Kanada", "Yaman", "Mian ki malhar", "Durga", "Jayjayanti" and "Hamsadhwani*" played in three different musical

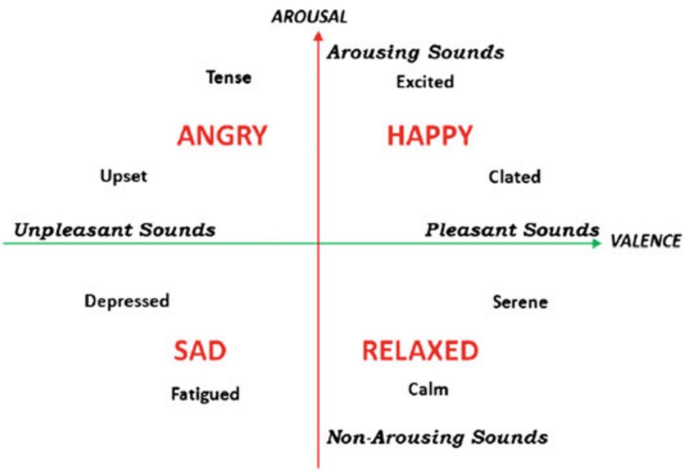


Fig. 8.1 Russell's 2D circumplex model of emotion

Table 8.1 Details of artists chosen

Artistes	Instruments used
Ustad Ali Akbar Khan (Artist 1)	Sarod
Pt. Hariprasad Chaurasia (Artist 2)	Flute
Pt. Nikhil Banerjee (Artist 3)	Sitar

instruments. The following table gives the details of the artistes and their respective instruments which we have used for our analysis (Table 8.1).

8.2.2 Analysis of the Acoustic Signal Using MFDFA

Musical structures can be explored on the basis of multifractal analysis and non-linear correlations in the data. Traditional signal processing techniques are not capable of identifying such relationships, nor do they provide quantitative measurement of the complexity or information content in the signal. The three pairs of *raga* signals were digitized at the rate of 22,050 samples/sec 16 bit format. The *alaap* part was considered for analysis because the characteristic features of the entire *raga* is present *in* this part and that it uses all the notes used in that particular raga and allowed transitions between them with proper distribution over time. Moreover this part is free from accompaniment. Each three minutes signal is divided into four equal segments of 45 s each. We measured the multifractal spectral width (or the complexity) corresponding to each of the 45 s fragments of the Hindustani *raga.*

8.2.3 Subjects Summary for EEG

10 right handed adults (8 male and 2 female) voluntarily participated in this study. None of them had any conventional musical training in Indian classical music. Their ages were between 18 and 28 years (SD = 2.25 years). None of the participants reported any history of neurological or psychiatric diseases, nor were they receiving any psychiatric medicines or using a hearing aid. Informed consent was obtained from each subject according to the ethical guidelines of the Ethical Committee of Jadavpur University. All experiments were performed at the Sir C.V. Raman Centre for Physics and Music, Jadavpur University, Kolkata.

8.2.4 Experimental Protocol

During the EEG acquisition period, the 10 subjects were made to listen to the same clips of 6 ragas for all 3 instruments. To prepare the input music stimuli for EEG experiments, about 2 min were extracted from each of the *raga* clips that were used during acoustical analysis. Subjects were asked to keep their eyes closed and to sit calmly during each condition. First, the baseline (that is, a resting condition) was recorded for each subject before the start of the experiment with 2 min of 'no music' condition. Then the music clips were played using the computer-sound system (Logitech R _ Z-4 speakers) with very low S/N ratio keeping the volume fixed throughout the experiment. The speakers which were used in the measurement room for giving music input to the subjects were placed 120 cm behind the head of the subjects. The EEG experiment was conducted in the afternoon (around 2 PM) in a room with the volunteers sitting in a comfortable chair.

From previous knowledge the frontal, temporal and occipital lobes of human brain were selected for analysis as the objective of this study was to find out the effect of listening to 3 pairs of different *ragas* of Hindustani music evoking two contrasting emotions. Each subject was prepared with an EEG recording cap with 19 electrodes (Ag/AgCl sintered ring electrodes) placed in the international 10/20 system. Figure 8.2 depicts the positions of the electrodes. Impedances were checked below 50 kΩ. The EEG recording system (Recorders and Medicare Systems) was operated at 256 samples/s recording on customized software of RMS. The data was band-pass-filtered between 0.5 and 35 Hz to remove DC drifts and suppress the 50 Hz power line interference. The ear electrodes A1 and A2 linked together have been used as the reference electrodes. The same reference electrode is used for all the channels. The forehead electrode, FPz has been used as the ground electrode. After initialization, a 21 min recording period was started, and the following protocol was followed: first the *raga* clips in sarod were played, and then the same procedure was followed for flute and sitar respectively with a 30 min interval between each set of 21 min recording. Markers were set at start, signal onset/offset, and at the end of the recording.

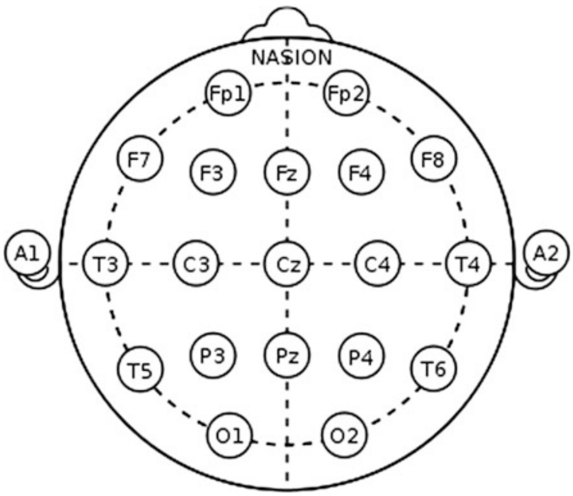


Fig. 8.2 The position of electrodes according to the 10–20 international system

1. 2 min Before Music (Resting Condition) (BM)
2. 2 min Clip 1(*Raga Jayjayanti)* (M1)
3. 1 min No Music (R1)
4. 2 min Clip 2 (*Raga Mian ki malhar)* (M2)
5. 1 min No Music (R2)
6. 2 min Clip 3 (*Raga Hamsadhwani)* (M3)
7. 1 min No Music (R3)
8. 2 min Clip 4 (*Raga Darbari Kanada)* (M4)
9. 1 min No Music (R4)
10. 2 min Clip 5 (*Raga Durga)* (M5)
11. 1 min No Music (R5)
12. 2 min Clip 6 (*Raga Yaman)* (M6)
13. 2 min After Music (Resting Condition) (AM).

8.3 Methodology

To analyze the non-linear complex EEG and music signals, MFDFA technique proposed by Kantelhardt et al. (2002) was used here. The 3 min music clips were divided into four equal parts of 45 s each and was subjected to multifractal analysis which gave the multifractal spectral width (or complexity) as the output. During EEG analysis, we considered each of the experimental conditions as a separate single window and analyzed their complexity using the same non-linear technique, so that we get a direct correspondence between the acoustic and neural characteristics of emotional appraisal. The detailed algorithm for this technique has been discussed elaborately in the second chapter of this book.

8.4 Results and Discussions

The following figures (Figs. 8.3, 8.4, 8.5, 8.6, 8.7 and 8.8) give the variation of complexity values for the chosen music signals for all the artistes in the different parts. The y-axis gives the variation of multifractal spectral width while the x-axis denotes the 4 parts of the 3 min music clip.

We see that in most cases the variation of multifractal widths within a particular *raga* is almost similar for all the artistes; though the characteristic values of multifractal widths are distinctly different from one clip to other. For example, in case of Artist 2, we find that the characteristic multifractal width is on the higher side for *raga Hamsadhwani* while the same is on quite lower side for *raga Darbari Kanada;* though the variation of spectral width is similar among the different artistes who played the same *raga.* The similarity in fluctuation patterns within each *raga* may be attributed to the strict intonation pattern followed by all the artistes

Fig. 8.3 Variation of multifractal width within *raga Hamsadhwani*

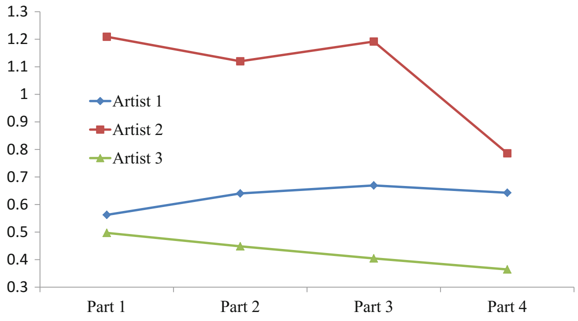


Fig. 8.4 Variation of multifractal width within *raga Darbari Kanada*

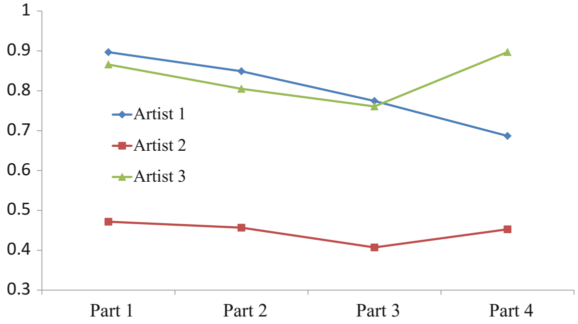
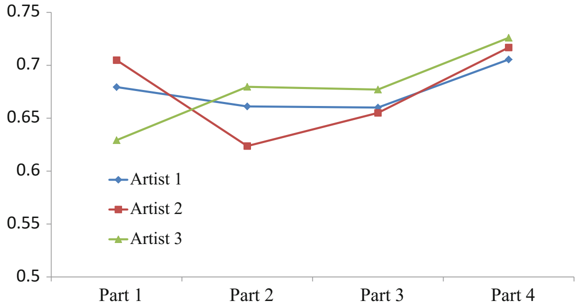


Fig. 8.5 Variation of multifractal width within *raga Jayjayanti*



during the performance of a *raga;* while the difference in the characteristic values may be a signature of artistic style as well as the instrument in use. This technique may thus be useful in getting a cue for timbral quantification of a musical instrument. Also, in many parts we find that an artist has deviated significantly from the characteristic pattern of that *raga;* herein lies the cue for artistic improvisation where the artist uses his own creativity to create something new from the obvious structure of *raga.* This modality of improvisation is very specific to Hindustani classical music form and has been extensively studied in the next chapter of this book. In Fig. 8.4, we see that in the last part the complexity value significantly increasing for the *sitar* clip as opposed to the *sarod* clip; while in Fig. 8.8 we find

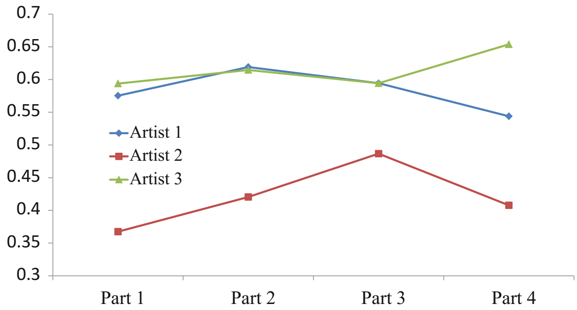


Fig. 8.6 Variation of multifractal width within *raga Mian ki malhar*

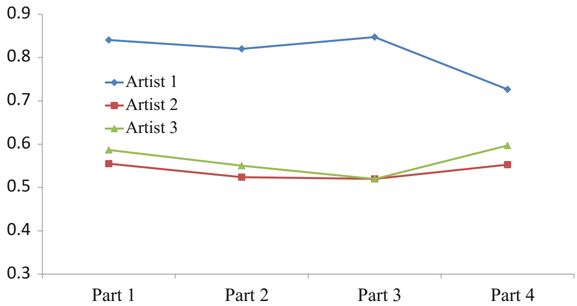


Fig. 8.7 Variation of multifractal width within *raga Durga*

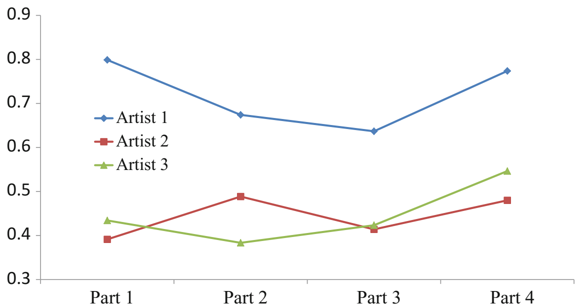


Fig. 8.8 Variation of multifractal width within *raga Yaman*

that in the 2nd part complexity value dipping for the *flute* clip as opposed to the other two clips where the complexity values are increasing. This feature elucidates how a particular artist of Hindustani music uses his/her own skills to create something new in each performance of the same *raga*. In this way, we can have an estimate of how much an artist improvises during the rendition of a particular *raga*.

The averaged values for each raga clips have been given in the following table (Table 8.2) and the corresponding fig (Fig. 8.9) shows the values for each artist. The SD values have also been computed for the rendition of each *raga* by an Artist.

From the above figure it is clear that there is distinct categorization of emotional responses corresponding to each *raga* clip. In case of *sarod* and *sitar*, we find that *raga Hamsadhwani* (corresponding to happy emotion) has a lower value of

Table 8.2 Variation of multifractal width corresponding to *ragas* by different artistes

	Hamsadhwani	Darbari	Jayjayanti	Mia ki malhar	Durga	Yaman
Artist 1 (Sarod)	0.62 ± 0.04	0.80 ± 0.02	0.67 ± 0.04	0.58 ± 0.03	0.81 ± 0.06	0.72 ± 0.03
Artist 2 (Flute)	1.07 ± 0.06	0.44 ± 0.04	0.67 ± 0.06	0.42 ± 0.07	0.54 ± 0.04	0.44 ± 0.04
Artist 3 (Sitar)	0.42 ± 0.03	0.64 ± 0.06	0.40 ± 0.02	0.61 ± 0.02	0.56 ± 0.02	0.45 ± 0.04

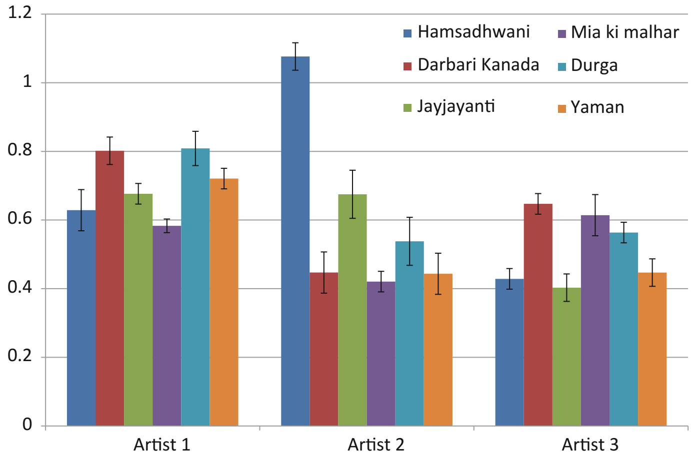


Fig. 8.9 Clustering of multifractal widths for each artist corresponding to each *raga*

complexity as opposed to the *flute* clip where the complexity value is significantly high. The complexity values corresponding to *raga Darbari* (depicting sad emotion) are consistently high for *sarod* and *sitar* while that is significantly low for *flute* clip. In case of the other pair *Jayjayanti* (happy clip) and *Mia ki malhar* (sorrow clip), we see that there is similarity in response for *sarod* and *flute,* i.e. complexity values on the higher side for happy clip while it is lower for sad clip; the response is vice versa for *sitar* clip. In case of the other pair, i.e. raga *Durga* (mainly on the happier side but is mixed with other emotions like romance, serene etc.) and *raga Yaman* (mainly on the negative side of Russel's emotional sphere but is mixed with other emotions like devotion etc.) there was considerable ambiguity even when it comes to human response psychological data. The same has been reflected in our results where the average difference in complexity of these two *ragas* is not so significant as compared to the other two pairs. Our study thus points in the direction of timbre specific categorization of emotion in respect to *Hindustani raga* music. We see that the emotion classification works the best for *flute* where the difference in complexity for the happy and sad clips is the maximum; while the difference is minimum for *sarod*, thus it is difficult to categorize emotions from acoustic *sarod* clips.

Now, analysis of human brain response (EEG signals) before, during and after listening to the six chosen *raga* clips played in three different instruments yield many interesting information in the domain of music cognition and emotion processing. First the complete 21 min raw EEG of a single subject was cut along the temporal markers for 13 different experimental conditions. Then using wavelet transformation technique alpha and theta frequency bands were extracted and Multifractal spectral width was calculated for each part using MFDFA technique. The same procedure is followed for each of the 10 subjects for all 3 instruments. The average changes in the spectral width values between two consecutive experimental conditions for both alpha and theta band are plotted in Figs. 8.10, 8.11, 8.12, 8.13, 8.14 and 8.15.

In the above figures we can observe distinct changes in the human brain response when a subject is listening to *raga* clips. These responses slightly vary from one instrument to another. Also a few major dissimilarities are found between the responses of frontal, occipital and temporal lobe. Though for all subjects the measure of baseline complexity i.e., spectral width value in initial rest state was different, but the pattern of change in spectral width values with the change of different experimental conditions remained same. From Fig. 8.10 we observe that in case of F3 (left frontal) electrode, for all happiness evoking *ragas* (i.e., *Jayjayanti, Hamsadhwani, Durga*) the spectral width increases from the previous rest state. The increment is highest during listening to *raga Hamsadhwani*. In case of the other three *ragas* evoking opposite emotion we observe a mixed response in F3 electrode, i.e., during listening to *Mia ki malhar* and *Yaman* in *sarod* and *sitar* the spectral width value decreases for both alpha and theta band, but when the same two *ragas* were played in *flute* spectral width increased, though in case of *Darbari* a dip is observed for all three instruments. This probably indicates towards the dependence of emotion on the particular piece the subject is listening to, rather than the entire *raga* and also the timbre of the concerned instrument plays an important role in it.

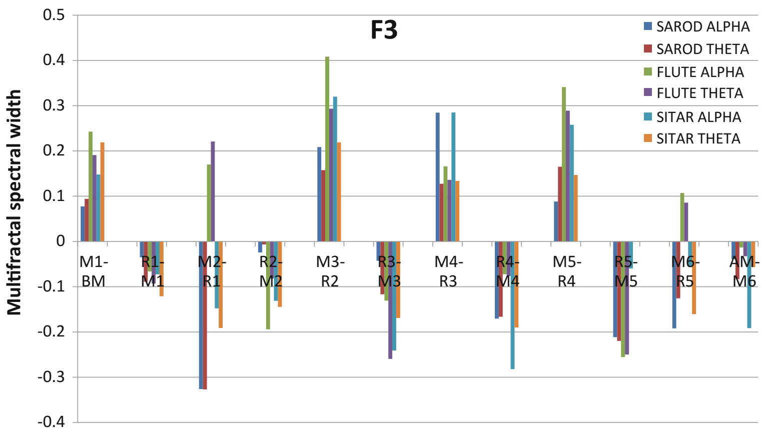


Fig. 8.10 Changes in spectral width values in F3 electrode for different experimental conditions

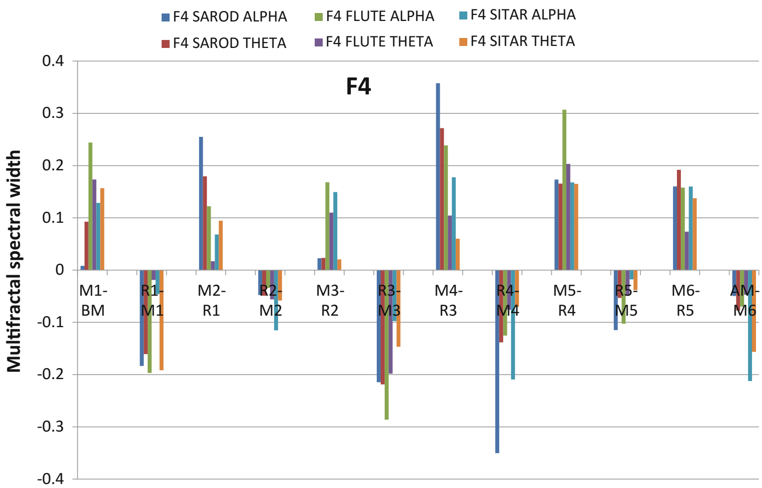


Fig. 8.11 Changes in spectral width values in F4 electrode for different experimental conditions

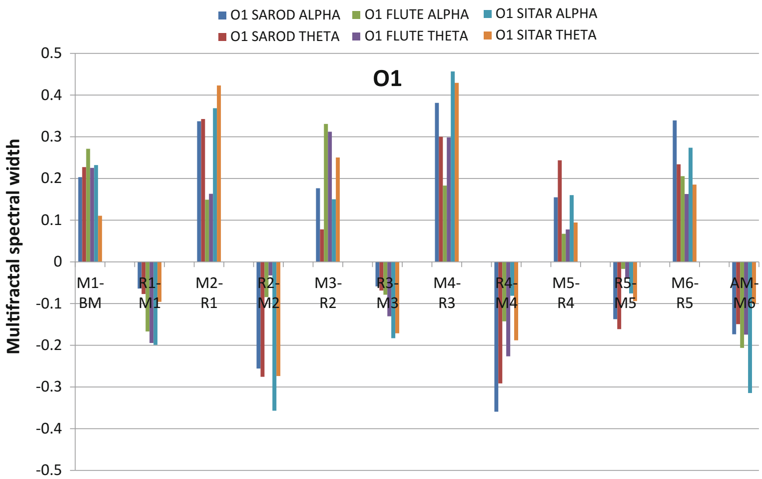


Fig. 8.12 Changes in spectral width in O1 electrode for different experimental conditions

Another observation is that "happy" *ragas* when played in *flute* lead to higher increment in spectral width compared to *sarod* and *sitar*, while for "sad" ones, more prominent changes are observed mainly in *sarod* or in few cases *sitar*. In every rest state following a particular music, the spectral width values changed to bring back the neural system towards its initial state, though some retention is always present. These retentions are usually more prominent in alpha band compared to the theta band. In right frontal F4 electrode, (Fig. 8.11) these results matched in some parts, but the major dissimilarity was that in F4 the spectral width increased both in alpha

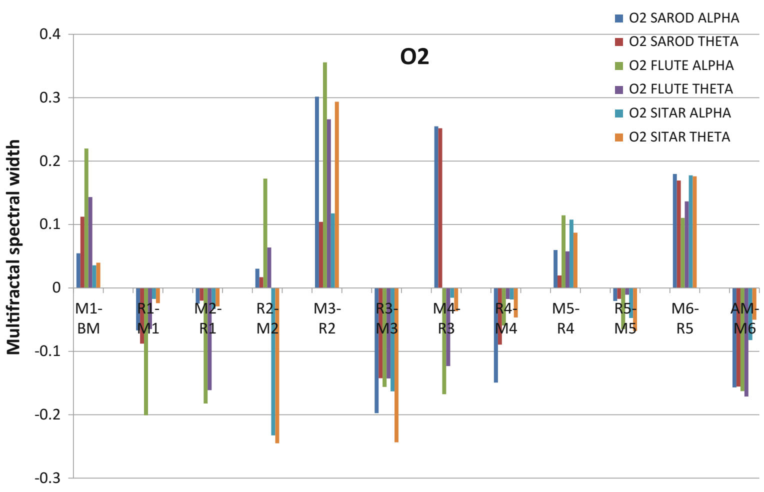


Fig. 8.13 Changes in spectral width in O2 electrode for different experimental conditions

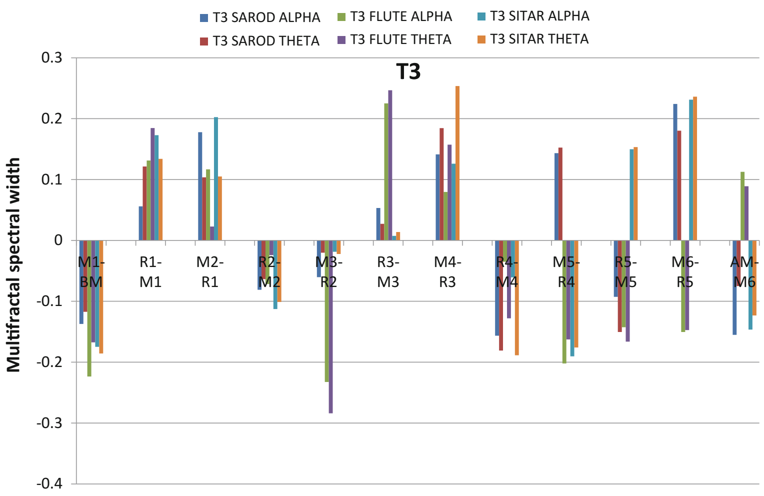


Fig. 8.14 Changes in spectral width in T3 electrode for different experimental conditions

and theta band during listening to all six *ragas*. *Raga Darbari* exhibits the most prominent increment in spectral width. Here the dominance of *flute* during happier parts and that of *sarod* in the opposite ones is revealed more distinctly. In the left occipital (O1 electrode) region, (Fig. 8.12) the results almost resonated with that of F4, though here the "sad" *ragas* feature significantly greater elicitation in spectral width on average compared to the "happy" ones. Another interesting observation is that during the last two music clips i.e., *Raga Durga* and *Yaman*, the average change in spectral width, both in alpha and theta band, is lesser than the other *ragas*

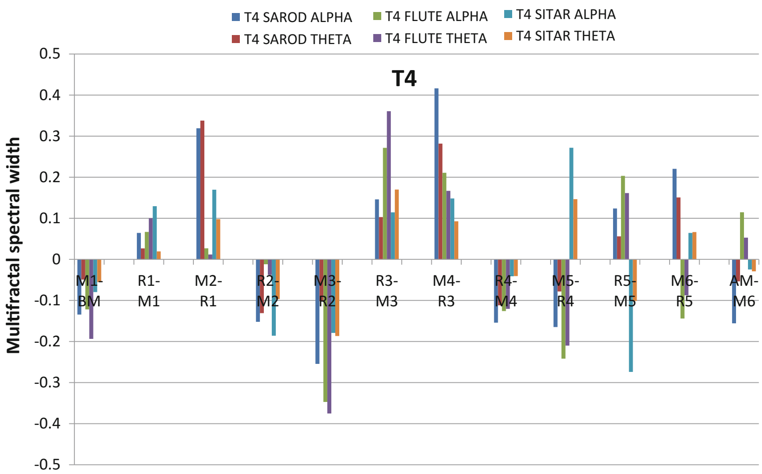


Fig. 8.15 Changes in spectral width in T4 electrode for different experimental conditions

in almost all the electrodes. This may indicate towards the emotional ambiguity present in those *ragas* as the inherent ambiguity could have denied a sharp increment or decrement in spectral width values during listening to them. In electrode O2, (Fig. 8.13) representing right occipital region, the response is more disordered than O1. All the happy ones trigger positive change in spectral width values of alpha and theta band but the response is strangely chaotic for the “sad” *ragas.* During *Mia ki malhar,* a dip is featured for all three instruments, while during *Darbari,* the *sarod* clips caused a sharp increment in both alpha and theta band on the contrary to that of *flue* and *sitar.* On the other hand, during *Yaman* an increment in width is observed for all the instruments. In O2 electrode, most prominent hike in spectral width is observed during *Raga Hamsadhwani.* The response of temporal region is somewhat different from the other two regions concerned. In left temporal T3 electrode (Fig. 8.14) the two prominently happy *ragas i.e., Jayjayanti* and *Hamsadhwani* caused a dip in spectral width for all three instruments whereas the sad ones i.e., *Mia ki malhar* and *Darbari* contributed in a hike for both alpha and theta band. The responses got mixed up during the “ambiguous emotion” conveying pair. During *Raga Durga, sitar* and *flute* featured a decrease in spectral width values but *sarod* caused an increment whereas during *Yaman,* only *flute* yielded a negative change. In right temporal T4 electrode, (Fig. 8.15) for all experimental conditions the change in fractal width values are much lesser than that of T3 on average but, the results are almost similar to that of left temporal region. The only difference is that in T4, during *Raga Durga, sarod* triggered a negative change along with *flute* and *sitar* reported a positive change in spectral width values for both alpha and theta frequency bands. These observations act as strong evidence for timbre dependence of emotion, especially in case of ambiguous emotion evoking *ragas.*

Fig. 8.16 Use of multifractal width as a tool to categorize emotions in different instruments

Thus, in this work we have developed an automated emotion classification algorithm with which we can quantify and categorize emotions corresponding to a particular instrument. Also, the complexity values give a hint for style recognition corresponding to a particular artist.

8.5 Conclusion

This study presents a first-of-its kind data in regard to categorization and quantification of emotional arousal based responses to Hindustani classical music. The inherent ambiguities said to be present in Hindustani classical music is also reflected beautifully in the results. That a particular *raga* can portray an amalgamation of a number of perceived emotions can now be tagged with the rise or fall of multifractal width or complexity values associated with that *raga*. The study presents the following interesting conclusions which have been listed below:

1. For the first time, an association has been made with the timbre of a particular instrument with the variety of emotions that it conveys. Thus for effective emotional classification, timbre of the instrument will play a very important role in future studies.
2. The multifractal spectral width has been used as a timbral parameter to quantify and categorize emotional arousal corresponding to a particular clip played in a specific instrument.
3. We try to develop a threshold value for a particular instrument using multifractal spectral width, beyond which emotions will change. The following figures (Fig. 8.16) summarize the results:

(i) From the plot it is clear that emotional classification can be best done with the help of *flute* where the complexity values of happy and sad clips are distinctly different from one another.

(ii) There is an overlap in case of *sarod* clips between happy and sad complexity values. This can be attributed to the inherent ambiguity present in the clips of Hindustani classical music, i.e. there cannot be anything as complete joy or complete sorrow, there remains always states which are between joy and sorrow, which is beautifully reflected in the overlap part of the two emotions.

Coming to the human response analysis part, the major observations are:

1. In all of the frontal and occipital electrodes (i.e., F3, F4, O1 and O2) happiness evoking *ragas* are triggering positive change in spectral width values in both alpha and theta frequency regions of human brain for all three instruments whereas the "sad" *ragas* tend to generate a mixed response in many cases. In F4 and O1 all the sad clips also feature an increase in the spectral width values but, in F3 and O2 we observe timbre dependence of emotion playing a major role as the same *raga* when played in *flute* is yielding a positive change in complexity measure whereas in case of *sarod* and *sitar* the changes are negative.
2. In temporal lobe the gross scenario is exactly the opposite to that of frontal and occipital lobe. Both in left and right temporal lobe the "conventionally happy" *raga*s (i.e., *Raga Jayjayanti & Hamsadhwani)* are causing a decrement in the spectral width values for both alpha and theta bands. The response is just opposite for "conventionally sad" *ragas* (i.e., *Raga Mia ki malhar & Darbari)* for which the width values increase for all three electrodes. The "ambiguous emotion evoking" third and last pair i.e., *Raga Durga & Yaman* produces a result where a perfect overlapping is observed between the responses for "conventionally happy" and "conventionally sad" *ragas*. Again, the timber difference is a key contributing factor in determination of emotion for these ambiguous *ragas.*
3. In all the six electrodes chosen for analysis, one strange similarity in response is observed—for the "happy" *ragas,* the rate of change in multifractal spectral width is maximum for both alpha and theta frequency band when the clips are played in *flute* and for "sad" *ragas, sarod* clips are contributing in maximum change of complexity. Among the three "happy" *ragas, Raga Hamsadhwani* when played in *flute* leads to an unusually high change in spectral width whereas among "sad" *ragas, Raga Darbari* in *sarod* yields the most prominent response.
4. The rest (or no music) state between any two consecutive music clips feature a response where the spectral width values adjust themselves intending to bring the complexity level back to their initial sate. But, some retention of emotional memory from the previous music clip is always present which resists the change. This hysteresis effect is more pronounced in alpha band than theta band.
5. Compared to the conventionally happy and sad *ragas,* the average change in complexity during *Raga Durga* and *Yaman* is much lesser in almost all the electrodes. This may have been caused due to the inherent emotional ambiguity present in different phrases of these two *ragas.*

Combining the results from acoustic and human brain response (EEG) analysis using the same technique, we can safely say that the results corroborate in almost every aspect. In acoustic analysis, we found that the spectral width values for "happy" *ragas* were most distinctly higher and wide stretched in case of *flute.* In brain response also, this result is resonated in both alpha and theta frequency domain. Similarly, following the trend of acoustic analysis, the "sad" *ragas* are found to evoke more prominent response when played in *sarod.* Like acoustic analysis it is evident from the brain response also that in Hindustani Classical Music, the concept of "absolute happy" and "absolute sad" music is not entirely true; rather the emotions fall in a grey region between these two. For some *ragas* the emotional response of the subjects are biased towards happiness, while for some others they are biased in the opposite direction. Also, an emotion, conventionally associated with a particular *raga,* is actually very much dependent on the particular piece of the *raga* the subject is listening to. In this context, the timbre of the musical instrument in which it the clip is being played also play an important role. In this experiment we chose the six *raga* clips played by same maestro for each instrument, but if this work can be repeated using clips from different artists playing the same *ragas* in same instrument, artist style dependence of emotion can be found also. In conclusion, this study provides a novel tool and a robust algorithm with which future studies in the direction of emotion categorization using music clips can be carried out keeping in mind the timbral properties of the sound being used. Improvisation—a term which involves a whole lot of features is something which gives Hindustani music its worldwide fame. But what is improvisation? Can it be defined objectively? The next chapter looks at this unique topic in light of robust scientific analysis.

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Chapter 9
Improvisation—A New Approach of Characterization

Improvisation enjoys the curious distinction of being the most widely practiced of all musical activities and the least acknowledged and understood.

—Bailey 1992 p. ix

9.1 Introduction

9.1.1 Complex Structure of Music Signals

From a physical point of view, musical signals are approximately periodic in micro and macro forms. In this approach, musical signals seem to have a deterministic behavior but this is not really the case, as music would then be a deterministic issue of rational human thought (Baroni et al. 1999). On the other hand, there is a widespread opinion (in linguistic, aesthetic and cognitive philosophy) that music is a complex, and multidimensional nonlinear system (Frova 1999). A number of earlier studies are based on rhythmic and harmonic structure of the musical notes, while frequency analysis may fail to decipher the real dynamics in case of polyphonic recordings. A few studies have been done to correlate complex actions coordinated by people with complex rhythmic musical sequence (Large 2000; Loehr et al. 2011). One such study (Large 2000) says that as people listen to rhythmic structure of music; a stable multi-periodicity pattern arises psychologically, which is a manifestation of the temporal structure of the rhythm. In this study, we want to specify some parameters with which we can quantify the improvisational cues in four different renditions of a single "*raga*" performance of a Hindustani music performer.

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9.1.2 *Brief Introduction to* Raga *in Hindustani Classical Music*

The *raga* is a sequence of musical notes and the play of sound which delights the hearts of people. The word Raga is derived from the Sanskrit word "Ranj" which literally means to delight or please and gratify (Brahaspati 2002). Although there are a number of definitions attributed to a Raga, it is basically a tonal multifarious module. The listener has to listen to several pieces of the Raga in order to recognize the Raga. The goal of a performer of Hindustani music is to convey the musical structure and expression so that the audience gets pleasantness. The presentation of a Raga is started with *Alap*. The *Alap* is the opening section of a typical Hindustani Music (HM) performance (Swarganga 2013). In the *alap* part, the *raga* is introduced and the paths of its development are revealed using all the notes used in that particular *raga* and allowed transitions between them with proper distribution over time. *Alap* is usually accompanied by the tanpura drone only and sung at a slow tempo or sometimes without tempo. Then comes the vilambit *bandish* part where the lyrics and *tala* are introduced. *Bandish* is a fixed, melodic composition in Hindustani vocal or instrumental music, set in a specific *raga*, performed with rhythmic accompaniment by a tabla or pakhawaj, a steady drone, and melodic accompaniment by a sarangi, harmonium etc. (Neuman 1990). *Vilambit* is a type of *bandish* which is sung at a very slow tempo, or *laya*, of 10–40 beats per minute. In HM the existing phrases are stretched or compressed, and the same may happen to motives from the phrases; further motives may be prefixed, infixed and suffixed. Phrases may be broken up or telescoped with others, and motives or phrases may be sequenced through different registers (Neuman 1990). Thus, during a performance, a singer steadily loosens the strangle hold of the rules of music in a subtle way. He does not flout them, he merely interprets them in a new way, which is the beauty of Hindustani classical music and there comes the wisdom that *Raga* and its grammar are only means and not ends in themselves. The way in which a performer interprets a *raga* during each specific performance is unique and is the very essence of improvisation in Hindustani music (HM). Unlike symphony or a concerto, *Raga* is unpredictable; it is eternally blooming, blossoming out into new and vivid forms during each and every performance which is the essence of "improvisation" (McNeil 2007).

9.1.3 *Improvisation: Hindustani Classical Versus Western Music*

Improvisation is a common form of musical practice across cultures, and yet remains scarcely studied or understood from a scientific musical analysis point of view. It is said that—in Hindustani music (HM), other than *Aarohan* (ascending), *Aborohan* (descending), *Chalan* (main phrase) and *Bandish* (composition), everything depends on the artist's own imagination, creativity, *Talim* (learning) and *Riyaz* (intense practice) (Ravi Shankar 1992). There is no notation in HM system like western music and the musician is himself the composer. Indian classical musicians as well as musicologists have excelled improvised music as part of a living oral tradition, whereas Western music as a dead tradition of replicating written scores. A musician while performing expresses the raga according to his mood and environment surrounding him. Thus there are differences from one rendition to another. Even if an artist sings or play same *Raga* and same *Bandish* twice then there is supposed to be some dissimilarity in between the two performances. These differences in the rendition of a raga several times on different days are generally called improvisation. A number of studies in ethnomusicology reports musical tradition among performers and the interactions that play an important role shaping the social hierarchy of North Indian Classical music (Clayton and Leante 2015; Clayton, 2005, 2007). In Western musicology, improvisation is considered as an opposite of composition, hence traditionally been regarded as an inferior to art music, where the importance of pre-composition is paramount (Sadie and Tyrell 2001). The situation is a stark contrast in Hindustani classical music, where "improvisation" is the central and defining term in any performance. Improvisation is crucial and indispensible feature of Hindustani Music (HM) which depends upon the imagination, originality and ingenuity of a particular artist (Hamill 2005) and can be best identified by analyzing the variation imposed by the artist in different renditions of the same musical piece. There have been a number of approaches to study improvisations, especially in jazz and folk music (Berliner 2009; Sertan and Chordia 2011; Johnson-Laird 1991) while in music therapy; the analysis of improvisations is gaining more ground in recent years, informing directly the therapeutic process (Thaut 1988; Lee 2000; Erkkila et al. 2004; Anagnostopoulou et al. 2012). Another recent study (Walton et al. 2015) using cross wavelet spectral analysis sheds new light on the spontaneous improvisation made by the coordination of the musician with his/her co-performers to produce novel musical expressions. Performative gestures are considered important to listening amongst all genres of music (Thompson et al. 2005). For e.g., in an analysis of B. B. King's music, it was found that some gestures have the effect of drawing the listeners' attention to local aspects of music, specifically to the nuanced treatment of individual notes, and away from larger scale musical structure (Gritten et al. 2011). The importance of gesture has been realized until recently (Kendon 2004; Parrill and Sweetser 2004) as something outside language; Indian music, with its emphasis on note combinations has often regarded gestures as something outside music. In Hindustani classical music, the gestures that accompany improvisation are closely coordinated with the vocal action; they are never taught explicitly and seem to come as an expression for melody. The importance of gestural dispositions in Hindustani *raga* performances has been extensively studied in (Rahaim 2008). A study (Wieczorkowska et al. 2010) on search for emotion in Hindustani vocal music based on human response data showed that segments from the same raga elicit different emotions which can be assigned into prescribed categories. Also cross-cultural similarity of the elicited response is significant. Another recent study on Indian classical instrumental music also based on human response data categorizes the *alap* and *gat* portion of *raga* as elicitor of specific distinct emotions (Mathur et al. 2015). In the present study, for the first time, we attempt to quantify the improvisational cues in a Hindustani music performance with the help of different non-linear parameters.

9.1.4 Earlier Studies to Capture Improvisation

Musical improvisation is generally defined as the creative activity of immediate ("in the moment") musical composition, which combines performance with communication of emotions and instrumental/vocal techniques (Alperson 1984). In Western music, there have been a number of studies which look to study the neuro-scientific basis of musical improvisation especially in case of Jazz musicians (Donnay et al. 2014; Berkowitz and Ansari 2010; Beaty 2015). The concept of musical improvisation was made distinct from the memory retrieval and the main objective being identifying brain regions involved in the spontaneous composition of novel melodic sequences, while controlling for the influence of simply recalling previously performed sequences from memory (Bengtsson et al. 2007; Limb and Braun 2008). In the study by Limb and Braun (2008), professional jazz musicians were asked to memorize a novel melody before the study. The experimental protocol involved performing musical sequences on an MRI-compatible keyboard while a pre-recorded jazz rhythm section played. Participants were cued to perform the memorized melody, freely improvise over the pre-recorded rhythm, play a one-octave scale, or improvise. In the case of Hindustani classical music, other than *Aarohan* (ascending), *Aborohan* (descending), *Chalan* (main phrase) and *Bandish* (composition), everything depends on the artist's own imagination, creativity, learning and practice of the musician. Hindustani musicians have ample liberty compared to their Western counterparts as there is no notation system like western music and the musician is himself the composer. A musician while performing a particular *raga* expresses it according to his/her mood and the ambiance. Hence, there are significant differences from one rendition to another. Even during the rendition of the same *Raga* and the same *Bandish* twice there is inevitably a number of dissimilarities in between two performances. These differences in the rendition of the same *raga* on different days are the essence of "improvisation" in Hindustani music.

9.1.5 Fractal Study on Music Signals

At first sight music shows a complex behavior: at every instant components (in micro and macro scale: pitch, timbre, accent, duration, phrase, melody etc.) are close linked to each other (Di Lorenzo 2002). All these properties (above stated in a heuristic characterization) are peculiar of systems with chaotic, self organized, and generally, non linear behavior. Therefore, the analysis of music using linear and deterministic frameworks seems not to be useful.

Music too, has non-uniform property in its movement (Su and Wu 2006; Telesca and Lovallo 2011). In another recent study (Oświęcimka et al. 2011), multifractal technique has been applied to separate different genres of music based on their multifractal spectral width.

Therefore, the melodic fragments of a raga sung by a musician of HM on different days will produce certain changes in nature of the phrases due to improvisation. It has been shown earlier that fractal dimension calculated from a song is a good measure of the complexity of its notation (Das and Das 2005; Su and Wu 2006). Also earlier studies showed that same song when sung by different performers, the fractal dimension changes (Das and Das 2010). The fractal character is only one of many aspects that define a composition. The human mind may use one or more models of perception in order to determine whether a given melody or musical structure is ugly or beautiful (Beran 2004). Fractal dimensions of time series data might reveal the presence of non-linearity in the art of production mechanism and therefore the complexity of the time sequences of the phrases where the performer have improvised, might vary. These may be reflected through the change in their fractal dimensions. Another major objective of the present study is to see whether fractal dimensions are related to the improvisations made by the artist. Non-linear dynamical modeling for source clearly indicates the relevance of non-deterministic / chaotic approaches in understanding the speech/music signals (Behrman 1999; Bigrelle and Iost 2009; Hsü and Hsü 1990; Sengupta et al. 2001, 2005, 2010). In this context fractal analysis of the signal which reveals the geometry embedded in signal assumes significance. Voss and Clarke (1975) showed that the frequency characteristics of musical signal behave similar to the 1/f noise. Interestingly, this type of noise, called pink noise occurs very commonly in nature (Bak 1996) and it is this noise which sounds most pleasant to the human ear. Some other studies (Su et al. 2008; Boon and Olivier, 2005) applied fractal tools to the pitch variations and revealed irregularities in scaling behavior and long range characteristics. Music data is a quantitative record of variations of a particular quality over a period of time. One way of analyzing it is to look for the geometric features to help towards categorizing the data in terms of concept (Devaney 1989). Hencefractal analysis would be a good technique to obtain the power exponent that defines the scale invariant structure of the whole signals.

9.1.6 Essence of Multifractal Study on Music Signals

It is well-established experience that naturally evolving geometries and phenomena are rarely characterized by a single scaling ratio; different parts of a system may be scaling differently. That is, the clustering pattern is not uniform over the whole system. Such a system is better characterized as ‘multifractal’ (Lopes and Bertouni 2009). A multifractal can be loosely thought of as an interwoven set constructed from sub-sets with different local fractal dimensions. Real world systems are mostly multifractal in nature. Music too, has non-uniform property in its movement (Su and Wu 2006). In the domain of music analysis, using multifractal detrended fluctuation analysis (MF-DFA) method, frequency series of Bach pitches have been analyzed and multifractality due to long range correlation and broad probability distribution function have been identified (Jafari et al. 2007). In (Su and Wu 2006), the authors show that both melody and rhythm can be considered as multifractal objects by separating both of them as series of geometric points, while in (Demos et al. 2014) the authors use the DFA technique to relate body movements of performers to the expression embedded in it. Live performances encompass a variety of such musical features including tempo fluctuations (Holden et al. 2009), notation and timbre variation to name a few. Several other researchers have used the fractal analysis technique to examine musical movements and musical structure (Das and Das 2006; Patra and Chakraborty 2013; Zlatintsi and Maragos 2013; Rankin et al. 2014). Thus, the multifractal nature of music signals is well established and could prove to be an important tool when analyzing improvisational cues in a specific performance of Hindustani *raga*. In this context, taking the entire signal as a time series for analysis can be interesting as we are considering all the properties as a whole to ratify the multifractal nature of music and to investigate cues which distinctly separates on performance from another.

9.1.7 Multifractal Cross Correlation Study and Its Implications

Detrended Cross-Correlation Analysis (DCCA) was proposed (Podobnik et al. 2008a) to investigate power-law cross-correlations between two simultaneously recorded time series in the presence of non-stationarity. As a generalization of the DFA method, the DCCA is proposed to investigate the long-term cross-correlations between two non stationary time series (Podobnik et al. 2008a, b, 2009a, b, 2011; Xu et al. 2010; Hedayatifar et al. 2011), and Multifractal Detrended Cross-Correlation Analysis (MF-DXA) can unveil the multifractal features of two cross-correlated signals (Zhou 2008; He and Chen 2011; Jiang and Zhou 2011; Wang et al. 2013; Ghosh et al. 2014). The noisy signals in many real-world systems display long-range autocorrelations and these cross-correlations can be accurately quantified with the help of DCCA (Horvatic et al. 2011) technique.

In this chapter, the main aim is to give the readers an insight on to how different linear and non-linear techniques can be utilized to decipher different cues to encapsulate improvisation in Hindustani music. We try to see the presence of multifractality as well as multifractal cross correlations in the music signal of Hindusthani classical music rendered by an eminent maestro. Four such renderings of the same maestro of raga *Sur Malhar* have been taken for analysis. The linear cues for improvisation include duration of pause between notes, duration of notes, total number of pauses, note pattern before and after pause, phrasal patterns, transition among notes etc. In the non-linear domain, our objective is to see the difference in complexity in the four signals though he sung the same raga. The results reveal interesting new information regarding the improvisation cue in Hindustani music which are discussed in detail.

9.2 Experimental Details

9.2.1 Choice of Ragas

Four different renderings of *raga Sur Malhar* by an eminent maestro of Hindustani Vocal Music was taken. The *raga* falls under the broad class *Kafi that*. Three minutes from the portion of *vilambit bandish* part in mid tempo was cut out from each rendering. The signals are digitized at the rate of 22,050 samples/sec 16 bit format. A *Bandish* provides the literature ingredient of the *raga* in each individual rendition for traditional structured singing. The *bandish* part was taken so that the notes used in all the renderings are same and hence the changes in musical structure will be mainly due to the improvisations made by the artist. Also, the artist makes his own improvisations in the *raga* predominantly in the *bandish* part. Each three minutes signal is divided into six equal segments of 30 s each. This was done to see the change of complexity in each time window for each song. Part 1 of all the four signals which were analyzed for multifractality have been plotted in the following Fig. 9.1a–d.

9.3 Methodology

Each of the music clips have been analyzed with the help of MFDFA technique proposed by Kantelhardt et al (2002) to assess the complexity values corresponding to each part. MFDXA technique proposed by Zhou (2008) have also been used to assess the degree of cross-correlation between parts of the same or different clips taken for our analysis. The detailed algorithm for MFDFA and MFDXA techniques are same as given in the Methodology chapter.

For the experiment in the linear domain, Pitch of each signal was extracted using standard software wavesurfer. From the pitch we have detected the notes and the pause parts of each piece of signals. For this we took help of expert musicians to locate and extract the tonic ‘sa’ (Datta et al. 2006). Once the frequency of tonic ‘sa’ is identified, the other notes can be measured using standard shruti ratios. Since all the four signals were sung by a single artist, we can neglect the timbre aspects as a cue for improvisation. From the data so obtained, duration and number of pause between notes, duration of notes, usage of notes between pause and phrasal patterns were measured.

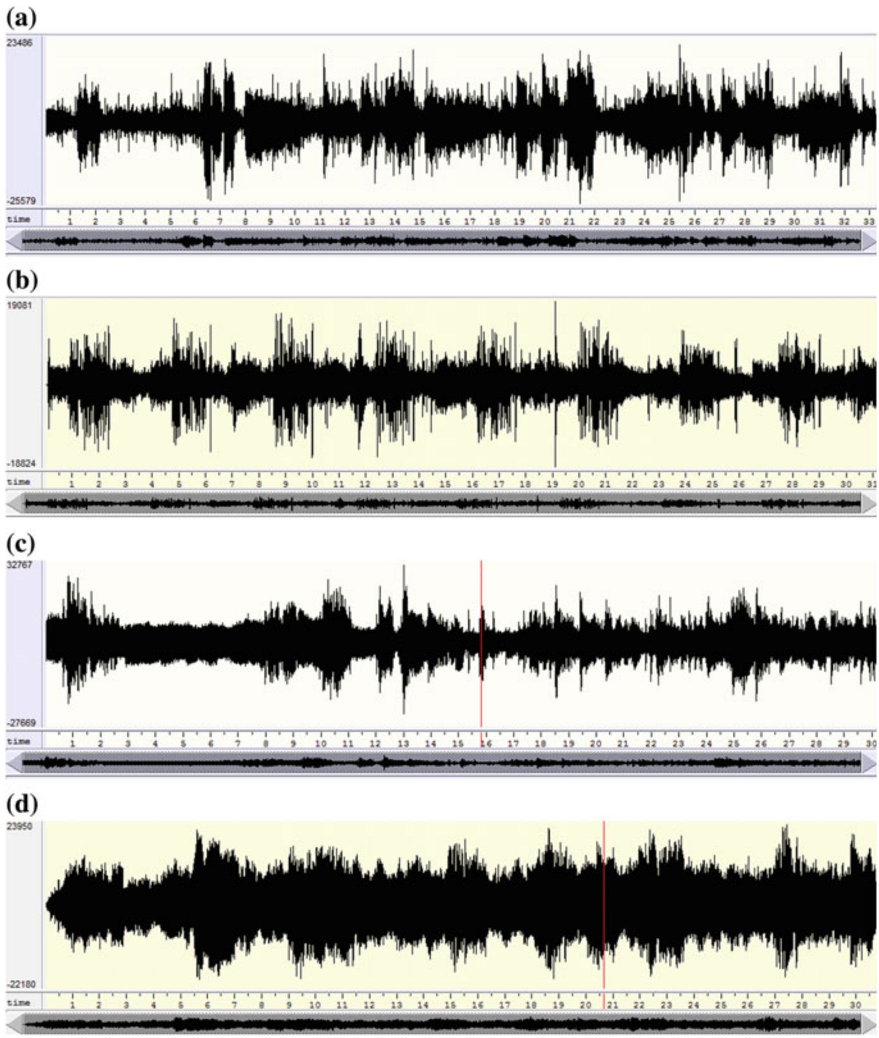


Fig. 9.1 **a** Waveform of 30 s Sample 1, **b** Waveform of 30 s Sample 2, **c** Waveform of 30 s Sample 3, **d** Waveform of 30 s Sample 4

9.4 Results and Discussion

Musical structures can be explored on the basis of multifractal analysis and nonlinear correlations in the data. Traditional signal processing techniques are not capable of identifying such relationships, nor do they provide quantitative measurement of the complexity or information content in the signal. Music signals can therefore generate fluctuations that are not best described by linear decomposition (Jennings et al. 2004). On the other hand, the classical nonlinear dynamics method such as correlation dimension and Lyapunov exponents are very sensitive to noise and require the stationary condition.

Every musical composition/element can be considered as a nonlinear complex time series—the multifractal width (w) being a quantitative measure of its complexity. In other words, more w—more local fluctuations in temporal scale and thus this parameter is very sensitive to characterize and quantify a particular music signal to a level which is not possible with any other method. In a similar manner, small w implies less local fluctuations in temporal scale. Thus, similar w means that the two musical signals have similar complexity (or same local fluctuations) in the temporal scale. Hence, multifractal spectral width can be considered as the best parameter for the characterization of a music sample. In this paper we verify the presence of multifractality in the same musical signals sung in four different days by an eminent vocalist. For this, we have taken 3 min from the *bandish* part of the rendering by the vocalist. The vocalist has rendered the same raga (Sur Malhar) in four different days. Since the raga is same, the notes and the phrases are same, though the vocalist and the raga rendered are same but there should be some difference in the phrasal structure. Hence, we have divided the 3 min song signal into six equal segments and studied mutifractality using MFDFA technique in all the segments for all the signals. Each of the 30 s segment was divided into 5 windows of 6 s each and the average multifractal width has been given in Table 9.1 along with the variance.

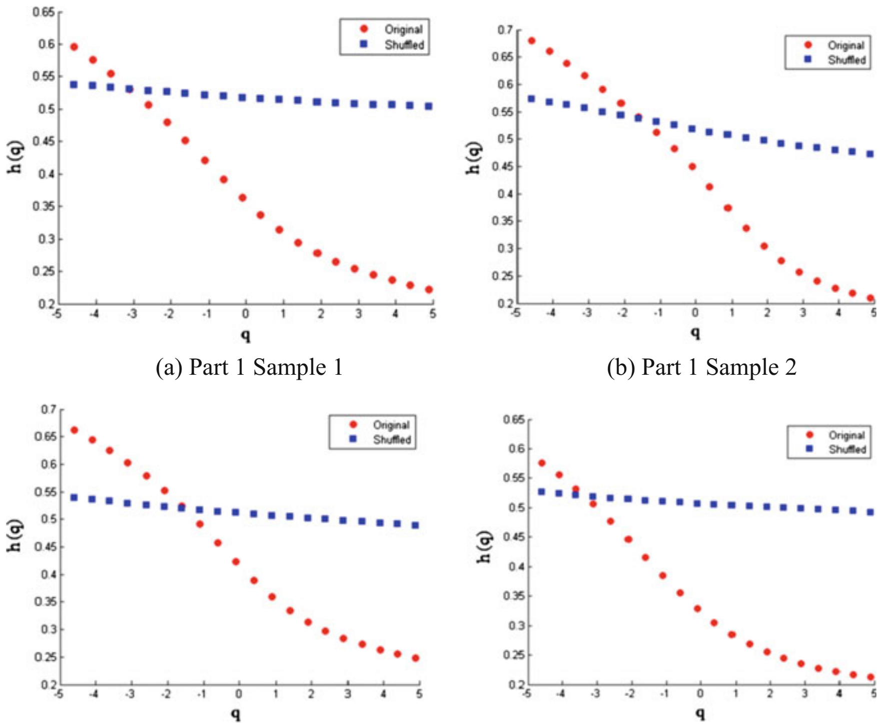
For a monofractal time series we get unique value of $h(q)$ for all q. If the small and large fluctuations scale vary differently, then $h(q)$ will depend on q or in other words the time series is multifractal. A representative figure for variation of $h(q)$ with q for a particular part of each signal for four different music signals have been shown in Fig. 9.2a–d. The shuffled values of $h(q)$ has also been shown in the same figure. The following representative figures show the variation of Hurst exponent $h(q)$ with q for the Part 1 of the four samples:

The variation of $h(q)$ with q clearly indicates multifractal behavior, the shuffled values showing remarkable difference from that of the original values. It is also evident from Fig. 9.2 that in all cases the values of $h(q)$ decreases with increasing q. Also, the shuffled values of $h(q)$ remains constant with the change of q, which is a characteristic of a monofractal scaling.

The amount of multifractality can be determined quantitatively in each of the windows of each signal from the width of the multifractal spectrum [$f(\alpha)$ vs α]. The multifractal nature of the scaling properties can be depicted by the multifractal spectrum $f(\alpha)$ versus α as shown in Fig. 9.3a–d. The multifractal spectrums were then fitted to eqn. 8 and the multifractal widths were obtained for all parts of the four samples. To ascertain the origin of multifractality the corresponding randomly shuffled series was also analyzed. The randomly shuffled series exhibits weaker multifractality indicating that the origin of multifractality is due to both long range correlations and broad probability distribution. In an ideal case, for a sufficiently long series the shuffled series would have monofractal properties when the randomly shuffled series has smaller width as compared to the original series. Figure 9.3a–d is a representative figure which shows that in Part 1 of all the four signals, the shuffled series $f(\alpha)$ versus α has a weaker

Table 9.1 Variation of multifractal spectral width in the four samples

Part no.	Sample 1		Sample 2		Sample3		Sample 4	
	Spectral width ($W_{original}$)	Shuffled ($W_{shuffled}$)	Spectral width ($W_{original}$)	Shuffled ($W_{shuffled}$)	Spectral width ($W_{original}$)	Shuffled ($W_{shuffled}$)	Spectral width ($W_{original}$)	Shuffled ($W_{shuffled}$)
1	0.733 ± 0.08	0.187	0.577 ± 0.07	0.107	0.370 ± 0.03	0.084	1.158 ± 0.08	0.076
2	0.645 ± 0.04	0.111	0.579 ± 0.05	0.080	0.482 ± 0.08	0.072	0.531 ± 0.05	0.048
3	0.587 ± 0.06	0.084	0.467 ± 0.06	0.110	0.521 ± 0.07	0.104	0.378 ± 0.04	0.0710
4	0.555 ± 0.07	0.077	0.443 ± 0.02	0.083	0.565 ± 0.06	0.098	0.495 ± 0.06	0.071
5	0.811 ± 0.13	0.242	0.558 ± 0.05	0.112	0.738 ± 0.05	0.080	0.270 ± 0.06	0.076
6	0.758 ± 0.08	0.072	0.639 ± 0.11	0.065	0.440 ± 0.07	0.115	0.380 ± 0.03	0.081



(a) Part 1 Sample 1

(b) Part 1 Sample 2

(c) Part1 Sample 3

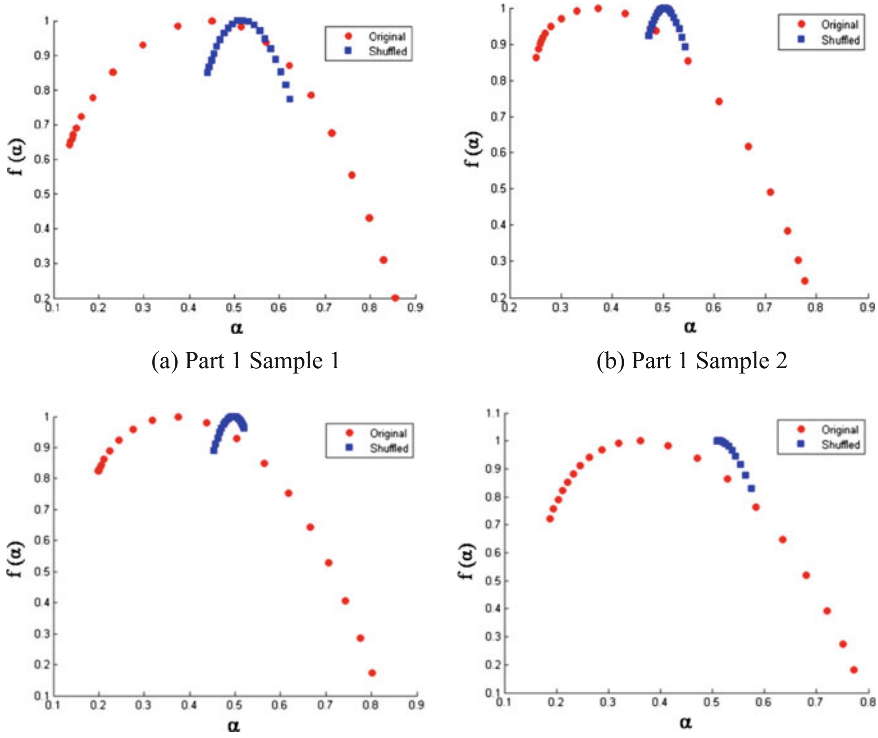
(d) Part1 Sample 4

Fig. 9.2 The variation of Hurst exponent for Part 1 of the 4 samples

multifractality as compared to the original signal. The same trend is observed in all the other parts of the four samples. The destruction of all long range correlations in the data makes the shuffled series monofractal in nature. Ideally f(α) should be independent of α. Since the data size is quite large in this case, the inference drawn from the results are reasonably significant and the difference in means is also relevant statistically as affirmed later by ANOVA and subsequent post hoc tests. Table 9.1 gives the values of mean multifractal spectral width for the six different parts of the four samples along with their Standard Deviation (SD) values computed analytically from the different parts of the same sample. The shuffled widths are also given in the adjacent column.

The variation of multifractal width for the 1st parts of the four music signals (both original and shuffled) is shown in a representative Fig. 9.4. The blue graphs give the randomly shuffled width. As is evident from the figure, the shuffled width ($W_{shuffled}$) in all cases is much smaller than the original width ($W_{original}$). This confirms that the multifractality in the music signal is due to both broad probability distribution as well as long range correlation.

Analysis of the values show that though the artist have sung the same raga having the same phrasal structure, still all the six parts for all the four signals show remarkably different values of multifractal spectral width. This difference is can be

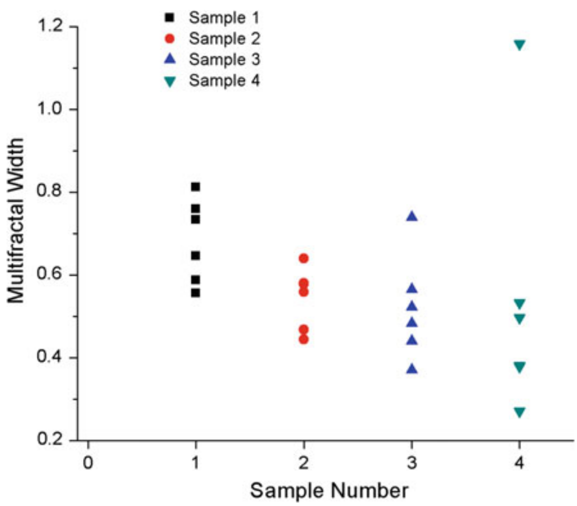


(a) Part 1 Sample 1 (b) Part 1 Sample 2

(c) Part1 Sample 3 (d) Part1 Sample 4

Fig. 9.3 f(α) versus α plot showing the original data as well as randomly shuffled data

Fig. 9.4 Variation of multifractal width within each sample



attributed to the change in the duration of notes, note to note transitions and the variation in the use of pauses within the phrasal structure. Thus, we can say that there is a change in amount of multifractality when the rendering of same raga music was on different days by the same vocalist. This may be caused due to the musical improvisation done by the singer on each day which singing the same raga. The audience is pleased on all the four days when the performer creates different mood or ambience while singing the same *raga*, in spite of the different modulations made by the artist keeping in mind the demand of the audience.

Apart from studying the variation of multifractality in different renditions, it will also be interesting to study the change of multifractal values in different parts within each sample. In that respect, Fig. 9.4 gives the variation of spectral widths in the various parts of each of the four samples.

As is evident from the figure, there is considerable variation multifractal width within different parts of the same sample. Thus there is significant variation of complexity in musical structure even in the same musical signal, for e.g. in Sample 4 the spectral width varies from as low as 0.27 to as high as 1.15. Such a large variation in complexity within different parts of the same sample can be ascribed to varying emotions conveyed to the audience by the artist during the performance. It can also be ascribed to the varying style of rendition of the same *raga* in different days which has led to the significant difference in their complexity.

One Way ANOVA (Coakes and Steed 2009) was performed to test the significance of the results obtained in Table 9.1. The six parts of four samples were analyzed with the help of ANOVA technique. The significance level was set to $p < 0.05$. Post hoc analysis in the form of Tukey's HSD test was performed only if ANOVA results were significant between the groups. The ANOVA results are elaborated in Table 9.2. All the tests were performed with 95% confidence intervals between the parts analyzed.

Tukey-Kramer multiple comparison tests were performed for Parts 2–6 which yielded significant results in the one way ANOVA tests. The results of post hoc analysis are reported in Table 9.3. Sample 1 versus 2 and Sample 2 versus 4 were reported to be highly significant in all the parts, while Sample 1 versus 3 and Sample 3 versus 4 reported to be mostly significant. Except with a few spurious aberrations, we can say that the means of the reported data varied significantly within themselves as well as within groups.

Next, MFDXA was performed for each part between all the samples using the methodology given above. All the data sets were first transformed according to relation 2 to reduce noise in the data. The integrated time series were then divided to Ns bins where Ns = int (N/s), N is the length of the series. The qth order detrended covariance Fq(s) was obtained from relations 3 and 4 for values of q from −5 to +5 in steps of 1 just like the MFDFA part. The values of cross correlation coefficient γ_x ($q = 2$), are provided in Table 9.4. We have also shown variation of $h(q)$ with q for Part 1 of the four clips by means of MF-DFA in Fig. 9.1. The plot depicts multifractal behavior of cross-correlations because for different q, there are different exponents; that is, for different q, there are different power-law cross-correlations. Further from the same figure we can see that the value of $H(q)$ depends on q for all the four samples that we have taken in this study.

Table 9.2 ANOVA values for the different parts of music samples

Parts of music sample		Part 1		Part 2		Part 3		Part 4		Part 5		Part 6	
Source	df	F	p	F	p	F	p	F	p	F	p	F	p
Treatment (between experimental conditions)	3	0.43	0.736	11.5	0.001	25.54	<0.001	4.58	0.032	25.99	<0.001	10.04	0.003
Residual (within experimental conditions)	9												
Total	12												

df degrees of freedom

Table 9.3 Tukey-Kramer multiple comparison test results

Part 2			
Comparison	Mean difference	q	p-value
Sample 1 vs 2	14.45	12.546	<0.001
Sample 1 vs 3	2.53	4.587	<0.0448
Sample 1 vs 4	1.96	2.1688	0.0979
Sample 2 vs 3	4.78	7.956	<0.0031
Sample 2 vs 4	12.35	10.378	<0.001
Sample 3 vs 4	1.34	2.419	0.228
Part 3			
Sample 1 vs 2	18.8	12.51	<0.0001
Sample 1 vs 3	15.76	11.33	<0.0001
Sample 1 vs 4	6.42	6.2125	<0.002
Sample 2 vs 3	4.93	9.104	0.003
Sample 2 vs 4	19.24	9.901	<0.0001
Sample 3 vs 4	8.42	7.337	<0.0065
Part 4			
Comparison	Mean difference	q	p-value
Sample 1 vs 2	6.92	9.4027	0.0004
Sample 1 vs 3	7.3	6.4988	0.002
Sample 1 vs 4	1.58	2.218	0.16
Sample 2 vs 3	4.85	6.904	0.0029
Sample 2 vs 4	12.85	7.1849	<0.0001
Sample 3 vs 4	7.19	9.712	0.0003
Part 5			
Comparison	Mean difference	q	p-value
Sample 1 vs 2	7.19	8.8636	0.0004
Sample 1 vs 3	4.04	6.663	0.0397
Sample 1 vs 4	2	2.3495	0.092
Sample 2 vs 3	5.23	5.9675	0.0119
Sample 2 vs 4	7.45	6.5138	<0.0003
Sample 3 vs 4	4.82	4.636	0.063
Part 6			
Comparison	Mean difference	q	p-value
Sample 1 vs 2	10.44	11.23	<0.0001
Sample 1 vs 3	4.24	6.46	<0.037
Sample 1 vs 4	3.24	3.81	0.048
Sample 2 vs 3	4.75	7.37	0.003
Sample 2 vs 4	11.18	9.426	<0.0001
Sample 3 vs 4	2.32	3.87	0.059

We know that $H(q) = 0.5$ indicates that the series is an independent random process, and for $H(q) < 0.5$ it is characterized by long-range anti-correlations while for $0.5 < H(q) < 1$, it is featured by long-term correlations. In this case the signal is

Table 9.4 Cross correlation coefficient (γ_x) for various combinations

Cross correlation coefficient (γ_x)						
	Sample 1–Sample 2	Sample 1–Sample 3	Sample 1–Sample 4	Sample 2–Sample 3	Sample 2–Sample 4	Sample 3–Sample 4
Part 1	0.092 ± 0.09	0.279 ± 0.02	0.017 ± 0.04	0.167 ± 0.03	1.345 ± 0.09	0.263 ± 0.06
Part 2	0.133 ± 0.05	−0.700 ± 0.17	−0.487 ± 0.05	−0.515 ± 0.05	−0.963 ± 0.13	−0.472 ± 0.03
Part 3	−0.396 ± 0.04	−0.276 ± 0.04	−0.356 ± 0.07	−1.081 ± 0.14	−1.349 ± 0.08	−1.021 ± 0.11
Part 4	−0.055 ± 0.07	−0.025 ± 0.06	−1.122 ± 0.16	0.235 ± 0.07	−0.083 ± 0.04	0.579 ± 0.07
Part 5	1.612 ± 0.03	−0.330 ± 0.05	−0.833 ± 0.09	0.509 ± 0.06	0.709 ± 0.05	0.282 ± 0.04
Part 6	0.605 ± 0.08	0.232 ± 0.09	0.163 ± 0.04	−0.430 ± 0.03	0.016 ± 0.07	−0.118 ± 0.06

Fig. 9.5 Variation of $\lambda(q)$ and $h(q)$ for two sound signals

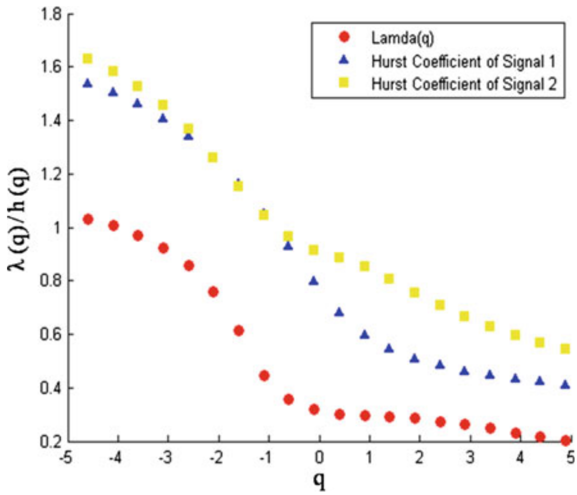
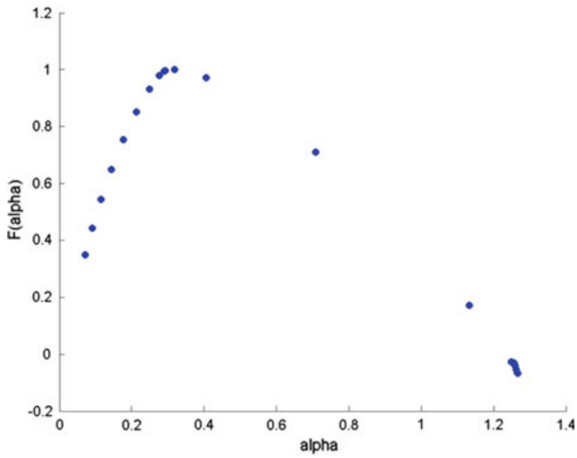


Fig. 9.6 Multifractal cross-correlated spectrum of Sample 1 and 2 (Part 1)



stationary. The exponent $H(q = 2)$ is equivalent with the well-known Hurst index. A representative figure (Fig. 9.5) reports the variation of cross correlation exponent $\lambda(q)$ with q for two particular samples (Part 1 for Sample 1 and Sample 2), also the variation of $h(q)$ with q for those two samples obtained from MFDFA technique are also shown in the same figure for comparison.

The variation of $\lambda(q)$ with q for the two cross correlated signals (Part 1 for Sample 1 and Sample 2) show that they are multifractal in nature. To illustrate further the presence of multifractality in the cross-correlated music signals, i.e. to have information about the distribution of degree of cross-correlation in various time scales, a representative multifractal spectrum was plotted for the two signals in Fig. 9.6. The way to characterize multifractality of cross correlation between two samples is to relate via a $\lambda(q)$ Legendre Transform as in the case of single series (Feder 2013). The growth of the width of $f(\alpha)$ or equivalently $\Delta\alpha$ shows the increase

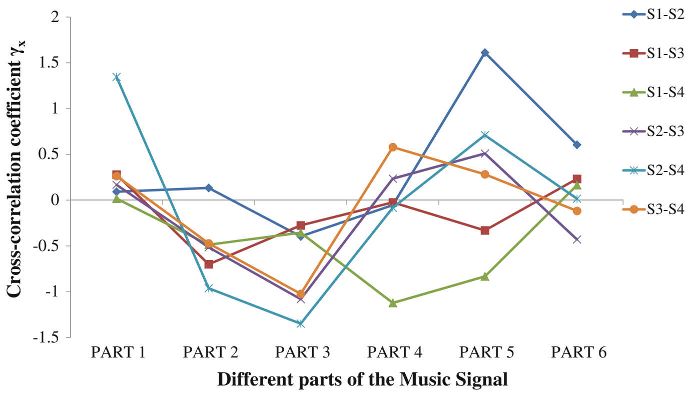


Fig. 9.7 Variation of cross-correlation coefficient among different samples

in degree of multifractality of the coupled signals. Again, it becomes evident from the spectrum that the cross correlated signals are multifractal in various time scales.

Jones and Kaul (1996) were the first to reveal a stable negative cross-correlation between oil prices and stock prices. The negative cross-correlations were also found by Refs (Chen et al. 2009; Berument et al. 2010; Reboredo et al. 2014). A negative value of cross correlation is an indication of strong cross-correlation between the two samples for which the cross correlation is being carried out. The cross correlation exponent γ_x reported in Table 9.4 along with the corresponding SD values. MFDXA was carried out amongst six parts of all the four signals taken for analysis. Figure 9.7 depicts the variation of cross correlation coefficient among the various parts of the 4 music signals, S1, S2… denote Sample Numbers in the Figure.

As is evident from the figure, strong cross-correlation is observed in Parts 2, 3 and 4 for almost all the samples i.e. for these parts the value of γ_x is negative for all the cases. Part 1 as well as the last two parts (Parts 5 and 6), in general do not have

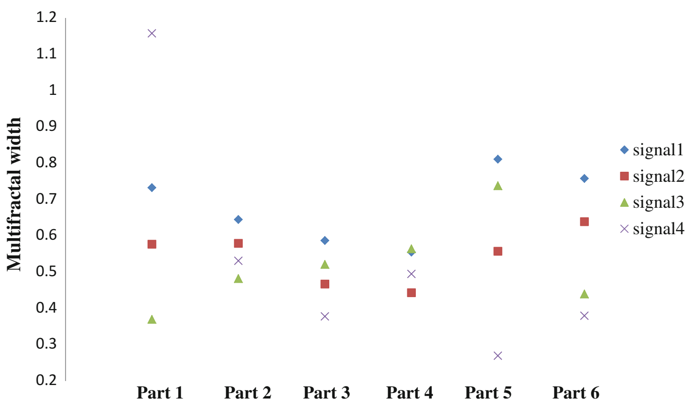


Fig. 9.8 Variation of multifractal spectral widths in different parts of the four samples

strong cross-correlation between them as is evident from the positive values of γ_x. The four renditions of the same raga are different from one another due to the variation of note-to-note sequences, interval between notes and other modulating factors which corresponds to the “improvisational modulation” made by the artist during each and every rendition. Thus we may hypothesize that the artist has made variation in the rendition of the raga in those parts for which we are not getting any strong cross correlation, in this case especially in Part 1 while to some extent in Parts 5 and 6. Every rendition of the raga is different and unique as it embodies elements of the musician’s vision, as well as his interpretation and this uniqueness might be manifested in those parts which do not have strong cross correlation coefficient among one another.

Further, the multifractal width (obtained from MFDFA technique) of the different parts of the four samples has been plotted in Fig. 9.8.

It is clearly observed from the figure that Parts 1, 5 and 6 of all the signals have varied multifractal width showing that the signals are quite different in complexity in those time windows. For other parts of the four signals, i.e. Parts 2–4, the multifractal widths form a cluster i.e. their spectral widths are almost same, depicting similar complexity. We can therefore say that the observed fluctuations of the mutifractal width along the music sequences confirm the non-uniformity feature in the structures of melodic and rhythmic motions of music. In Parts 2–4, the multifractal widths are almost of the similar order for all the four signals studied, implies that the local fluctuations are comparable for these. This in turn substantiates our notion that the pattern of rendition in these parts mostly remains similar and the performer has stuck to the protocol during these parts. While in Parts 1, 5 and 6 the multifractal widths (and hence complexity of the signal) have shown considerable variation implying that the vocalist has made a number of subtle improvisations in the *raga* which has lead to the huge variety in the complexity patterns of these parts. This curve of mutifractal width characterizes the melodic as

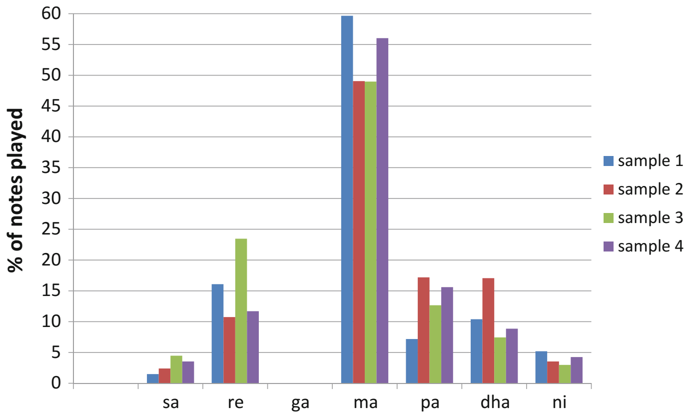


Fig. 9.9 % of notes played by the artist

well as the rhythmic phrasal patterns of music in different time windows. Thus, it is evident multifractal width can be used as parameter with which it may be possible to characterize and quantify improvisational cues in Hindustani music performances.

In the linear domain, Fig. 9.9 shows the % use of notes by the artist in his four raga renderings.

It clearly indicates that there is no definite rule in using notes for the raga in Hindustani music (HM). Artist improvised his performance in every raga. Here we can definitely say that the artist's most preferable note for this raga is 'ma'. Notes 'sa' and 'ni' were least sung by the artist. If the peaks of each note are joined by a line then we will find that the nature of the curves for the four ragas is similar and hence the use of notes is almost similar in all the four ragas. We also measured the total number of notes along with the number of cycles (number of phrasal patterns repeats within the time frame). Artist used 404, 791, 537 and 282 notes within the time three second along with cycles of phrases 26.1, 34.4, 27.5 and 20.1. This gives the information about tempo. So, tempo is directly proportional to the number of cycles. It was found that Sample 2 shows the highest tempo while Sample 4 is of slowest tempo. Tempo of Sample 2 is slower than Sample 3. Hence it can be safely said that the artist used his liberty to improvise his every performance in terms of tempo or rhythm, usage of notes and also the uses of sequence of notes.

Meend is the transition between two notes with a sliding tone. It is an essential and integral part of HM that gives the essence of HM which is strictly prohibited in western music (Datta et al. 2009). We measured *meend* used by the artist for the whole signal. Along with this, we also measured the % of ascending *meend* (AM) which means the sliding from lower note to higher note and % of descending *meend* (DM) which means the sliding from higher note to lower note. Table 9.5 gives the percentage use of AM and DM in the four experimental samples.

From the table we find that there is very little difference in AM and DM for four signals when measured for the whole signal at a time. Such difference cannot play any significant role in discussing about improvisation in performance. So we extended our study further and measured the % use of *meend* between two successive notes (like sa ⇔ re, ma ⇔ pa, etc.), between two alternate notes (like sa ⇔ ga, ma ⇔ dha, etc.), between 2 jump note (like sa ⇔ ma, ma ⇔ ni, etc.), between 3 jump notes (like sa ⇔ pa, ma ⇔ sa, etc.) and between 4 jump notes (like sa ⇔ dha, ma ⇔ re, etc.). Artist has an unique preference of using *meend* between successive notes and alternate notes. *Meend* between higher orders notes were rarely used (none found for Sample 1 and 2). *Meend* patterns are different for the four signals and hence can be considered as an important cue for improvisation in musical performances.

Figure 9.10(a–d) shows the relationship of the ratio of duration of pause to the duration of note vs. number of notes.

The pause to note ratio can be considered as a cue for evaluation of tempo of a rendition. From the distribution of Sample 1, it is seen that the artist hardly used long pause between notes, whereas artist used frequent short durational pause and hence tempo was slow. Distribution for Sample 2 shows that the artist used a few

Table 9.5 Percentage use of Ascending *meend* and Descending *Meend*

	Overall meend		Meend between successive notes		Meend between alternate notes		Meend between 2 jump notes		Meend between 3 jump notes		Meend between 4 jump notes	
	% of AM	% of DM	% of AM	% of DM	% of AM	% of DM	% of AM	% of DM	% of AM	% of DM	% of AM	% of DM
Sample 1	50.82	49.18	21.31	29.51	24.59	13.11	4.92	6.56				
Sample 2	54.10	45.90	27.05	29.51	22.95	15.57	4.10	0.82				
Sample 3	57.65	42.35	31.76	23.53	11.76	10.59	5.88	3.53	5.88	3.53	2.35	1.18
Sample 4	55.56	44.44	38.89	16.67		22.22	5.56	5.56	11.11	0.00		

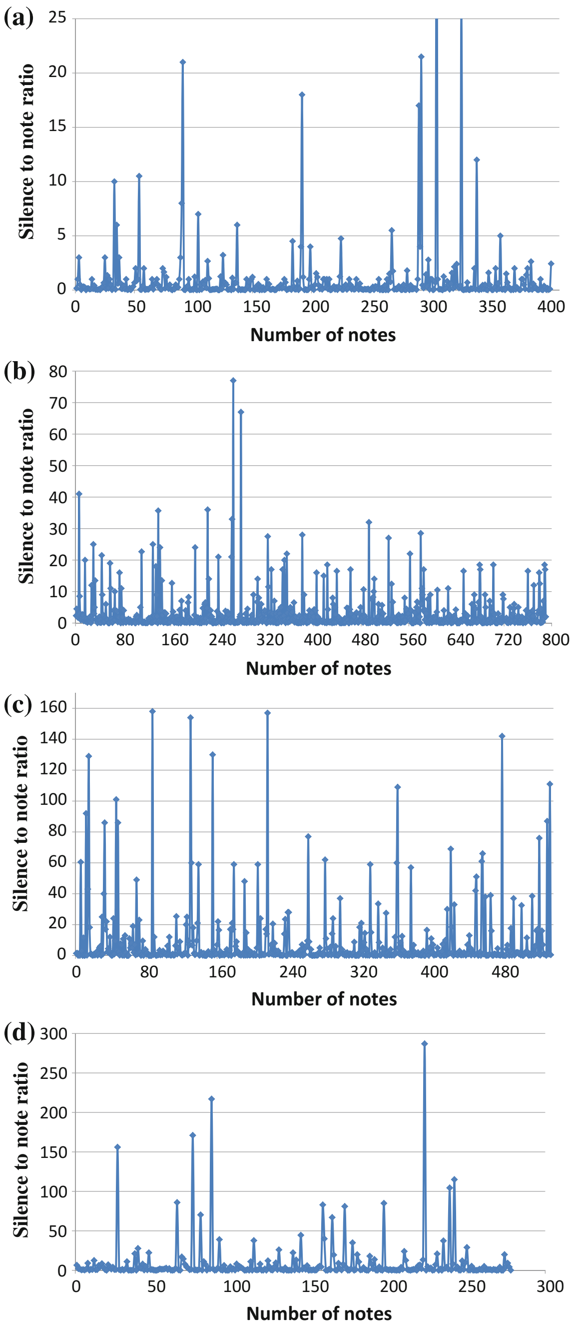


Fig. 9.10 **a** Pause to note ratio for Sample 1, **b** Pause to note ratio for sample 2, **c** Pause to note ratio for sample 3, **d** Pause to note ratio for sample 4

long pauses between notes, but here artist also resorted to lesser number of short durational pause compared to the others and hence the tempo of the rendering was faster. But the distribution for Sample 4 shows that the artist used maximum number of long durational pause between notes and so this is the signal with lowest tempo. In Sample 3, artist also used considerable number of long durational pause. From all the four distributions we can observe that no definite rule of using pause between notes is there in HM, rather artist have complete liberty to use pause as they wish or needed as per extracting the perfect essence and mood of the raga.

With the help of different rigorous non-linear techniques we have thus studied the variation of complexity of musical structure in different portions of *bandish* of a raga and the results show that complexity varies appreciably within the same performance as well as within different performances. A high value of cross correlation coefficient γ_x signifies those portions of the *raga* which are strongly correlated i.e. they are bound by a tight framework of notes, note sequences etc., while the less correlated portions are those where the artist improvises and shows his uniqueness. In the linear domain also, a number of interesting features were studied in this chapter which further reinforces the concept of improvisation in Hindustani music. We have therefore provided an innovative mean to disclose the intrinsic property of Hindustani music called improvisation.

9.5 Conclusion

"Improvisation" refers to those elements of a musical performance which are generated spontaneously by the performer. Even during the performance of a musical composition, there will be some elements that are not pre-conceived, which will become the amazement factor for the audience. Examples of such improvisation can be variations in different parts of the *raga* added by the performer during the course of performance. Hindustani classical vocal music stands apart as one of the more difficult vocal forms, wherein the artist acts both as composer as well as singer; improvising at every instant during the performance. Improvisation is crucial and indispensible feature of Indian Classical Music which depends upon the imagination, originality and ingenuity of a particular vocal artist. Keeping within a fixed framework of the *raga,* a musician makes variation in the scansion of the lyrics over the period of rhythm as well as in the intricate details of the melodic structure. This is the essence of improvisation in Hindustani classical music, whose cues can only be identified with rigorous nonlinear techniques; such as MFDFA or MFDXA. The work leads to the following interesting conclusions:

1. MFDFA performed on the four vocal musical performances (in a 30 s window) by the same artist based on the same *raga* show clear evidence of multifractal nature. This multifractal nature of music signals may be coming from the multidimensional nature of music. The origin of multifractality in the music signals can be ascribed to the presence of long range correlation and broad

probability density function as confirmed by randomly shuffling the original data. The presence of long range temporal correlations in music signal may be the cause why it sounds pleasant to the human ear and the reason why it is a source of delight for people throughout the Globe.

2. The multifractal widths (obtained from MFDFA technique) show significant variation for different samples. But, we have found a clustering area which consists of Parts 2, 3 and 4 for each sample, where the values of multifractal widths are more or less close to each other indicating close proximity of temporal fluctuations and complexity features of all the signals in these parts. We thus hypothesize, that these are the parts where the four different renditions are quite similar to one another and the performer is following the rigid framework of notes to establish the *raga*.
3. In Parts 1, 5 and 6 the multifractal widths (obtained from MFDFA) for each of the sample are considerably different from one another; i.e. the complexity features of the signal are greatly different. We hypothesize these portions as the "improvisation" part which makes each rendition unique from the other even though they have the same characteristic of that particular *raga* (here Sur Malhar). Each unique rendition is able to create a different mood or ambience in which the audience is captivated because of the improvisation part. The performers use his/her own artistic experience and tradition to improvise and reinvent each individual performance in a new light.
4. Multifractal Detrended Cross Correlation Analysis (MFDXA) was done between the different samples for specific parts to ascertain the degree of cross correlation (in the form of cross correlation exponent, γ_x) among the signals. The results corroborated our previous findings and strong correlation was noted for Parts 2, 3 and 4 in case of all the possible combinations of correlation between samples. Other parts showed varying degree of cross correlation. Thus, it can be concluded that those parts which are strongly cross correlated are the parts which are alike one another and those parts which are not strongly correlated (but also not anti-correlated) are the parts in which improvisation takes place.
5. Note patterns before onset and after offset of phrasal patterns do not change from one rendition to other. Number of notes used by the artist is another important cue. This reflects the preference of artist's stress on a particular note or notes. This also could be treated as the style of the artist. Ratio of pause duration and non-pause duration reflects the tempo of the rendering and an important cue of improvisation. The sliding pattern (*meend*) between notes also changes among different renditions. These features are the key that an expert musician keeps on changing from one performance to another as per the then mood of the artist and his surroundings. Also some parameters like stress on note, stress on silence etc. can be the cue of style of the artist

Thus, with the help of rigorous latest nonlinear analysis techniques (MFDFA and MFDXA), we have proposed an automated algorithm with which one can identify the improvisational cues in a performance. MFDFA technique is by far the most suitable method—where in the measurement of ‘*w*’ (the multifractal spectral width), ideas of complexity and determinism are reintroduced and embedded. This method exhibits its novelty to use ‘*w*’ as the cue for improvisation at the deepest level of understanding and measurement. One should note that the multifractal width of the cross correlated signals (obtained from the MFDXA technique) can show signs of improvisation, but the cross correlation exponent (used in this study) is a more rigorous parameter for the assessment of improvisation. A naïve listener, who can recognize the changes in different performance perceptually, will now be able to conclusively identify the improvisational cues in each performance. Several linear features have also been studied in this context which can also be categorized as important improvisational cues in Hindustani music performances. From the performer’s point of view, this study will help the performer to have a quantitative assessment of his improvisation. This in turn will help in the popularization of Hindustani classical music. We conclude emphasizing that the importance of this study in application area for cognitive music therapy is also immense. As we near the end of this book, the need arises for exploring new and novel methods for feature extraction from raw EEG signals. The next chapter introduces three unique features of EEG viz. neural jitter, shimmer and neural pitch. These features have been utilized in a number of studies in the acoustic domain but, in the neural domain, for the first time they have been applied in the next chapter.

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Chapter 10
Neural Jitter-Shimmer and Extraction of Pitch from EEG Signals

When I was dealing with cancer, I was working on a book about finances.
I realized that the same methodology that the doctors were using to cure me,
you could use to cure your finances.
Health and wealth are so linked, it's amazing.

—Hill Harper

10.1 Introduction

The Electroencephalography (EEG) signal is a temporal record of the complex neuronal fluctuations arising from different locations of the human brain. In the last few decades there have been extensive research to extract emotional attributes from EEG signals as they provide specific features in regard to specific emotional state of a person (Liu et al. 2010; Wang et al. 2011; Petrantonakis and Leontios 2014; Liu and Sourina 2014). Emotion is defined as "a complex set of interactions among subjective and objective factors, mediated by neural/hormonal systems, which can give rise to affective experiences such as feelings of arousal, pleasure/displeasure" (Mulligan and Scherer 2012). Music is considered to be a very important aspect of music research because of its ability to induce "emotional powers" i.e. expression of a wide variety of emotions in humans (Juslin and Laukka 2004; Juslin and Västfjäll 2008). This complex set of interactions can be assessed with the help of a variety of linear as well as non-linear EEG features such as power spectral features (Sammler et al. 2007; Trainor and Schmidt 2003; Logeswaran and Bhattacharya 2009), wavelet transform (Murugappan et al. 2010), Support Vector Machine (Lin et al. 2008), entropy features (Duan et al. 2013), neural network (Chai et al. 2010) as well as fractal dimension based methods (Sourina and Liu 2011; Sengupta et al. 2016; Banerjee et al. 2016). Chapter 3 in this book deals with how emotional cues arising from Hindustani music stimuli can be quantified with the application of scale-free fractal techniques; in this chapter we make use of the same music stimuli and analyze the EEG signals with few

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novel techniques—such as neural jitter/shimmer and estimation of fundamental frequency, which have long been used for speech/music signal analysis.

10.1.1 Application of Jitter/Shimmer and Pitch in Speech and Music Analysis

Acoustic jitter and shimmer are measures of the cycle-to-cycle variations of fundamental frequency and amplitude, respectively, which have long been used for the description of pathological voice quality in a number of studies (Farrús 2007; Gelfer and Fendel 1995; Teixeira et al. 2013), while a few studies deal with emotional classification of speech using these features (Li et al. 2007; Yacoub et al. 2003; Casale et al. 2008). Jitter and shimmer are commonly measured for long sustained vowels, and values of jitter and shimmer above a certain threshold value are said to be related to pathological voices, which are perceived by humans as breathy, rough or hoarse voices (Brockmann et al. 2008; Wolfe et al. 1995; Dejonckere et al. 2001). Brockmann et al. (2008) reported that significant differences can occur in jitter and shimmer measurements between different speaking styles, especially in shimmer measurement. Jitter is a measure of vocal stability and for normal voices, the jitter value for normal voices are less than 1%. Vocal shimmer is same as frequency perturbation, but analogous to amplitude where amplitude perturbation or vocal shimmer serves as an index of vocal stability. Excessive shimmer in any voice is a measure for the perception of hoarseness. A mean cycle-to-cycle amplitude difference of 0.7 dB or variation of less than 7% of mean amplitude is normal. Jitter is affected mainly because of lack of control of vocal fold vibration and shimmer with reduction of glottic resistance and mass lesions in the vocal folds, which are related with presence of noise at emission and breathiness (Slyh et al. 1999). In depth studies on jitter and shimmer was also done in case of Hindustani classical music signals (Sengupta et al. 2000, 2001, 2003, 2007). In all these studies it was observed that jitter and shimmer are significantly less in case of non singers compared to the singers. In case of Tanpura also, jitter and shimmer are less compared to human voice. Also there is no correlation of jitter and shimmer with pitch. Classification of tanpuras could be done by studying their jitter and shimmer and complexity perturbations. In case of Harmonium, jitter is negligible but shimmer is comparable to those found in human speech. No correlation was found for jitter with respect to pitch in harmonium.

Pitch is the perceptual correlate of the fundamental frequency f_0 but perception is not equivalent to measurement. The musical pitch of an audio signal is a perceptual feature, relevant only in the context of a human listening to that signal. f_0 is determined by rate of vocal fold vibration and is often used in voice assessment. According to Behlau (2001), fundamental frequency is determined physiologically by the number of cycles that the vocal folds make in a second, and they are the natural result of the length of these structures. The fundamental frequency f_0 is usually the lowest frequency component, or partial, which relates well to most of the other partials. In the domain of audio signal processing, pitch detection or fundamental frequency estimation has been done in a number of studies where the goal of a f_0 estimator is to find f_0 in the midst of the other harmonically related components of the sound. A number of time-domain methods are used for f_0 extraction which deciphers how often the waveform fully repeats itself working on principle that if a waveform is periodic then there exist extractable time-repeating events that can be counted. Of these, Zero Crossing Rate (ZCR) technique (Hess 2012; Kedem 1986; Roads 1996; Scheirer and Slaney 1997) has been used in a number of studies which essentially computes the number of times waveform crosses zero per unit time. The ZCR has been often accused of computational errors since the speech signals contain a number of higher harmonic which signifies that the waveform might cross the zero line more than twice per cycle. An initial filtering of the higher harmonics is a good way to develop a robust f_0 detector which removes the higher partials, but the threshold frequency needs to be chosen meticulously, so as not to remove the f_0 partial while removing as much high-frequency information as possible. In case of EEG signal analysis, the scenario is not so complex because the sampling frequency of EEG is much lower than that of speech or music signals and hence pitch detection algorithms do not suffer from such drawbacks. In this chapter we make a novel attempt to device a robustalgorithm for automated pitch/fundamental frequency determination for EEG data.

10.1.2 Different EEG Frequency Bands and Their Importance

The complex EEG signals arising from different electrodes of human brain can be transformed to five different frequency bands depending on the correlates of emotion processing:

(i) delta (δ) 0–4 Hz, (ii) theta (θ) 4–8 Hz, (iii) alpha (α) 8–13 Hz and (iv) beta (β) 13–30 Hz and (v) gamma (γ) 30–50 Hz. In the past decades, each frequency band has been related to specific functions, which will be briefly reviewed here for alpha, theta and gamma frequency ranges as these have been found to be most significant in case of emotion appraisal. One of the common indicators of emotional states is the alpha-power asymmetry derived from the spectral differences between a symmetric electrode pair at the anterior areas of the brain (Allen et al. 2004; Schmidt and Trainor 2001). Other spectral changes and brain regions were also reported, which are associated to emotional responses, such as the alpha-power changes at right parietal lobe (Heller 1993; Sarlo et al. 2005, the theta-power changes at right parietal lobe (Aftanas et al. 2004), the frontal midline (Fm) theta power (Schutter et al. 2001), the beta-power asymmetry at the parietal region (Sammler et al. 2007), and the gamma spectral changes at the right parietal regions (Balconi and Lucchiari 2008). Although emotion is one of complex and less-understood cognitive functions generated in the brain and associated with several brain oscillations in combinations (Basar et al. 1999), the aforementioned evidences proved the feasibility of using EEG to characterize emotional states. Recent researches have demonstrated that the modulation of gamma band activity (GBA) in time windows between 200 and 400 ms following the onset of a stimulus is associated with perception of coherent visual objects (Balconi and Lucchiari 2008), and may be a signature of active memory. GBA has also been found sensitive to emotional versus non emotional stimuli and more specifically it was related to the arousal effect: GBA was enhanced in response to aversive or highly arousing stimuli compared to neutral picture. While listening to music, degrees of the gamma band synchrony over distributed cortical areas were found to be significantly higher in musicians than non musicians (Bhattacharya et al. 2001; Bhattacharya and Petsche 2001a, b). Another study reports higher order inter-frequency phase synchrony between delta oscillations in anterior and gamma oscillations in posterior region for musicians. Also, consistent left hemispheric dominance, in terms of the strength of phase synchrony, was observed in musicians while listening to music, whereas right hemispheric dominance was observed in non-musicians (Bhattacharya and Petsche 2005). The gamma band EEG distributed over different areas of brain while listening to music can be represented by a universal scaling which is reduced during resting condition as well as when listening to texts (Bhattacharya and Petsche 2005). Specifically, (Summerfield et al. 2002) have found that gamma activity increases after subjects had been made aware of the stimulus. In this context, it would be interesting to see how the jitter/shimmer characteristics in the EEG domain vary under the influence of same Hindustani music stimuli used in Chap. 3.

10.1.3 Evaluation of Neural Jitter/Shimmer and Extraction of Fundamentals

The EEG time-series signals possess almost the same properties as that of speech/music signals except that they are far less complex due to much lower sampling rate and hence the presence of higher harmonics is much subdued. Hence the standard techniques applicable to speech/music signal analysis must also be applicable for EEG signal analysis for extraction of certain features or characterization of EEG signal. The frequency perturbation in alpha, theta and gamma range has been termed as neural jitter while the analogous feature in the amplitude domain has been termed as neural shimmer. Similar to the case of acoustic signals, using these features we look for some threshold values which will characterize the neuronal cognitive state of consciousness of a subject or a group of subjects. Similarly, using the ZCR technique we have extracted the pitch/fundamental frequency (ies) corresponding to each frequency group of EEG signals. The pitch of an EEG signal may be an characteristic of the individual and the variation of pitch under the influence of any external stimuli could help in the categorization and quantification of emotional cues. The variation of neural jitter/shimmer and fundamental frequency under the effect of musical stimuli has been used in this study as a parameter with which one can categorize and quantify emotional states of listeners. While this is a very specific nature of study using these robust parameters, the authors hope that this would carve the way for a wide vista of studies using these features.

10.1.4 Probability of Occurrence of Fundamentals? Does a Preferred Fundamental Exist?

The EEG signals have been acquired for 10 participants under the influence of two Hindustani music clips of contrast emotions with sufficient rest time in between them as in the protocol described in Chap. 3. For each experimental condition, the fundamental frequency was extracted using the ZCR technique as explained above. The probability of occurrence of a particular fundamental has been computed in the form of a distribution curve plotted for each particular experimental condition. The probability distribution curves revealed that there are certain fundamentals which are more probable in case of rest state while there exists some other fundamentals which are more probable under the influence of specific type of music. This interesting observation leads to another apparent question i.e. whether there exists a preferred fundamental for each and every cognitive task that we perform. We also found the existence of different categories of preferential fundamental frequencies under the effect of emotional Hindustani music.

10.2 Experimental Details

The experimental protocol is exactly the same as that in Chap. 3 and the dataset is also the same. EEG recording was done with two *ragas—Chayant and Darbari Kanada* of Hindustani music for the 5 subjects. From the complete playing of the ragas, segments of about 2 min were cut out for analysis of each raga. Listening test was conducted beforehand with 100 participants to standardise the emotional content of each musical clip. 75% of the participants found Chayanat to be joyful, 80% found Darbari to convey pathos emotion. These findings were corroborated with the brain response data. The drone signal has been used as a baseline over which the emotional arousal corresponding to other musical clips have been taken. The tanpura drone creates a repetitive buzzing sound which helps to create an atmosphere without evoking any specific emotion.

After initialization, a 12 min recording period was started, and the following protocol was followed:

1. 2 min No Music
2. 2 min Tanpura Drone
3. 2 min With Music 1 (Chayanat)

4. 2 min No Music
5. 2 min With Music 2 (Darbari Kannada)
6. 2 min After Music

Markers were set at the start and the end to mark the onset and completion of each experimental paradigm.

10.3 Methodology

In order to eliminate all frequencies outside the range of interest, data was band pass filtered with a 0.5–35 Hz FIR filter. The amplitude envelope of the alpha (8–13 Hz), theta (4–7 Hz) and gamma (30–50 Hz) frequency ranges were obtained using wavelet transform technique The amplitude envelope of the different frequency rhythms were obtained for 'before music', 'with music' as well as 'without music' conditions for total 19 electrodes Fz, Cz, Pz, Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T6. EEG signals have played a crucial role in the domain of music cognition (Maity et al. 2015; Banerjee et al. 2016; Banerjee et al. 2017). The jitter and shimmer components were computed for each of the three frequency ranges followed by the existence of a fundamental. estimation of pitch for alpha and theta frequency range. The probability distribution was also computed for each fundamental frequency obtained from the ZCR technique to get a cue for To simplify the measurements, six electrodes, F3, F4, O1, O2, T3 and T4 i.e. a pair from each lobe was considered for estimation of neural pitch.

10.4 Results and Discussion

The jitter and shimmer values were calculated for each of the experimental conditions as illustrated in the Experimental Protocol Section. The neural jitter computed showed very little variance across the six different experimental conditions; the variance occurring mostly after the fourth places of decimal. So we can safely assume that there is negligible or almost no change in the neural jitter values under the effect of various stimuli, and therefore it can be considered as a source characteristic. The neural shimmer values, however showed significant changes under the effect of different emotional stimuli and could prove to be a robust parameter for categorization and classification of perceived musical emotions. In the following figures (Figs. 10.1, 10.2, 10.3, 10.4, 10.5 and 10.6) the variation of neural shimmer values have been plotted for different frequency ranges under the effect of a particular stimuli and also what happens after the removal of that stimuli. The after stimulus part have been incorporated to have a look at the retentive capacities of the different lobes of brain when the music stimulus have been removed.

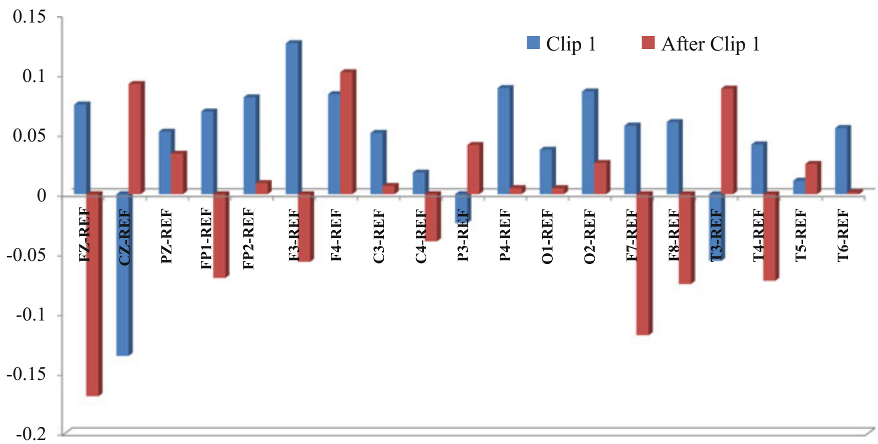

Fig. 10.1 Neural shimmer (alpha) during and after *Chayanat*

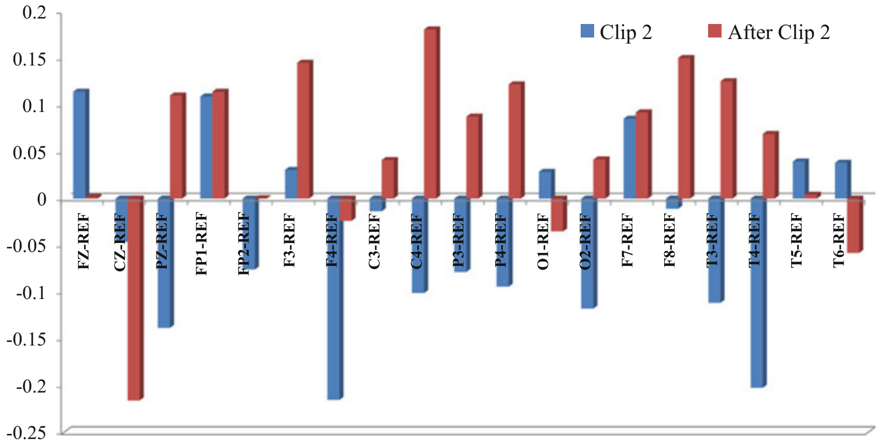

Fig. 10.2 Neural shimmer (alpha) during and after *Darbari Kanada*

In case of alpha frequency range, we find that the shimmer values increase for most of the electrodes under the effect of *raga Chayanat*. The increase is most prominent in the frontal electrodes with the highest being noted in the left frontal F3 electrode, indicating the greater involvement of left frontal lobe in the processing of positive emotions. The neural shimmer also increases quite consistently in the two fronto-parietal electrodes (FP1 and FP2) as well as in the right parietal (P4) and occipital (O2) electrodes. The central midline electrode (Cz) registers a significant dip in neural alpha shimmer along with left temporal (T3) one. Another interesting observation that comes from the plot is that except for a few electrodes, the aroused

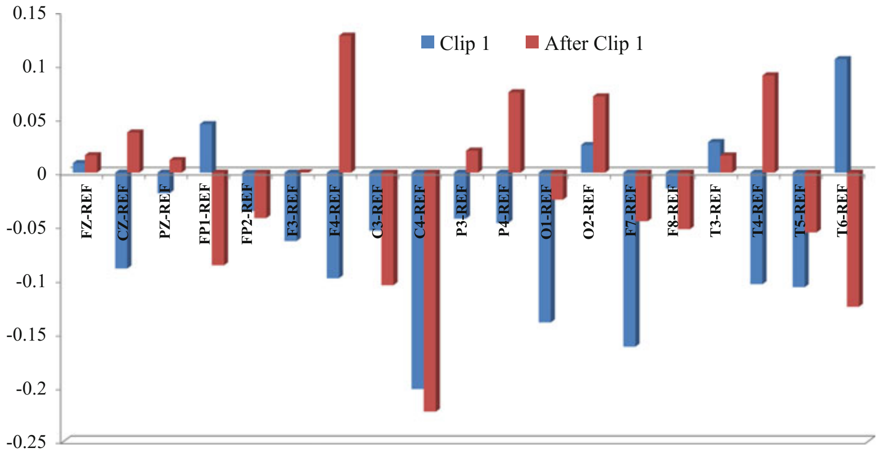

Fig. 10.3 Neural shimmer (theta) during and after *Chayanat*

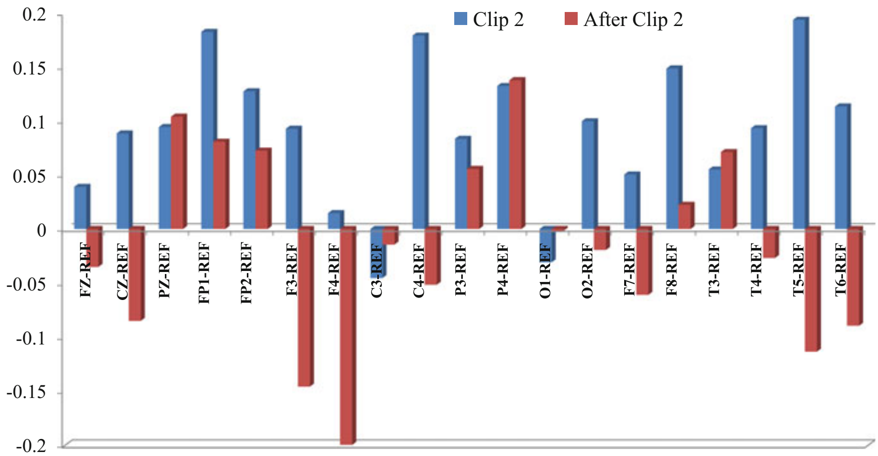

Fig. 10.4 Neural shimmer (theta) during and after *Darbari Kanada*

level of neural shimmer does not change even after the removal of stimuli, but is retained for some time. Except for few electrodes like Fz, Cz and F7, F8 where there is significant dip in the alpha neural shimmer values after the removal of stimulus. Thus, we can say that a *raga* of positive emotion increases the neural simmer of alpha range mostly in a positive manner and that is retained for quite some time even after the removal of the stimuli.

In case of *raga Darbari,* conventionally associated with sad emotion, we find the effect in neural shimmer is exactly in contrast with the first case. Here, we find that the neural shimmer values are decreasing significantly under the effect of *raga*

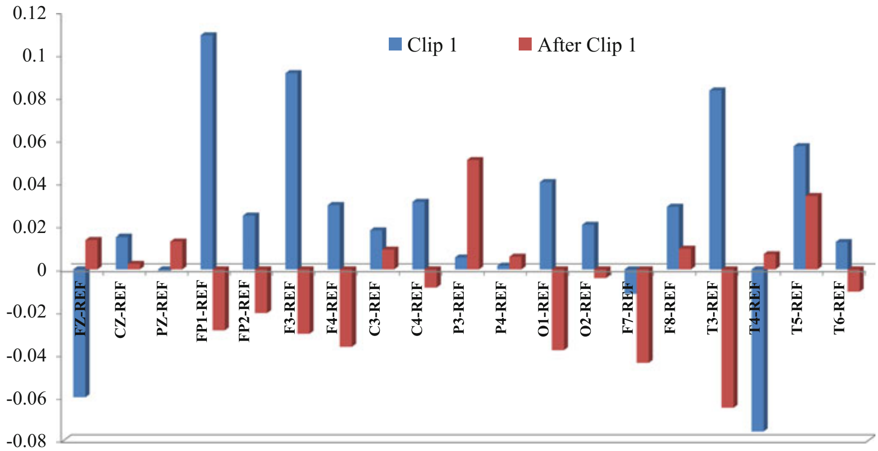

Fig. 10.5 Neural shimmer (gamma) during and after *Chayanat*

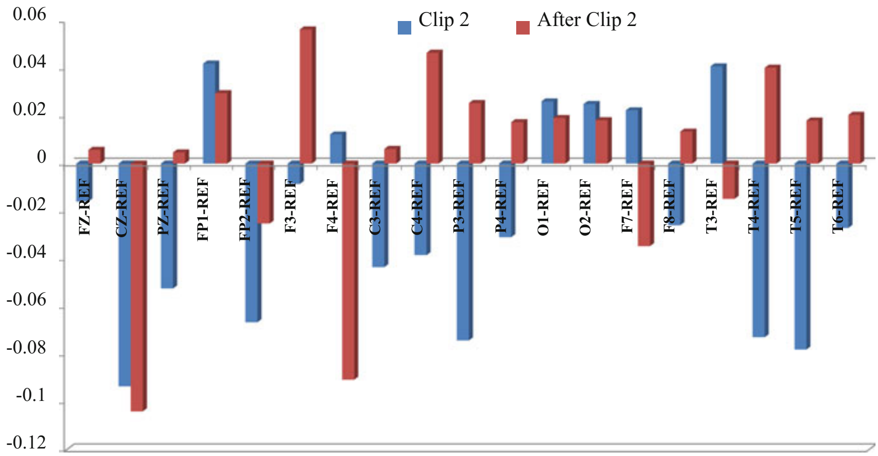

Fig. 10.6 Neural shimmer (gamma) during and after *Darbari Kanada*

Darbari in most of the electrodes, with the dip being most significant in case of right frontal (F4) and temporal (T4) electrode. This may be an indication in the direction of negative emotions being processed in the right hemisphere of brain. The right central (C4), parietal (P4) and occipital (O2) electrodes also display consistent fall in the neural shimmer values. In this case, we also see that the retention is not so pronounced as in the previous case and the neural shimmer values increase consistently after the removal of stimuli. The results point strongly in the direction of valence lateralization theory or that the different lobes are involved in processing different emotions.

In case of theta frequency range, we find that the shimmer values decreases for most of the electrodes under the effect of *raga Chayanat*. The decrease is most prominent in the right central (C4) electrode, followed by the O1, F7, F4, T4 and Cz electrodes. The right temporal, i.e., the T6 electrode shows a significant increase in neural shimmer value. After removal of stimuli the dip in the neural shimmer values is retained for few electrodes, especially which is significant for the right Central (C4) electrode which also showed the most drop while the clip was on. Also, the right frontal electrode F4 shows a significant rise in the neural shimmer value after the removal of stimuli. Thus, we can say that a *raga* of positive emotion decreases the neural shimmer of theta range.

In case of theta frequency range, we find that the shimmer values increase for most of the electrodes under the effect of *raga Darbari* which is just in contrast with that of *raga Chayanat*. The increase is prominent in the right central (C4), left fronto-parietal (Fp1) and left temporal (T5) electrodes, followed by FP2, P4, F8, T6 and O2 electrodes. The left central (C3) electrode shows a decrease in neural shimmer value along with left Occipital (O1) electrode. After the removal of stimuli the aroused level of the neural shimmer values is retained for few electrodes, while there is a significant dip in the neural shimmer value for right frontal (F4) electrode which in case of *raga Chayanat* showed an increased value of neural shimmers.

In case of gamma frequency range, we find the shimmer values increase for most of the electrodes under the effect of *raga Chayanat*. The increase is most prominent in most of the electrodes with the highest being noted in the left fronto-parietal Fp1 electrode, which implies that fronto-parietal lobe plays an important role in the processing of positive emotions. The neural shimmer also increases quite consistently in the two fronto-parietal electrodes (FP2 and FP3) as well as in the left temporal (T3) and occipital (O1) electrodes. The frontal midline electrode (Fz) registers a significant dip in neural gamma shimmer along with right temporal (T4) one. Another interesting observation that comes from the plot is that except for a few electrodes, the aroused level of neural shimmer changes after the removal of stimuli except for few electrodes like Fz, Pz and T5, P3 where there is significant rise in the gamma neural shimmer values after the removal of stimulus. Thus, we can say that a *raga* of positive emotion increases the neural shimmer of gamma range mostly in a positive manner.

In case of *raga Darbari* for gamma frequency range, we find the effect in gamma neural shimmer is exactly the opposite with what we have found in case of *raga Chayanat*. Here, we find that the neural shimmer values are decreasing significantly under the effect of *raga Darbari*in most of the electrodes, with the dip being most significant in case of central midline (Cz), left temporal (T5) and right temporal (T6) electrodes. The left and right central (C3, C4) and parietal (P3, P4) electrodes also display consistent fall in the neural shimmer values. The left and right occipital (O1 and O2) shows an increase in the shimmer values along with Fp1 and T3. In this case, we also see that the retention is not pronounced after the removal of stimuli but Cz electrode shows the maximum drop in the shimmer value both before and after the removal of clip.

Jitter is conventionally defined as the cycle-to-cycle variation of fundamental frequency, that is, the average absolute difference between consecutive periods divided by the average value of the individual periods, expressed as in Eq. 2. When applied to the neural domain, jitter may be considered as a measure of perturbation suffered by the fundamental EEG frequency; since this perturbation is essentially constant for a particular person, we could not find significant variations in the jitter parameter under the influence of a variety of stimuli. But, the analysis may be carried out differently using other parametric measures to evaluate neural jitter which may have definite far reaching conclusions in the modeling of emotions.

The next section focuses on the probability distribution of various fundamental frequencies in the alpha and theta range for the six electrodes viz. F3, F4, O1, O2, T3 and T4 taken for our experiment. Figures 10.7, 10.8 and 10.9 give the probability distribution in respect to the alpha frequency range. The numbers in brackets

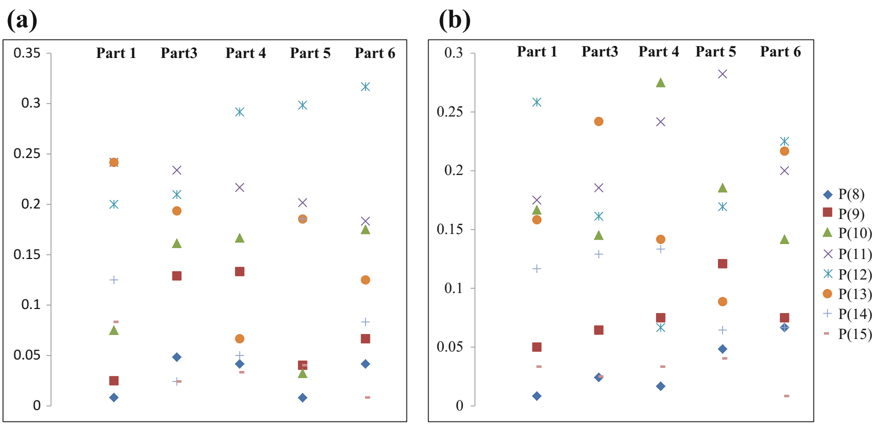

Fig. 10.7 Alpha probability distribution for **a** F3 and **b** F4 electrode

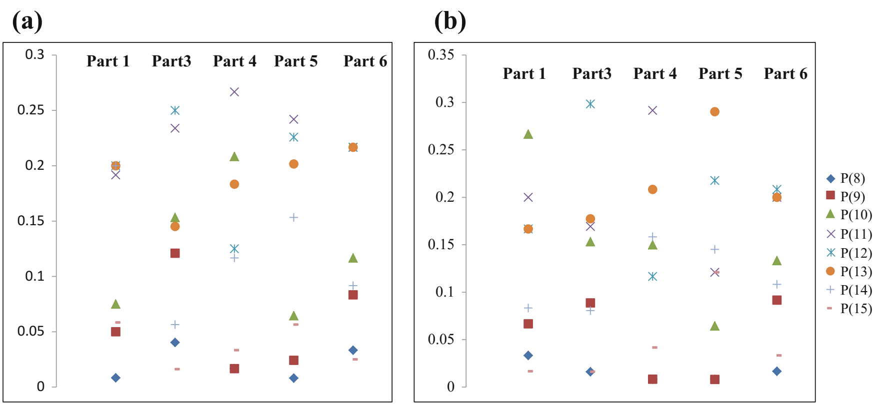

Fig. 10.8 Alpha probability distribution for **a** T3 and **b** T4 electrode

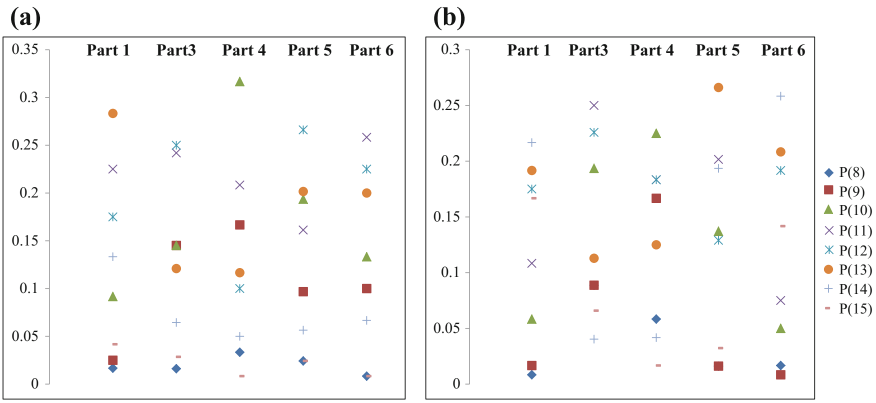

Fig. 10.9 Alpha probability distribution for **a** O1 and **b** O2 electrode

indicate the probability of getting that frequency in a particular experimental condition.

In the F3 electrode, we find that Probability of getting frequency 11 (or P(11)) is the highest for Music 1 while P(12) or the probability of getting frequency 12 is the highest for Music 2 or sad clip. It is also noted that the preferred fundamental for a particular emotion remains high even in the next 'no music' state, which is the case that we obtained in Chap. 3 also. In case of right frontal electrode, the case becomes almost reverse with P(13) showing the highest probability for Music 1 and P(11) showing the highest probability for Music 2 i.e. for sad clip. This observation speaks in favor of valence lateralization theory which says that there is differential processing of emotions in right-left lobes of human brain. In the temporal lobe, again we see the same response with P(12) being the highest for Music 1 while P (11) being the highest for Music 2 in T3 electrode, while P(11) is the highest for Music 1 and P(13) is highest for Music 2 in T3. Again, we see that the preferred fundamental remains with high probability even after the removal of stimulus or the 'no music' condition. In the occipital electrodes, an interesting observation is that in the period between two contrast emotional music clips, we find that the probability of frequency 10 or P(10) increases considerably. Since the occipital lobe is associated with visual imagery mainly, the ZCR of 10 may correspond to some sort of visual imagination/memory in the mind of the participants. Apart from this, P(11) is the maximum for Music 1 while P(12) is the maximum for Music 2. In the right occipital electrode, O2 again we find that P(11) is maximum for Music 1 but P(13) is the maximum for Music 2. Thus, we see that when we say of response in the alpha frequency range it essentially means response within a range of 11–13 Hz frequency which have shown to play a key role in most of the emotional parts here. Although, the other frequencies are present but their response is not that significant which may lead to effective categorization of emotion from EEG data only. The next set of Figs. (10.10, 10.11 and 10.12) show the identical response only in the theta frequency range i.e. 3–8 Hz.

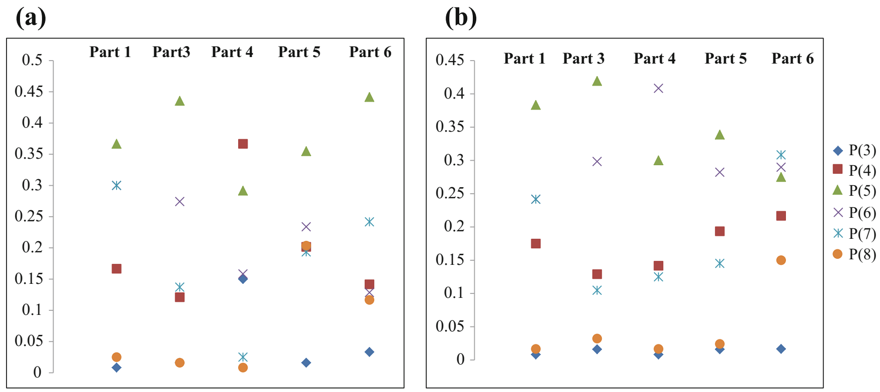

Fig. 10.10 Theta probability distribution for **a** F3 and **b** F4 electrode

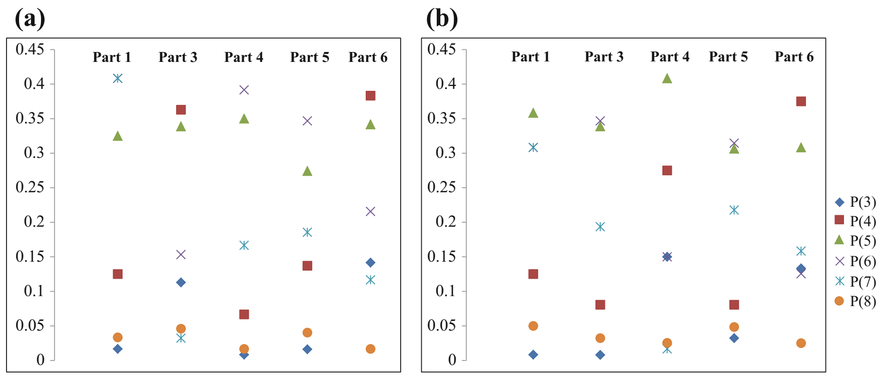

Fig. 10.11 Theta probability distribution for **a** T3 and **b** T4 electrode

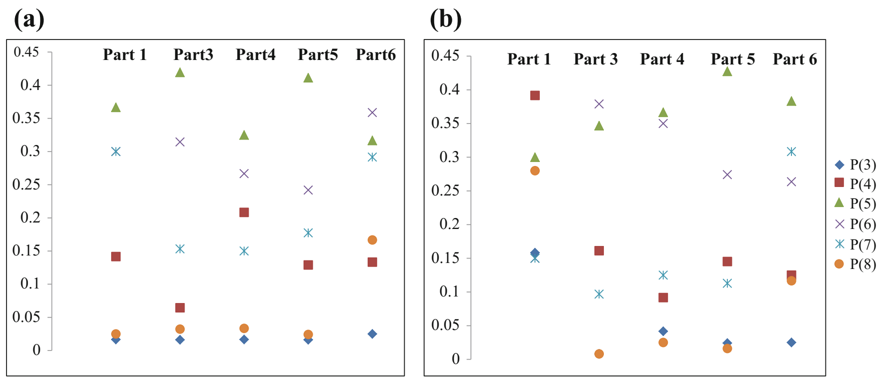

Fig. 10.12 Theta probability distribution for **a** O1 and **b** O2 electrode

For both the frontal electrodes, F3 and F4 we find that P(5) is the most preferred fundamental for both Music 1 and Music 2, while during the 'no music' state we see that F3 has P(4) as the highest value while for F4 P(6) has the highest value. Thus, the retention factor for the happy music is not that significant here, while for the sad music i.e. after Music 2 we find P(5) remain considerably high in the 'after music' part also. In the temporal electrodes, T3 has P(4) highest for Music 1 while P(6) highest for Music 2, while T4 has P(6) as the highest probability for both the music clips. In O1, again we find that P(5) has the highest value for both the clips with the retention factor quite high again for the sad clips, though in case of happy clip there are signs of good retention in occipital lobe. In case of O2, P(6) is the highest probability for Music 1 while again P(5) scores very high for Music 2 again with strong retention i.e. the value of P(5) is quite high even in the 'after music' state or Part 6. Thus, we can say that the response in theta frequency range is not as noteworthy as that of alpha frequency range when it comes to categorization of human emotions. Although we find the presence of a preferred fundamental under the effect of emotional music clips, it is not being possible to label emotions using theta frequency range. Also in this study it has been observed that response in theta frequency range means the activation of the three main fundamentals viz. 4–6 Hz. Other fundamentals do not play any major role in the response corresponding to theta region.

10.5 Conclusion

In this work, we propose three novel parameters—neural jitter, shimmer and pitch whose variations has been used as a parameter to quantify and categorize emotional arousal using Hindustani classical music as a stimuli. This is the first of its kind study which delves into such depth of the complex EEG signal never done before. The resolution of these techniques are so high, that it is possible for the first time to see, scale and manipulate individual frequency fundamentals from each of the conventional frequency ranges of EEG signals. The study yields the following interesting conclusions:

1. The neural jitter is a subjective parameter which is very much dependent on the state of consciousness of a particular person and thus remains mostly unaffected by any type of emotional music stimuli. In the domain music signal analysis, jitter has largely been used as a parameter which defines the timbral characteristic of a musical instrument. In the same way, we propose to use neural jitter as a parameter which defines the state of consciousness of a human being.
2. The neural shimmer has been calculated for different frequency bands of EEG, reveals interesting data regarding the arousal and retention of different emotions in human brain. In the alpha frequency range, elevated levels of neural shimmer are representation of positive emotion while diminished levels are marker for negative emotion. The retention is higher in case of positive emotion as compared to negative.

3. In case of theta frequency range, just the opposite response is found in case of arousal by positive and negative emotional music. The central lobe seems to be the most affected by positive stimuli while the temporal and fronto-parietal electrodes are mostly affected in case of negative stimuli. Again, the retention based effects are more prominent in case of the 1st clip as compared to the 2nd.
4. The gamma frequency range reveals almost the same result as the alpha range, with elevated and diminished levels are markers of positive and negative emotional stimuli respectively. The left fronto parietal, frontal and temporal lobe plays significant part in the processing of positive emotion, while the central, parietal and temporal lobes are strongly associated with negative emotions.
5. The EEG pitch estimation with ZCR technique proves to be quite effective for the alpha frequency region with clear distinction being obtained in the probability distribution values for happy and sad emotion. There is also an indication of differential processing of emotion with contrast response being obtained in the opposite lobes.
6. The probability distribution in theta region does not effectively distinguish the two emotional states but it gives a cue about the arousal based response. We find the same fundamental frequency with high probability in both the emotional clips. Thus, we can conclude that we can identify the valence of emotional state in the alpha frequency range while the arousal can be extrapolated from the response in theta frequency range.
7. It becomes a reality for the first time to monitor individual EEG frequencies and see how their contribution varies in totality when we talk about changes in a particular frequency range of EEG signals. Using this method, we have found that 11–13 Hz is the most significant contributor for the alpha frequency response, while 4–6 Hz is the highest contributor in the theta response.

In this way, we propose a novel algorithm which can be utilized for quantification and categorization of emotional arousal in respect to musical clips. More rigorous works being carried out in this domain include the variation of neural jitter or shimmer values within the span of particular emotional stimuli- i.e. we envisage to characterize the fluctuation of fluctuations. The probability distribution that we obtain here using the ZCR algorithm is essentially the void probability distribution (Bhaduri and Ghosh 2016, 2017; Mondal et al. 2014) which is being widely used in high energy physics to study its scaling phenomenon. The pitch analysis of EEG is also being extended in the form of DFA/MFDFA analysis to study the fluctuation pattern of the void probability distribution. This will enable us to have a look at the fractal/multifractal scaling pattern (if any) of the probability distribution of voids.

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Epilogue

The book is a comprehensive record of novel ideas and experiments traversing across various discipline viz. physics, mathematics, musicology, psychology, psycho-acoustics and most importantly neuro-science. This epilogue looks at themes and trends that hint at future journey of exploring musical rhythm of brain in the light of findings detailed in this book. In this age of nano-technology, when the focus is mostly on the finest details of matter, there is a need to revisit the idea of keeping “mind over matter”. The ambitious Big Brain Project of the US Government hopes to obtain brain wiring diagrams that will reveal patterns of neural activity giving insight into the underlying basis for sensory function, thought, memory and emotion—and will provide a new understanding of what in these circuits goes awry in psychiatric and neurodegenerative diseases. Similarly, the experiments reported in this book try to harnesses the immense power that music (specifically Hindustani music) has to offer in regulating or often changing the brain states of individuals. We sincerely hope that this book will encourage more people to take up music as an effective therapeutic agent and use it in a more scientific way. A number of novel signal processing tools for feature extraction from EEG/sound signals which will be beneficial for future students/researchers who wish to do innovative works in this eccentric field of research.

Future works in this direction include one of the most challenging one i.e. “music of the brain”, which essentially means sonification of the low-frequency EEG signal and making it audible to the human ear. This will also lead to the manifestation of a direct correlation between an EEG signal and a music signal—a pioneering work in this domain. The simultaneous neural processing of melody and rhythm in different sections of the human brain is also an interesting area of future research. How do the variations of linear features like amplitude, pitch, timbre etc. affect the non-linear parameters like Hurst exponent, Multifractal spectral width is also a fascinating area of research. We know that if the dynamics of a certain *raga* goes wrong, or certain phrases are interchanged, seasoned listeners can identify perceptually, but what are the neural manifestations of the same is unknown and could have enthralling implications. Summing up, this extraordinary research area throws wide a number of problems for inquisitive researchers.

D. Ghosh et al., *Musicality of Human Brain through Fractal Analytics*, Signals and Communication Technology,
https://doi.org/10.1007/978-981-10-6511-8

It may not be out of place to mention that Sir C V Raman Centre for Physics and Music, Jadavpur University, India, since 2010 is relentlessly working to develop fractal analytics representation as a superior alternative to linear analytics approach for scientific study of the cognitive aspect of Hindustani music. This book will go a long way with the aspiration that physicists, musicians and neuroscientists are woven in the same fabric. Remembering Tolstoy's expression "*Music is the shorthand of emotion*"…

Thus, Quest for Knowing the Unknown Continues………..