Classification and Mathematical Modeling of Human Emotions from EEG Signal

by

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A Thesis Submitted to the Department of Electrical and Electronic Engineering in partial fulfillment of the requirements for the degree of **Masters of Science** in Engineering at Khulna University of Engineering & Technology

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Declaration

This is to certify that the thesis work entitled ***"Classification and Mathematical Modeling of Human Emotions from EEG Signal"*** has been carried out by ***Monira Islam*** in the Department of Electrical and Electronic Engineering, Khulna University of Engineering & Technology, Khulna-9203, Bangladesh. The above thesis work or any part of this work has not been submitted anywhere for the award of any degree or diploma.

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List of Publications

1. Monira Islam, Tazrin Ahmed, Md. Salah Uddin Yusuf, and Mohiuddin Ahmad, "Cognitive State Estimation By Effective Feature Extraction and Proper Channel Selection of EEG Signal," Journal of Circuits, Systems, and Computers, World Scientific Publishing Company, vol. 24, No. 2, February 2015.
2. Monira Islam, Md. Salah Uddin Yusuf, and Mohiuddin Ahmad, "Selection of Effective EEG Band for Estimation of Cognitive State while Listening Music," International Journal of Electronics Communication and Computer Engineering, vol. 6, no. 6, pp. 719-726, 2015.
3. Monira Islam, Mohiuddin Ahmad, Md. Salah Uddin Yusuf, and Tazrin Ahmed, "Mathematical Modeling of Human Emotions Using Sub-band Coefficients of Wavelet Analysis", Proc. of 2nd International Conference on Electrical Engineering and Information & Communication Technology (iCEEiCT 2015), Jahangirnagar University, Dhaka, Bangladesh, May 2015.
4. Monira Islam, Mohiuddin Ahmad, and Md. Salah Uddin Yusuf, "An Approach to Estimate Cognitive State with the Impact of Listening Music on Brain Activity", Proc. of 2nd Int'l Conf. on Electrical Information and Communication Technology (EICT2015), 10-12 December, 2015, Khulna, Bangladesh.
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6. Muhammad Masud Rana, Monira Islam, Debarati Nath, Shabnam Wahed, Protik Chandra Biswas, and Mohiuddin Ahmad, "Inherent Features Extraction for Different Colors Stimulation of EEG Signal", Proc. of 2nd International Conference on Electrical Engineering and Information & Communication Technology (iCEEiCT 2015), Jahangirnagar University, Dhaka, Bangladesh, May 2015.
7. Shabnam Wahed, Monira Islam, Protik Chandra Biswas, Muhammad Masud Rana, Debarati Nath, Mohiuddin Ahmad, "An Approach for Letter Recognition System Modeling Based on Prominent Features of EEG", Proc. of Int'l Conference on Electrical & Electronic Engineering, 4-6 November, 2015, Rajshahi, Bangladesh.

Abstract

Cognitive state estimation shows the subjective mental changes with the environmental constraints which can be used for diagnosis of cognitive behavior. A cognitive model will support and facilitate the development of affective systems in emotion studies and act as a unifying platform in physiological research area. In recent years, there has been an increasing interest in applying techniques from the domains of nonlinear analysis in studying the mental behavior of a dynamical system from an experimental time series such as EEG signals. A lot of research has been carried out to study on human brain response while the subject is in relax or performing different mental task with sustained attention or listening to different kinds of music, as well as different emotion related activity. High frequency component and low frequency component contained in a brain signal with different mental activity is proven as a cognitive factor to human emotion recognition system and can be shown through the variations of human brain signal. Electroencephalographic (EEG) technology has enabled effective measurement of human brain activity, as functional and physiological changes within the brain may be registered by EEG signals from the variations of alpha, beta, delta, theta frequency bands. The EEG signals are collected from several healthy adult subjects and processed using signal processing algorithms in C/C++ source code and MATLAB to extract the effective features to classify the emotional states through the spatial and temporal analysis, discrete wavelet transform, fast Fourier transform etc. Useful information is extracted from the processing of EEG signal, and different machine learning algorithm are used to identify the different brain response from the signals to classify the emotional states using multiclass support vector machine (MCSVM). The classification of different emotions is validated using artificial intelligent techniques, i.e. neural network.

The recognition of human emotion plays a vital role in physiological research area but in case of real-time application and practical hardware implementation of human emotion based systems a mathematical background of emotions is really needed. Mathematical modeling of emotional states plays a significant role in this scope which can correlate between human cognition, emotion and mental behavior. In this work, new approach is proposed to model the emotional states with mathematical expressions based on wavelet analysis and trust region algorithm for the non-linearity and non-stationarity of EEG signal. Daubechies4 wavelet function ("db4") is applied on different recognized emotional states such as relax, memory, pleasant, fear, motor action (MA), enjoying music (EM) to extract the wavelet coefficients of these different states. The emotional states are modeled with different mathematical

expressions. The brain signals are composed of composite frequency components. So, the proposed model of the emotional states will be the sum of the sinusoidal functions consisting the composite frequency components. To model the emotional states the coefficients can be obtained by trust-region algorithm for non-linear EEG data which can be verified with these subband wavelet coefficients. The adjusted R- square percentage and the sum of square error will optimize the performance of proposed model. The higher rate of adjusted R-square percentage and lower percentage of SSE and RMSE will validate the developed cognitive model.

To propose a proper mathematical model of the brain signal of different emotional states proper effective channel is needed to select in order to reduce the feature size without any performance degradation. In this work a way is develop to propose the effective channel for emotion classification based on temporal and spectral analysis. The performance of the proper selected channel is more robust to classify and model the effective emotional states.

List of Abbreviations

3D	Three-dimensional
AEP	Audio evoked potential
Ag-AgCl	Silver–silver chloride
AMI	Average mutual information
ANN	Artificial neural network
AP	Action potential
AR	Autoregressive modeling
BCI	Brain computer interfacing/interaction
BMI	Brain–machine interfacing
BSS	Blind source separation
Ca	Calcium
Ch	Channel
Cl	Chloride
CNS	Central nervous system
CSD	Current source density
CT	Computerized tomography
DCT	Discrete cosine transform
DWT	Discrete wavelet transform
ECG	Electrocardiogram/electrocardiography
ECoG	Electrocorticogram
EEG	Electroencephalogram/electroencephalography
EKG	Electrocardiogram/electrocardiography
EMG	Electromyogram/electromyography
EM	Enjoying music
EOG	Electrooculogram
EP	Evoked potential
ERP	Event-related potential
ERS	Event-related synchronization
fICA	Fast independent component analysis
FIR	Finite impulse response
HCI	Human–computer interfacing/interaction

HMM	Hidden Markov model
HPF	High pass filter
ICA	Independent component analysis
IIR	Infinite impulse response
IR	Impulse response
k-NN	k-Nearest Neighbors
K	Potassium
LD	Linear discriminants
LDA	Linear discriminant analysis
LE	Lyapunov exponent
LLE	Largest Lyapunov exponent
LMS	Least mean square
LPF	Low pass filter
LRT	Low-resolution tomography
LS	Least squares
MA	Motor action
MCSVM	Multiclass support vector machine
MI	Mutual information
MIL	Matrix inversion lemma
ML	Maximum likelihood
MLE	Maximum likelihood estimation
MLE	Maximum Lyapunov exponent
MLP	Multilayered perceptron
MMN	Mismatch negativity
MR	Memory related
MRI	Magnetic resonance imaging
MS	Mean square
MSE	Mean-squared error
MUSIC	Multichannel signal classification
Na	Sodium
NN	Neural network
OA	Ocular artifact
PCA	Principal Component analysis
PLS	Pleasant

PR	Problem reading
PS	Problem solving
RBF	Radial basis function
RLS	Recursive least squares
RLX	Relax
RMSE	Root mean square error
SDFT	Short-time DFT
SNR	Signal-to-noise ratio
STFT	Short-time frequency transform
SV	Support vector
SVM	Support vector machine
TF	Time–frequency
TR	Text reading
VEP	Visual evoked potential
WN	Wavelet network
WT	Wavelet transform

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Chapter 1

Introduction

Emotion modeling with the recognized mental states has drawn extensive attention from disciplines such as psychology, cognitive science and engineering in the field of human-machine interaction and brain computer interface. Establishing a new communication of human behavior to interact with the outside world through their brain waves has become an active research area in the physiological signal analysis field. The human brain is the part of the body that regulates almost all of the human behavioral activity. Emotion is the reflection by human brain of its quality and magnitude in which the brain estimates with genetic and previously acquired experiences expressed with mathematical structural formulas and different functions. Emotion can be viewed as a lack of fit (mismatch) between the ready-made inner stereotype prepared in advance by the brain and the changing circumstances [1]. Mathematical modeling is the process of constructing mathematical objects whose behaviors or properties correspond in some way to a particular real-world system. Research in the field of emotional states modeling with mathematical expressions is not only challenging due to the interdisciplinary aspects of the topic, but it is also hindered by the fact that human cognition, emotion and behavior are investigated by researchers from different disciplines. This leads to dissimilar research methods, goals, specifications and results. A mathematical description of research results from the area of emotion studies will support and facilitate the study and development of affective systems [2]. In recent years the focus of this physiological research with brain signals is to classify the emotional states with different environmental conditions and to establish the possibility of successful mathematical modeling of the highly complex phenomenon representing human emotional states. To explain any emotional state with mathematics is really complex because the functional activity of human brain is related with time and the environments and also the frequency components are the unique parameters which primarily related with emotional activity. The useful information contained in the raw EEG signal cannot be visualized with just bare eyes. On top of that, raw EEG signals usually contain artifacts that will complicate the analysis of EEG signal. There have been a lot of research work on EEG signal processing, as well as classification of EEG signal. All these methodologies from previous work provide good references for future research and exploration on EEG technology.

1.1 Background of EEG

Establishing a new communication of human behavior to interact with the outside world through their brain waves has become an active research area in the physiological signal analysis field. The human brain is the part of the body that regulates almost all of the human behavioral activity. Therefore the activity of the brain contains a lot of information about one's mental behavior and its structure and functions have become a great source for the research of mental state evaluation. The recording of the brain's activity obtained by using electrodes is called electroencephalogram or EEG (electro = electrical, encephalon = brain, gram = record). It is the recording of electrical activity along the scalp. EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. The detection, amplification, recording, and interpretation of the patterns of electrical activity associated with functioning of the cerebral cortex became known as electroencephalography. The hardware used to record such patterns is called an electroencephalograph, and the record obtained from its use is called an electroencephalogram, or EEG. EEG mainly detects the signal of task performed by the specific brain region where the electrodes are placed as shown in Fig. 1.1. The corresponding EEG signals are shown in Fig. 1.2. The signal characteristics vary from one state to another, such as wakefulness/sleep or normal/pathological. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 10–20 minutes, as recorded from multiple electrodes placed on the scalp. Diagnostic applications generally focus on the spectral content of EEG, that is, the type of neural oscillations that can be observed in EEG signals. In neurology, the main diagnostic application of EEG is in the case of epilepsy, as epileptic activity can create clear abnormalities on a standard EEG study.

An EEG electrode will mainly detect the activity in the brain region just under it. Nevertheless, the electrodes receive the activity from thousands of neurons. In fact, one square millimeter of cortex has more than 100,000 neurons. Since each region of the cerebral cortex of an alert person is busy receiving, integrating, and sending many impulses, this activity is detected in the EEG. It is only when the input to a region is synchronized with electrical activity occurring at the same time that we begin to distinguish simple, periodic waveforms in an EEG.

1.1.1 Physiological Concepts

The brain is encased by the cranium, bones of the skull that immediately cover and protect brain surfaces. A thin cover of skin, called the scalp, covers most of the cranium. The largest part of the brain, located immediately beneath the cranium, is the cerebrum. The cerebrum is the cerebrum is divided into hemispheres and each hemisphere is divided into frontal, parietal, temporal, and occipital lobes. The outer cell layers of the cerebrum form the cerebral cortex-the "gray matter" of the brain often referred to in popular literature. The cerebral cortex contains billions of nerve cells (neurons), many of which are functionally connected to each other and connected to other parts of the brain.

Functions of the cerebral cortex include abstract thought, reasoning, memory, voluntary and involuntary control of skeletal muscle, and the recognition and differentiation of somatic, visceral, and special sensory stimuli. Specific regions of the cerebral cortex process or generate various kinds of information. For example, the frontal lobe generates nerve signals that voluntarily control skeletal muscle contractions such as in walking or riding a bicycle. The occipital lobe processes visual (sight) information, and the temporal lobe processes auditory (hearing) information. Cutaneous pain and temperature information and other somatosensory information is processed in the parietal lobe. Electrical activity in the form of nerve impulses being sent and received to and from cortical neurons is always present, even during sleep or other states when the level of consciousness is reduced. In a legal sense as well as a medical or biological sense, absence of electrical activity in the human cerebral cortex signifies death. Fig. 1.3 shows the major parts of the brain on which the different emotional activity occurs.

1.1.2 EEG Generation

An EEG signal is a measurement of currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. When brain cells (neurons) are activated, the synaptic currents are produced within the dendrites. This current generates a magnetic field measurable by electromyogram (EMG) machines and a secondary electrical field over the scalp measurable by EEG systems. Differences of electrical potentials are caused by summed postsynaptic graded potentials from pyramidal cells that create electrical dipoles between the soma (body of a neuron) and apical dendrites, which branch from neurons as shown in Fig. 1.4. The current in the brain is generated mostly by pumping the positive ions of sodium, Na^+, potassium, K^+, calcium, Ca^{++}, and the negative ion of chlorine, Cl−, through the neuron membranes in the direction governed by the membrane potential.

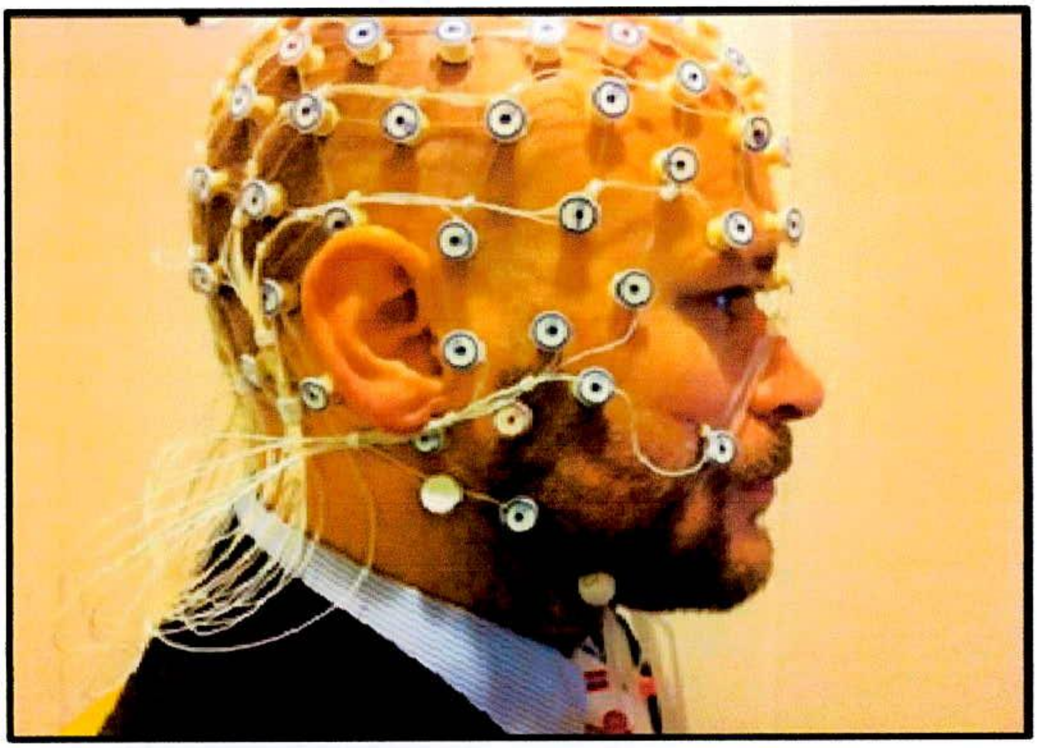


Figure 1. 1 An EEG recording at the phonetics lab, Stockholm University [6]

Figure 1. 2 Wave discharges monitored with EEG signal [6]

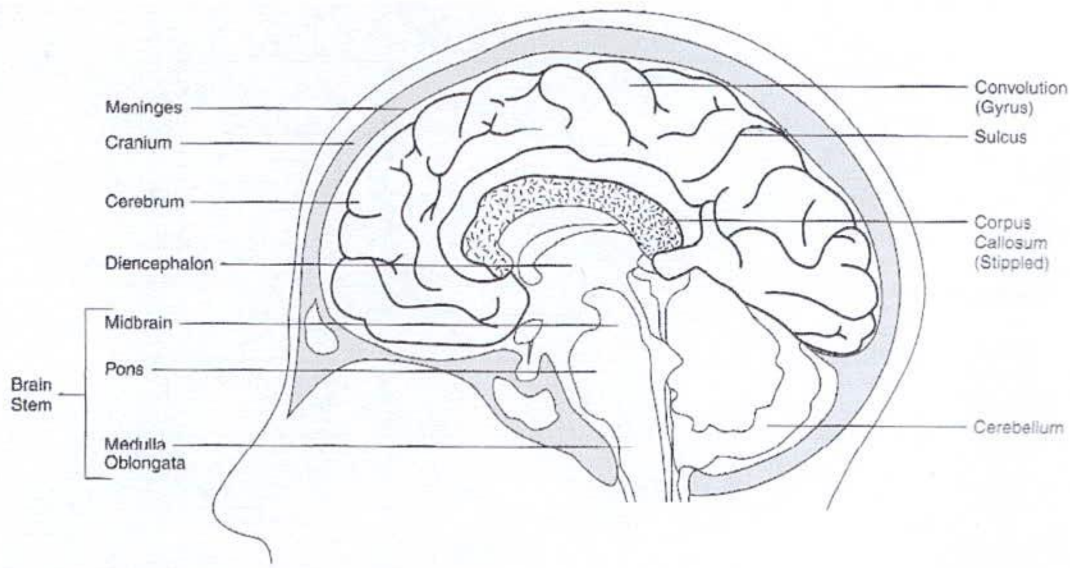


Figure 1.3 The major portions of the brain: The cerebrum, cerebellum, and brain stem [17]

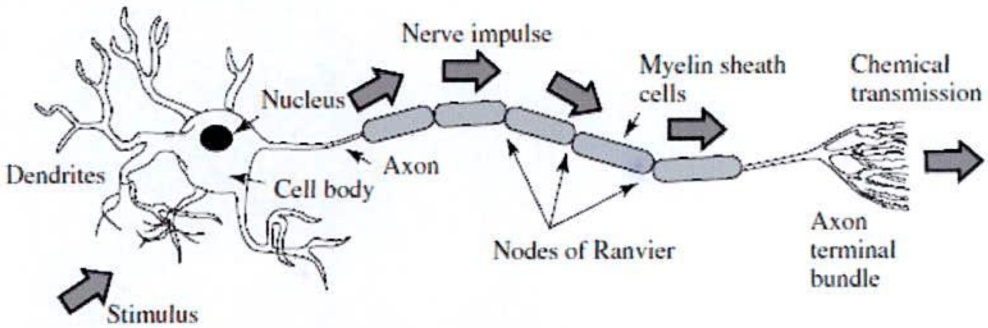


Figure 1.4 Structure of a neuron (adopted from Attwood and MacKay) [78]

The human head consists of different layers including the scalp, skull, brain as shown in Fig. 1.5, and many other thin layers in between. The skull attenuates the signals approximately one hundred times more than the soft tissue. On the other hand, most of the noise is generated either within the brain (internal noise) or over the scalp (system noise or external noise). Therefore, only large populations of active neurons can generate enough potential to be recordable using the scalp electrodes. These signals are later amplified greatly for display purposes. Approximately 10^{11} neurons are developed at birth when the central nervous system (CNS) becomes complete and functional. This makes an average of 10^4neurons per cubic mm. Neurons are interconnected into neural nets through synapses. Adults have approximately 5×10^{14} synapses. The number of synapses per neuron increases with age, whereas the number of neurons decreases with age.

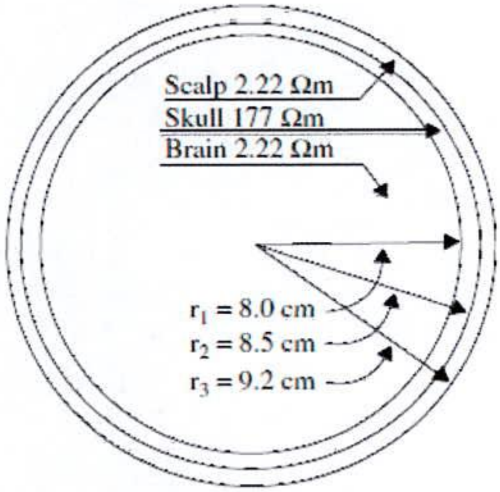


Figure 1.5 The three main layers of the brain including their approximate resistivities and thicknesses (Ω= ohm) [78]

From an anatomical point of view the brain may be divided into three parts: the cerebrum, cerebellum, and brain stem as shown in Fig.1.6. The cerebrum consists of both left and right lobes of the brain with highly convoluted surface layers called the cerebral cortex. The cerebrum includes the regions for movement initiation, conscious awareness of sensation, complex analysis, and expression of emotions and behavior. The cerebellum coordinates voluntary movements of muscles and maintains balance. The brain stem controls involuntary functions such as respiration, heart regulation, biorhythms, and neurohormone and hormone sections. Based on the above section it is clear that the study of EEGs paves the way for diagnosis of many neurological disorders and other abnormalities in the human body.

1.1.3 Brain Rhythms

Many brain disorders are diagnosed by visual inspection of EEG signals. The clinical experts in the field are familiar with manifestation of brain rhythms in the EEG signals. In healthy adults, the amplitudes and frequencies of such signals change from one state of a human to another, such as wakefulness and sleep or other emotional activities. The characteristics of the waves also change with age. There are five major brain waves distinguished by their different frequency ranges. These frequency bands from low to high frequencies respectively are called alpha (α), theta (θ), beta (β), delta (δ), and gamma (γ). The alpha and beta waves were introduced by Berger in 1929. Jasper and Andrews (1938) used the term 'gamma' to refer to the waves of above 30 Hz.

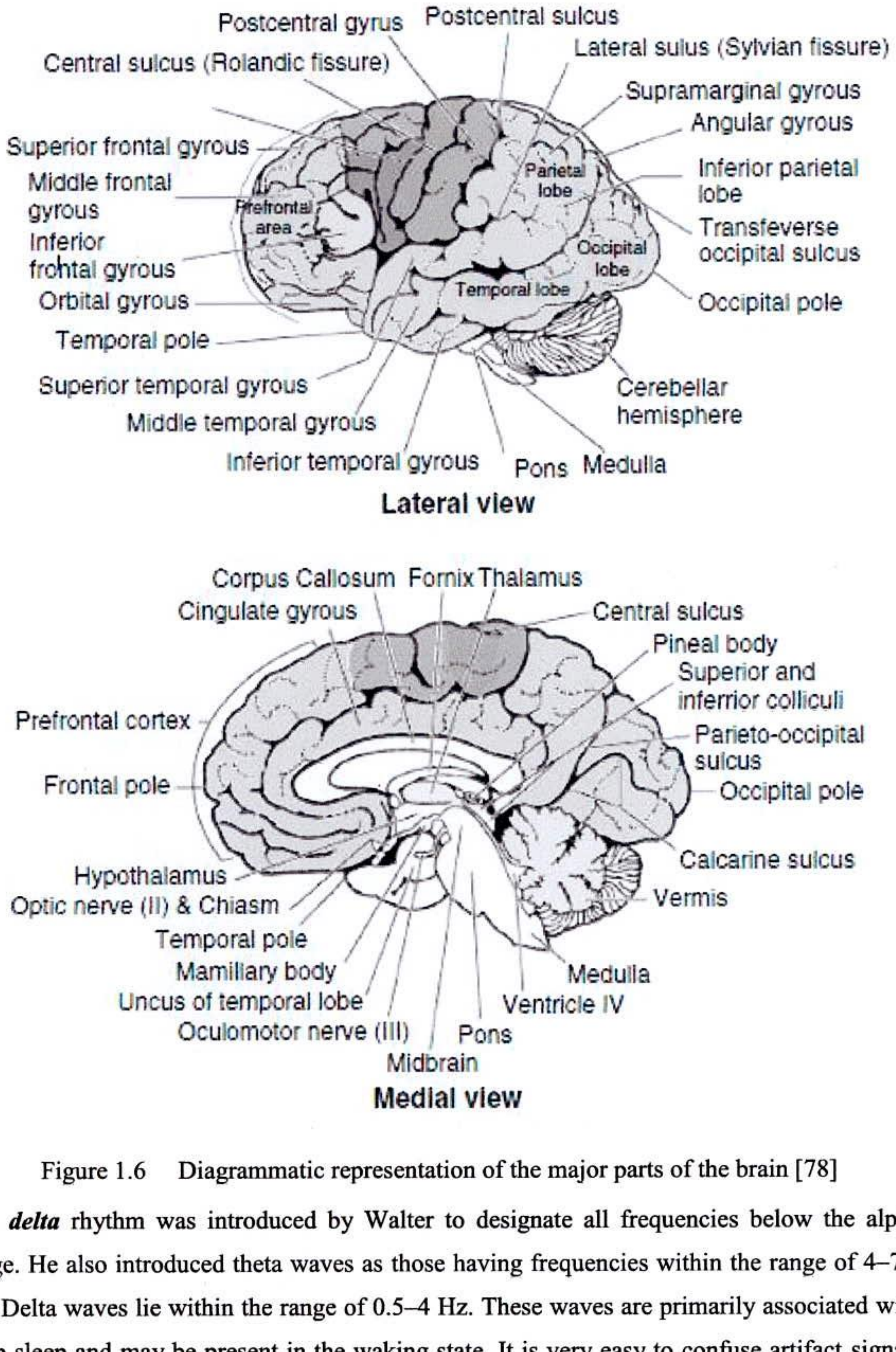


Figure 1.6 Diagrammatic representation of the major parts of the brain [78]

The ***delta*** rhythm was introduced by Walter to designate all frequencies below the alpha range. He also introduced theta waves as those having frequencies within the range of 4–7.5 Hz. Delta waves lie within the range of 0.5–4 Hz. These waves are primarily associated with deep sleep and may be present in the waking state. It is very easy to confuse artifact signals caused by the large muscles of the neck and jaw with the genuine delta response. This is because the muscles are near the surface of the skin and produce large signals, whereas the signal that is of interest originates from deep within the brain and is severely attenuated in passing through the skull. Nevertheless, by applying simple signal analysis methods to the EEG, it is very easy to see when the response is caused by excessive movement.

Theta waves lie within the range of 4–7.5 Hz. The term theta might be chosen to allude to its presumed thalamic origin. Theta waves appear as consciousness slips towards drowsiness. Theta waves have been associated with access to unconscious material, creative inspiration and deep meditation. A theta wave is often accompanied by other frequencies and seems to be related to the level of arousal. It is known that healers mediators have an alpha wave that gradually lowers in frequency over long periods of time. The theta wave plays an important role in infancy and childhood. Larger contingents of theta wave activity in the waking adult are abnormal and are caused by various pathological problems. The changes in the rhythm of theta waves are examined for maturational and emotional studies.

Alpha waves appear in the posterior half of the head and are usually found over the occipital region of the brain. They can be detected in all parts of posterior lobes of the brain. For alpha waves the frequency lies within the range of 8–13 Hz, and commonly appears as a round or sinusoidal shaped signal. However, in rare cases it may manifest itself as sharp waves. In such cases, the negative component appears to be sharp and the positive component appears to be rounded, similar to the wave morphology of therolandic mu (μ) rhythm. Alpha waves have been thought to indicate both a relaxed awareness without any attention or concentration. The alpha wave is the most prominent rhythm in the whole realm of brain activity and possibly covers a greater range than has been previously accepted. A peak can regularly be seen in the beta wave range infrequencies even up to 20 Hz, which has the characteristics of an alpha wave state rather than one for a beta wave. Again, very often a response is seen at 75 Hz, which appears in an alpha setting. Most subjects produce some alpha waves with their eyes closed, which is why it has been claimed that it is nothing but a waiting or scanning pattern produced by the visual regions of the brain. It is reduced or eliminated by opening the eyes, by hearing unfamiliar sounds, by anxiety, or mental concentration or attention. An alpha wave has a higher amplitude over the occipital areas and has an amplitude of normally less than 50 μV. The origin and physiological significance of an alpha wave is still unknown and yet more research has to be undertaken to understand how this phenomenon originates from cortical cells.

A ***beta*** wave is the electrical activity of the brain varying within the range of 14–26 Hz. A beta wave is the usual waking rhythm of the brain associated with active thinking, active attention, focus on the outside world, or solving concrete problems, and is found in normal adults. A high-level beta wave may be acquired when a human is in a panic state. Rhythmical beta activity is encountered chiefly over the frontal and central regions. Importantly, a central beta rhythm is related to the rolandic mu rhythm and can be blocked by motor activity or tactile stimulation. The amplitude of beta rhythm is normally under 30 μV. Similar to the mu rhythm, the beta wave may also be enhanced because of a bone defect and also around tumoural regions. The frequencies above 30 Hz (mainly up to 45 Hz) correspond to the gamma range (sometimes called the fast beta wave). Although the amplitudes of these rhythms are very low and their occurrence is rare, detection of these rhythms can be used for confirmation of certain brain diseases. The regions of high EEG frequencies and highest levels of cerebral blood flow are located in the front central area.

The gamma wave band has also been proved to be a good indication of event-related synchronization (ERS) of the brain and can be used to demonstrate the locus for right and left index finger movement, right toes, and the rather broad and bilateral area for tongue movement. Waves in frequencies much higher than the normal activity range of EEG, mostly in the range of 200–300 Hz, have been found in cerebellar structures of animals, but they have not played any role in clinical neurophysiology. Figure 1.7 shows the typical normal brain rhythms with their usual amplitude levels. The delta wave is observed in infants and sleeping adults, the theta wave in children and sleeping adults, the alpha wave is detected in the occipital brain region when there is no attention, and the beta wave appears frontally and parietally with low amplitude leptomeninges, cerebrospinal fluid, dura matter, bone, galea, and the scalp. Cartographic discharges show amplitudes of 0.5–1.5 mV and up to several millivolts for spikes. However, on the scalp the amplitudes commonly lie within 10–100 μV.

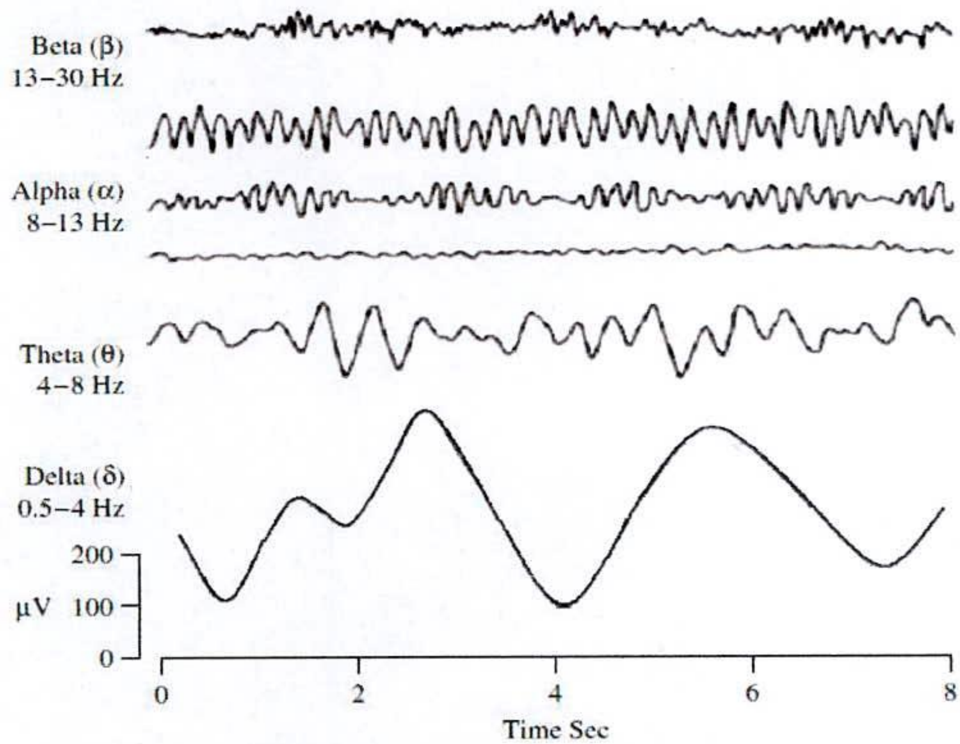


Figure 1.7 Four typical dominant brain normal rhythms, from high to low frequencies [78]

The above rhythms may last if the state of the subject does not change and therefore they are approximately cyclic in nature. On the other hand, there are other brain waveforms, which may:

i) Have a wide frequency range or appear as spiky-type signals, such as K-complexes, vertex waves (which happen during sleep), or a breach rhythm, which is an alpha type rhythm due to a cranial bone defect, which does not respond to movement, and is found mainly over the midtemporal region (under electrodes T3 or T4), and some seizure signals.
ii) Be a transient such as an event-related potential (ERP) and contain positive occipital sharp transient (POST) signals (also called rho (ρ) waves).
iii) Originate from the defective regions of the brain such as tumoural brain regions.
iv) Be spatially localized and considered as cyclic in nature, but can be easily blocked by physical movement such as mu rhythm. Mu denotes motor and is strongly related to the motor cortex. Rolandic (central) mu is related to posterior alpha in terms of amplitude and frequency. However, the topography and physiological significance are quite different. From the mu rhythm the cortical functioning and the changes in brain (mostly bilateral) activities subject to physical and imaginary movements can be

investigated. The mu rhythm has also been used in feedback training for several purposes such as treatment of epileptic seizure disorder.

There are also other rhythms introduced by researchers such as:

v) Phi (φ) rhythm (less than 4 Hz) occurring within two seconds of eye closure.

vi) Kappa (κ) rhythm, which is an anterior temporal alpha like rhythm. It is believed to be the result of discrete lateral oscillations of the eyeballs and is considered to be an artifact signal.

vii) The sleep spindles (also called the sigma (σ) activity) within the 11–15 Hz frequency range.

viii) Tau (τ) rhythm, which represents the alpha activity in the temporal region.

ix) Eyelid flutter with closed eyes, which gives rise to frontal artifacts in the alpha band.

x) Chi (χ) rhythm is a mu-like activity believed to be a specific rolandic pattern of 11–17 Hz. This wave has been observed during the course of Hatha Yoga exercises.

xi) Lambda (λ) waves are most prominent in waking patients, but are not very common. They are sharp transients occurring over the occipital region of the head of walking subjects during visual exploration. They are positive and time-locked to saccadic eye movement with varying amplitude, generally below 90 μV.

It is often difficult to understand and detect the brain rhythms from the scalp EEGs, even with trained eyes. Applying different analysis technique the variation of different effective bands of human brain is observed which indicate the emotional states.

1.2 Significance of Emotion modeling

Human emotions are, to a large extent, subjective and non-deterministic. In the present context, emotions are considered to be relatively short-duration intentional states that entrain changes in motor behavior, physiological changes, and cognitions. The same stimulus may create different emotions in different individuals, and the same individual may express different emotions in response to the same stimulus, at different times. In spite of this variability, it is assumed that there are basic principles, perhaps even basic mechanisms that make a particular event 'emotional'. To find these principles and their underlying mechanisms, researchers typically study specific emotions, using specific tasks. As is appropriate, they use a combination of animal and human preparations, yielding various types of data, from single neuron firing patterns, to activation levels of a whole brain area. The approach, while rigorous, is slow and yields an increasingly complex body of often conflicting data. The problem of identifying emotions using bio-signals is quite difficult, so an integrative approach is needed to create a computational model of emotion. Although recently there have been many attempts to classify emotions but to build an automatic emotion recognition systems a proper mathematical model is essential to express and test hypotheses regarding the bases of emotions. In case of HCI, audio signal processing, call centers (identifying the valuable callers), human-to-human intercommunication, human-to-robot interaction, medical diagnosis purpose, physiological research and to develop a real time patient monitoring system, this research topic can play a vital role by further exploring the cognitive model in practical real time implementation.

1.3 Motivations

Nowadays, new forms of human-centric and human-driven interaction with digital media have the potential of revolutionizing entertainment, learning, and many other areas of life. Since emotions play an important role in the daily life of human beings, the need and importance of automatic emotion recognition has grown with an increasing role of human computer interface applications. Emotion can be defined as follows: "The bodily changes follow directly the perception of the exciting fact, and that our feeling of the changes as they occur is the emotion". Emotion recognition could be done from the text, speech, facial expression or gesture. Recently, more researches were done on emotion recognition from EEG signal. The EEG signal is extracted from brain and brain signal is the core of all emotional activities which controls human mental behavior. Traditionally, EEG-based technology has been used in medical applications. Therefore a mathematical model form EEG signal is required to develop the real time emotion recognition system.

In this thesis, the spatio-temporal analysis will be applied to extract the effective features to estimate the emotional states in an efficient manner. The suitable analysis technique and efficient features to classify the emotions are according to their classification rate of human emotions. Furthermore, an emotion model has been developed for further implementation of real time monitoring system. In this thesis, we concentrate on recognition of the "inner" emotions from EEG signals as humans could control their facial expressions or vocal intonation. To evoke emotions, different stimuli could be used: visual, auditory, and combined. They activate different areas of the brain. Moreover to get better performance accuracy for emotion estimation and to develop the proper model of the emotional states, proper channel selection technique is developed. The proper channel of data acquisition unit can reduce the performance complexity by reducing the size of features but increase the emotion recognition performances as well as the proposed model of emotions.

1.4 Research Questions

The theories of emotions have inspired the researchers to continue the theoretical investigation of emotions in various directions, thus making available a wide spectrum of ideas and concepts that taken together can capture the main aspects of the nature of emotions. However through such investigation, several issues of contention have arisen that are crucial to be addressed and begun to be resolved in order to design suitable automatic architectures. So, in case of emotion studies the major research questions are:

- Is there any necessity of dealing with human emotion in our practical life?
- Is there any way of classifying human emotions from brain activities?
- How the researchers can classify different emotional states from different environmental conditions?
- How human emotion can be made unifying language for implementation of emotion based system or hardware structure?

1.5 Objectives of the thesis

The objective measures for inferring the human cognitive activities are hard to obtain as they occur inside the human mind. It is quite difficult, however, to effectiveness of the man machine interface, because human being (operator) is included as the system component interacting with the machine.

Many works have been done in this emerging area to find the relation between the changes in signals and emotional states with their mental behavior. Some researchers in [1]-[2] categorized the emotional states and extracted different features using time-frequency analysis to correlate and estimate the emotional states efficiently. Emotion is detected from alpha EEG powers related to different regions of brains from audio induced activity [3]. In [4]-[5] spatial and temporal features have been selected by applying Gabor functions and wavelet transform for classifying different emotional states. In [6]-[7] authors tried to structure a model according to the strength and actual need of human behavior to predict emotions and support Human-Computer-Interaction (HCI). The mental behavior detection from the EEG signal was proposed with the findings of effective data recording from physiological signals, feature extraction through wavelet transform, data reduction, feature classification using various classification methods implied for real time applications in [8]. Swangnetr et.al attempted to develop a new computational algorithm for accurate emotional state classification in interaction with nursing robots during medical service [9]. In [10]-[11] authors tried to achieve the theoretical developments and applications in traditional cognitive psychology domains, and attempted to model human performance to evaluate human cognitive behavior. In order to reduce the complexity of emotion recognition system a huge number of data is processed to reduce the feature size without little loss of performances [12]-[13]. In this thesis different statistical and spectral features are extracted for selecting the effective channel in order to classify the emotional states [14]-[15]. The details of the proposed approach are discussed later in different chapters. The different research techniques, specifications and results limit their applications in real time monitoring system. So, a mathematical model is essential to monitor the emotion related activity in a unifying frame. The main difficulty lies in the fact that, it is very hard to uniquely map physiological patterns onto specific emotion types and the physiological data are sensitive to artifacts and noises. The main purpose of this thesis is to establish the successful modeling of the highly complex phenomenon representing human cognitive states. For successful implementation of our proposed approach the following measures are taken:

i) Selection of proper channel for effective classification of different cognitive states in order to reduce the feature size without any performance degradation.
ii) To evaluate the emotional states from the signal characteristics using different time-domain or frequency-domain transformation technique.
iii) To classify the emotional states from the EEG signal from the effective features and the variations of effective frequency bands of the brain signal.
iv) To determine the efficacy of the proposed approach using SVM and other machine learning tools.
v) To develop a mathematical model of the emotional states using time-frequency analysis and trust region algorithm.
vi) Performance optimization of the proposed model will be carried out using the R-square percentage and adjusted R-square percentage and the validation of the proposed model depends on the Sum of square error and Root mean square error.

In this work, we suggest that a mathematical formalization of emotion theories can support the study of emotions regarding origin, alteration and interaction with cognition and behavior. We further claim that a mathematical description of research results from the area of emotion studies will support and facilitate the study and development of affective systems.

1.6 Contribution of the thesis

Recent years have seen a significant expansion in research on computational models of human emotional processes, driven both by their potential for basic research on emotion and cognition as well as their promise for an ever increasing range of applications. Research has revealed the powerful role that emotion and emotion expression play in shaping human social interaction, and this in turn has suggested that computer interaction can exploit (and indeed must address) this function. Emotional displays convey considerable information about the mental state of an individual. So emotion recognition plays a vital role in physiological research area. To implement this in real time monitoring or diagnostic system the emotion modeling is significant. But there is lack of accuracy to recognize the emotional states due to lack of proper effective features in the proper channel. To classify as well as to model emotions effectively the EEG signal should be collected from the proper channel. Otherwise the effective features would be rarely to extract to meet the final goal of the research. To overcome the limitations of emotion classification as well as emotion modeling, some novel and efficient approach have been developed which brought significant contribution in emotion based system and in this approach following contributions has been made. For the assistance of this work implementation of BIOPAC MP36 system and AcqKnowledge software plays a significant role [17].

i) This dissertation proposes a minimum redundancy maximum relevance method for extracting some salient features for emotion recognition. Some attempts have been taken to classify emotion with limited number of features. In this work statistical, frequency and time-frequency analysis is applied to extract the temporal, spectral and spatio-temporal features individually which overcome the limitation of accuracy and upgrade system performance in case of emotion recognition system.

ii) In case of classification of emotions a well-known machine learning algorithm SVM is applied being one of the most important high generalization capacities for a reduced number of training trials. The nonlinear SVM puts the boundary that the algorithm calculates does not have to be a straight line. The benefit is that much more complex relationships between the can be captured without having to perform difficult transformations. The classified emotional states are validated with other machine learning algorithms to evaluate our proposed technique.

iii) A new approach has been proposed to classify mental states due to sustained mental activities during a test or musical impact on brain rhythms in certain environmental conditions form the impact in the effective frequency band of EEG signal.

iv) This work proposes a framework based on mutual information maximization to solve the EEG feature/channel selection and dimensionality reduction problems in order to perform cognitive state classification. In EEG classification, one of the major problems is the huge number of features to be classified. In this work, channel selection method is developed to alleviate "the curse of dimensionality" in EEG classification without degrading system performance.

v) A novel approach is developed to model the emotional states with mathematical expressions based on wavelet analysis and trust region algorithm. This model of emotional states can be utilized in practical hardware implementation of human emotion based systems.

1.7 Approach

Since this work is very multidisciplinary the approach taken is to break down the dissertation into subproblems. Each subproblem will be handled in separate chapters where results, discussion and part conclusions will be made for each topic. Each topic can therefore be seen as independent chapters and can be read as such. Concerns and thoughts raised along the research into the modeling of emotions from the different environmental activity based on EEG signal, will be dealt with by introducing sections labeled e.g. initial considerations in each chapter.

1.8 Organization of the thesis

The thesis is organized as follows:

Chapter 1 presents the introduction to this thesis, includes the background of the EEG signal, motivations, problem statements, contributions and scopes of the study.

Chapter 2 is entitled "Literature Review on Classification and Modeling of Human Emotion". It introduces critical points of other related researches and comparing with our proposed work on Emotion classification and recognition and modeling.

Chapter 3 is entitled "Effective Channel Selection Technique for Emotion Recognition and Modeling". It is devoted to describe the entire steps taken to analyze the collected EEG signal and estimate the individual emotional states. This chapter also mentions which channel and features are effective for emotion classification.

Chapter 4 is entitled "Human emotion classification". This chapter describes the captured and transformed data as well as the classification result of the emotional states based on the extracted features from the analysis of these data. The classification accuracy is evaluated with SVM and ANN classifier.

Chapter 5 is entitled "Modeling Approach of Human Emotions". This chapter describes the modeling of emotions for different environmental conditions.

Chapter 6 concludes the overall work done of this thesis. Shortcoming of the system designed in this thesis is discussed, and recommendation for future work is discussed as well.

Chapter 2

Literature Review on Classification and Modeling of *Human Emotion*

The emotional or cognitive state estimator is utilized in the context of an augmented cognition system that aims to enhance the cognitive performance of a human user through computer-mediated assistance based on electroencephalogram (EEG). Emotions have also attracted the attention of researchers in the field of human computer interaction, where studies have been carried out on facial expressions [18] or on the recognition of emotions through a variety of sensors [19] according to the internal changes of emotional activity of brain signal. Emotion is an important aspect for interaction and communication between people. Even though emotions are intuitively known to everybody, it is difficult to define emotion. The Greek philosopher Aristotle thought of emotion as a stimulus that evaluates experiences based on the potential for gain or pleasure. In the seventeenth century, Descartes considered emotion to mediate between stimulus and response [20]. Nowadays there is still little consensus about the definition of emotion. Kleinginna and Kleinginna gathered and analyzed 92 definitions of emotion from literature present that day [21]. They conclude that there is little consistency between different definitions and suggested the following comprehensive definition for emotion:

Emotion is a complex set of interactions among subjective and objective factors, mediated by neural/hormonal systems, which can:

i) give rise to affective experiences such as feelings of arousal, pleasure/displeasure;
ii) generate cognitive processes such as emotionally relevant perceptual effects, appraisals, labeling processes;
iii) activate widespread physiological adjustments to the arousing conditions; and
iv) lead to behavior that is often, but not always, expressive, goal directed, and adaptive.

This definition shows the different sides of emotion. On the one hand emotion generates specific feelings and influences mental behavior. This part of emotion is well known and is in many cases visible to a person himself or to the outside world. On the other hand emotion also adjusts the

Figure 2. 1 Different types of emotions

state of the human brain, and directly or indirectly influences several processes. In spite of the difficulty of precisely defining it, emotion is omnipresent and an important factor in human life. Figure 2.1 shows different types of human emotions.

2.1 Related Works on Emotion Study

The EEG is a complex and aperiodic time series, which is a sum over a very large number of neuronal membrane potentials. EEG provides a window into the functioning of the brain. By observing behavior and brain activity researchers can gain insight into how the two are correlated. EEG plays a vital role in health and medical applications. But it is very difficult to ensure that a person is in one particular mental state at any particular time as human being has the supernatural power of doing parallel activities. So it is assumed that a subject is in one condition at a particular time due to the heterogeneity of physiological signal. Another significant problem is that, physiological signals are affected by motion artifact. Again, the results can be varied from man to man with their age, gender, weight, height, etc. The objective of this work is to study changes in physiological variables with respect to changes in human emotional states.

2.2 Emotion Classification

The emotional states occur very differently according to the situation, personality, growth and environment, etc. And even for a person, it changes day in and day out. However, it is very difficult to keep a subject in one specific mental state due to the environmental effects. The definition and the assumption for the categorization of the human cognitive states are quite important in case of emotion classification in different environmental conditions. Emotions can be defined as the functional activity of brain and a concept of involving human expressions and biological stimulation for specific person for the specific task in different environmental conditions. A lot of research work has been performed in order to estimating human emotional states. In case of estimation of emotional states emotion classification is the primary concern of the researchers. Different researchers classify the emotional states with different approaches.

There are different emotion classification systems. The taxonomy can be seen from two perspectives: dimensional and discrete one. Another fundamental dimension is an approach-withdrew dimension which is based on the motivating aspects of the emotion is discussed in [22]. For example, in this theory, anger is an approach motivated emotion in some cases, as it could encourage the person to make effort to change the situation. The dimensional model is preferable in emotion recognition experiments due to the following advantage: dimensional model can locate discrete emotions in its space, even when no particular label can be used to define a certain feeling.

Emotion is a phenomenon that is difficult to grasp. In order to classify and represent emotions, some models have been proposed. There are two dominant models. One of the models uses the idea that all emotions can be composed of some basic emotions, just as colors can be composed of primary colors. Plutchik defines eight basic emotion states: anger, fear, sadness, disgust, surprise, anticipation, acceptance and joy. All other emotions can be formed by these basic ones, for example, disappointment is composed of surprise and sadness [23].

Another approach towards emotion classification is advocated by Paul Ekman. He revealed the relationship between facial expressions and emotions. In his theory, there are six emotions associated with facial expressions: anger, disgust, fear, happiness, sadness, and surprise. Later he expanded the basic emotion by adding: amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure, and shame [24]. Authors proposed another model which is composed of multiple dimensions, and places every emotion on a multidimensional scale. The first dimension is emotional valence, with positive on the one and negative on the other side. The second axis contains the arousal, from calm to excited. The third dimension is not always used, and when used, it is not always the same. Sometimes dominance is used as the third dimension. Other times it is

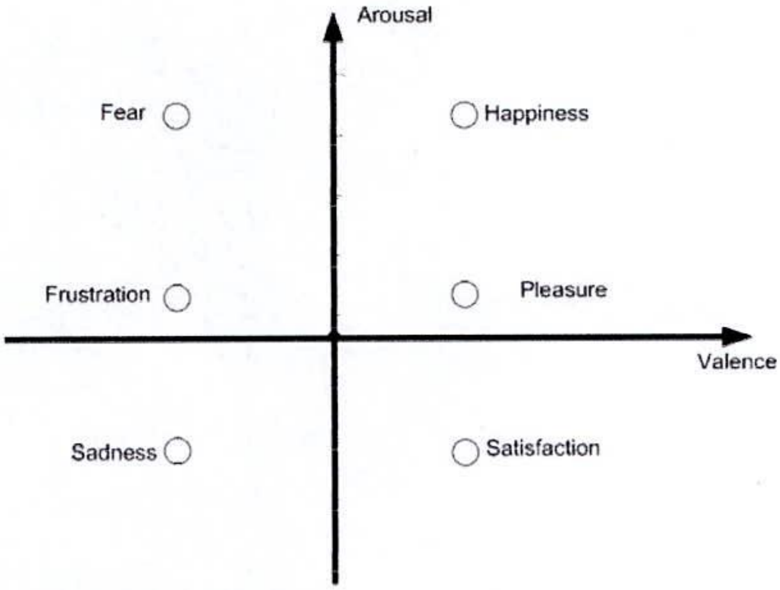


Figure 2.2 Bi-dimensional valence-arousal approach [25]

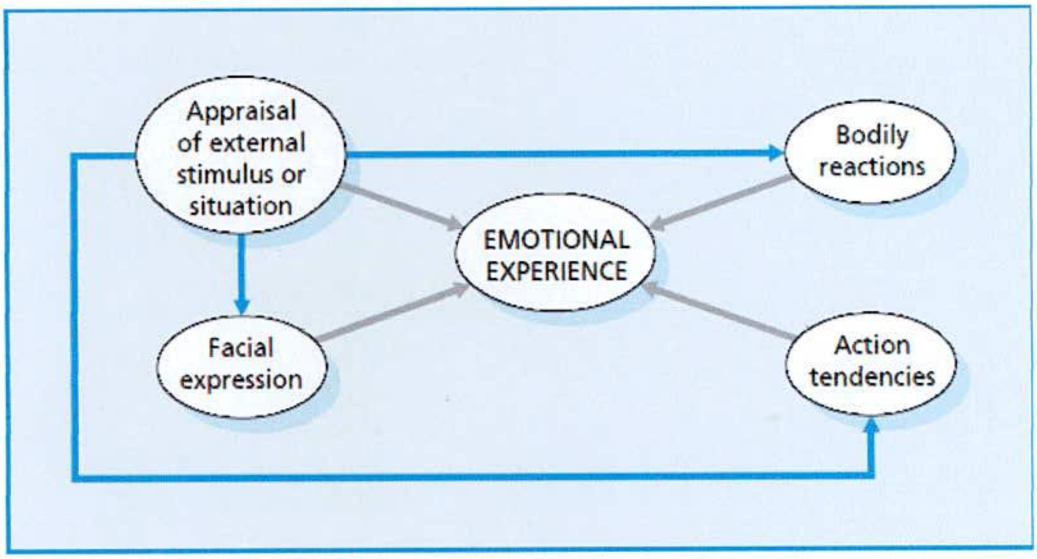


Figure 2.3 Factors influencing emotional experience

Brain signals are a reliable information source due to the fact that the process of emotion interpretation starts in the central nervous system. Furthermore, an individual cannot control his brain signals to simulate a fake emotional state. Due to changes of time and state of mind there consists an overlapping of basic human emotions. In our present study the basic emotions are classified according to their different environmental conditions based on the brain EEG signals. The categorization is based on the model of human mental activities, pleasant and unpleasant states

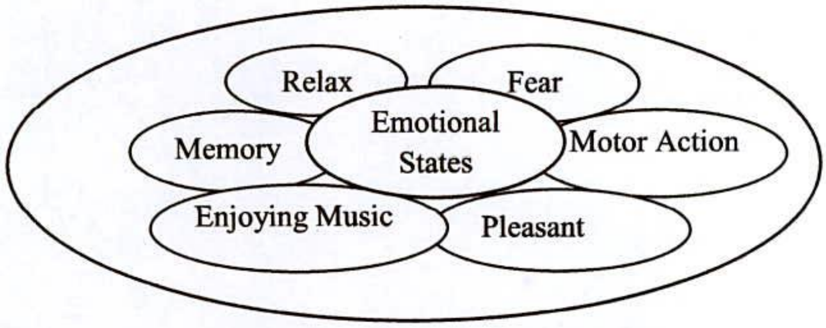


Figure 2.4 Classification of emotional states

of human mind: (a) Relax (RLX); (b) Mental task (TH); (c) Motor Action (MA); (d) Emotional state (Pleasant); (e) Emotional state (Fear) and (f) Enjoying Music (EM). The subjects were properly trained to perform the specific mental tasks during data collection.

Figure 2.4 illustrates the six categories of human emotional states in this thesis. The subjects were properly trained to perform specific mental tasks sequentially during data collection as stated below:

i) Relax (RLX) with eye closed

ii) Memory related task (MR) state

iii) Motor action (MA) state

iv) Fear State (FS)

v) Pleasant State (PLS)

vi) Enjoying music (EM)

2.3 Emotion Induction Experiments

Human emotion classification and modeling of emotions plays a vital role in the field of cognitive neuroscience and real time monitoring system. The brain activities changes with the effect of audio or video stimuli or with different environmental conditions during mental task performed. In order to obtain affective EEG data, experiments are carried out with different kinds of stimuli such as audio, visual, and combined ones to induce emotions. Among the EEG based emotion recognition works which implemented experiments using audio stimuli to collect EEG data, there are some works where subjects' emotions were elicited by pre-labeled music with emotions.

Authors in [27], it was reported that emotions were induced in 26 subjects by pre-assessed music pieces to collect EEG data and 90% classification accuracy rate was received to distinguish four kinds of emotions: joy, anger, sadness and pleasure.

In [28], four kinds of emotion states including positive/aroused, positive/calm, negative/calm and negative/aroused were induced by sounds clips. The Binary Linear Fisher's Discriminant Analysis was employed to do the classification. They achieved 97.4% maximum rate for arousal levels recognition and 94.9% maximum rate for valence levels. For experiments using visual stimuli, three emotional states were elicited as follows: exciting positive, exciting negative, and calm state. Though this project did not target emotion recognition from EEG signals, they published EEG data labeled with emotions that were cited by other works on EEG-based emotion recognition as a benchmark [29].

In reference [6] authors proposed an EEG based emotion recognition algorithm based on spectral, spatial and temporal features. To obtain an optimal algorithm, the emotion related EEG signals were decomposed by Gabor functions and wavelet transform. Then spectral and spatial features were extracted from sub representations and subbands. To reduce the computational cost of the Gabor function, a simplified Gabor function that called Gabor SD was introduced. EEG signals were represented in several sub representations by filtering them with the sum over scales and direction of Gabor function. Then several features were extracted from each sub representation. Since the non/ effective features increase computational cost and decrease the performance of algorithm, principal component analysis (PCA) is employed to select R effective features among of the several features, without supervisory. Furthermore, the neural network classifiers was developed such as improved particle swarm optimization (IPSO) and probabilistic neural network to create a non/linear decision boundary between the selected features. Four algorithms were developed. The specific algorithm consisting minimum latency and maximum accuracy was specified as optimal algorithm in case of recognizing human emotion.

Authors in [8] discussed the issues and challenges to access human emotion from EEG signal. In this work a protocol has been designed to stimulate unique emotion than multiple emotions. An efficient algorithm was developed for removing noises and artifacts from the EEG signal. Emotional activities of the brain causes difference in EEG characteristics waves, it has been attempted to investigate the brain activity related to emotion classification through analyzing EEG using artificial intelligence technique.

In [14]–[15] the mental behavior detection from the EEG signal and also the findings of effective data recording from physiological signals, feature extraction through wavelet transform, data reduction, feature classification using various classification methods have been discussed. Authors in Ref. [30] introduced an emotion recognition system based on electroencephalogram (EEG) signals. Experiments using movie elicitation are designed for acquiring subject's EEG signals to classify four emotion states, joy, relax, sad, and fear. After pre-processing the EEG signals, various kinds of EEG time and frequency domain features are investigated to build an emotion recognition system.

Many body functions including blood pressure, heart rate, respiration rate are controlled by autonomic nervous system. This part of nervous system can be influenced by external stimuli and cognitive states of the individuals. The qualitative changes of these physiological variables presented a classification system based on BIOPAC system, which robustly estimated the cognitive state using histograms methods as discussed in [31].

Authors in Ref. [32] classified three different emotions (pain, boredom, and surprise) using multi-channel physiological signals (ECG, EDA, PPG, and SKT) and identified the optimal algorithms being able to recognize them. The authors operationally defined that surprise emotion is 'startle' response to a sudden unexpected stimulus such as a flash of light, a loud noise, or a quick movement near the face. Authors in Ref. [33] classified two emotions: pleasure and non-pleasure. In this work power at each frequency band and mean of raw signals are used as feature for emotion classification. The larger value of power at specific frequency band mentioned the positive or pleasure state and when the power reduces for the raw signal at specific band it mentioned negative or non-pleasure state.

Various signal processing techniques have already been proposed for classification of non-linear and non- stationary signals like EEG in [34]. In this work, SVM (support vector machine) based classifier was employed to detect epileptic seizure activity from background electro encephalographs (EEGs). Five types of EEG signals (healthy subject with eye open condition, eye close condition, epileptic, seizure signal from hippocampal region) were selected for the analysis. Signals were preprocessed, decomposed by using discrete wavelet transform DWT till 5th level of decomposition tree. Various features like energy, entropy and standard deviation were computed and consequently used for classification of signals. The results show the promising classification accuracy of nearly 91.2% in detection of abnormal from normal EEG signals.

Authors as in Ref. [35] have extracted relevant features for the mental state detection from EEG signal task based on neuroscience findings with a fewer number of electrodes that ranges from 4 to 25 electrodes and reached an average accuracy of 51%, 53%, 58% and 61% for joy, anger, fear and sadness, respectively.

Authors in Ref. [36] used asymmetrical alpha power for classification of four emotions (angry, sadness, pleasure and joy) using MLP network. In this study an electroencephalography (EEG) signal-based emotion classification algorithm was investigated. Several excerpts of emotional music were used as stimulus for elicitation of emotion-specific EEG signal. Besides, the hemispheric asymmetry alpha power indices of brain activation were extracted as feature vector for training multilayer perceptron classifier (MLP) in order to learn four targeted emotion categories, including joy, angry, sadness, and pleasure. The results demonstrated that the average classification accuracy of MLP could be 69.69% in five subjects for four emotional categories.

In [37] the conventional feature selection methods based on five moments applied to three wavelet transform sequences has been proposed and used in pattern classification. The new method has essentially extended the Englehart's discrete wavelet transform and wavelet packet transform by introducing more efficient feature reduction method that also offered better generalization. The approaches were empirically evaluated on the same set of signals recorded from two real subjects, and by using the same classifier, which was the Vapnik's support vector machine. The conventional feature selection methods were based on principal component analysis (PCA), independent component analysis (ICA), fast independent component analysis (FICA), and moments-based feature reduction (MBFR).

Author in Ref. [38] have focused on recognizing emotion from human brain activity, measured by EEG signals and proposed a system to analyze EEG signals and classify them into 5 classes on two emotional dimensions, valence and arousal. Emotion recognition was done by measuring EEG signals from people that were emotionally stimulated by pictures to show the relationship between the characteristics of the brain activity and the emotion. The authors used a 3-fold cross validation method for training and testing, frequency band power, cross correlation coefficients, peak frequency in alpha and beta band, and Hjorth parameters in case of emotion classification in valence-arousal space using three classifiers: Naive Bayes classifier, SVM and neural network through International Affective Picture System (IAPS) to classify emotions. They reached classification rates of 32% for recognizing the valence dimension from EEG signals and 37% for the arousal dimension. Much better classification rates were achieved when using only the extreme values on both dimensions, the rates were 71% and 81%.

Authors in Ref. [39] analyzed energies at various frequency bands of EEG signal, and power at selected frequency bands to detect positive (happy) and negative emotions (sad). The high energy detects the positive emotions and low energy mentions the negative emotions. From the power of the selected band it is also mentioned which band is effective for positive or negative emotions.

Authors in Ref. [40] recognized the five emotions (joy, anger, sadness, fear and relax) through multimodal bio-potential signals with Gaussian kernel function. They selected mean, variance, mean with first difference of raw signal and normalized signal, mean with second difference of raw signal and normalized signal as features. When single sensor was used the recognition rate was found to be average i.e. 41%. When 2 sensors were used then recognition of single emotion was increased as well as increase of misclassification with other emotional states. In case of 3 sensors The SVM classifier shows good recognition results in joy, anger, and fear emotions while has some difficulty in recognizing sadness and relax emotions. Also the researchers showed that emotion recognition is feasible for EEG signal but it seems to be hard with only the features obtained from pulse rate or skin conductance.

Authors in [14]-[15] emotion recognition system was developed through feature extraction of EEG signals using some salient global features such as amplitude (maximum and minimum, peak to peak value), mean, median, standard deviation, skew, kurtosis, frequency components and wavelet coefficients using FFT and DWT transformation. Six emotional states are created with audio as well as visual stimuli and the collected EEG signals are analyzed for time and frequency based feature extraction for the analysis. In this work the time domain, frequency domain and time-frequency domain features are utilized individually to show the classification of different states and determine which features are more significant for emotion classification.

2.4 Emotion Recognition Algorithms

There are an increasing number of researches on EEG based emotion recognition algorithms. Although in recent years the number of researches performed on EEG based emotion recognition has been increasing, it is still a new area of research.

For emotion classification, authors in [32] used Decision Tree (which is a decision support tool that uses a tree-like graph or model of decisions and their possible consequences), kNN (k-nearest neighbor algorithm, which is a method for classifying objects based on closest training examples in the feature space), LDA (linear discriminant analysis, which is a method used in statistics, pattern recognition and machine learning to find a linear combination of features which characterizes or separates two or more classes of objects or events), and SVM (support vector machine, supervised learning models with associated learning algorithms that analyzed data and recognized patterns which are used for classification and regression analysis.

For an extensive evaluation of emotion recognition performance, classification of four emotional states is achieved by using three kinds of classifiers, kNN algorithm, MLPs, and SVMs in [30]. These classifiers have been separately applied to all of the aforementioned features. In this study, the Euclidean distance method is used as the distance metric for kNN algorithm. In MLPs, a three-layer neural network is adopted, and the activation function is the sigmoidal function. In SVMs, a radial basis function kernel is used in this work.

In [40], short-time Fourier Transform was used to calculate the power difference between 12 symmetric electrodes pairs with 6 different EEG waves for feature extraction and Support Vector Machine (SVM) approach was employed to classify the data into different emotion modes. The result was 90.72% accuracy to distinguish the feelings of joy, sadness, anger and pleasure. A performance rate of 92.3% was obtained in [3] using Binary Linear Fisher's Discriminant Analysis and emotion states among positive/arousal, positive/calm, negative/calm and negative/arousal were differentiated. By applying lifting based wavelet transforms to extract features and Fuzzy C-Means clustering to do classification, sadness, happiness, disgust, and fear were recognized in [27]. Three emotion states: pleasant, neutral, and unpleasant were distinguished. By using relevant vector machine, differentiation between happy and relaxed, relaxed and sad, happy and sad with a performance rate around 90% was obtained in [41]. The effectiveness and the efficiency of these algorithms, however, are somewhat limited. Some unsolved issues in existing algorithms and approaches are listed as follows:

i) Time constrains: The performance time consists from the time of feature extraction and time of classification. The number of electrodes used in the emotion recognition puts another time constrain on the algorithms. As a result, to our best knowledge, most of the algorithms were proposed for off-line emotion recognition.

ii) Accuracy: The accuracy of the EEG based emotion recognition still needs to be improved because the accuracy decreases when more emotions are needed to be recognized.

iii) Number of electrodes: From the perspectives of the time to set up the EEG device, the comfort level of the subjects who wear the device and the amount of features to process, the number of electrodes should be reduced. However, most of the current works still require relatively large number of electrodes.

iv) Number of the recognized emotions: Although there are varieties of emotional states to describe the human's feelings, until now only limited type of emotions can be recognized using EEG. The best performance obtained was reported in where 3 channels were used and 83.33% maximum accuracy was achieved for differentiating 6 emotions.

v) Benchmark EEG affective databases: So far, a very few benchmark EEG databases with labeled emotions are available. EEG affective databases with different stimuli such as visual and audio are needed to be set up for future researches.

Emotion recognition is the most significant and effective in case of evaluation of mental behavior and cognitive states. Several researchers have shown that it is possible to measure emotional cues using EEG measurements, which is an important condition to be able to find emotion from EEG activity. In literature, emotion classification can be done with extraction of different features and applying different emotion recognition algorithms. In this thesis an emotion recognition approach has been proposed with the efficient features of EEG signal. In this thesis multiclass support vector machine is used to classify six different emotions using EEG signal. Different effective features are extracted to classify the emotional states and other machine learning tools are also applied to validate the performance of our proposed work. The efficient features will be further applied for emotion modeling which will open a new era of emotion based systems.

2.5 Emotion Modeling

Human emotions are, to a large extent, subjective and non-deterministic. The same stimulus may create different emotions in different individuals, and the same individual may express different emotions in response to the same stimulus, at different times. In spite of this variability, it is assumed that there are basic principles, perhaps even basic neural mechanisms that make a particular event 'emotional'. To find these principles and their underlying mechanisms, neuroscientists typically study specific emotions, using specific tasks. As is appropriate, they have used a combination of animal and human preparations, yielding various types of data, from single neuron firing patterns, to activation levels of a whole brain area. The approach, while rigorous, is slow and yields an increasingly complex body of often conflicting data. An integrative approach is needed. Modeling of emotions has emerged as a promising tool for integration. They require that all assumptions be made explicit, they offer a new language in which to express and test hypotheses regarding the neural bases of emotions [42].

Research in the field of emotion recognition and modeling is not only challenging due to the interdisciplinary aspects of the topic, but it is also hindered by the fact that human cognition, emotion and behavior are investigated by researchers from different disciplines [43]. This leads to dissimilar research methods, goals, specifications and results. While a psychologist's research on emotion will focus on the origin, identification and perception of emotions, engineers will want to understand if and how emotions can be recognized, predicted or influenced in terms of human computer interaction. Both engineers and psychologists do fundamental research on the topic and their goals are interconnected but both will have difficulties to use the results obtained by the other group's investigations.

Modeling of emotions can assist to combine research results of groups originating from different disciplines. This may lead to a better understanding of the interdisciplinary field of study and enhance research on the topic. In this paper, we suggest that a mathematical formalization of emotion theories can support the study of emotions regarding origin, alteration and interaction with cognition and behavior. We further claim that a mathematical description of emotional states can be further extended for hardware implementation as well as developing real time monitoring system.

2.6 Summary

Emotion recognition is the most significant and effective in case of evaluation of mental behavior and cognitive states. Several researchers have shown that it is possible to measure emotional cues using EEG measurements, which is an important condition to be able to find emotion from EEG activity. In literature, emotion classification can be done with extraction of different features and applying different emotion recognition algorithms. In this thesis an emotion recognition approach has been proposed with the efficient features of EEG signal.

Chapter 3

Effective Channel Selection Technique for Emotion Recognition and Modeling

Many researches had been introduced for human emotion estimation using EEG signal. The main difficulty lies in the fact that, it is very hard to uniquely map physiological patterns onto specific emotion types and the physiological data are sensitive to artifacts and noises. Besides these limitations, it also has some substantial advantages. The information about the users' can be continuously congregated emotional changes through biosensors even in millisecond time resolution and available at low cost. The information extracted from the multi-sensors or electrodes reduces the recognition rate due to huge number of data and lack of effective features. So effective channel selection is essential which increases the efficacy of the recognition rate as well as proposed model of human emotions. The objective of this work is to study changes in physiological variables with respect to changes in human cognitive state with the proper channel selection of the BIOPAC automated EEG analysis system. For this reason some important aspects are held, (i) to propose a minimum redundancy maximum relevance method for extracting some salient spectral analysis based features for cognitive state estimation, and (ii) to evaluate and compare the accuracy of the extracted features to compare the efficacy of different channels in different cognitive states using support vector machine (SVM). This method has the following two features. One is the elaboration of laboratory experiments (BIOPAC System) for obtaining physiological variables. Another is the utilization of BIOPAC AcqKnowledge Software for the classification of the physiological data. BIOPAC are adopted for the following reasons. Firstly, inbuilt band pass and 50 Hz noise filters are available. Therefore, the signals obtained are free from noise and no need for further filtering. Secondly, BIOPAC AcqKnowledge Software has inbuilt modules for signal analysis. Some of the important issues to be carefully discussed in the aspect of increasing classification accuracy of cognitive states are:

i) proper positioning of electrodes and depth of placement of electrodes on the scalp;
ii) time duration of video clips; and
iii) Proper design of acquisition protocol.

3.1 State of Art

Several studies have been proposed for channel selection on EEG signals for feature reduction. While collecting measurements from all EEG channels and then projecting their combined feature vector to a lower dimensional linear or nonlinear manifold would be desirable, the hardware limitations and the prohibitive cost of collecting and processing each additional EEG channel signal beyond the capacity of the hardware imposes us to focus on identifying the salient EEG channels that contain the most useful information for accurate estimation of the cognitive state in the design phase. The conventional feature selection methods were based on principal component analysis (PCA), independent component analysis (ICA), fast independent component analysis (FICA), and moments-based feature reduction (MBFR) [44].

Schaaff and Schultz (2009) used 4 electrodes (FP1, FP2, F7, F8) for EEG recording. The main purpose of this research is to classify among positive, negative and neutral emotions. To reach their goal, they selected peak alpha frequency, alpha power, cross-correlation features and some statistical features such as the mean of the signal, the standard deviation. They used support vector machines for classification and they reached an average accuracy of 47% [45]. Authors in Ref. [40] recognized the different emotions (joy, anger, sadness, fear and relax) through multimodal bio-potential signals using SVM with Gaussian kernel function. They selected mean, variance, mean with first difference of raw signal and normalized signal, mean with second difference of raw signal and normalized signal as features.

One of the earliest attempts to identify whether EEG signals can be used for emotion detection is proposed by Chanel et al. [46]. They tried to distinguish among excitement, neutral and calm signals and compared the results of three emotion detection classifiers. The first one was trained on EEG signals, the second classifier was trained on peripheral signals such as body temperature, blood pressure and heart beats and the third classifier was trained on both EEG and peripheral signals. To stimulate the emotion of interest, the user was seated in front of a computer and viewed an image that provided information about what emotion to think of. Then the signals were captured from 64 different channels that cover the whole scalp in order to capture signals in all the rhythmic activity of the brain neurons. As for feature extraction, they transformed the signal into the frequency domain and used the power spectra as the EEG feature. Finally, Naive Bayes classifier was used which resulted in an average accuracy of 54%. The problem with the research done by Chanel et al. (2006) is the idea of using 64 channels for recording EEG as well as other electrodes to capture physiological signals make this approach impractical to be used in real-time situation.

Ansari-Asl et al. [47] improved the work done by Chanel et al. (2006). They proposed using synchronization likelihood (SL) method as a multichannel measurement which allowed them along with anatomical knowledge to reduce the number of channels from 64 to 5 with a slight decrease in accuracy and huge improvement in performance. The goal was to distinguish between three emotions which are exciting-positive, exciting-negative and calm. For signal acquisition, they acquired the signal from (AFz, F4, F3, CP5, CP6). For feature extraction, they used sophisticated techniques such as Hjorth Parameters and Fractal Dimensions and they then applied linear discriminant analysis (LDA) as their classification technique. The results showed an average accuracy of 60% in case of using 5 channels compared to 65% in case of using 32 channels.

A different technique was taken by Musha et al. [48]. They used 10 electrodes in order to detect four emotions: anger, sadness, joy and relaxation. They rejected frequencies lower than 5 Hz because they are affected by artifacts and frequencies above 20 Hz because they claim that the contributions of these frequencies to detect emotions are small. They then collected their features from the theta, alpha and beta ranges. They performed cross-correlation on each channel pair. The output of this cross-correlation is a set of 65 variables i.e. linearly transformed to a vector of 1×4 using a transition matrix. Each value indicates the magnitude of the presence of one of the four emotions. This means that any testing sample is a linear combination of the four emotions. After that they applied certain threshold to infer the emotion of interest.

Authors in Ref. [49] analyzed energies at various frequency bands of EEG signal, and power at selected frequency bands to detect positive (happy) and negative emotions (sad). They also mention the effective channel at which the energy and power are distinctive and show this channel effectiveness in the particular frequency band for the detection of positive and negative emotions.

When assessing human emotion using EEG classification, one of the critical problems was to deal with the very large number of features to be classified. ARs are used for determining the alpha band asymmetry in brain hemisphere studies on human cognition [50]. In this work, the ratio of variances between hemisphere channels is considered as a physiological indicator for assessing the region of brain and the channels which was responsible for detecting the emotions. In addition, ratios of spectral power between two hemispheres were used to accurately estimate the changes of electrical activity.

Authors in Ref. [51] presented channel selection and feature projection for cognitive state estimation to assess the subject's mental load using ambulatory EEG signal. The ambulatory cognitive state estimator is utilized in the context of a real-time augmented cognition system that aims to enhance the cognitive performance of a human user through computer-mediated assistance based on assessments of cognitive states using physiological signals including EEG. This paper focuses particularly on the offline channel selection and feature projection phases of the design and aims to present mutual-information-based techniques that use a simple sample estimator for this quantity. Analyses conducted on data collected from 3 subjects performing 2 tasks at 2 difficulty levels (low/high) demonstrate that the proposed mutual-information-based dimensionality reduction scheme can achieve up to 94% cognitive load estimation accuracy.

Author in Ref. [52] used frequency band power, cross correlation coefficients, peak frequency in alpha and beta band, and Hjorth parameters in case of emotion classification in valence-arousal space using three classifiers: Naive Bayes classifier, SVM and neural network through International Affective Picture System (IAPS).

For emotion classification as well as emotion modeling various features have been used in different research such as wavelet coefficients, autoregressive model parameters, signal energy in different frequency bands, fractal dimension, and Lyapunov exponents. In dealing with EEG classification, an important problem is the huge number of features. It comes from the fact that (i) EEG signals are non-stationary, thus features must be computed in a time-varying manner, and (ii) the number of EEG channels is large due to the experimental settings. Solutions to alleviate this problem, "the curse of dimensionality," consist of feature selection and channel selection methods. In this work a channel selection approach has been proposed to reduce the curse of dimensionality.

3.2 Proposed Approach for Effective Channel Selection

The total work has been divided into two phases - Process & Feature space and Detection space. In the Process & Feature space, the raw EEG data set are processed in such a manner in order to extract some identical features from them. The main purpose of signal analysis is to derive some salient features which can map the EEG data into consequent cognitive states. Again in Detection space, the features extracted from the analyzed signal are considered as the ideal characteristics of the individual cognitive states which are compared with some testing signal in order to identify the unknown states. And finally the classification rate has been compared to select the proper channel.

3.2.1 Subject Selection and preparation

In order to select the effective channel the first step is to collect the EEG signals in the categorized emotional states. The EEG signal for various states are evaluated in biomedical signal processing laboratory, Department of BME of EEE Faculty, Khulna University of Engineering & Technology (KUET), Bangladesh. The whole experimental data were collected from several subjects of this university. From them several data sets have been collected in various mental states.

Different affective states were created by giving several instructions and training among people of different age, weight and height. The subject preparation schedule for EEG recording according to the categorized cognitive states is shown in Table 3.1 including subject's average age, weight, and height. Consequently, the variation in EEG signal is evaluated for various states.

In case of data acquisition the subjects were male, and were in good physical and mental conditions. Their average age was 23 years so that they are sensitive to all the cognitive states and able to response with each instruction given to collect data. After arrival of each subject they were first relaxed for 10 to 15 minutes. They are given a short briefing about all steps of data collection and trained how to perform different tasks.

3.2.2 Signal Acquisition and Equipment Setup

All physiological variables of EEG measurement, the required equipment as shown in Figs. 3.1(a)-(e) are:

- i) BIOPAC electrode lead set (SS2L)
- ii) BIOPAC disposable vinyl electrodes (EL503)
- iii) BIOPAC electrode gel (GEL1) and abrasive pad (ELPAD) or Skin cleanser or alcohol prep, Lycra® swim cap (such as Speedo® brand)
- iv) Supportive wrap (such as 3M Coban™ Self-adhering Support Wrap) to press electrodes against head for improved contact)
- v) BIOPAC Student Lab 3.7
- vi) BIOPAC data acquisition unit (MP36 and MP150) with cable and power

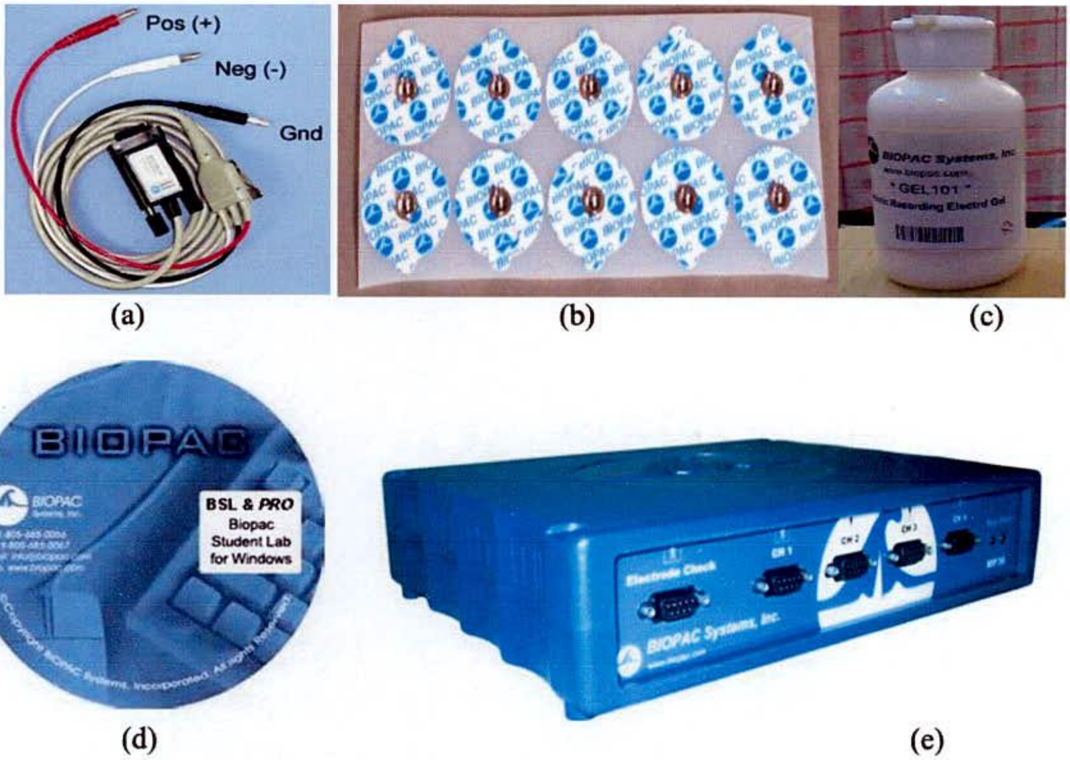


Figure 3. 1 (a) BIOPAC electrode lead set (SS2L) (b) Vinyl electrode (EL503), (c) Electrode gel (GEL 101), (d) BIOPAC Student Lab 3.7 and (e) BIOPAC data acquisition unit (MP36 and MP150)

3.2.3 Hardware & Software description

In this research, the BIOPAC data acquisition unit (MP36 and MP150) is used as shown in Fig. 3.2, 3.3 and 3.4. The MP system is a complete data acquisition system that includes both hardware and software for the acquisition and analysis of life science data. The MP system not only makes data collection easier, but also allows users to perform analysis quickly and easily that are impossible on a chart recorder.

The MP System is a computer-based data acquisition system that performs many of the same functions as a chart recorder or other data viewing device, but is superior to such devices in that it transcends the physical limits commonly encountered. The MP data acquisition unit (MP3X or MP100) is the heart of the MP System. Figure 3.5(a) and (b) show the front panel and back panel of the MP3X system. The MP unit takes incoming signals and converts them into digital signals that can be processed with the computer. Data collection generally involves taking incoming

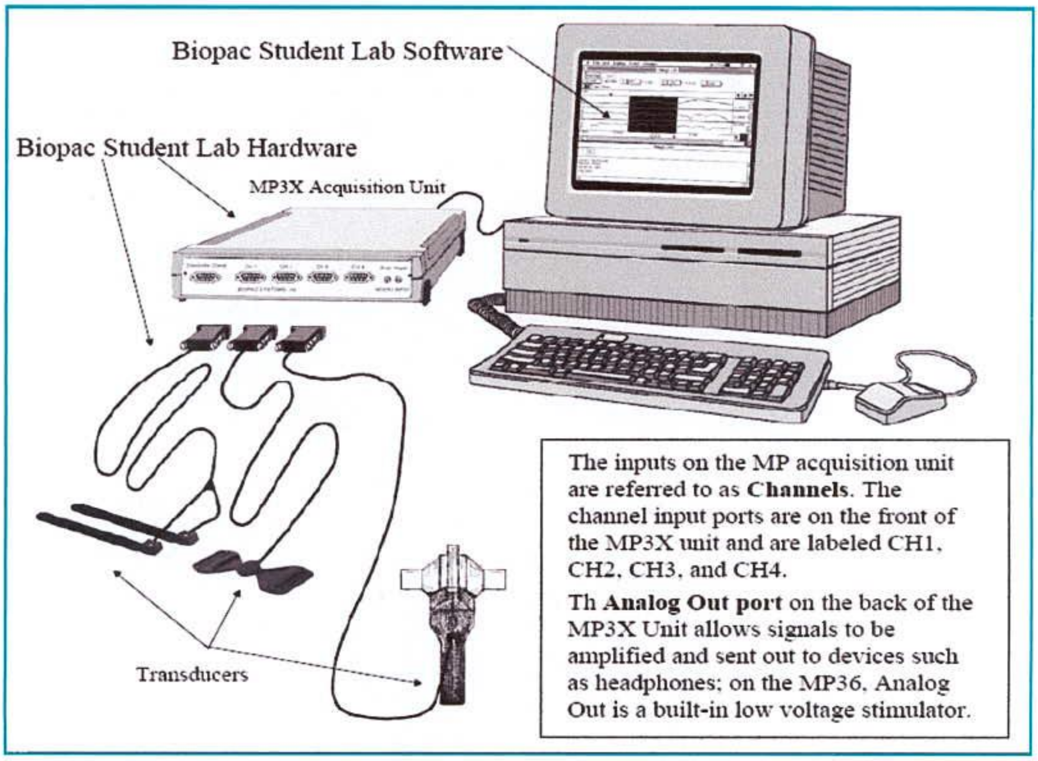


Figure 3.2 BIOPAC system

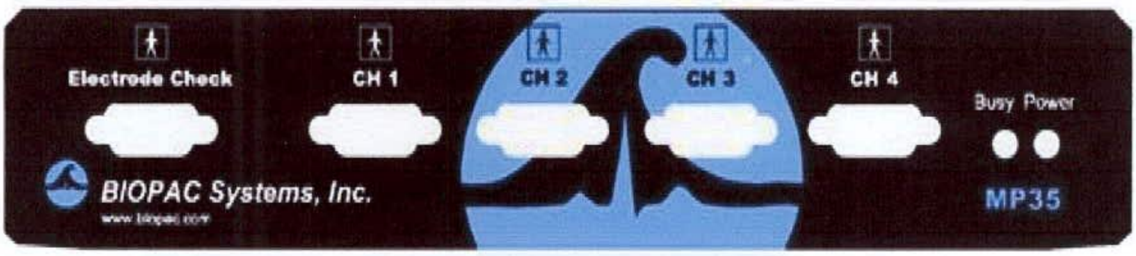


Figure 3.3 The front panel of the MP3X has an electrode check port, four analog input ports, and two status indicators. Input ports: CH 1, CH 2, CH 3, and CH 4

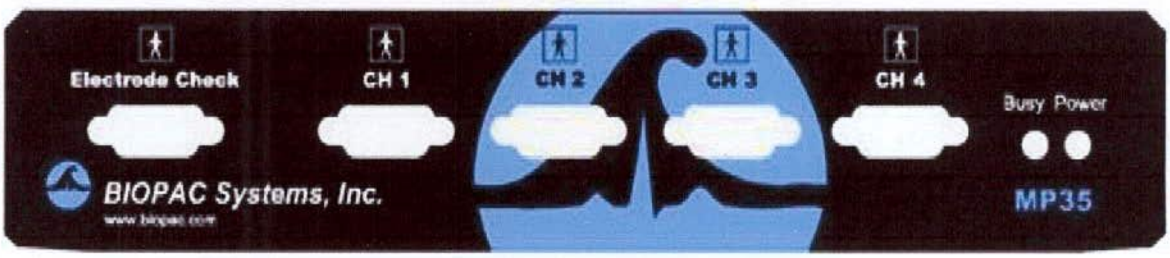


Figure 3.4 The back panel of the MP36/35 has an analog output port, a USB port, an I/O Port, a Trigger

signals (usually analog) and sending them to the computer, where they are (a) displayed on the screen, and (b) stored in the computer's memory (or on the hard disk).

These signals can then be stored for future examination, much as a word processor stores a document or a statistics program saves a data file. Graphical and numerical representations of the data can also be produced for use with other programs. Port, a DC input, a fuse holder, and a power switch, and the unit's serial number. Each MP System (MP100 or MP150) is a complete and expandable data acquisition system that functions like an on screen chart recorder, oscilloscope and X/Y plotter, allowing us to record, view, save and print data. It includes all the necessary hardware and software required to turn any computer into a powerful data acquisition workstation specifically designed for life science applications. Since the MP System takes advantage of the capabilities of the computer, it's as powerful as larger and more expensive data acquisition systems, but has a familiar, easy to use graphical interface. The MP System will reduce the equipment setup time and increase the quality of your results. By harnessing the power of the computer, the MP System gives us publication-quality results with minimum effort. The MP3X has an internal microprocessor to control data acquisition and communication with the computer. There are four analog input channels, one of which can be used as a trigger input. It is needed to connect the MP3X to the computer and connect electrodes, transducers, and I/O devices to the MP35/30. There are three types of devices that connect to the MP3X: electrodes, transducers, and I/O devices.

i) Electrodes are relatively simple instruments that attach to the surface of the skin and pick up electrical signals in the body.
ii) Transducers, on the other hand, convert a physical signal into a proportional electrical signal.
iii) Input/output devices (I/O for short) are specialized devices like pushbutton switches and headphones.

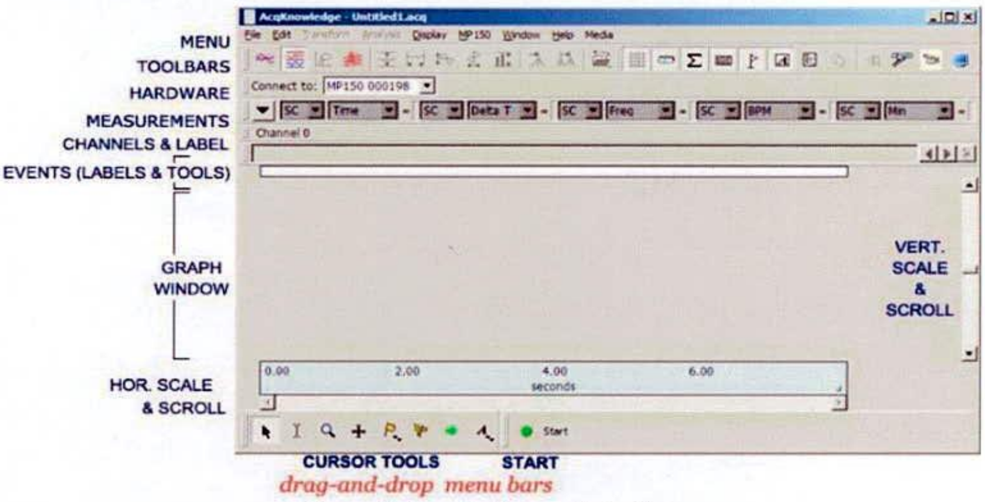


Figure 3.5 Software interface

For analyzing the collected or stored data we two types of software available (a) BIOPAC Student Lab Pro, and (b) Acknowledge. The Acknowledge software interface is shown in Fig. 3.5. AcqKnowledge is an interactive, intuitive program that lets us instantly view measure, analyze, and transform data. Perform complex data acquisition, stimulation, triggering and analyses using simple pull-down menus and dialogs—no need to learn a programming language or new protocol. AcqKnowledge software not only makes data collection easier, but also allows to perform analyses quickly and easily that are impossible on a chart recorder. We can edit data, cut and paste sections of data, perform mathematical and statistical transformations, and copy data to other applications (such as a drawing program or spreadsheet) for reports and publication. Multiple display options are available during and after acquisition—just click on an icon to flip between Chart, Scope, X/Y, Overlapped segments, Histogram, or FFT. The software also includes quality presentation capabilities. AcqKnowledge is extremely flexible, giving us full control over how data is collected. The AcqKnowledge software allows us to perform a range of measurements, calculations, and transformations after the data has been collected.

3.2.4 Subject Collection and Data Acquisition

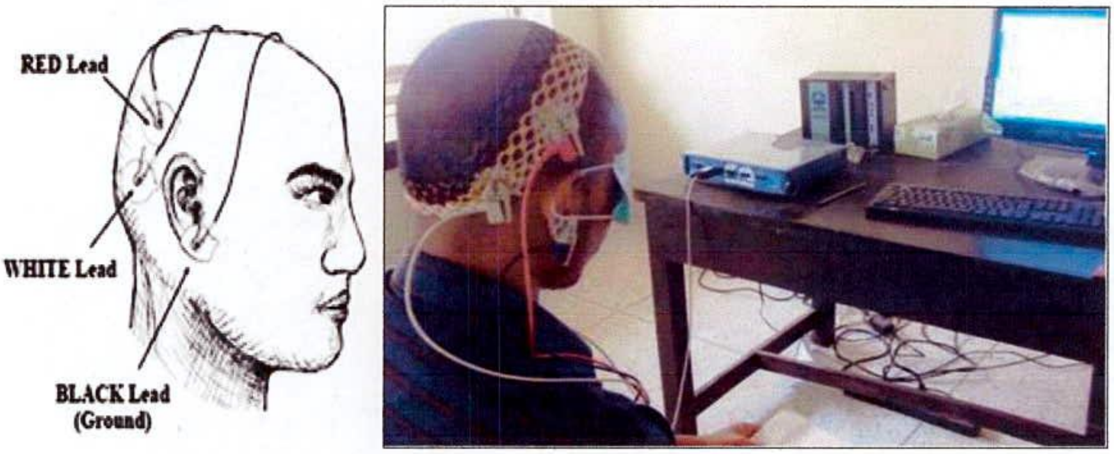
For physiological variables of EEG measurement, the required equipments are BIOPAC [53] electrode lead set (SS2L), BIOPAC disposable vinyl electrodes (EL503), BIOPAC data acquisition unit (MP36 and MP150) with cable and power.

For effective EEG measurement, electrodes should be kept on one side (right or left) of the head. Electrode placement for EEG data extraction is shown in Fig. 3.6(a) in which the red electrode is placed on the occipital lobe, the white electrode is placed behind ear and the ground black lead is placed on ear lobe. Good electrical contact is essential to minimize noise and increase signal amplitude. Fig. 3.6(b) shows the hardware and software interface for data acquisition at BME lab at KUET in mental task (MR) state.

In case of signal acquisition, the electrodes are placed in occipital lobe region which gives the variation of EEG with different states. Alpha, beta, delta, theta wave amplitudes vary with the subjects attention to mental tasks performed with eyes closed. A mask is used on subject's eye so that the concentration would not divert as well as the ocular artifacts might be avoided. Then the electrodes are placed on particular places for different data collection as described above.

Table 3. 1 Subject preparation for EEG recording according to the categorized cognitive states

Subject Description				Subject Mental State	Subject Condition	Duration
Gender	Age	Weight	Height			
M	23	62	5' 8''	Relax	Lying with Eye closed	30 sec
				Take 2 minutes break (time for setup of next recording)		
				Thought	Asking some mathematical problems and intellectual questions	1 min
				Take 2 minutes break (time for setup of next recording)		
				Memory Related task	Showing pictures of some familiar things	3 min
					Involving into other task(as a break)	3 min
					Recalling the pictures	As required
				Take 2 minutes break (time for setup of next recording)		
				Motor Action	Shaking hand	20 sec
				Take 2 minutes break (time for setup of next recording)		
				Pleasant	Making a funny environment	1 min
				Take 2 minutes break (time for setup of next recording)		
				Fear	Watching violent scenes	1.5 min
				Take 2 minutes break (time for setup of next recording)		
				Enjoying Music	Listening music	2 min



(a) (b)

Figure 3.6 (a) EEG standard electrodes position, (b) Pictorial view of EEG measurement in BME Lab KUET at MR state with hardware and software interface.

After that certain mental condition is created by showing video clips, slide show, solving mental mathematics and asking questions. Whole procedure of data collection is designed such that data of one step has no effect on other step as proper interval was given between two steps.

3.3 Channel Selection Technique with SVM

In this thesis, all physiological variables were measured using BIOPAC data acquisition unit (MP36 and MP150) unit. This system automatically filters the raw EEG signal for the appropriate band widths such as Alpha, Beta, Theta and Delta. Moreover, the system records and displays three channels containing the raw EEG together with the alpha wave and alpha-RMS activity. The wave generated mainly from occipital region is Alpha brain waves which oscillate about 10 times per second, and the range is 8-13 cycles per second. Alpha brain waves are seen in wakefulness where there is a relaxed and effortless alertness. The derive Alpha RMS script constructs a standard alpha RMS waveform from an EEG signal. Alpha RMS is the windowed root mean square value of the alpha signal using a window width of 0.25 seconds. Afterward, the spectral analysis based selection of salient homogeneous pair of electrodes for mental state detection is obtained. In the proposed method, the frequency based salient feature extraction is devised for proper selection of channel according to the classification rate of cognitive states. In case of channel selection the raw EEG signals from several subjects over six discrete emotions are collected using three electrodes in BIOPAC system, which are placed on the scalp. This collected different EEG frequency bands in different channel EEG, Alpha and Alpha RMS signal is analyzed to extract some identical features. The real (value), imaginary (value), magnitude (peak to peak), phase angle and power spectral density are the calculated features for the homogeneous pair of electrodes on each subject. The block diagram of proposed approach for channel selection is shown in Fig.3.8. The channel with higher classification accuracy among the cognitive states for these features is sorted as the most significant channel for cognitive state estimation. Figure 3.9 shows the basic structure of SVM where the extracted features are taken as input and the classification accuracy of different channels are taken as output. SVM maximizes the margin between the separating hyper plane and the training data points. Basically it is designed for binary classification problems, and many different forms of SVM algorithms have been introduced for different purposes. Here multiclass support vector machine is used to determine the classification accuracy of different channels from which the efficacy of effective channel is determined. This classifier is advantageous with respect to others, being one of the most important its high generalization capacity for a reduced number of training trials. It is based on the idea of a hyper plane classifier that works by a separating surface (linear or nonlinear) in the input space of the data set. SVM transform the data and then based on these transformations it finds an optimal boundary between the possible outputs. Simply, it does some extremely complex data transformations, and then figures out how to separate the data based on the labels or outputs as it has been defined. Besides, the non-linear SVM puts the boundary that the algorithm calculates doesn't have to be a straight line. In applying SVM, the human emotions are classified into the defined classes. The learning and classification component consists of a training module and a testing module for different cognitive states. All the features are used as the input of SVM. In this structure different extracted salient features was taken as input and classification accuracy was the output of SVM. The EEG signal and their training and testing sequence for pleasant state are shown in Fig. 3.7(a)-(c).

Here, Input of SVM: Different time, frequency and time-frequency domain features

Output of SVM: Accuracy for maximum different channels

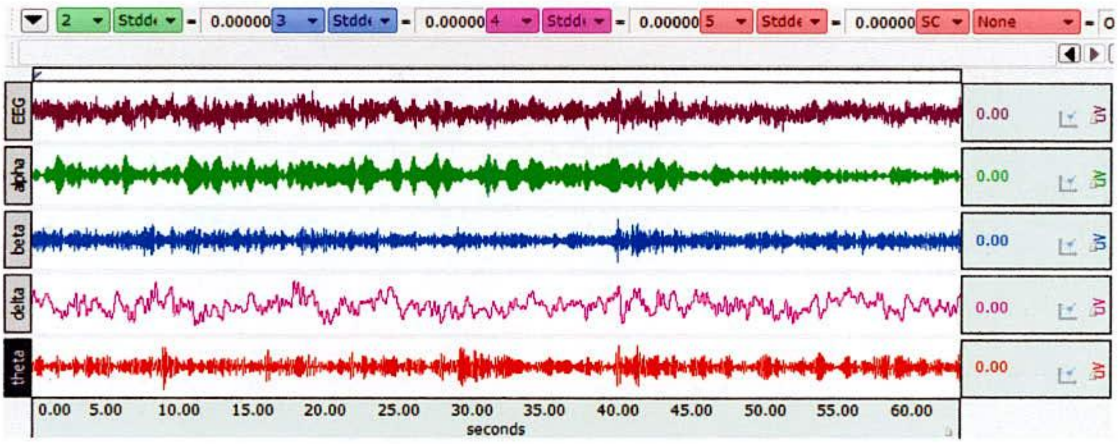
Selected channel= arg max {ach1, ach2, ach3}

Where, ach1= accuracy of channel 1 (EEG channel)

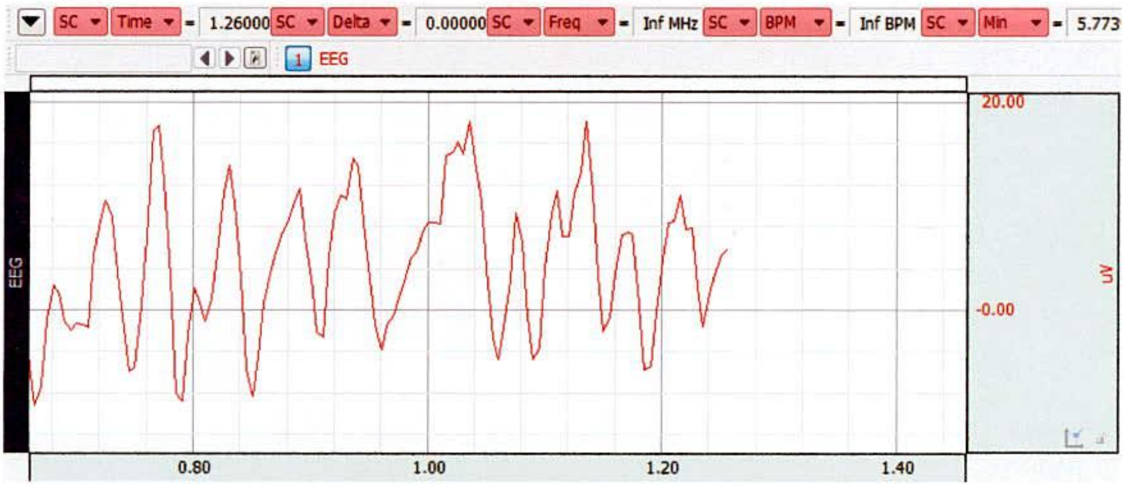
ach2= accuracy of channel 2 (Alpha channel)

ach3= accuracy of channel 3 (Alpha RMS channel)

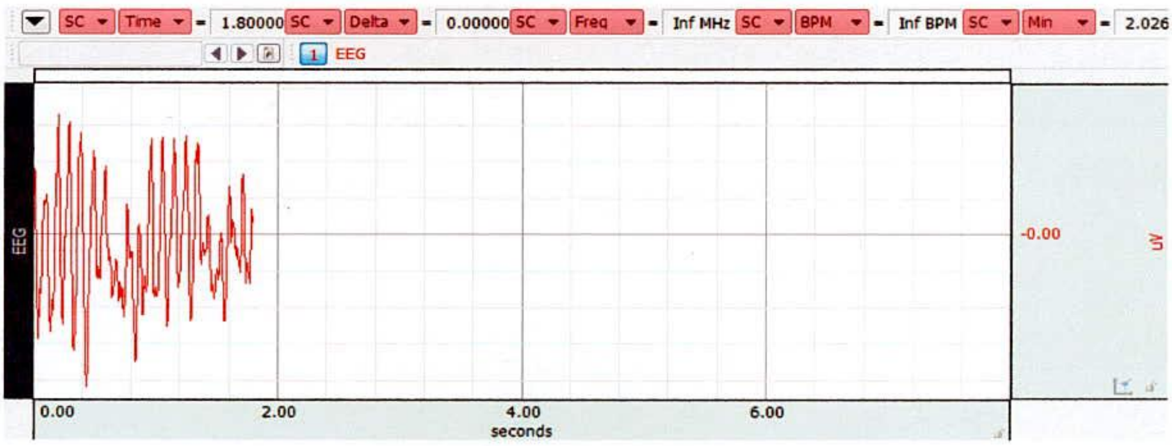
Decision: Finally, channel is selected on the basis of highest accuracy in different conditions.



(a)



(b)



(c)

Figure 3. 7 (a) EEG signal of pleasant state, (b) Training data sequence of EEG data set, (c) Testing data sequence for SVM.

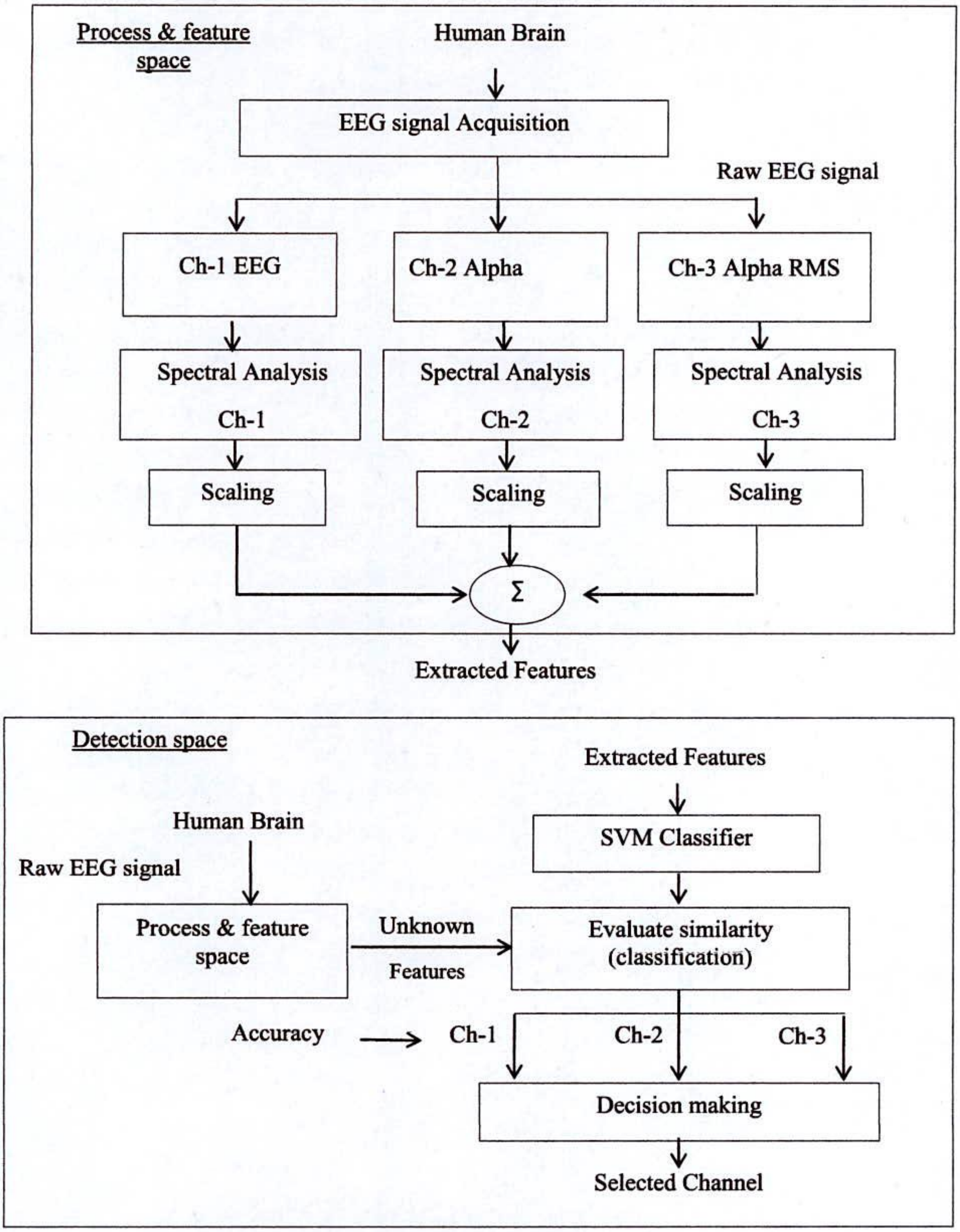


Figure 3.8 Block diagram of effective channel selection approach

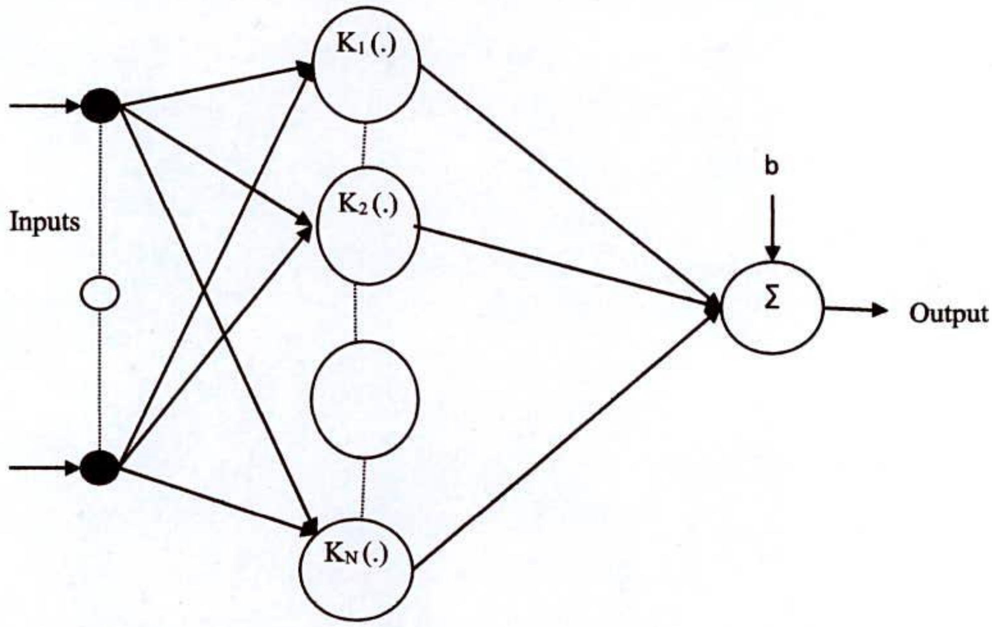


Figure 3.9 Architecture of SVM (n numbers of support vectors).

3.4 Feature Extraction

Various temporal and spectral approaches have been applied to extract some salient features from the EEG signal. For a comparison study, three different methods are investigated, one is based on statistical features in the time domain, other based on power spectrum in the frequency domain and rest is based on time-frequency domain. In this analysis FFT, Statistical and DWT features are taken in case of proper channel selection.

3.5 Results and Discussion

In this thesis the features are extracted using spectral analysis to represent the EEG signal which is particularly important for cognitive state estimation and channel selection purpose. In this work, the SVM algorithm LIBSVM 2.8 [54] has been applied to perform the classification. Table 3.2 represents the number of training and testing data sequence for SVM classifier where each number of data contains 128 samples.

The SVM algorithm requires a training phase in which the feature vectors generated for a series of trials a provided, together with the corresponding class identifiers, or labels, in order to obtain a model which can separate the different classes considered. The train data is labeled of each action manually by an integer number. For example, Relax = 1, Memory related task = 2, Motor Action = 3, Pleasant = 4, Fear = 5 and Enjoying Music = 6 in case of multiclass support vector machine (MCSVM). The MCSVM predicts the class label information for an arbitrary action.

3.5.1 Selection of effective channel with FFT features

Various spatial approaches have been applied on the EEG signal because the pathological condition of bio-signals can sometimes be diagnosed even more easily when the frequency contents of the signal are analyzed. For this study the real value, imaginary value, magnitude and phase, power spectrum of brain signal in the frequency domain are analyzed for feature extraction in case of cognitive state estimation and proper channel selection. Frequency analysis shows the changes in spectral power and phase which can characterize different features in case of cognitive state estimation for brain signals. Each signal is divided into 128-point of data samples and each epoch is analyzed to extract the hidden information and characteristics in frequency domain.

The frequency-domain features used in this paper are based on the fast Fourier transform analysis of each 128-point of EEG samples. Each epoch of the EEG data is processed with Hamming window by zero padding for 128-point fast Fourier transform. Analysis of changes in spectral power and phase can characterize the perturbations in the oscillatory dynamics of ongoing EEG. The power spectrum of all the sub-epochs within each epoch is averaged to minimize the artifacts of the EEG in all sub-windows. Finally, EEG frequency spectrum features are extracted in different channels such as EEG, Alpha and Alpha RMS. After these operations, five kinds of frequency features are obtained. The dimension of each feature is 30, and the number of data sequence for each feature from each subject for each cognitive state is about 190.The relative equations of extracted features in these channels are given in Eqs. (3.1) - (3.6). The Fourier transform of the EEG signal *x (n)* is expressed as,

$$X(k)_{EEG} = \sum_{n=n_s}^{n_e-1} x(n)\exp\left(-j2\pi\frac{nk}{n_e-n_s}\right) \tag{3.1}$$

In Eq. (3.1), k represents the harmonic number of frequency components, n_s represents starting point and n_e represents ending point of the sample of data and $n_e - n_s = N$ (total number of samples). It transforms the time domain EEG signal into frequency domain. Equation (3.1) can be expressed as,

$$X(k)_{EEG} = \sum_{n=n_s}^{n_e-1} x(n)\cos\left(2\pi\frac{nk}{n_e-n_s}\right) - j\sum_{n=n_s}^{n_e-1} x(n)\sin\left(2\pi\frac{nk}{n_e-n_s}\right) = R(k) - jI(k) \tag{3.2}$$

Finally, the magnitude, $|X(k)_{EEG}|$ of frequency transformed data is given by Eq. (3.3).

$$|X(k)_{EEG}| = \sqrt{R^2(k) + I^2(k)} \tag{3.3}$$

Here, $R(k)$ and $I(k)$ gives the real and imaginary value of EEG signal in different cognitive states. Equation (3.4) represents the expression of phase angle, ϕ in frequency domain.

$$\phi = \tan^{-1} \frac{\mathrm{Im}_{X(k)_{EEG}}}{\mathrm{Re}_{X(k)_{EEG}}} \tag{3.4}$$

The power spectral density (PSD) divides up the total power of the EEG signal. To see this, it is integrated over its entire one-sided frequency domain (0, F):

$$\int_0^F PSD(k)dk = \int_0^F 2|X(k)_{EEG}|^2 /(t_2 - t_1)dk \tag{3.5}$$

Equation (3.5) represents the expression of power spectral density in frequency domain where the average power of the signal is in the time range (t_1, t_2). Different features for FFT analysis of each channel signal is given by,

$$X(k)_{EEG/Alpha/AlphaRMS} = \{X(0), X(1), \ldots X(n-1)\} \tag{3.6}$$

In Eq. (3.6), Here, $X(n)$ is the discrete time EEG signal in the time domain, and $X(k)_{EEG/Alpha/AlphaRMS}$ is either the discrete frequency domain signal in three different channels.

Table 3.2 Training and Testing Data Sequence of SVM Classifier.

Data sequence in SVM		No. of Training data sequence	No. of Testing data sequence
Real value	EEG	180	175
	Alpha	172	165
	Alpha-RMS	178	162
Imaginary value	EEG	142	140
	Alpha	142	140
	Alpha-RMS	142	141
Magnitude	EEG	154	135
	Alpha	153	135
	Alpha-RMS	146	135
Phase	EEG	142	141
	Alpha	144	144
	Alpha-RMS	142	141
Power	EEG	150	140
	Alpha	153	136
	Alpha-RMS	150	137

Table 3.3 represents the classification accuracy in each cognitive states for all the spectral features and it is found that the classification rate for the power spectral density much higher for Alpha channel and for relax (RLX) state it is 93.9% and for enjoying music (EM) state it is 92.1%. The alpha activity largely depends on subject's attention to mental task performed and there is an inverse relationship between alpha activity and mental task performed and the classification rate is also higher in the Alpha channel for individual cognitive states. Figure 3.10 (a)-(e) represents the plots of classification accuracy for different channels for different mental states. From Fig. 3.10 (a)-(e) it may be noticed that for real value the classification rate is higher for thought and enjoying music state for Alpha channel whereas for the other channels the rate is much lower. In case of imaginary value the classification rate is high for relax state for Alpha RMS value and for EM state EEG channel shows higher accuracy but for other states these channel accuracy is much lower which cannot model the cognitive states. In case of magnitude and phase angle of spectral features of EEG signal the classification accuracy is higher for Alpha channel for almost every states which is essential for cognitive state estimation. The classification rate for the power spectral density much higher for Alpha channel and for relax (RLX) state it is 93.9% and for enjoying music (EM) state it is 92.1% whereas for EEG channel it is 57.14% and 57.7% respectively and for Alpha RMS it is 27.2% and 51.2% respectively.

Table 3.3 Accuracy of Cognitive State (individual) classification using SVM

FFT Features	Channels	RLX (%)	TH (%)	MR (%)	MA (%)	Pleasant (%)	Fear (%)	EM (%)
Real value	EEG	44.50	33.35	22.10	24.50	47.10	14.30	74.20
	Alpha	45	60.46	48.15	45.60	53.19	45.00	54.19
	Alpha-RMS	27.10	12.10	15.20	22.00	37.50	38.20	52.00
Imaginary value	EEG	39.23	62.30	50.10	43.06	61.36	47.05	94.10
	Alpha	65.96	44.12	73.17	47.10	71.05	46.34	92.30
	Alpha-RMS	94.20	11.60	12.43	12.70	28.16	10.10	43.80
Magnitude	EEG	54.62	22.10	18.00	25.00	32.10	27.30	82.30
	Alpha	68	33.20	22.10	12.10	84.50	87.20	96.20
	Alpha-RMS	88.10	12.20	11.20	13.20	18.00	12.00	14.20
Phase	EEG	61.30	47.05	47.82	52.94	47.92	52.27	51.11
	Alpha	68	49.60	73.17	47.06	59.18	50.00	93.30
	Alpha-RMS	71.20	38.57	37.80	22.82	43.02	42.37	61.12
Power Spectral density	EEG	57.14	65.00	45.00	36.20	38.42	47.30	57.70
	Alpha	93.90	83.33	91.83	56.00	86.50	77.00	92.14
	Alpha-RMS	27.20	23.50	21.80	18.10	27.64	33.03	51.20

3.5.2 Selection of effective channel with Statistical features

Mathematical transformations are applied to signals in order to obtain further information from that signal that is not readily available in the raw signal. A feature is a distinctive characteristic of a set of data that sets it apart from similar items obtained from different types of mathematical transformation. In case of this work the some identical features such as maximum value, minimum value, mean, median, skewness, kurtosis and standard deviation have been extracted using statistical analysis to detect the predetermined emotional states. The inherent characteristics of the statistical data are that they will vary in magnitude but without losing the essential element of homogeneity.

The maximum and minimum value shows the maximum amplitude and minimum amplitude value of the collected EEG data samples between the endpoints of the selected area. These values are required to compare the highest and lowest peak of the signals in different mental states.

Mean computes the mean amplitude value of the collected EEG data samples between the endpoints of the selected area. Equation (3.7) is used to extract the mean value of EEG signal.

$$mean = \frac{1}{n_e - n_s} \sum_{i=n_s}^{n_e - n_s} x_{i_{EEG}} \tag{3.7}$$

Where, n_s represents starting point and n_e represents ending point of the sample of data and the total number of samples ($n_e - n_s$) and i represents the values of points at horizontal axis. Here, x_{iEEG} are the values of points of a curve at vertical axis.

The median separates the higher half of the collected EEG data samples from the lower half and shows the mid-value of the selected area using Eq. (3.8). Here, x is the rearranged data (in ascending or descending order) of x_{iEEG}.

$$median = \begin{cases} x_{\frac{1}{2}(n_e - n_s + 1)} & \text{if } n \text{ is odd} \\ \frac{1}{2}\left(x_{\frac{n_e - n_s}{2}} + x_{\frac{n_e - n_s}{2} + 1} \right) & \text{if } n \text{ is even} \end{cases} \tag{3.8}$$

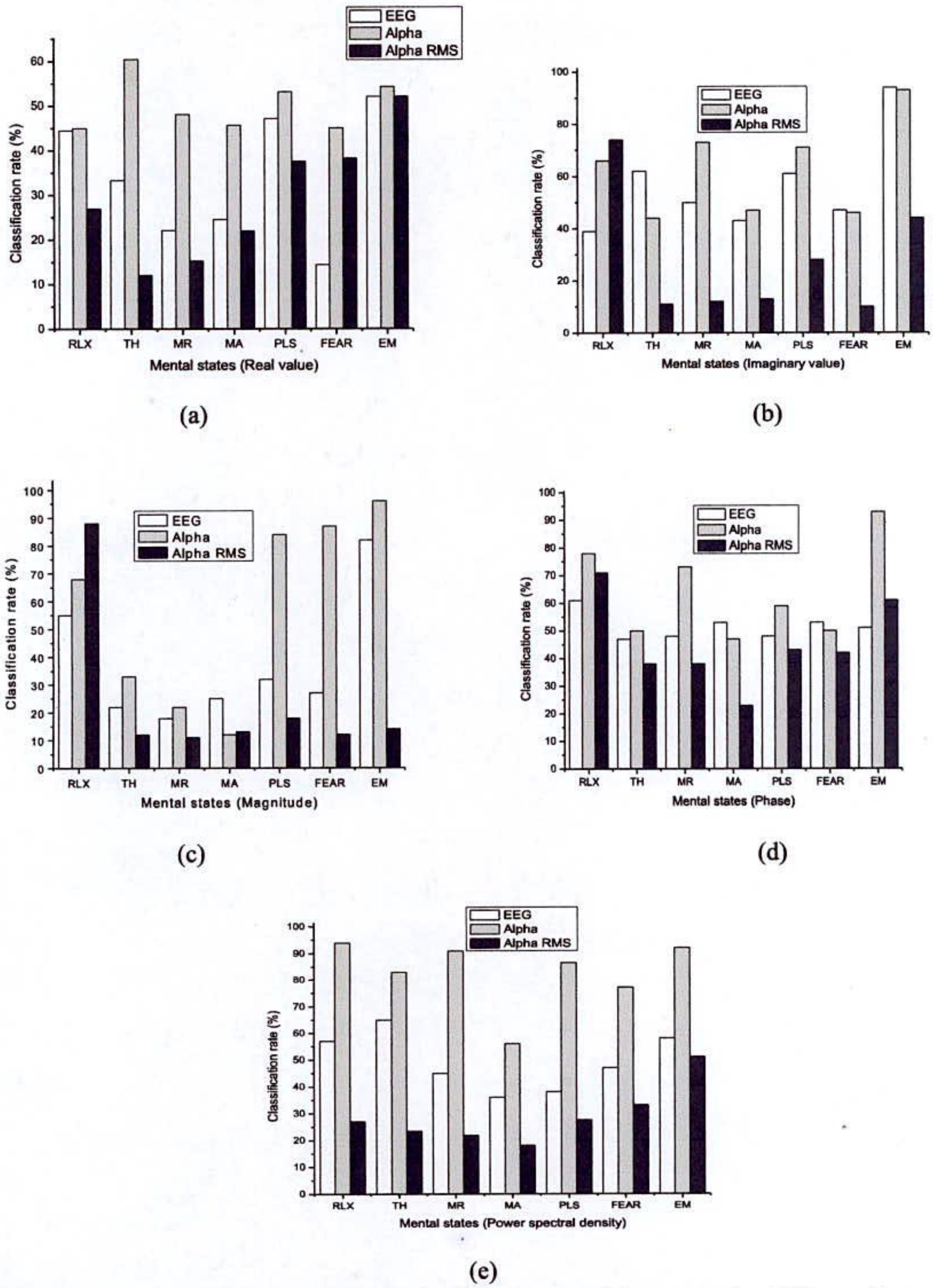


Figure 3.10 Classification accuracy in different cognitive states for different frequency components (a) Real value, (b) Imaginary value, (c) Magnitude, (d) Phase angle, (e) Power spectral density.

Standard deviation computes a standard deviated value from the mean value of the EEG data samples between the endpoints of the selected area. The formula used to compute standard deviation is shown in Eq. (3.9).

$$Stddev = \sqrt{\frac{1}{(n_e - n_s) - 1} \sum_{i=n_s}^{n_e - n_s} \left(x_{i_{EEG}} - \bar{x}_{EEG}\right)^2} \tag{3.9}$$

Where, $\bar{x}_{EEG}$ is the mean value of the EEG data set.

The change in the distribution of the signal segments can be measured in terms of both the parameters of a Gaussian process and the deviation of the distribution from Gaussian. The non-Gaussianity of the signals can be checked by measuring or estimating some higher-order moments such as skewness, kurtosis. Skewness shows the degree of asymmetry in a distribution (away from normal Gaussian distribution) of EEG signal. Equation (3.10) is used to extract skewness from the EEG data.

$$skew = \frac{\sum_{i=n_s}^{n_e} \left(x_{i_{EEG}} - \bar{x}_{EEG}\right)^3}{n_e - n_s} \Big/ \left(\sqrt{\frac{\sum_{i=n_s}^{n_e} \left(x_{i_{EEG}} - \bar{x}_{EEG}\right)^2}{n_e - n_s}} \right)^3 \tag{3.10}$$

Where, a signal x_{iEEG} contains $i \in (n_e - n_s)$points.

Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution; i.e. data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. Kurtosis indicates the degree of peakedness in the distribution of EEG signal and Eq. (3.11) is used to extract kurtosis.

$$kurtosis = \frac{\sum_{i=n_s}^{n_e} \left(x_{i_{EEG}} - \bar{x}_{EEG}\right)^4}{n_e - n_s} \Big/ \left(\frac{\sum_{i=n_s}^{n_e} \left(x_{i_{EEG}} - \bar{x}_{EEG}\right)^2}{n_e - n_s} \right)^2 \tag{3.11}$$

Table 3.4 shows the classification accuracy for different statistical features (max value, min value, mean and standard deviation). The standard deviation shows more accuracy than other features and it was found 65.4% for alpha channel.

3.5.3 Selection of effective channel with DWT features

The extracted wavelet coefficients provide compact representation that shows all the physical parameters of the EEG signal in different frequency bands. In order to reduce the increased dimensionality of the extracted features, some statistics over the set of the wavelet coefficients are applied.

Table 3.4 Accuracy of All Cognitive States for statistical features using SVM

Different features	Channel 1 EEG	Channel 2 Alpha	Channel 3 Alpha RMS
Maximum value	36.2%	47.6%	37.1%
Minimum value	57.73%	58.1%	43.1%
Mean	47.5%	48.3%	34.8%
Standard deviation	51%	65.4%	32.7%

In order to process digital nonstationary EEG signal a discrete approximation of the wavelet coefficients is required. The time-frequency analysis can be applied to extract the wavelet coefficients of discrete time signals. The EEG signal, consisting of many data points, can be compressed into a few parameters. These parameters characterize the behavior of the EEG signal. DWT analyzes the signal at different frequency bands by decomposing of signal into a coarse approximation and detail information. The decomposition of the signal is simply obtained by successive highpass and lowpass filtering of the time domain signal as shown in Eqs. (3.12) & (3.13) as illustrated in Fig. 3.11. The original signal $x_{EEG}[n]$ is first passed through a half band highpass filter g[n] and a lowpass filter h[n]. After the filtering, half of the samples can be eliminated according to the Nyquist's rule. The signal can therefore be subsampled by 2, simply by discarding every other sample.

$$y_{high}[k]=\sum_{n} x_{EEG}[n]\cdot g[2k-n] \tag{3.12}$$

$$y_{low}[k]=\sum_{n} x_{EEG}[n]\cdot h[2k-n] \tag{3.13}$$

Where, $x_{EEG}(n)$ is the discrete time EEG signal, $y_{high}[k]$ and $y_{low}[k]$ are the outputs of the high-pass and low-pass filters, the number of data samples n=256 for each emotional states. In the present paper, the Daubechies4 wavelet function ("db4") is used for extracting the statistical feature from the EEG signal. The number of decomposition levels was chosen to be 4 based on the dominant frequency components of EEG signal. Thus, the EEG signals were decomposed into the details D_1, D_2, D_3, D_4 and one final approximation A_4. For each EEG segment, the detail wavelet coefficients (D_k, k = 1, 2, 3, 4) at the first, second, third, and fourth levels (128 + 65 + 33 + 18 coefficients) and the approximation wavelet coefficients (A_4) at the fourth level (8 coefficients) were computed. Then, 252 wavelet coefficients were obtained for each EEG segment. The following statistical features are taken for representing the EEG signals wavelet coefficients in each band:

i) Maximum value of the wavelet coefficients in each subband,
ii) Minimum value of the wavelet coefficients in each subband,
iii) Mean value of the wavelet coefficients in each subband,
iv) Standard deviation of the wavelet coefficients in each subband.

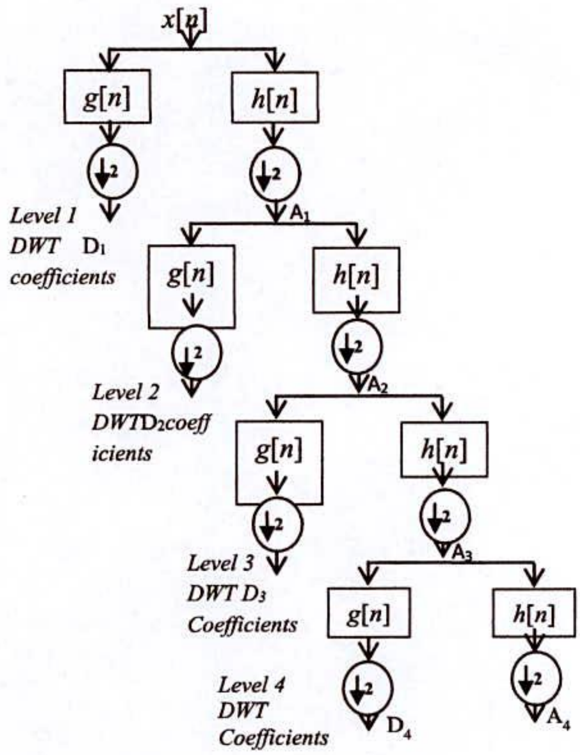


Figure 3.11 Sub-band decomposition of DWT implementation: h[n] is low-pass filter, g[n] is the high pass filter

Table 3.5 shows the time-frequency domain analysis which was done by DWT coefficients and several features were extracted on statistical measures. Mean value and standard deviation show better performance for channel selection purpose.

3.6 Performance Evaluation of the Proposed Method

Table 3.6 shows the average classification performance of SVM classifier using frequency-domain features at different cognitive states as well as the table includes the classification rate of another well-known classifier k-nearest neighbor algorithm (kNN) in order to evaluate the performance of SVM classifier. Figure 3.12 shows the classification accuracy for overall cognitive states at different frequency components. In case of overall accuracy of all cognitive states magnitude shows higher classification rate for Alpha channel and it is found 70% whereas for EEG channel it is 33.43% and Alpha RMS it is 34.89%. For power spectral density it is 69.17% whereas EEG channel it is 47.22% and Alpha RMS it is 32.21%. It can be noticed that the classification performance based on the frequency domain features were better for power spectral density than other ones. In addition, an important finding can be implied that the alpha channel for power spectral density give the best results than the other channels to classify the cognitive sates. Again the highest classification accuracy using k-nearest neighbor algorithm was found 66.26% using power spectral density of Alpha component. Therefore the performance of SVM also found better than those of kNN for almost all of the features and channel.

Table 3.5 Accuracy of different channels for DWT features using SVM

Different features	Channel 1 EEG	Channel 2 Alpha	Channel 3 Alpha RMS
Maximum value	46.5%	67.6%	57.3%
Minimum value	55.3%	78.3%	63.5%
Mean	77.5%	81.3%	64.7%
Standard deviation	64.1%	75.4%	52.8%

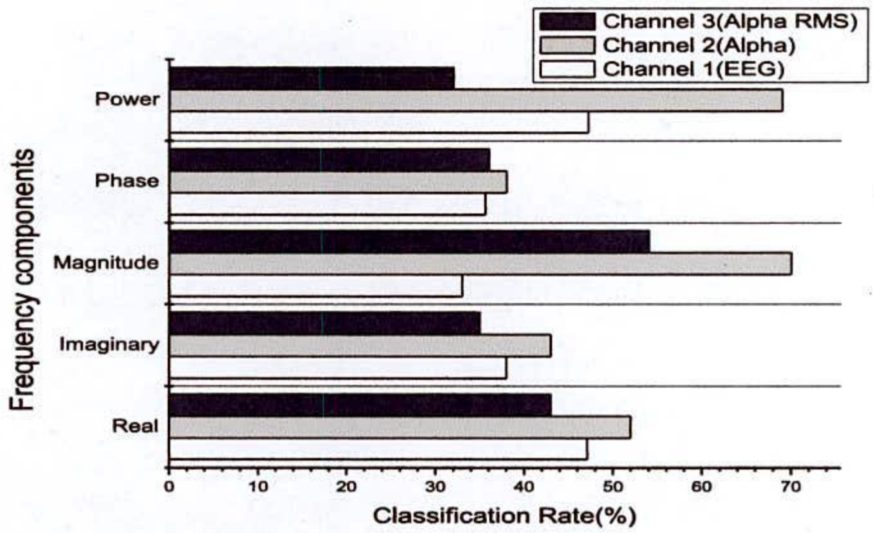


Figure 3.12 Classification accuracy for overall cognitive states for different frequency components

Table 3.6 Overall accuracy of different channels for Identical Features using SVM and comparing with kNN classifier

Spectral Features	Channel 1 EEG		Channel 2 Alpha		Channel 3 Alpha RMS	
	kNN (k=3)	SVM	kNN (k=3)	SVM	kNN (k=3)	SVM
Real value	44.26%	47.12%	52.15%	52.13%	43.3%	42.87%
Imaginary value	36.82%	37.73%	42.15%	43.40%	34.23%	34.89%
Magnitude	32.87%	33.43%	66.25%	70.00%	51.25%	54.33%
Phase	35.98%	35.66%	36.03%	38.18%	36.13%	36.08%
Power	46.65%	47.22%	66.26%	69.17%	29.79%	32.21%

Table 3.7 Overall Accuracy of All Cognitive States for combination of all features using SVM

Different subjects	Channel 1 EEG	Channel 2 Alpha	Channel 3 Alpha RMS
Subject 1	56%	67.3%	46.2%
Subject 2	47.73%	73%	33.1%
Subject 3	41.2%	69.7%	42.5%
Subject 4	43%	62.8%	44.3%

The significant features are tried to identify for each classification problem and thereby to investigate the consequent cognitive state. Feature extraction methods select or omit dimensions of the data that correspond to one EEG channel depending on a performance measure. Thus they seem particularly important not only to find the cognition-specific features but also expand the applicability of using fewer electrodes for practical applications. Considering all the performances of all features, power spectral density shows much improved result than other frequency based features. From the result it is shown that among all the features real value, imaginary value, magnitude (peak-peak), phase and power spectral density the classification rate is much higher for power spectral density for all cognitive states. So it is determined that in case of spectral analysis power spectrum density gives much improved result than other features. Moreover, the Table 3.7 includes the classification accuracy by considering all the time, frequency, time-frequency domain features of EEG signals for four different subjects. From the table it can be noticed that the highest accuracies of classification are obtained for EEG channel 41.2%, for Alpha channel 73% and for Alpha RMS 46.2% i.e. the classification rate has been degraded with taking all the features. From the experimental results and the classification rate of different subjects, it can be concluded that alpha channel proved better for cognitive state estimation as the classification accuracy for this channel is higher in individual cognitive states for different features. Alpha component occurred in the occipital region of brain and the electrode positions on the scalp was also in the occipital lobe which makes alpha band more effective for classification.

3.7 Summary

This section described a framework based on mutual information maximization to solve the EEG feature/channel selection and dimensionality reduction problems in order to classify emotions. In EEG classification, one of the major problems is the huge number of features to be classified. In this analysis, channel selection method has been developed to alleviate "the curse of dimensionality" in EEG classification. The result of this study could help for cognitive states estimation and proper channel selection by using physiological brain signals. Considering the classification rate it is determined that power spectral density is the most efficient feature than the other frequency based features and the alpha channel is the most significant channel in case of cognitive state estimation. Alpha channel also shows better performance for time domain and time-frequency domain analysis and DWT features are the most effective features in case of effective channel selection as well as cognitive state estimation and emotion modeling.

Chapter 4

Human Emotion Classification

To design an EEG based emotion model, effective feature selection and accurate classification are the two important factors in order to improve the performance. The useful features need to be extracted from the EEG signals with appropriate signal processing. These extracted features are the basic inputs to the classifier for identification of different frequency bands from EEG signal. The extracted features include the statistical value from DWT and FFT analysis as well as statistical measures of raw EEG signal as well as the EEG band of EEG signal. Emotions occur due to different environmental effects and also different audio and visual stimulus. In this thesis different approaches have been applied to classify the emotional states. The block diagram of the proposed approach of emotion classification and modeling is shown in Fig. 4.1.

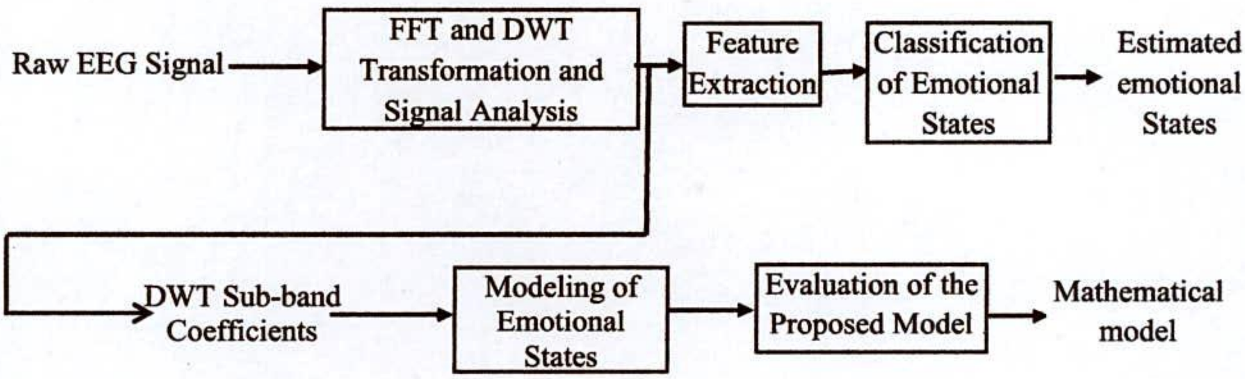


Figure 4. 1 Block diagram of the proposed approach of emotion classification and modeling

4.1 An Approach of Emotion Classification

The emotional states are created with different environmental impacts and the EEG signals are collected from the brain. In this research the emotional states are classified while listening different types of songs and also performing sustained mental task during test.

4.1.1 EEG Signal Processing

The EEG signals are collected according to the categorized emotional states as discussed preciously. In this section, the collected data sets, their wavelet transform and FFT transform have been discussed with feature extraction. Then the classification rate for different emotional states are observed for different time domain, frequency domain and time-frequency domain analysis. Then the emotional states are modeled with mathematical expressions with the wave band coefficients.

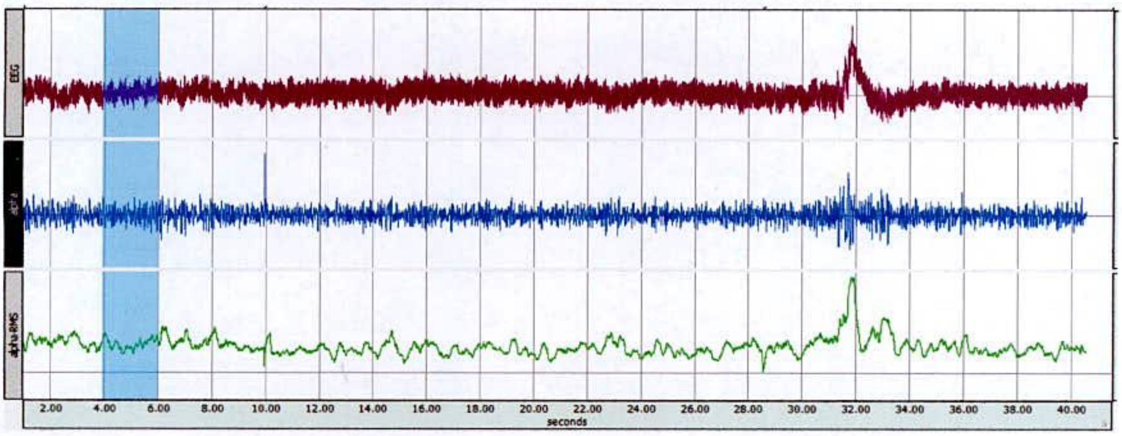
4.1.2 Wavelet and FFT Transformation of Raw EEG data

To implement an effective EEG based system a proper mathematical background emotional states is needed. So a proper suitable data collection protocol for EEG signal in different states is the first important factor in order to improve the performance. In this thesis the BIOPAC electroencephalography II (EEG II) signal has been used to capture the raw EEG signal which measures mainly the brain activity of EEG signal [17]. The captured raw data and the transformed DWT and FFT data of EEG signal at relax and pleasant condition are shown in Figs. 4.2 and 4.3 respectively.

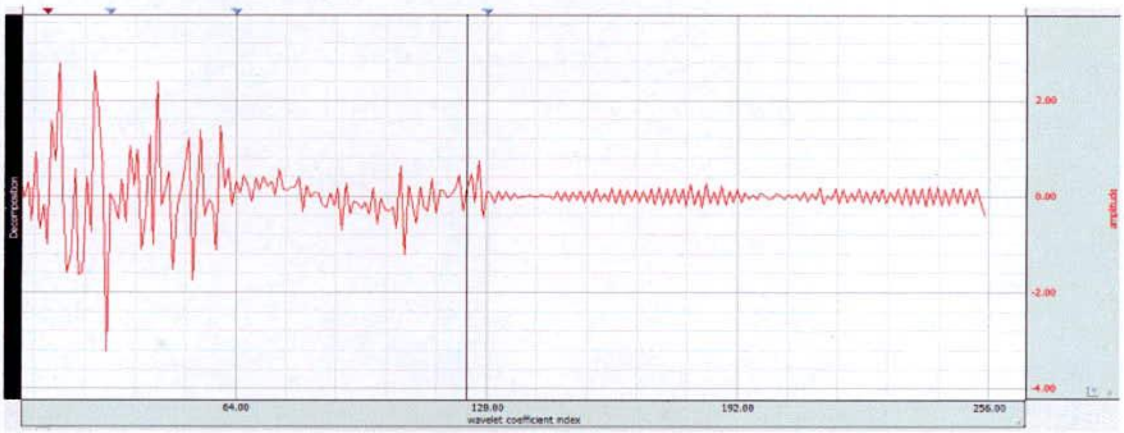
4.1.3 Feature Extraction from EEG Signal for DWT Analysis

The recognition system of different emotional states has been performed using different features extracted from EEG signals. The extracted wavelet coefficients provide compact representation that shows all the physical parameters of the EEG signal in different frequency bands. In order to reduce the increased dimensionality of the extracted features, some statistics over the set of the wavelet coefficients are applied. The following statistical features are taken for representing the EEG signals wavelet coefficients in each band: (i) Maximum, (ii) Minimum (iii) Mean, and (iv) Standard deviation.

The extracted features after transforming the raw signals into DWT and FFT are shown in Table 4.1 and Table 4.2 respectively. The transformed (FFT) signal shows the deviations in amplitude and frequency in different mental states. The maximum and minimum value with different mental states for FFT and DWT is shown in Fig.4.4 (a) and Fig.4.4 (b) respectively. The variations of maximum and minimum FFT magnitude cannot differentiate the mental states clearly whereas the maximum and minimum values of 4th level subband coefficients clearly detect different mental states. In response to dynamical changes in the function of these organs, the signals may exhibit time-varying as well as nonstationary responses. The wavelet approach decomposes the EEG signal into its frequency components according to its range while maintaining the time resolution. So certain frequency domain properties in different emotional states can be obtained in particular time series.



(a)



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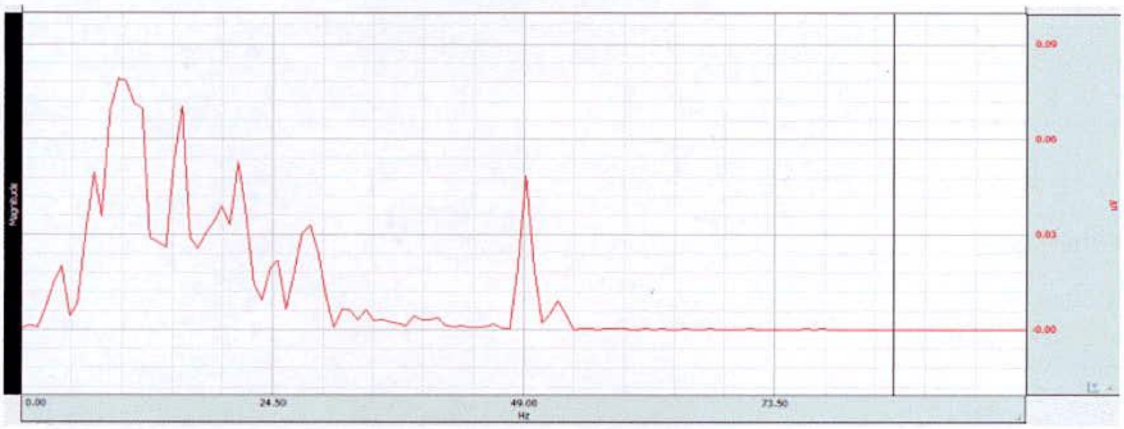
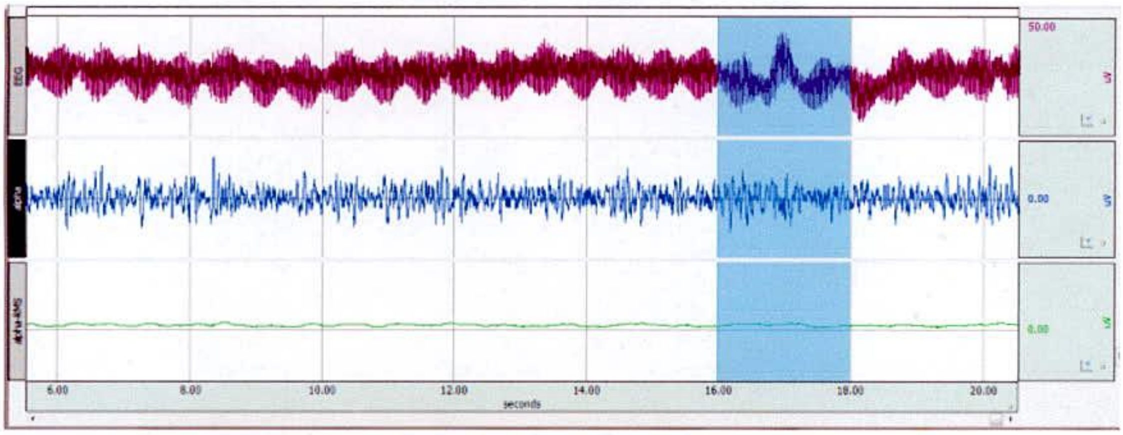
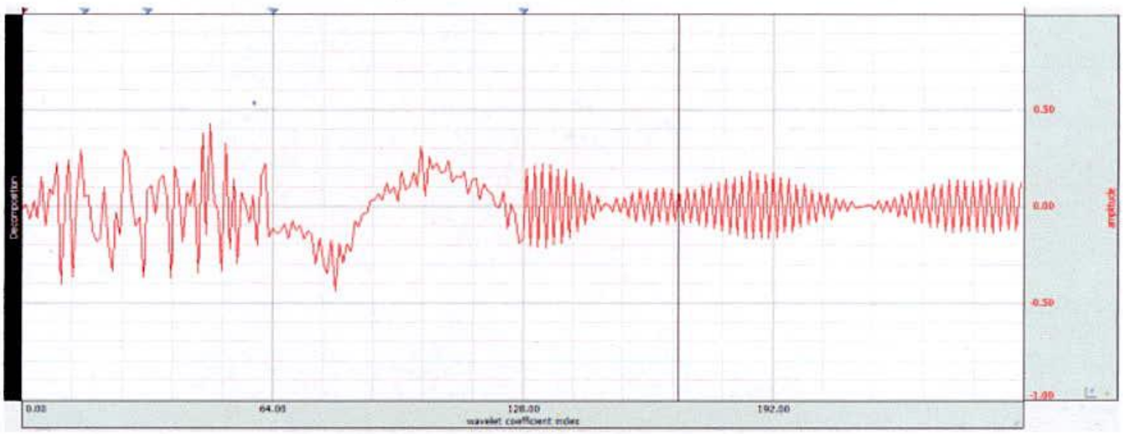


(c)

Figure 4. 2 The EEG signal at relax condition, (a) raw data, (b) DWT signal, (c) FFT signal



(a)



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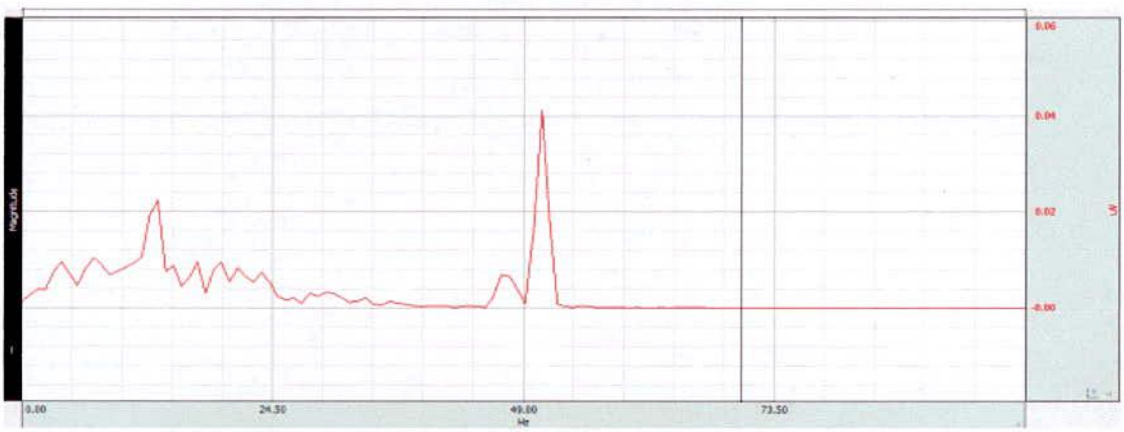


(c)

Figure 4. 3 The EEG signal at pleasant condition, (a) raw data, (b) DWT signal, (c) FFT signal

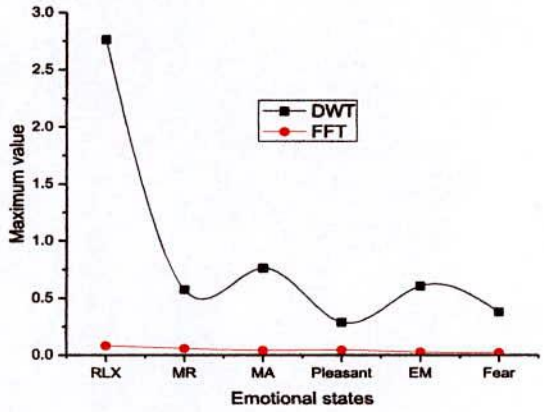
The features are accurately captured and localized in both time-frequency contexts for the estimation of emotions that cannot be obtained by FFT. In Fig. 4.5 the classification rate of different emotional states are shown for statistical, FFT and DWT based features. So in our proposed method the combination of wavelet features have proved the better consideration for emotion classification so wavelet coefficients are considered for the mathematical modeling of emotional states.

Table 4. 1 Extracted Features for Six Emotional States by DWT

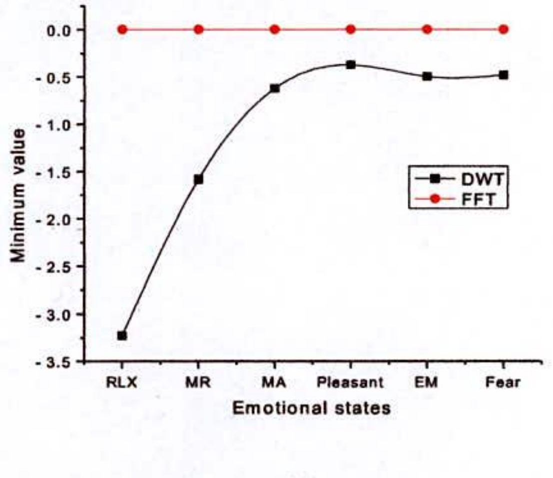
Mental states	Extracted features	Subbands Coefficients of Wavelet				
		D_1	D_2	D_3	D_4	A_4
RLX	Maximum	0.26783	0.74121	2.38683	2.76374	0.911114
	Minimum	-0.39378	-1.22042	-1.74029	-3.22820	-0.99828
	Mean	0.00266	0.00071	0.10691	0.00464	-0.10520
	Standard deviation	0.13894	0.34938	0.89386	1.63026	0.61962
MR	Maximum	0.26752	0.38553	1.04740	0.57264	0.60856
	Minimum	-0.28120	-0.77295	-1.69796	-1.57946	-0.48784
	Mean	-0.00207	-0.01164	-0.02152	-0.14150	0.03588
	Standard deviation	0.16761	0.23181	0.47988	0.49296	0.32039
MA	Maximum	0.34934	0.24737	0.42874	0.76200	0.88096
	Minimum	-0.14148	-0.23056	-0.296	-0.62133	-0.94222
	Mean	0.00193	0.03021	0.01156	0.03337	0.04697
	Standard deviation	0.09510	0.10439	0.19989	0.50958	0.46321
PLS	Maximum	0.21722	0.30657	0.42664	0.28811	0.28867
	Minimum	-0.21972	-0.44256	-0.37298	-0.36932	-0.40428
	Mean	-9.43E-005	-0.01330	0.00733	-0.05271	0.01227
	Standard deviation	0.11884	0.1636	0.20334	0.18184	0.18529
EM	Maximum	0.11503	0.29909	0.38840	0.60569	0.62840
	Minimum	-0.11414	-0.37688	-0.39099	-0.49465	-0.41847
	Mean	0.00044	0.02273	-0.04357	0.02281	-0.00032
	Standard deviation	0.06306	0.11584	0.17089	0.27774	0.29538
Fear	Maximum	0.07622	0.20831	0.33731	0.37702	0.2775
	Minimum	-0.08182	-0.12551	-0.43828	-0.48087	-0.27239
	Mean	-0.000855	0.01839	-0.01236	-0.04448	-0.00795
	Standard deviation	0.03457	0.07698	0.18909	0.22184	0.17976

Table 4. 2 Extracted Features of for Six Emotional States by FFT

Emotional States	MaximumValue (µV)	Frequency at Maximum value (Hz)	MinimumValue (µV)	Frequency at Minimum value (Hz)
RLX	0.07909	9.375	3.42E-005	65.62
MR	0.05571	12.5	9.54E-005	97.65625
MA	0.03757	5.46875	1.37E-005	58.59375
PLS	0.04102	50.78125	3.46E-006	76.56250
EM	0.02324	7.03125	66.25E-006	71.09375
Fear	0.01752	14.84375	3.21E-006	78.90625



(a)



(b)

Figure 4. 4 Comparison of results obtained from DWT and FFT at different mental states (a) Maximum value (b) Minimum value

Table 4. 3 Accuracy of different emotional states using SVM

Features	Classification Accuracy					
	RLX	MR	MA	EM	Pleasant	Fear
Statistical	36.67%	44.19%	37.8%	42.5%	30.56%	38.2%
FFT	55.30%	58.15%	45.6%	64.1%	73.19%	65.10%
DWT	66.84%	67.69%	52.3%	72.1%	82.35%	79.22%
All (Both spatial and temporal)	74.5%	91.83%	76%	57.7%	86.50%	77.00%

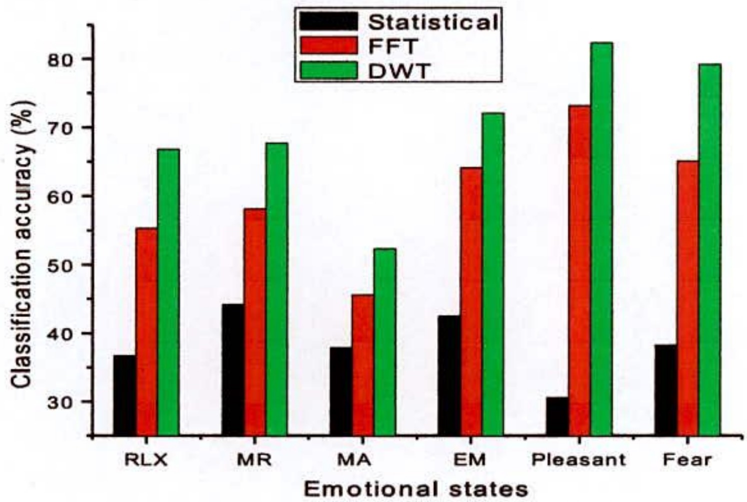


Figure 4. 5 Plot of classification accuracy of different emotional states with statistical, FFT and DWT features

In case of mathematical modeling of emotional states it is very essential to know which features are more efficient for classifying the emotional states effectively. Table 4.3 shows the classification rate of different emotional states using SVM classifier.

4.2 Performance Evaluation of our proposed method

In order to obtain a perfect performance evaluation of the proposed method the other presented work in the literature review section has been compared with it. Exactly all the similar cognitive states that are considered in this work have not found in the related works, but few have been found and their highest classification rates are mentioned in Table 4.4. In this table it can be noticed that M. Takahashi [33] proposed a system for estimating the states of information acquisition, memory related terms, motor action and thought by using Artificial neural network, and the highest accuracy rate obtained respectively for them are 50.0%, 80.8%, 66.0% and 46.7%. Similarly S. Nasehi [6] used a Probabilistic Neural Network (PNN) to predict six basic mental states to taking the Gabor-based features with

Table 4. 4 The comparison between the proposed method with others

Approaches	Features used by the previous researchers	Cognitive states	Accuracy obtained (%)	Accuracy obtained in the proposed work (%)
M. Takahashi [33]	Absolute level of Heart Rate, Respiration Rate , Blood Pressure, Skin Potential Response, Blink rate	Thought	46.7	83.33
		Memory Related task	80.8	91.83
		Motor Action	66.0	76.00
Saadat Nasehi [6]	Gabor-PCA based features of EEG signal	Happiness	58.76	86.50
		Fear	56.79	77.00
Mina Mikhail [35]	Power spectral density of EEG signal	Happiness	51	86.50
		Fear	58	77.00

accuracy rate of 58.76% for happiness 56.79% for fear state. Again Mina Mikhail [35] reported an average accuracy of 51%, 53%, 58% and 61% for joy, anger, fear and sadness, respectively using Support Vector Machines (SVM). Comparing with the related works, the proposed method gives better accuracy and shows much improvement to estimate thought, memory related task, motor action pleasant and fear state.

4.3 An approach of emotion classification with musical activity

The basic socio-cognitive domain of human life is music. Different researchers from different eras used music for therapeutical purposes are trying to establish the relationship of music with emotional activity. The inner mechanism of the brain evoked cognitions and changes mental behavior while listening music because it has been proven that music as a consequence to evoke emotions. Listening music helps to keep the neurons and synapses more active and which varies the effective frequency bands of brain signal. When sound waves are listened or pronounced, they have an impact in neurological (brain and nerve) system work in human body. When neurons are activated, local current flows and generate electrical activity. This electrical activity activates different parts of the human brain during listening music. It also indicates the emotional states with the variations of functional activities of brain which are more influenced by exposure to music. Each of the music or song has specific frequency and bits according to which the brain activity and the effective frequency band of EEG signal may vary and the cognitive activities also change according to the frequency bands. Fig. 4.6 shows the corresponding EEG signal when human brain is stimulated with audio signal. The assignment of different cognitive states with their effective frequency band is shown in Table 4.5.

Figure 4. 6 Brain stimulation while listening songs and corresponding EEG signal

Table 4. 5 Different frequency band region of EEG signal for different cognitive state

EEG wave	Frequency band region	Cognitive states
Delta (δ) wave	(0.4-4) Hz	Unconsciousness (Associated with deep sleep)
Theta (θ) wave	(4-8) Hz	Catnap (Associated with drowsiness)
Alpha (α) wave	(8-14) Hz	Relax (Associated with relaxed, alert state of consciousness)
Beta (β) wave	(14-35) Hz	Stress/Tension (Associated with active, busy or anxious thinking)

Table 4. 6 Category of songs selected for cognitive state estimation

Song type	Soft song	Medium fast song	Fast song
Bangla	Rabindra Sangeet	Adhunik Sangeet	Hard Rock
Hindi	Carnatic	Patriotic Song	Pop
English	Melody	Folk song	Hard Rock

The categorization of selected songs for cognitive state estimation is shown in Table 4.6. In Table 4.6 the soft music is selected which composes a softer, more toned-down sound putting more emphasis on melody and vocal harmonies. The medium and fast music are selected according to the tempo of music i.e. rate of speed or number of beats per minutes. While listening different types of songs such as loud or soft, high pitch or low pitch, audible or inaudible etc., our brain responses differently. Low frequency indicates the state of relax while high frequency indicates the state of stress [55]. The human brain produces different electrical activity due to the different levels of music [56]. Each type of music or songs has its own frequency. While listening music the frequency of the music can be either resonate or in conflict with the body's rhythms (heart rate) and also with the frequency bands of EEG rhythm which authorizes specific functions of brain [57]. Music can be used as a tool to estimate the cognitive states such as tension/stress, solitude, relax and these changes are reflected clearly in physiological system for human body [58]. The block diagram of the proposed approach for cognitive state estimation during hearing music is shown in Fig. 4.7.

A lot of works have been carried out for addressing the problem of musical influences on the functional responses of human brain. Gerra et al. found that while listening music the corresponding changes will be induced in neurotransmitters, peptides and hormonal reactions [59]. In [60]-[62], Authors show the variations of functional activities of different frequency band relating the cognitive activity with music levels. They found that beta activity relates to increased alertness and cognitive processes [60] and unpleasant music produces decrease in alpha power at the right frontal lobe [61]. Alpha waves have been thought to indicate both a relaxed awareness without any attention or concentration whereas a beta wave is the usual waking rhythm of the brain associated with active thinking, active attention, focus on the outside world, or solving concrete problems. A high-level beta wave may be acquired when a human brain is in a panic state while listening different unpleasant music. Authors in [62] showed when subjects listen to the pleasant music the changes were reflected in the EEG and there was an increase in frontal midline (Fm) theta power. Authors in [63] showed the dependence of EEG spectral power on the intensity and style of music. The effect of Indian classical music and rock music on brain activity was studied using Detrended fluctuation analysis (DFA) algorithm, and Multi-scale entropy (MSE) method [64]. The brain wave variation was monitored in [65] by changing the music type (techno and classical) and the results showed that 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. R.S. Schaefer et al. showed a difference in alpha power in different directions to indicate that both the tasks and the stimuli modulate an attentional network, which may relate to the inhibition of non-task relevant cortical areas, as well as engagement with the music [66]. In this section, a new approach is proposed to identify the cognitive states from the variation of effective EEG band. The effective features show the how the brain activity varies during listening different types of music.

In this section, statistical and frequency based salient feature extraction are proposed for particular EEG bands under the influence of different types of songs for selection of brain activities according to the classification rate of efficient frequency bands and their power spectrum analysis. The steps in effective band selection for the proposed method are given below:

i) The raw EEG signals from several subjects during hearing of different types of music are collected using three electrodes in BIOPAC data acquisition unit which are placed on the scalp.

ii) This preprocessed signal is divided into different EEG frequency bands such as Alpha, Beta, Delta and Theta and the salient global features are extracted from the specific frequency bands.

iii) From the classification rate of effective frequency band wave the pre-specified cognitive states can be determined.

4.4 EEG Signal Recording while Listening Music

In case of mental state evaluation brain signal is most essential so EEG data acquisition plays a significant role in this research. While listening music the electrical activity of human brain gets affected. The electrical activity is measured at the scalp through a set of electrodes which are rich in information about the cognitive activity at different frequency bands of EEG signal.

In this research brain signals had been captured while subjects were listening to emotional evoking music in different categories: relax, stress and catnap. Due to musical preferences is a subjective matter the participants were asked to pick three songs (one song for each category). Moreover three songs (one song for each category) were chosen that the songs were previously classified according to their frequency to make a relation with the variation of human brain with musical activity. The acquired EEG data and musical features are classified by machine learning algorithms and correlations among them were investigated.

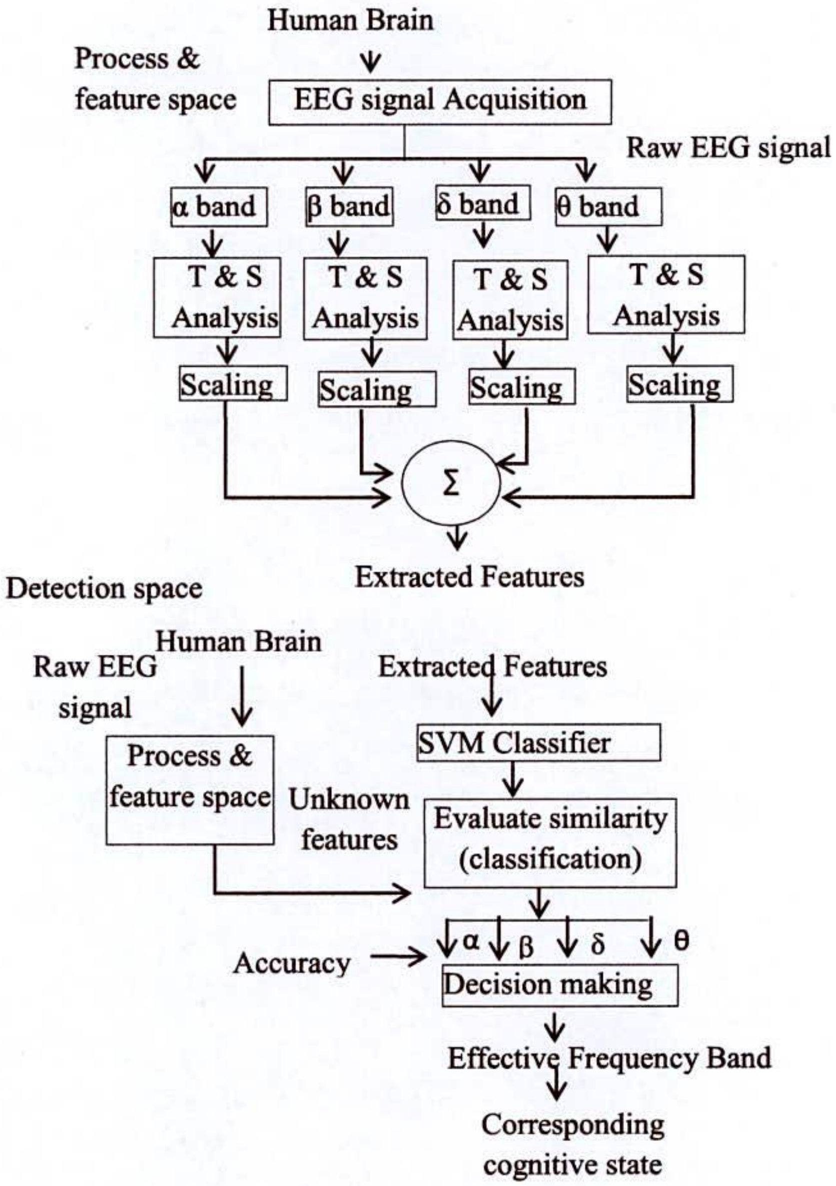


Figure 4. 7 Proposed approach for cognitive state estimation

4.4.1 Music Selection for Cognitive State Estimation

Several research in this field mentioned that different music has different physiological effect on human body rhythms and brain. The effect of music on brain functions rate based on subject's choice of like music (slow, medium and fast song) at different languages such that Bangla, English, Hindi. The selected songs have different spectral stimuli depending on their number of bits per second and affect separately on the EEG band waves and changes the signal characteristics. According to the selected salient features it is determined that which state is more affected with the effective frequency band influenced by the different types of selected songs. Figs. 4.8(a), 4.9(a) and 4.10(a) show the frequency spectrum of soft, medium and fast song and Figs. 4.8(b), 4.9(b) and 4.10(b) show the corresponding brain signals respectively. In this work the Bangla, English and Hindi slow, medium and fast songs were played one after another taking a proper interval to evaluate the effect of cognitive activities of brain influenced by these songs. It is observed that the power spectral density is higher for fast song than medium and slow depending which the effect of frequency bands for brain signal varies with the cognitive activities of brain.

4.4.2 Subject Selection and Data Acquisition

The EEG signals were collected in biomedical signal processing laboratory, KUET. The experimental data were collected from 48 numbers of subjects and the subjects were male, and were in good physical and mental conditions and able to react with different types of songs. Their average age was 23 years so that they are sensitive to all the mental activities. The room was air conditioned and approximately noise free. In Fig. 4.11 the position of electrode on the scalp is shown for EEG data acquisition in the period of listening music.

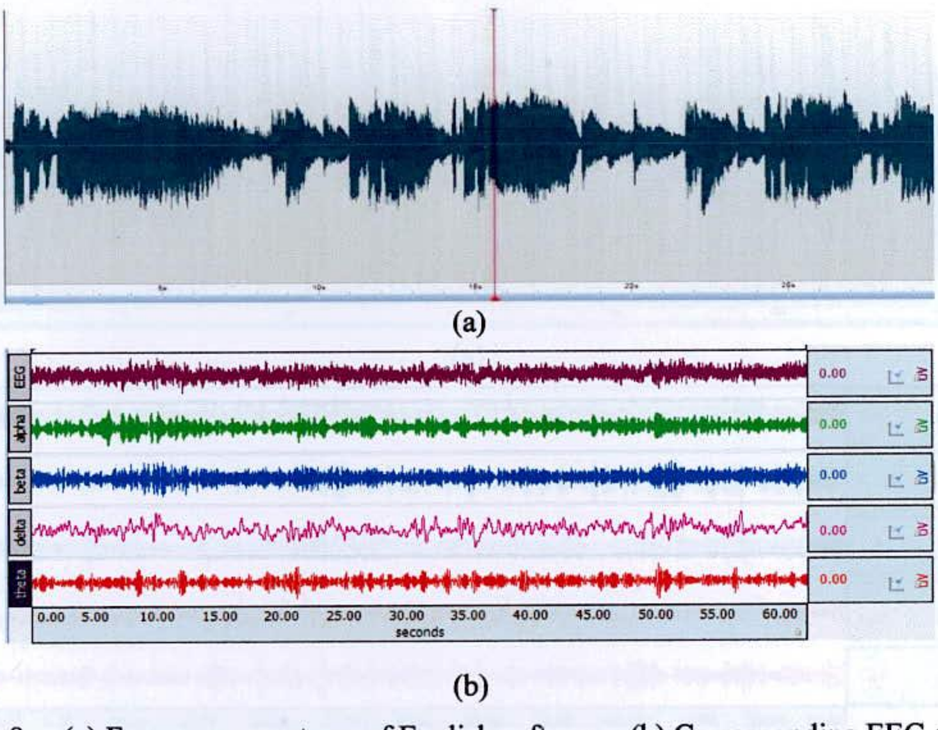


Figure 4. 8 (a) Frequency spectrum of English soft song; (b) Corresponding EEG signal for soft song

effective for Bangla medium and fast song and they are 86.5%, 71.18%, and 97% respectively. When human brain is subjected to Bangla soft song the cognitive state was drowsiness or may be called catnap and when medium and fast Bangla song was played the cognitive states indicate relax and tension respectively.

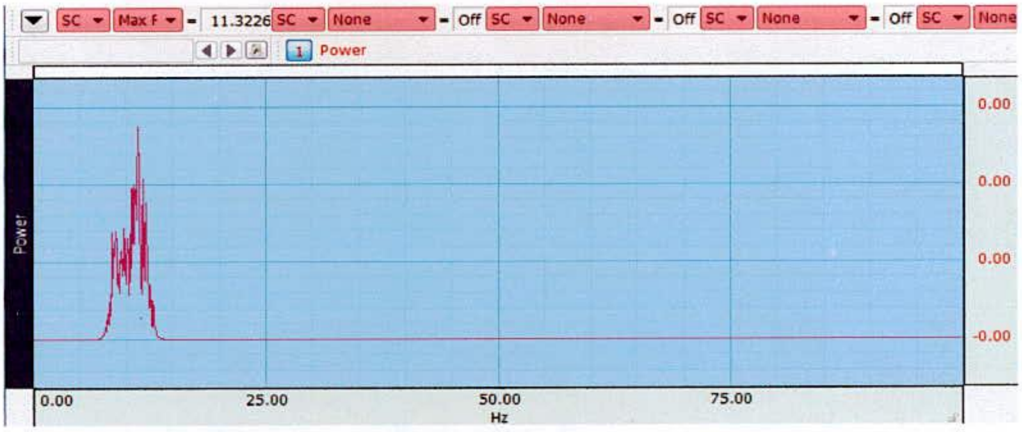
Table 4. 7 Classification accuracy at different effective bands using SVM for Bangla song

Song type	EEG frequency band	Train dataset	Test dataset	Classification accuracy
Bangla soft song	Alpha(α)	58	36	64.28%
	Beta(β)	58	35	20%
	Delta(δ)	58	36	36.11%
	Theta(θ)	58	37	86.5%
Bangla medium song	Alpha(α)	62	35	71.18%
	Beta(β)	62	36	3.61%
	Delta(δ)	62	37	23.35%
	Theta(θ)	62	35	23.1%
Bangla fast song	Alpha(α)	56	32	2.5%
	Beta(β)	56	33	97%
	Delta(δ)	56	32	65.68%
	Theta(θ)	56	34	39.47%

Table 4. 8 Classification accuracy at different effective bands using SVM for English song

Song type	EEG frequency band	Train dataset	Test dataset	Classification accuracy
English soft song	Alpha(α)	51	36	41%
	Beta(β)	51	35	31.76%
	Delta(δ)	51	36	44.44%
	Theta(θ)	51	37	84.85%
English medium song	Alpha(α)	49	35	85.7%
	Beta(β)	49	36	43.53%
	Delta(δ)	49	37	45.75%
	Theta(θ)	49	35	11.43%
English fast song	Alpha(α)	47	32	5%
	Beta(β)	47	33	88.57%
	Delta(δ)	47	32	54.54%
	Theta(θ)	47	34	31.81%

(a)



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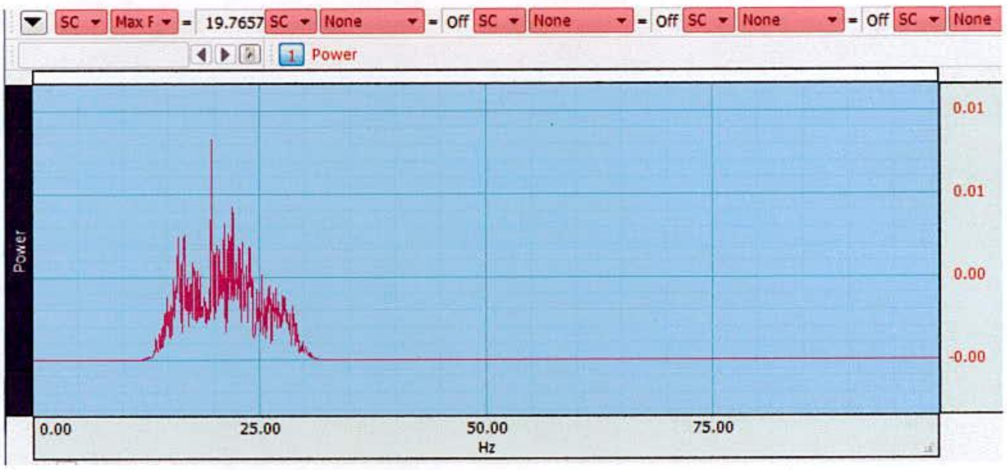
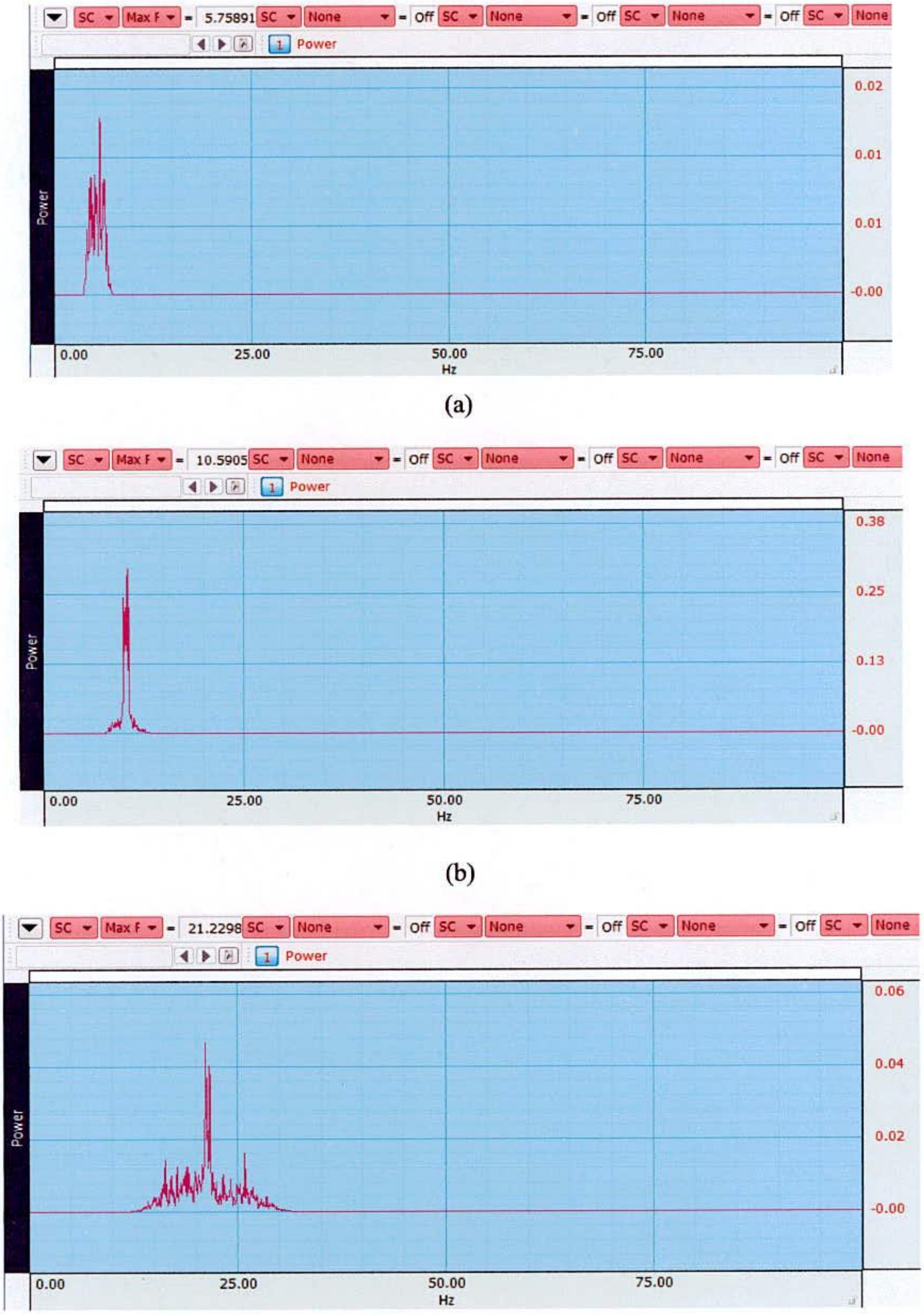


(c)

Figure 4. 13 Power spectral density of EEG signal when subjected to (a) English slow song, (b) English medium song, (c) English fast song.



(a)

(b)

(c)

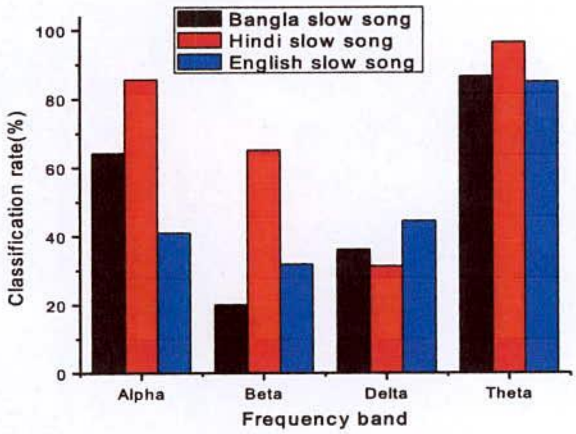
Figure 4. 14 Power spectral density of EEG signal when subjected to (a) Hindi slow song, (b) Hindi medium song, (c) Hindi fast song

Table 4. 9 Classification accuracy at different effective bands using SVM for Hindi song

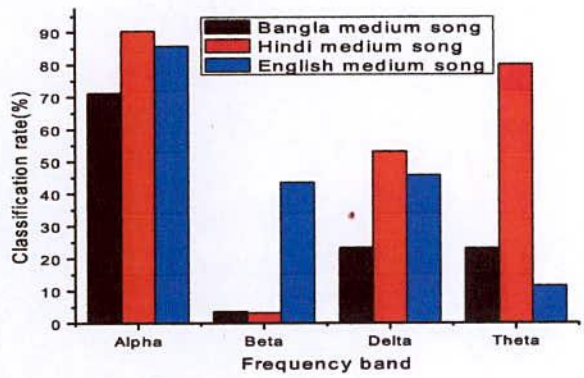
Song type	EEG frequency band	Train dataset	Test dataset	Classification accuracy
Hindi slow song	Alpha(α)	46	36	85.6%
	Beta(β)	46	35	65.1%
	Delta(δ)	46	36	31.25%
	Theta(θ)	46	37	96.37%
Hindi medium fast song	Alpha(α)	63	35	90.32%
	Beta(β)	63	36	3.12%
	Delta(δ)	63	37	53.12%
	Theta(θ)	63	35	80%
Hindi fast song	Alpha(α)	56	32	35.29%
	Beta(β)	56	33	94.11%
	Delta(δ)	56	32	17.14%
	Theta(θ)	56	34	54.11%

The power spectral density when subjected to English slow, medium and fast song are shown in Figs. 4.13 (a)-(c) respectively. It indicates that the maximum power occurs at frequency 19.76 Hz fast song but in case of slow and medium song they are 4.8 Hz and 11.32 Hz respectively. So in case of English fast song the beta activity is prominent which indicate stress or tension for the subject and theta and alpha band are most prominent for slow and medium types of song.

Table 4.8 and Table 4.9 shows the classification accuracy of the different effective frequency bands for English song and Hindi song which can detect the effective cognitive states when respective songs were played. In case of English fast, medium and soft song the higher accuracy is found at beta and alpha and theta band which indicate the stress, relax and catnap state respectively. Table 4.9 shows that theta and alpha band are more effective for Hindi slow song and medium song and they were found 96.37% and 90.32% respectively. Hindi fast song shows the effectiveness of beta band which was 94.11%. So from this analysis it is observed that slow song detects the catnap state and medium fast song shows the relax state whereas fast shows the state at stress. So the cognitive state can be evaluated from the larger activity of alpha or beta or theta band. The maximum power occurs at 5.7 Hz and 10.59 Hz for Hindi slow and medium song respectively as shown in Figs. 4.14 (a) and 4.14 (b) whereas at frequency 21.22 Hz for Hindi fast song which indicates the beta frequency band as shown in Fig.4.14 (c).



(a)



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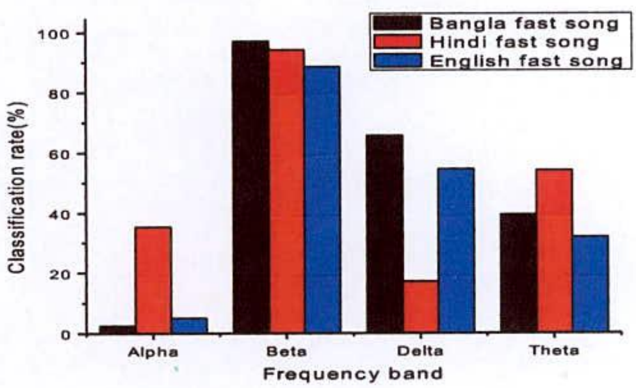


(c)

Figure 4. 15 Classification accuracy of different types of music; (a) classification rate for slow types of song, (b) classification rate for slow types of song, (c) classification rate for slow types of song

The Classification accuracy of different types of music is shown in Fig. 4.18. So, the beta activity is more effective for fast song and the high frequency spectrum with fast bit of music leads human mind to stress.

4.6 Artificial Neural Network for EEG Signal Classification

Artificial Neural Network (ANN), an idea based on parallel processing of our human brain, is a computing system made up of large number of simple, highly interconnected processing elements. ANN can abstractly emulate the structure and operation of the biological nervous system, which yields high predictive ability. Fig. 4.16 shows an example of NN with one hidden layer. Unlike the input and output layers, there is no prior knowledge as to the hidden layers. A network with too few nodes would be incapable of differentiating between complex patterns leading to only a linear estimate of the actual trends. On the other hand, if there are too many hidden nodes, it will follow the noise in the data due to over-parameterization and eventually more time consuming in training phase.

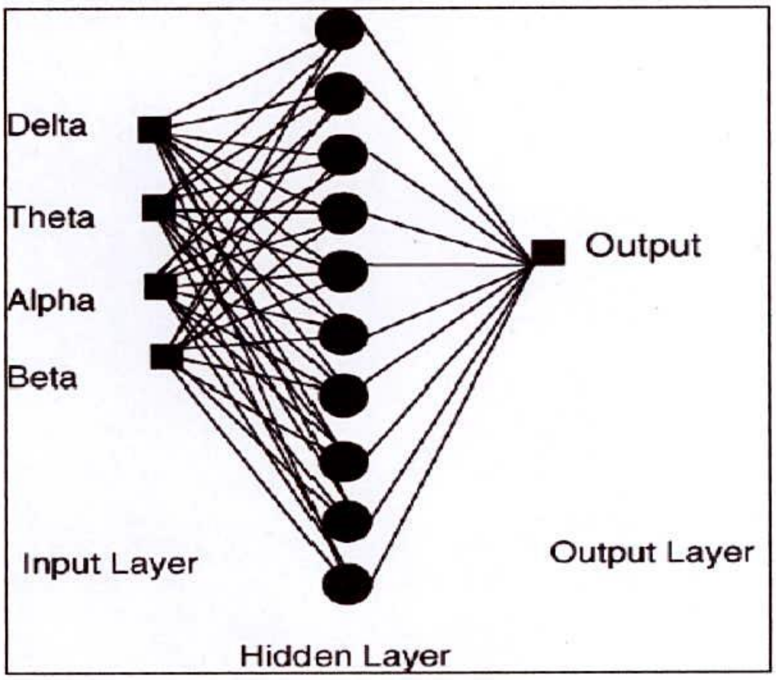


Figure 4. 16 An example of Neural Network with one hidden layer

To find the optimal number of the hidden layers of a neural network, the most popular approach is by trial and error. Besides the determination of appropriate hidden layers, training algorithm is also an important aspect in designing the ANN. A good training algorithm will shorten the training time, while achieving a better accuracy. There are a number of training algorithms available to train a MLPNN, and back-propagation algorithm is the one commonly used.

The MLPNN was designed with statistical features of the EEG signals as the inputs to the input layers and the output layer representing the effective band for classification of emotional states. The preliminary architecture was examined using one and two hidden layers with a variable number of nodes. It was found that one hidden layer was adequate to achieve their objective to determine which EEG band is more effective during the time of listening music. By trial and error, it was found that the optimum number of nodes in the hidden layer was 3.The study can be extended to other applications to identify various EEG signals with different characteristics. The basic concept will be the same, but the number of nodes at the input or output layers might be different from case to case. Even with number of nodes and hidden layers, the computation work

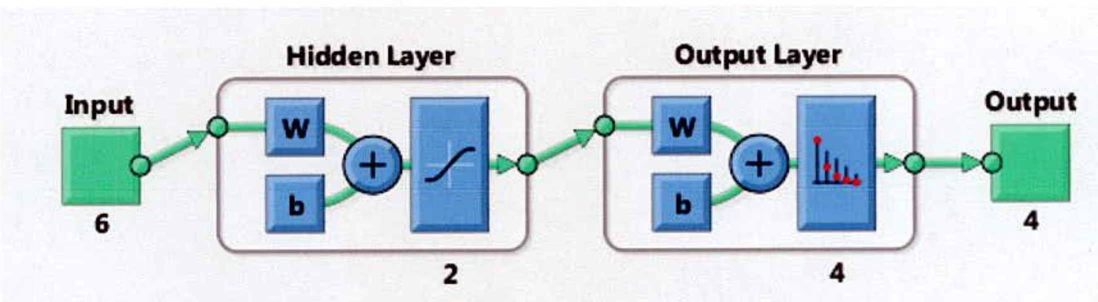


Figure 4. 17 Work flow of MATLAB neural network classification GUI

is much simpler than the statistical analysis as the EEG signals are highly non-linear and non-stationary. A sample ANN architecture consisting of 6 input, 2 hidden neuron and 4 target output is shown in Fig. 4.17. Input data here is a 6×48 matrix of 6 features of 48 subjects. Target data is a 4×60 matrix, which indicates the effective EEG bands to classify the emotional states for these 48 subjects i.e. 1000 for alpha, 0100 for beta, 0010 for delta and finally 0001 for theta band. After filling those data, next step is to randomly choose the percentage of input data into 3 categories namely training, validation and testing. Where training set is used to fit the parameters of the classifier i.e. to find the optimal weights for each feature. Validation set is used to tune the parameters of a classifier that is to determine a stop point for training set. Finally test set is used to test the final model and estimate error rate. The default value sets training in 70 percent and 15 percent each for the rest. Then number of hidden layer is chosen.

4.6.1 Back Propagation Neural Network

Artificial Neural Network (ANN) is an efficient pattern recognition mechanism which simulates the neural information processing of human brain. The ANN processes information in parallel with a large number of processing elements called neurons and uses large interconnected networks of simple and nonlinear units. The quantitative modeling and processing of data using neural networks is effectively performed using the Supervised Learning Neural Network Back-Propagation Algorithm. For a given set of training input output pair, this algorithm provides a procedure for changing the weights in a back propagation network (BPN) to classify the input patterns correctly. The aim of this neural network is to train the network to achieve a balance between the network's ability to respond (memorization) and its ability to give reasonable responses to the input that is similar but not identical to the one that is used in training (generalization). A BPNN is a multi-layer, feed-forward neural network consisting of an input layer, a hidden layer and an output layer. The hidden layers are used to classify successfully the patterns into different classes. The inputs are fully connected to the first hidden layer, each hidden layer is fully connected to the next, and the last hidden layer is fully connected to the outputs.

4.6.2 Artificial Neural Network for Attention to Emotion

It is possible to extract from the previous discussion an architecture for artificial neural networks which has attention as a feedback modulation, and produces emotional classification output from a set of input features (the output is taken in (1) as a single node, but can be easily extended to one of numerous possible multi-node classifier modules). The basic architecture is thus a standard feed-forward network, but with additional attention feedback from the hidden layer h, to modulate activity in the inputs to that layer. Thus the equations of activation for this system, without feedback, are in the universal approximation form (using $f(w_{i.}x)$ as the usual sigmoid response from a graded neuron):

$$Out = \sum_i a_i \; h_i(x) \qquad 4.1$$

Where

$$h_i(x) = f(w_{i.}x) \qquad 4.2$$

and where a_i , $w_{i.}$, and x are the linear output weights, the vectors of input weights to hidden node i, and the overall input vector to all hidden layer neurons, respectively. When attention feedback is included, we consider the hidden layer as the source of such attention modulation to its own input. The activations of the hidden node i must then be replaced by the attention-modulated term

$$W_{i.}x \to \sum_j w_{ij.}\, x\left[1 + A_{ij}h_i(x)\right] \quad 4.3$$

So that the output of a given hidden node is finally defined as:

$$out_i(x) = f\left(\sum_j w_{ij.}\, x\left[1 + A_{ij}h_i(x)\right]\right) \quad 4.4$$

Where,$h_i(x)$ is given in (4.2). We use (4.1) to give the output of the overall network, with $h_i$there replaced by out_i of equation (4.4).

4.6.3 Selection of Effective frequency band with ANN

Table 4.10 shows the classification accuracy at different effective EEG bands for different types of songs. The training, testing and validation sets are also shown in the table. Training sets are presented to the network during training, and the network is adjusted according to its error.

Table 4. 10 Classification accuracy at different effective bands using ANN for different types of song

Types of Songs	Training data set (%)	Testing data set (%)	Validation (%)	Number of Neurons in Hidden Layer	Classification Accuracy of testing data sets (%)
Bangla fast song	70	20	10	2	100
Bangla medium song	65	20	15	1	100
Bangla slow song	70	20	10	1	100
English fast song	70	20	10	5	100
English medium song	70	20	10	1	100
English slow song	70	20	10	1	88.9
Hindi fast song	70	20	10	2	100
Hindi medium song	70	20	10	2	100
Hindi slow song	70	20	10	5	88.9

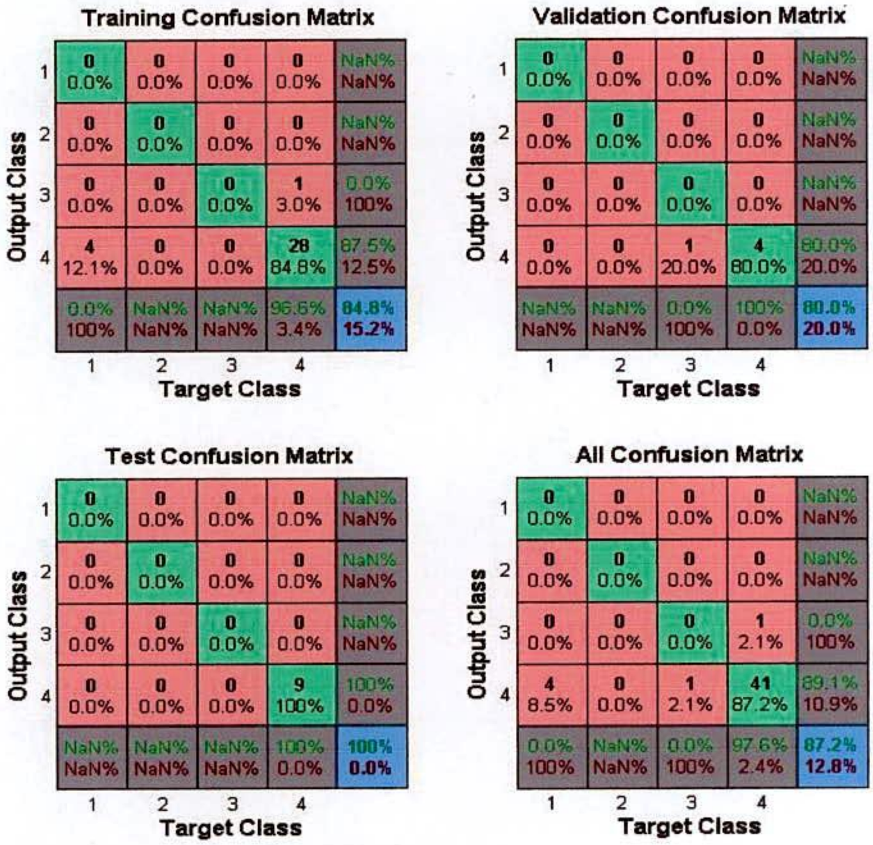
Validation sets are used to measure network generalization, and to halt training when generalization stops improving. Test sets have no effect on training and so provide an independent measure of network performance during and after training. Figures in 4.18(a) - 4.26(a) show the confusion matrices for training, testing, and validation and of the data sets for different types of songs. The network outputs are very accurate, as you can see by the high numbers of correct responses in the green squares and the low numbers of incorrect responses in the red squares. The lower right blue squares illustrate the overall accuracies.

The diagonal cells show the number of cases that were correctly classified, and the off-diagonal cells show the misclassified cases. The blue cell in the bottom right shows the total percent of correctly classified cases (in green) and the total percent of misclassified cases (in red). The results show very good recognition. Each time a neural network is trained, can result in a different solution due to different initial weight and bias values and different divisions of data into training, validation, and test sets. As a result, different neural networks trained on the same problem can give different outputs for the same input. To ensure maximum accuracy of a neural network the data sets need to train several times.

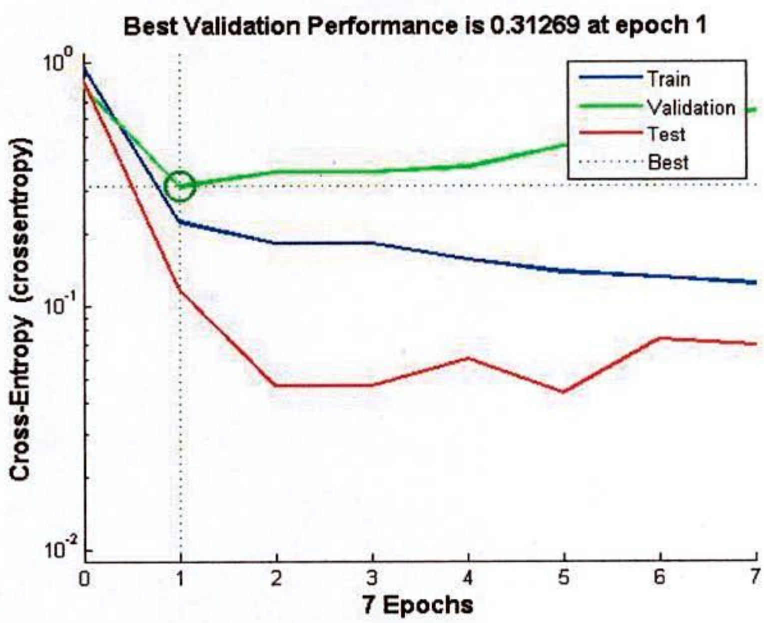
Figure 4.18(b) – 4.26(b) shows the validation performance for different effective EEG bands in case of emotion classification for different types of slow, medium and fast song respectively. Minimizing Cross-Entropy results in good classification. Lower values are better to show better classification performance. Zero cross-entropy means no error.

4.7 Summary

This work proposes an approach for classification of human emotion during different environmental conditions and impacts of musical activity on brain. The emotions are classified with SVM classifier and this classification results are verified with ANN based on different extracted features. This approach plays an effective way to model the classified emotional states.

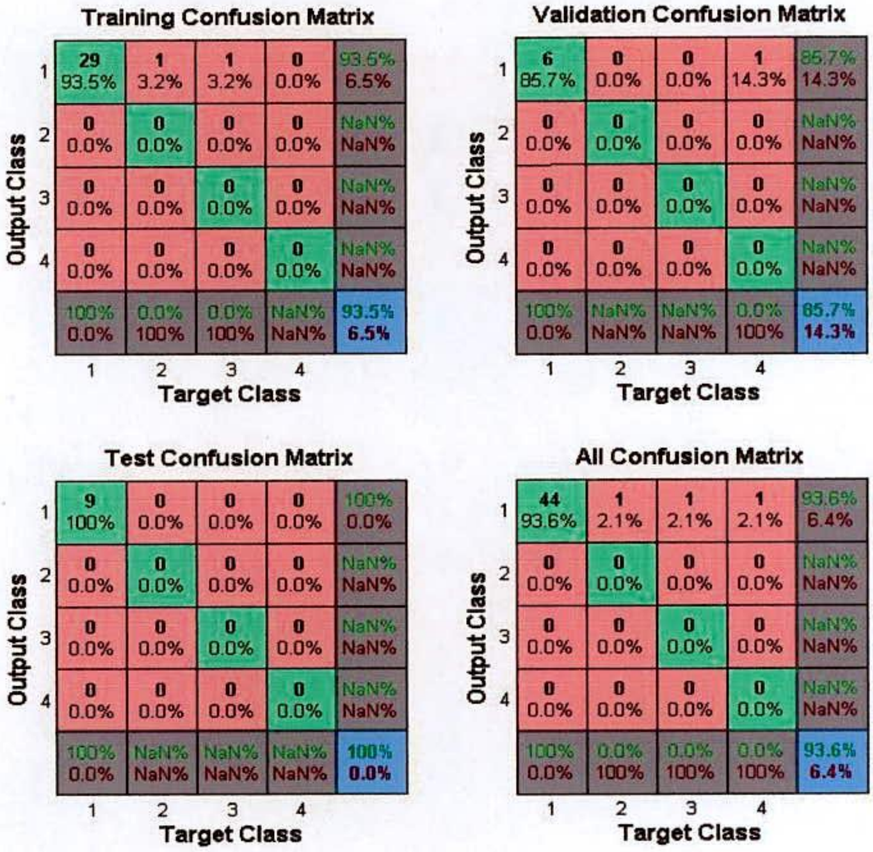


(a)



(b)

Figure 4. 18 Effective EEG band for Bangla fast type of song (a) Confusion matrix (b) Validation performance



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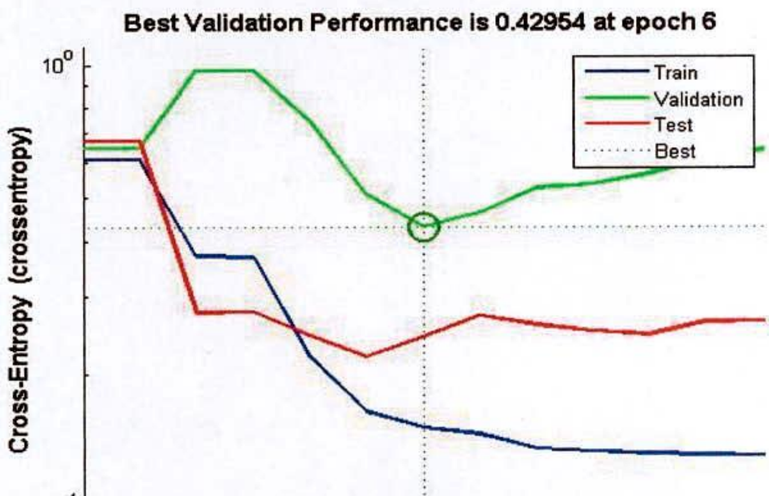
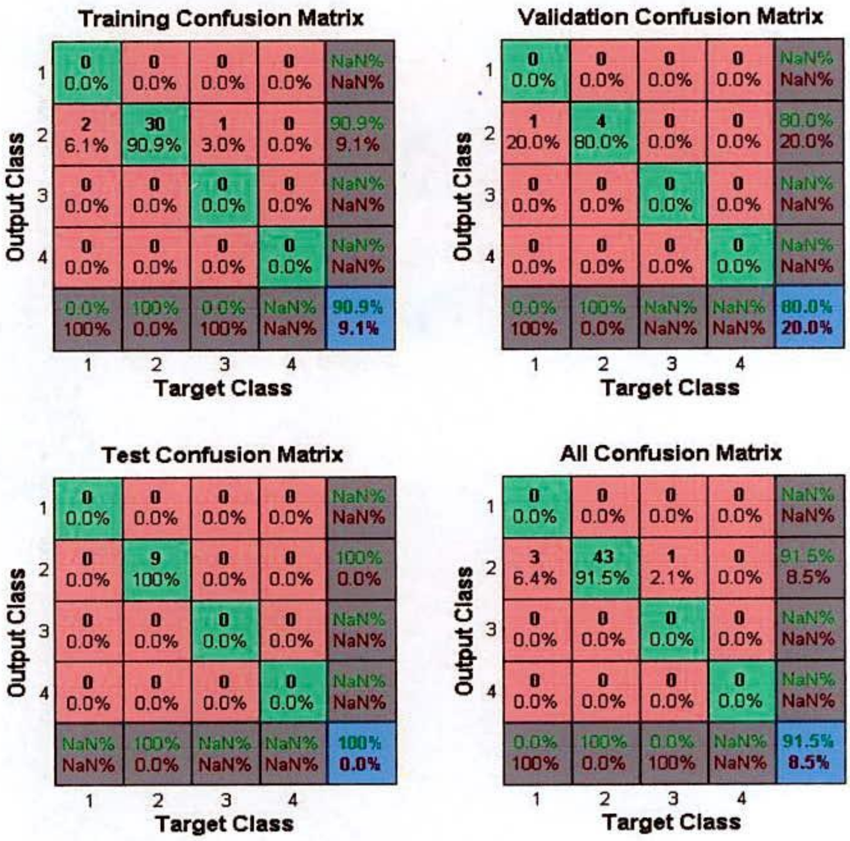


(b)

Figure 4. 19 Effective EEG band for Bangla medium type of song (a) Confusion matrix (b) Validation performance



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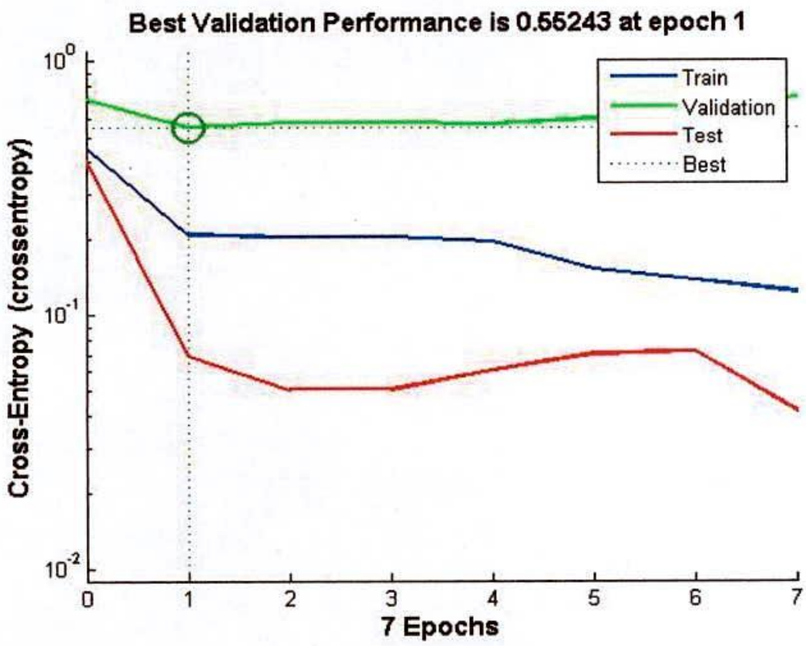
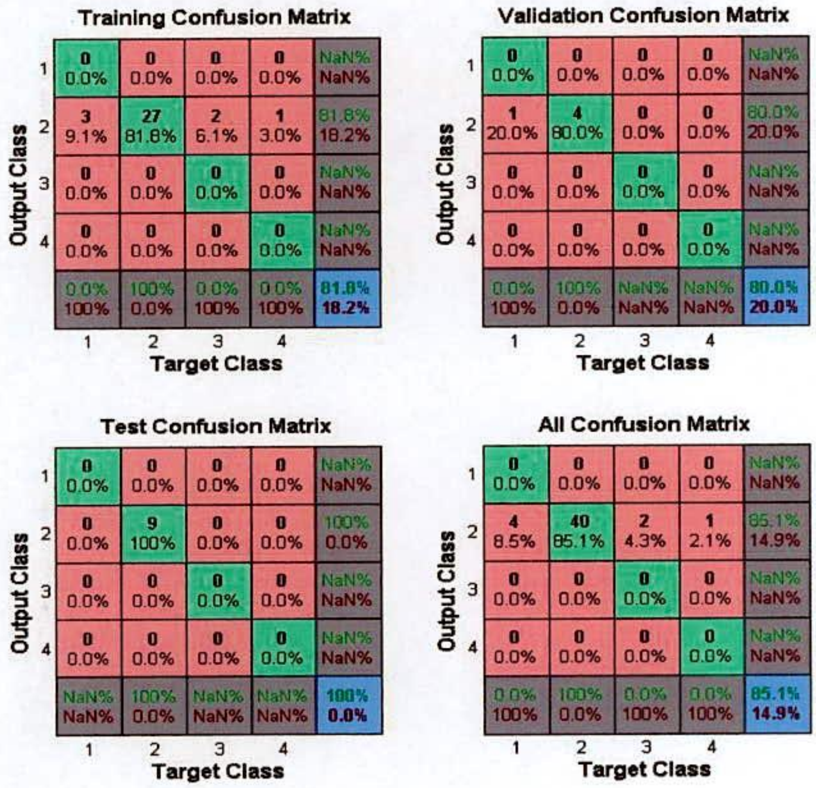


(b)

Figure 4. 20 Effective EEG band for Bangla slow type of song (a) Confusion matrix (b) Validation performance



(a)

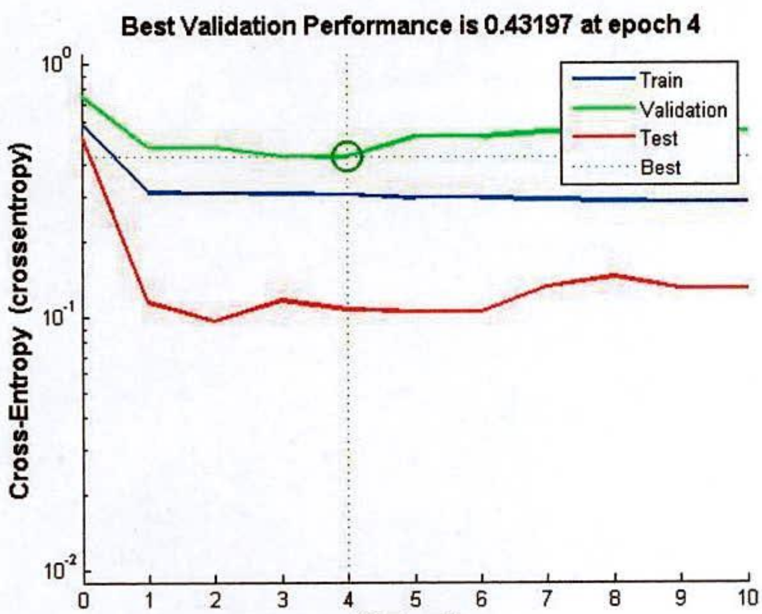


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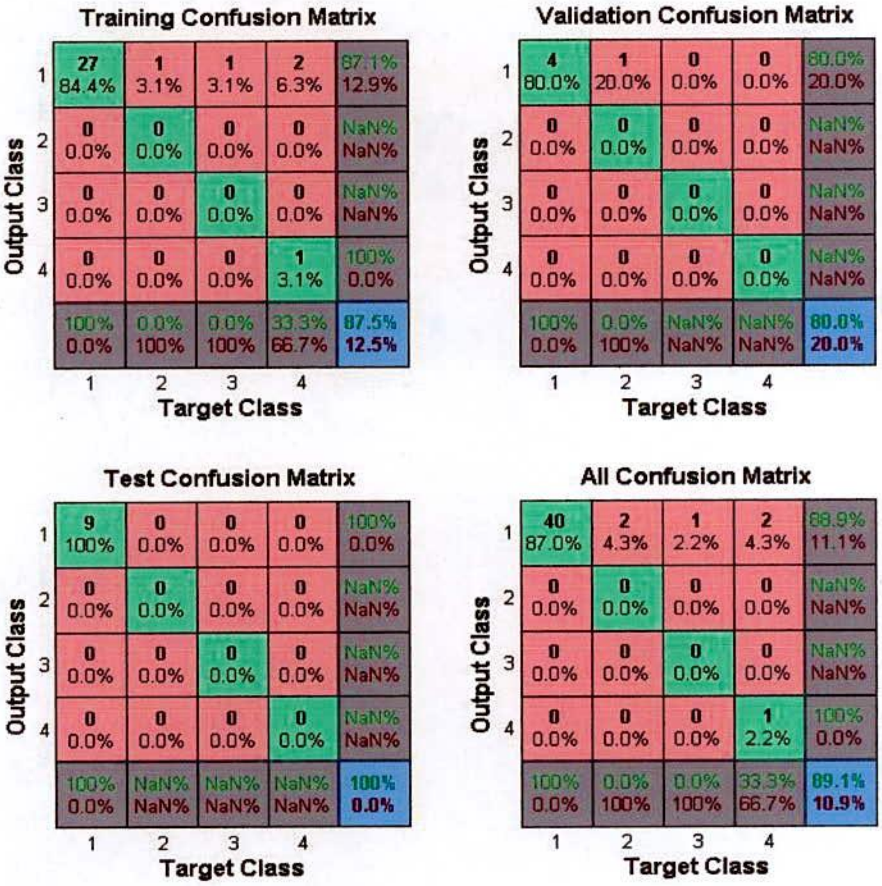
Figure 4. 21 Effective EEG band for Hindi fast type of song (a) Confusion matrix (b) Validation performance



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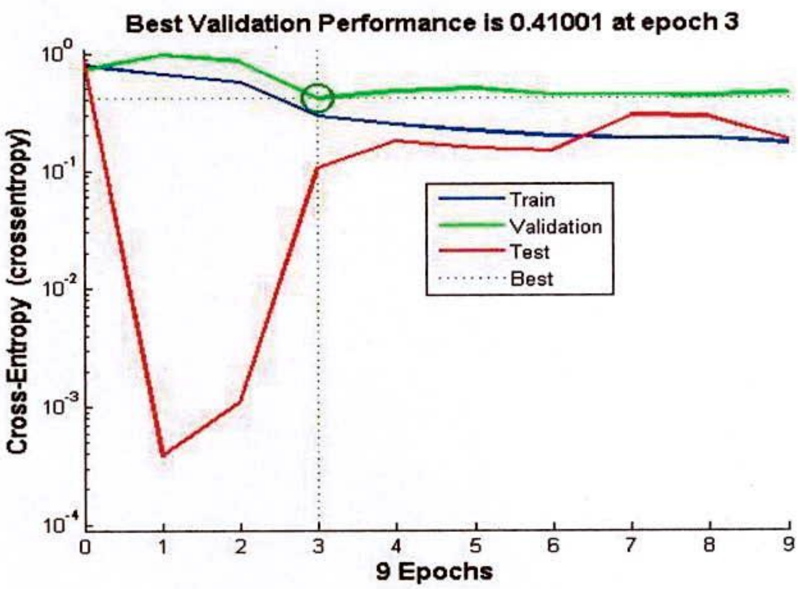

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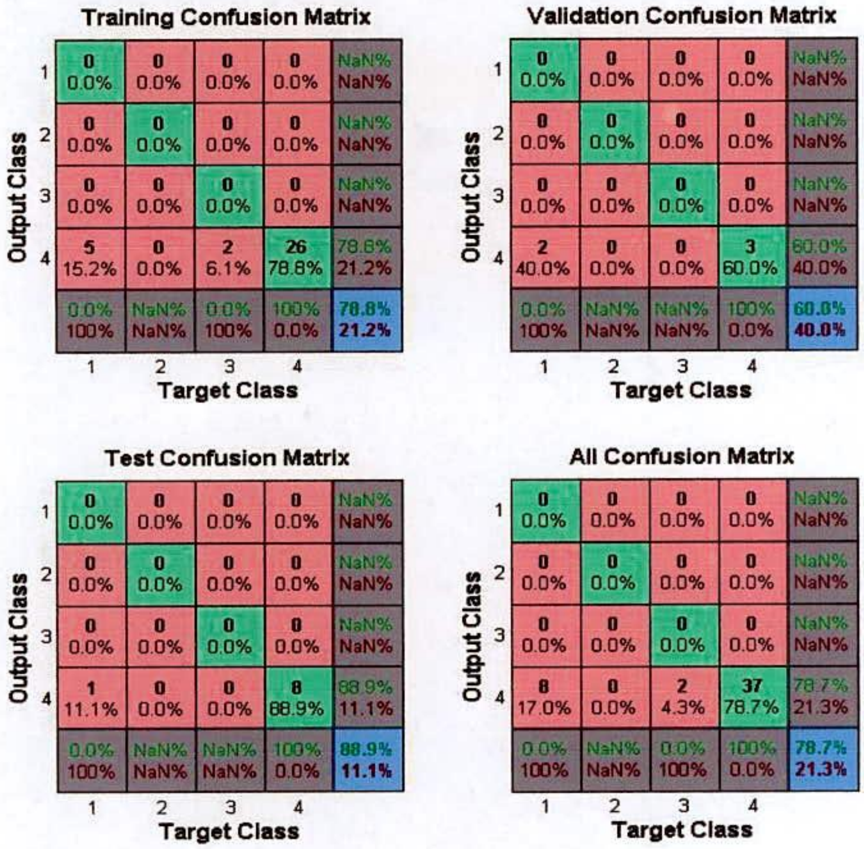
Figure 4. 22 Effective EEG band for Hindi medium type of song (a) Confusion matrix (b) Validation performance



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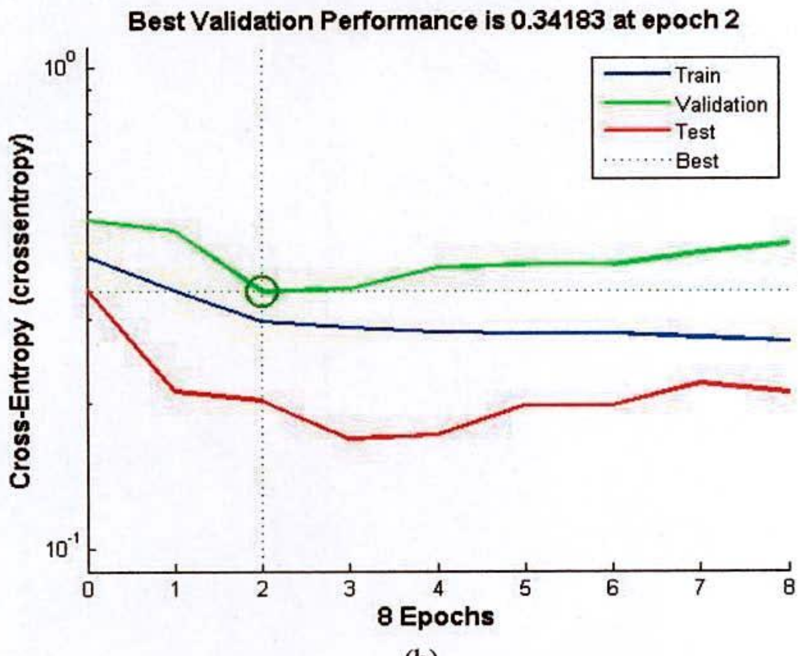

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Figure 4. 23 Effective EEG band for Hindi slow type of song (a) Confusion matrix (b) Validation performance

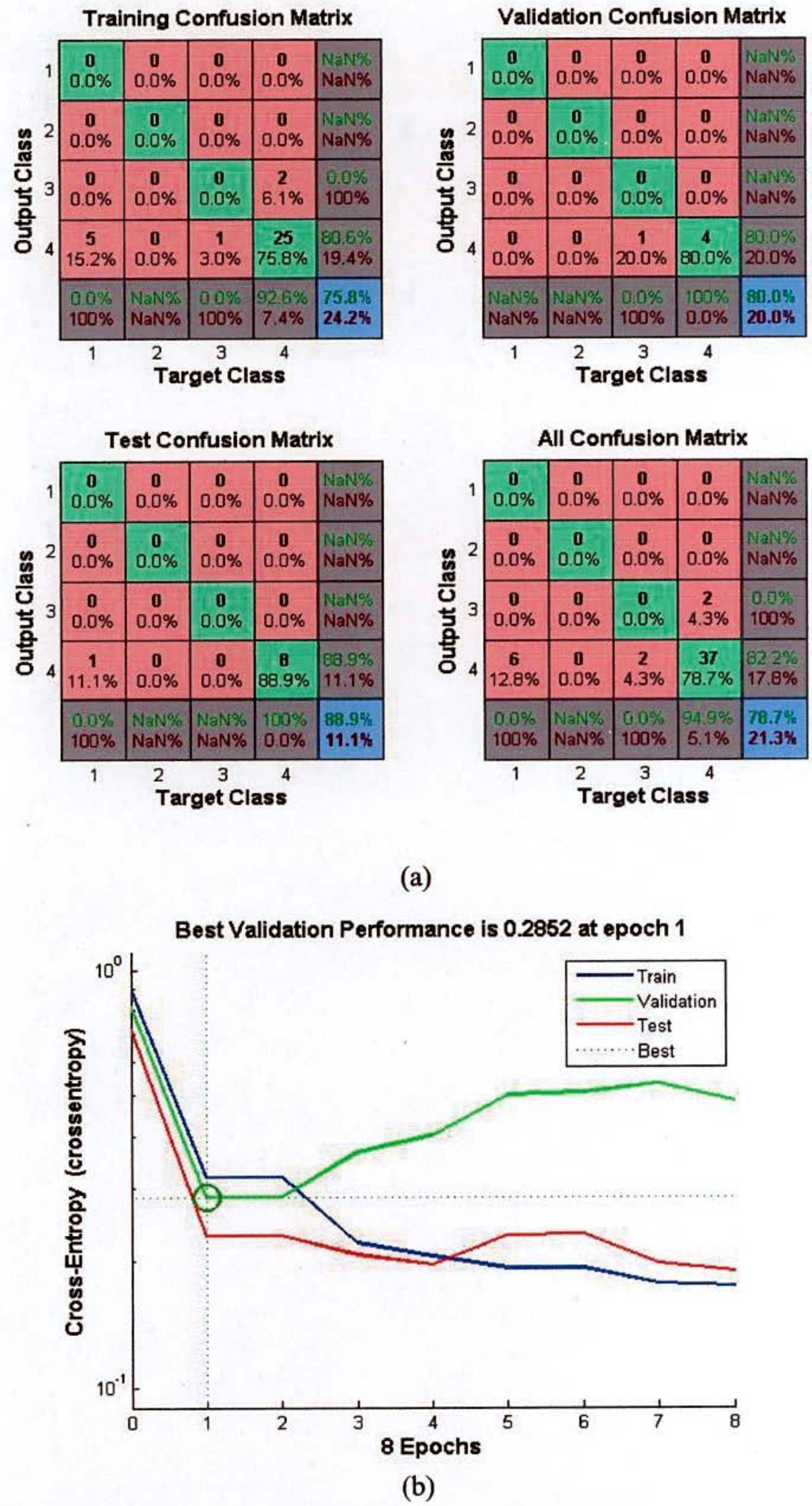
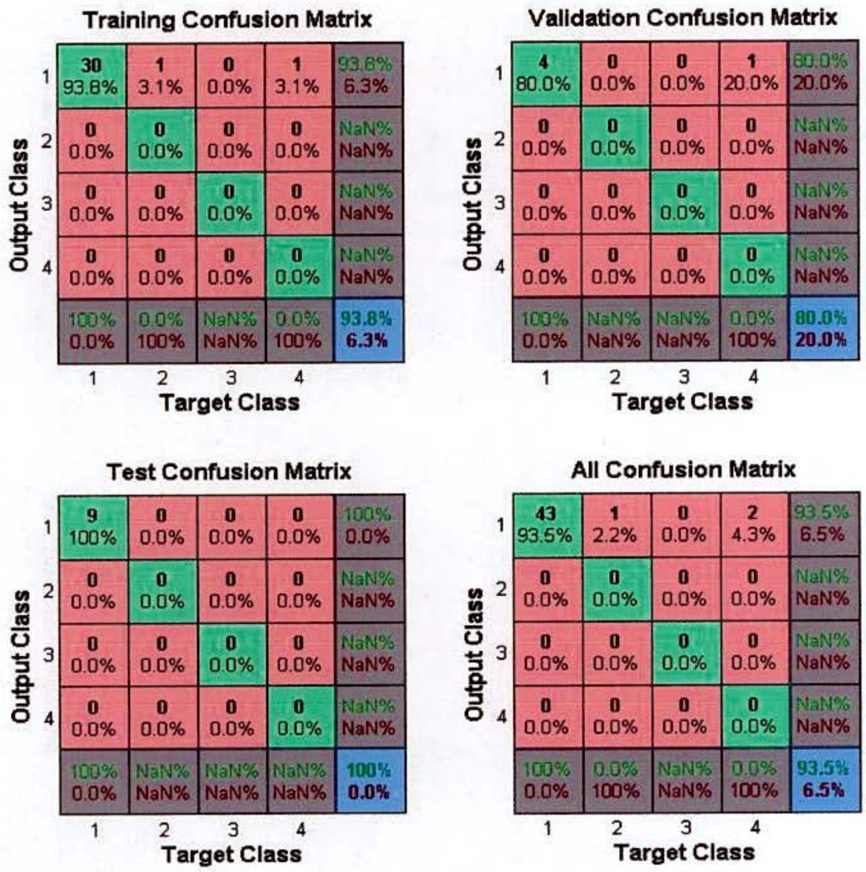
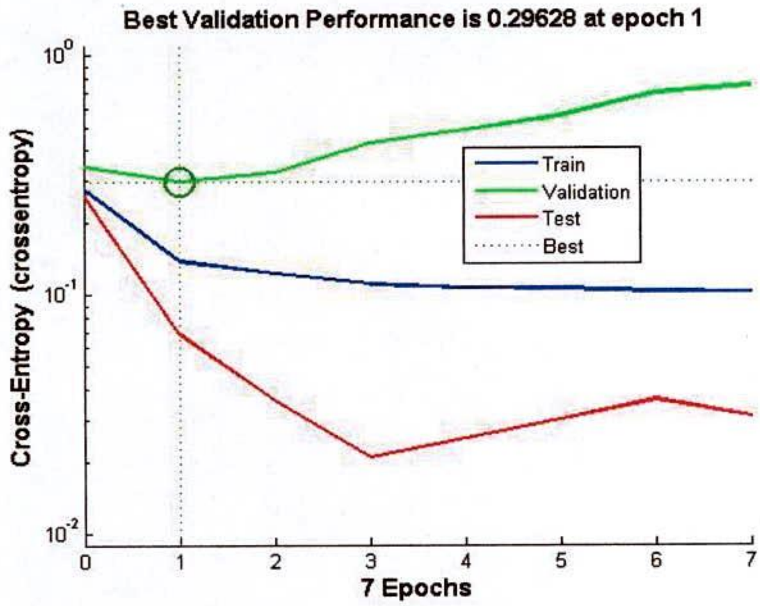


Figure 4. 24 Effective EEG band for English fast type of song (a) Confusion matrix (b) Validation performance

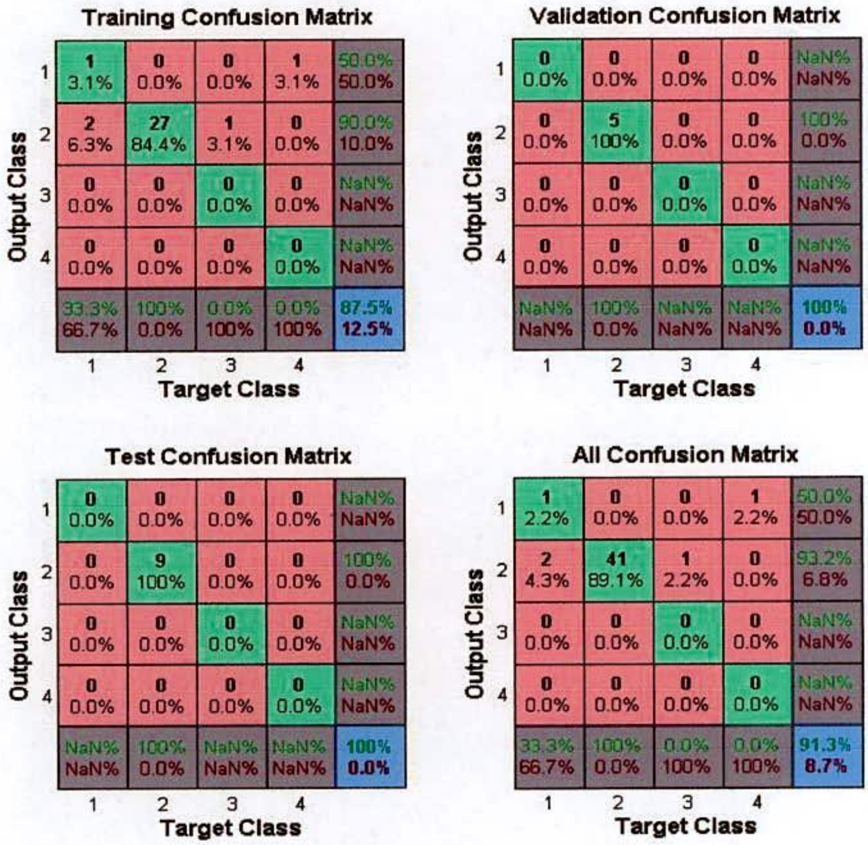


(a)

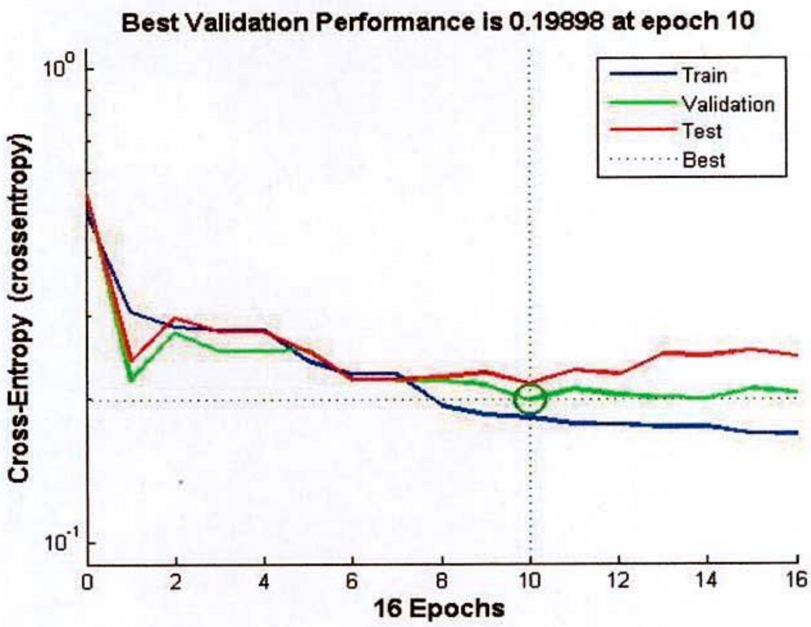


(b)

Figure 4. 25 Effective EEG band for English medium type of song (a) Confusion matrix (b) Validation performance



(a)



(b)

Figure 4. 26 Effective EEG band for English slow type of song (a) Confusion matrix (b) Validation performance

Chapter 5

Modeling Approach of Human Emotions

Emotion is the reflection by human brain of its quality and magnitude in which the brain estimates with genetic and previously acquired experiences expressed with mathematical structural formulas and different functions. The focus of this paper is to establish the possibility of successful mathematical modeling of the highly complex phenomenon representing human emotional states. To explain any emotional state with mathematics is really complex because the functional activity of human brain is related with time and the environments and also the frequency components are the unique parameters which primarily related with emotional activity. So, for expressing of emotional states time associated with its frequency information is the most feasible which have made more interest to model the states with different mathematical expressions and functions based on the discrete wavelet transformation and different time-frequency based coefficients.

5.1 Literature Review

Many works has been done in physiological signal analysis to characterize the emotional states with mathematical expressions and modeling human behavior. Authors in [1] applied a model of information processing by memory by human adaptation to emotional factors. They structured a mathematical formula according to the strength and actual need of human behavior based on some factors. The appraisal theory model is focused in [2] to predict emotions and determine the appropriate system behavior to support Human-Computer-Interaction. The use of mathematical modeling was investigated as a unifying language to translate the coherence of appraisal theory and found that the mathematical category theory supports the modeling of human emotions according to the appraisal theory model. The mental behavior detection from the EEG signal was proposed in [8] with the findings of effective data recording from physiological signals, feature extraction through wavelet transform, data reduction, feature classification using various classification methods, real time applications. Swangnetr et.al in [9] developed a new computational algorithm for accurate patient emotional state classification in interaction with nursing robots during medical service. They collected physiological signals, including heart rate (HR) and galvanic skin response (GSR), as well as subjective ratings of valence (happy–unhappy) and arousal (excited–bored) and applied a three-stage emotional state classification algorithm to these data. Arousal and valence were significantly explained by statistical features of the HR signal and GSR wavelet features. Wavelet-based de-noising of GSR signals led to an increase in the percentage of correct classifications of emotional states and clearer relationships among the physiological response and arousal and valence. A detailed domain-independent model based was discussed in [67] and it had been applied to the problem of generating behavior for a significant social training application which is useful not only for deriving emotional state, but also for informing a number of the behaviors that must be modeled by virtual humans such as facial expressions, dialogue management, planning, reacting, and social understanding. Author in [68]-[69] showed the nonstationaries of EEG signal and explained the basic of trust-region algorithm for modeling the nonstationary signal. An emotional cognitive architecture CELTS was investigated for showing that the emotional component of the architecture is an essential element of CELTS value as a cognitive architecture in [70]. The use of multi-modal sensor data discussed in [71] implied difficulties in the fusion process which may arise and must be treated predictions regarding the expressed emotion based on different databases. But in case of practical orientation of emotional states and also in hardware implementation a mathematical background is essential which can be used as a model of significant emotional states.

There is little work in the field of emotion modeling with the effective features and proper selected channel. If the channel is properly selected then the emotion model of the selected channel will be more exact in case of practical application area. Moreover if the effective frequency band of a particular emotion is selected the mathematical model will be more justified if emotion is modeled with that particular frequency band of that emotional state. In this work, a mathematical modeling of the emotional states have been developed that can support the study of emotions regarding origin, alteration and interaction with cognition and behavior. The block diagram of our proposed approach is shown in Fig. 5.1.

5.2 Trust Region Algorithm for Emotion Modeling

Trust region methods are robust, and can be applied to ill-conditioned problems and applicable for nonlinear optimization [69]. It optimizes the unconstrained minimization problem by minimizing a function, f(x), where the function takes vector arguments and returns scalars. In this algorithm, the approximate model is only "trusted" in a region near the current iterate. It seems reasonable, because for general nonlinear functions local approximate models can only fit the original function locally. The region that the approximate model is trusted is called trust region. A trust region is normally a neighborhood centered at the current iterate. In this algorithm an approximation model is developed with the actual current point data by adjusting the fit ratio and trusted region of the neighborhood data point. The trust region is adjusted from iteration to iteration. If computations indicate the approximate model fit the original data well, the trust region is enlarged otherwise it is reduced.

In order to demonstrate how a trust region algorithm can be constructed, a model algorithm for unconstrained optimization problem is given in Eqs. 5.1 & 5.2. At the k -th iteration, the trial step is computed by solving the equations.

$$\min_{d\in\Re^n} g_K^T d + \frac{1}{2} d^T G_K d = \phi_K(d) \tag{5.1}$$

$$s.t.\|d\|_2 \leq \Delta_K \tag{5.2}$$

Where $g_K = \nabla f(x_K)$ is the gradient at the current iterate x_K, B_K is an $n \times n$ symmetric matrix which approximates the Hessian of $f(x)$ and $\Delta_K > 0$ is a trust region radius. Let s_K be a solution of Eqs. 5.1 and 5.2. The predicted reduction $Pred_k$ is defined by the reduction in the approximate model, $\varphi_K(0)$- $\varphi_K(s_K)$. Unless x_K is a stationary point and B_K is positive semi definite, $Pred_k$ is always positive. The actual reduction $Ared_K = f(x_K) - f(x_K + s_K)$ is the reduction in the objective function. The ratio between the actual reduction and the predicted reduction $r_K = Ared_K/Pred_K$ plays a very important role in the algorithm. This ratio is used to decide whether the trial step is acceptable and to adjust the new trust region radius [69].

The basic idea is to approximate f with a simpler function q, which reasonably reflects the behavior of function f in a neighborhood N around the point x_K. This neighborhood is the trust region. A trial step s is computed by minimizing (or approximately minimizing) over N. This is the trust region subproblem as in Eq. 5.3 which is applied on a well-known least square method (LSM),

$$\min_{s_K} \{q(s), s_K \in N\} \tag{5.3}$$

The current point is updated to be $x_K + s_K$ if $f(x_K + s_K) < f(x_K)$; otherwise, the current point remains unchanged and N, the region of trust, is shrunk and the trial step computation is repeated. In the standard trust region method, the quadratic approximation q is defined by the first two terms of the Taylor approximation to F at x and the neighborhood N is usually spherical or ellipsoidal in shape. Mathematically, the trust region sub-problem is typically stated.

$$\min\{\frac{1}{2}s_K^T Hs + s_K^T g_K, \| Ds \| \leq \Delta\} \qquad 5.4$$

Where g_K is the gradient of f at the current point x_K, H is the Hessian matrix (the symmetric matrix of second derivatives), D is a diagonal scaling matrix, Δ is a positive scalar, and //.// is the 2-norm. A sketch of unconstrained minimization using trust-region ideas is:

i) Formulate the two-dimensional trust-region subproblem.

ii) Solve equation 5.4 to determine the trial step s.

iii) If $f(x_K + s_K) < f(x_K)$, then $x_K = x_K + s_K$.

iv) Adjust Δ.

These four steps are repeated until convergence. The trust-region dimension Δ is adjusted according to standard rules. In particular, it is decreased if the trial step is not accepted, i.e., $f(x_K + s_K) \geq f(x_K)$. In this work, this algorithm is efficiently used to obtain the coefficients for the proposed mathematical modeling of emotional states.

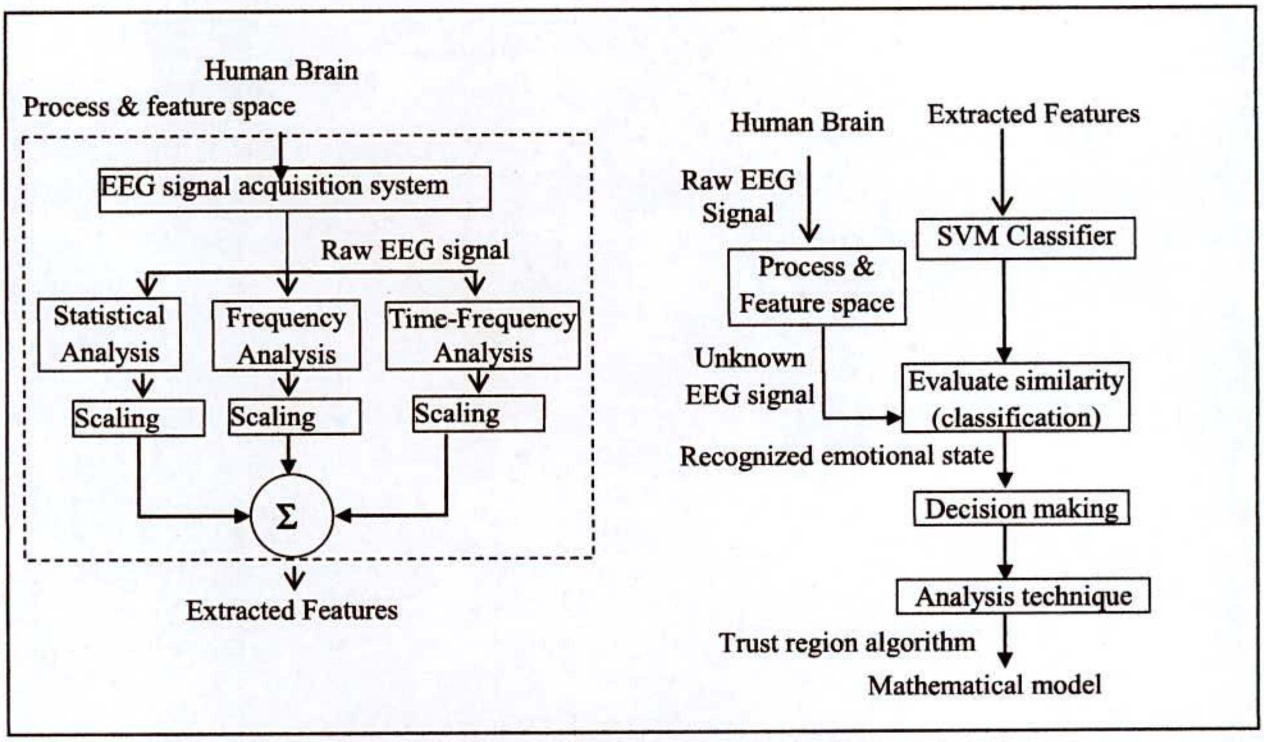


Figure 5. 1 Block diagram of our proposed approach for modeling of human emotion

5.3 Mathematical modeling of emotions

In recent years, in the field of psychology there has been a consensus that emotions are a dynamic process and that to understand emotion a dynamic analysis of state changes must be analyzed and mathematical analysis of emotional states plays a vital role in this purpose. In case of practical orientation of emotional states and also in hardware implementation to interact with cognition and behavior, a mathematical background is essential which can be used as a model of significant emotional states. In our proposed approach the time-frequency analysis is considered the best suit for mathematical modeling of different emotional states. For the purpose of mathematical modeling of categorized emotional states the time-frequency analysis have been proved the most suitable analysis technique.

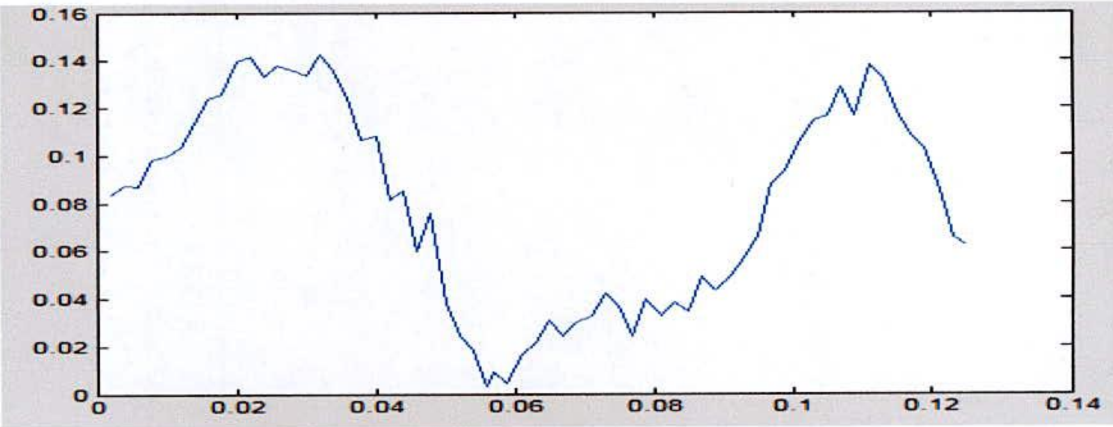
The main purpose of time-frequency analysis is to derive the wavelet coefficients which can map the EEG data into consequent emotional states. The time-frequency domain features used in this paper are based on the spectrum analysis of each 128-point of EEG samples which is extracted as the sub-band coefficients (D_4) of EEG data. Then the sub-band coefficients are plotted as the reference one. According to the trust region algorithm the coefficients are obtained which can model the emotional states and applicable for nonlinear optimization. From the adjusting percentage of the predictor variables in the model and the percentage errors the efficiency of our proposed model can be justified. The actual wave shape of the wavelet coefficients for relax state is shown in Fig. 5.2(a) and Fig. 5.2(b) shows the wave shape of the mathematical expression which has modeled this state based on the coefficients as shown in Table 5.1. Equation 5.5 shows the mathematical expression of relax state which can model this state on the basis of the amplitude, frequency and phase constant of this sine wave series. Although the brain signals are probabilistic but in this work the noise function is much less. Although trust region algorithm gives the probable coefficients but the probable obtained coefficients $P(f(x))$ can be expressed as the $f(\mathrm{x})$.

$$f_{RLX}(x) = \sum_{i=1}^{6} a_i \sin(b_i x + c_i), where\, x \in N \qquad 5.5$$

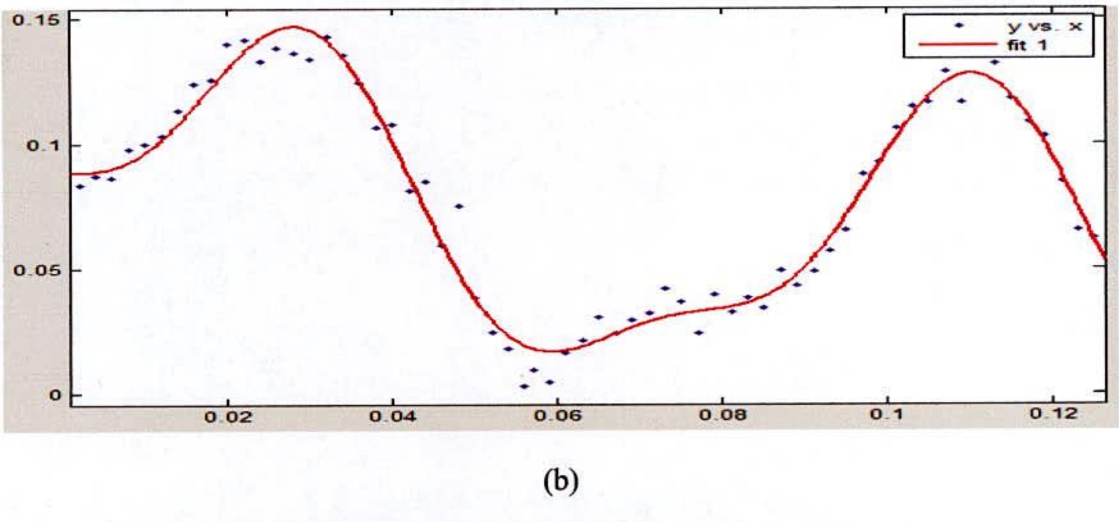
Here, N is a set of 128 real numbers of the sub-band coefficients. The wave shape of MA state of the wavelet coefficients are shown in the Fig. 5.3(a) and the wave shape of the mathematical expression which can model this state is shown in the Fig. 5.3(b).The mathematical modeling of motor action (MA) is given in Eq. 5.6.

Figure 5.5(a) & 5.6(a) represents the actual wave shapes with wavelet coefficients and 5.5(b) & 5.6(b) represent the plot of mathematical expression which modeled the fear state and EM state respectively. The mathematical model of fear state and EM state is given in Eqs. 5.9 & 5.10 respectively.

$$f_{fear}(x) = \sum_{i=1}^{7} a_i \sin(b_i x + c_i), \text{ where } x \in N \qquad 5.9$$

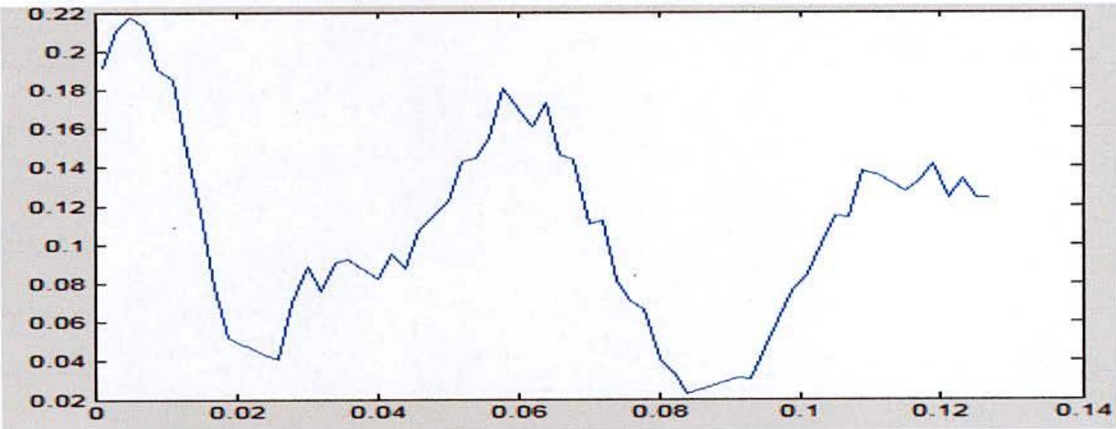


(a)

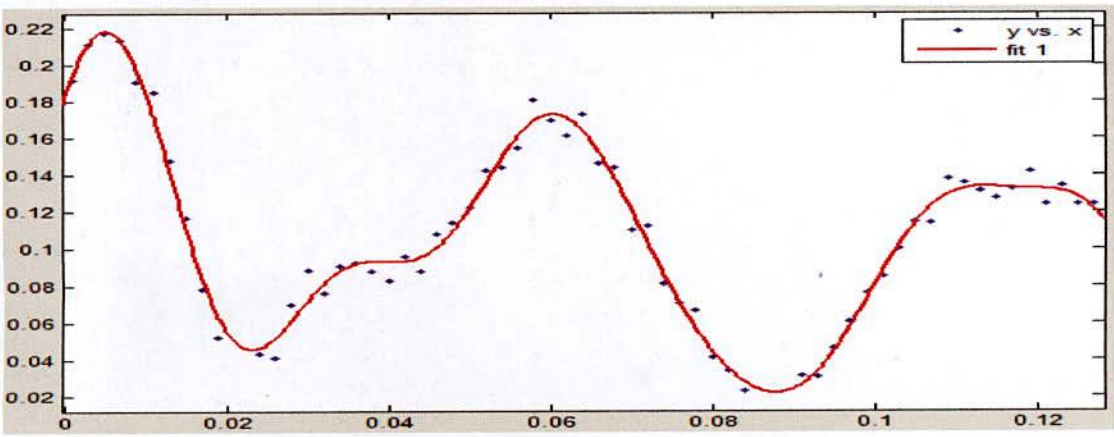


(b)

Figure 5. 3 (a) Plot of Detail wavelet coefficients of motor action (MA); (b) Plot of mathematical model of motor action (MA)



(a)



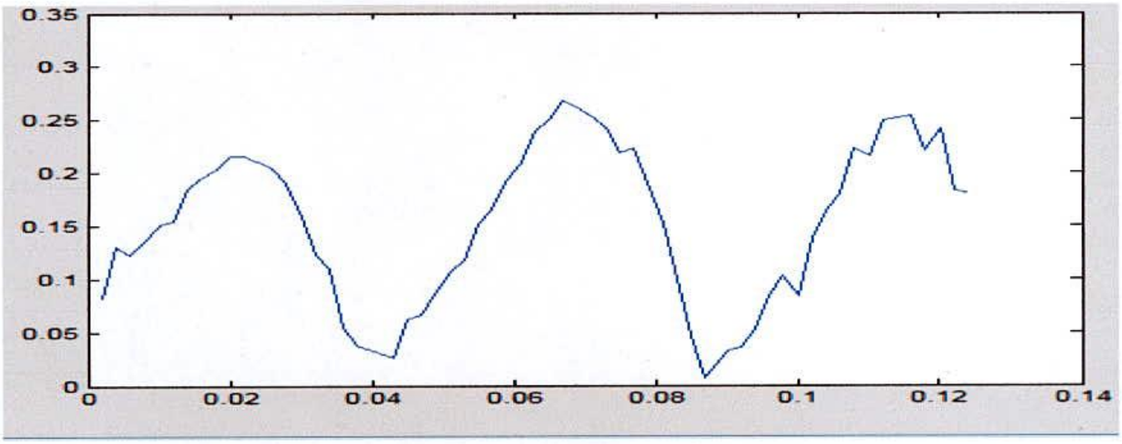
(b)

Figure 5. 4 (a) Plot of Detail wavelet coefficients of pleasant state; (b) Plot of mathematical expressions for pleasant state modeling

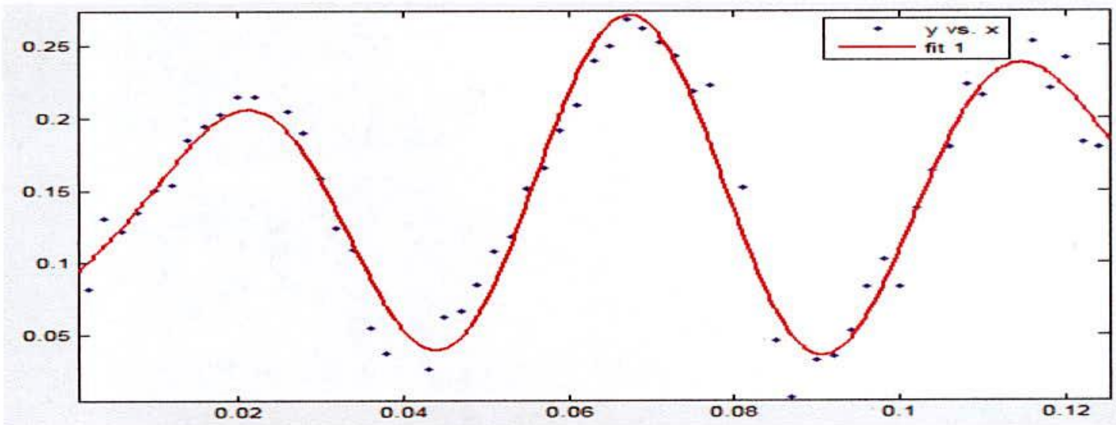
$$f_{EM}(x) = \sum_{i=1}^{4} a_i \sin(b_i x + c_i), \text{ where } x \in N \tag{5.10}$$

Where a_i, b_i, c_i are the coefficients of the summation of sinusoidal series which represents the amplitude, frequency and phase constants respectively in which i is the iteration of sine series for each sine series expressions in specific emotional states.

In Fig. 5.2(a) ~ 5.7(a) the plot of detailed wavelet coefficients for the specific emotional states are shown. Where x-axis represents the sampled value of EEG data and the y-axis represents the detailed wavelet coefficients (D_1) of the transformed EEG data. In Fig. 5.2(b) ~ 5.7(b) the dotted values are the actual wavelet transformed EEG coefficients and the continuous shape of the plot is the acquired shape based on mathematical modeling of the specific mental states.



(a)

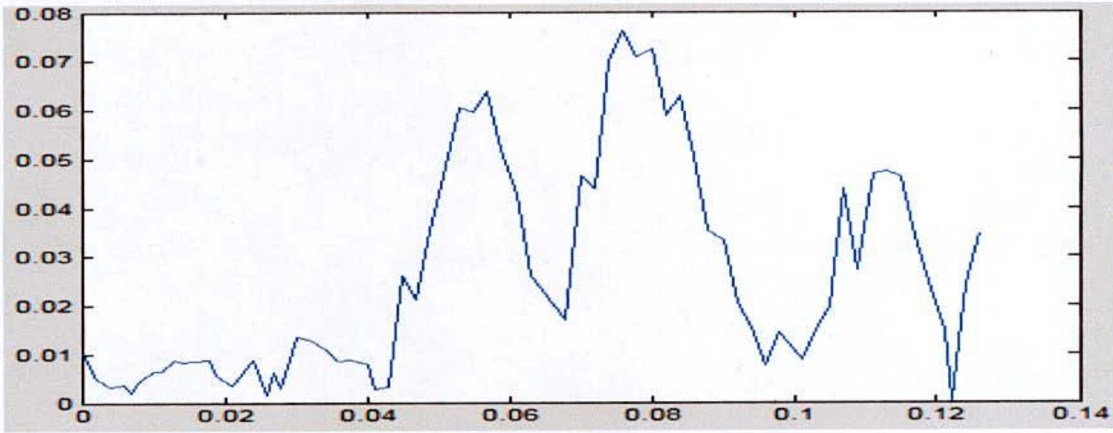


(b)

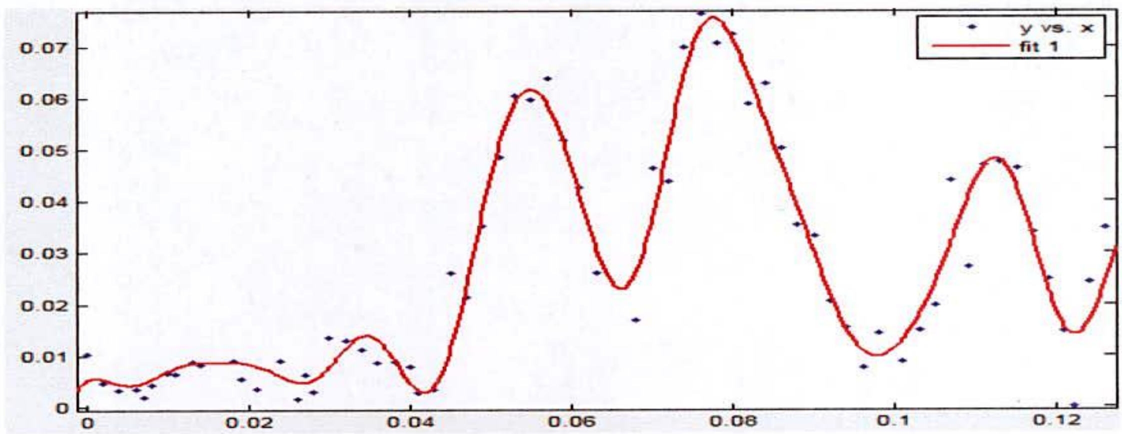
Figure 5. 5 (a) Plot of Detail wavelet coefficients of memory related task; (b) Plot of mathematical expressions which is best fit for memory related task.

The modeling of emotions is based on the different coefficients as shown in Table 5.1 for different emotional states where, a is the amplitude, b is the frequency, and c is the phase constant for each sine wave term. i is the number of terms in the series and $1 \leq i \leq 8$. Depending upon these values the different emotional states are modeled with different mathematical equation. In Table 5.1 it is shown that the value of a_3 coefficient for relax sate is much larger than the other states because the brain signal is modeled with alpha channel. The activity of brain is inversely proportional to the alpha activity. So in relax state the amplitude is much larger than the than the other state.

In Table 5.2 R-square computes the coefficient of determination (R-square) value from actual data and modeled data. The larger the R-squared is, the more variability is explained for the mathematical modeling. R-squared increases with added predictor variables and the adjusted



(a)

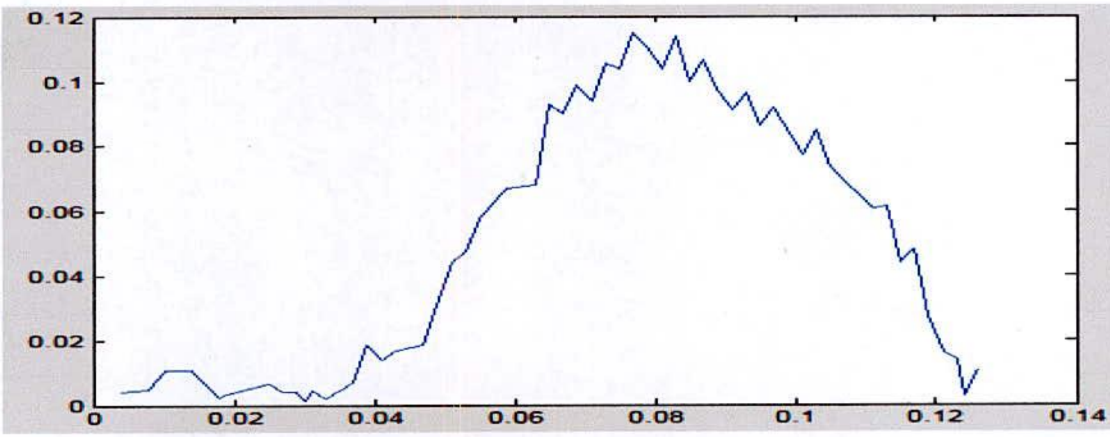


(b)

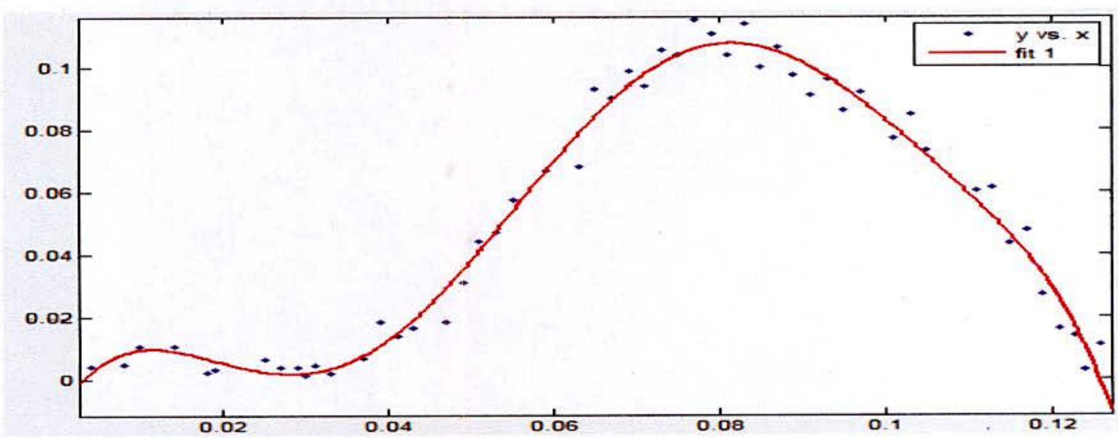
Figure 5. 6 (a) Plot of subband wavelet coefficients of fear state; (b) Plot of mathematical expressions which models the fear state

R-squared adjusts for the number of predictor variables in the model. R-square also outputs the root mean squared error (RMSE) and sum of squared errors (SSE) for convenience. From the values of SSE it can be determined that how much the proposed model is valid for each emotional state. In case of our modeling the adjusted R-square values for relax, MA, memory, pleasant, EM and fear states are 0.7849, 0.7718, 0.9327, 0.9559, 0.9771 and 0.9149 respectively which can be further improved by modifying the parameters on which the fitting of the curve depends. Among the all states the pleasant and the enjoying music (EM) states are the best mathematical model in this analysis and their deviations from the proposed model is 0.001742 and 0.00213 respectively.

Experimental result shows that the modeled mathematical expressions represent the sum of sinusoidal series which varies with number terms of sine series, i and the value of the coefficients amplitude, frequency and phase constant of each sine series. Here, i = 6 represents the relax state. The term of sine series, $i = 3, 5, 7, 4, 4$ represents the MA, pleasant, fear, memory states and EM states respectively according to different coefficients a_i, b_i, c_i.



(a)



(b)

Figure 5. 7 (a) Plot of subband wavelet coefficients of enjoying music (EM) state; (b) Plot of mathematical expressions which has modeled the enjoying music (EM) state

Table 5. 1 Coefficients of the mathematical expressions for modeling the emotional states

Coefficients for modeling emotional states	Emotional States					
	Relax	MA	Memory	Pleasant	Fear	EM
a_1	0.3385	0.1336	0.4645	0.1389	0.0424	0.0761
b_1	24.78	30.5	31.43	25	14.74	14.74
c_1	-0.8322	-0.3293	-0.6147	0.2056	0.0372	1.464
a_2	0.2593	0.1196	0.3392	0.2258	0.0105	0.00731
b_2	38.32	56.93	41.82	90.7	253.2	126.5
c_2	1.224	0.9673	1.827	2.473	-1.282	-1.118
a_3	24.29	0.01793	0.08284	0.2012	0.0217	0.0778
b_3	135.1	164.8	102.7	78.38	220.8	43.07
c_3	0.6373	2.306	0.9824	0.03406	-3.465	3.885
a_4	0.223	0.0	0.06213	6.58	0.9438	0.00376
b_4	142.5	0.0	152.7	229.7	108.3	129.7
c_4	3.303	0.0	-2.475	-1.471	0.8613	0.2212
a_5	0.03524	0.0	0.0	6.574	0.0045	0.0
b_5	189.5	0.0	0.0	229.8	355.5	0.0
c_5	3.436	0.0	0.0	1.667	0.0370	0.0
a_6	0.007478	0.0	0.0	0.0	0.9345	0.0
b_6	604.6	0.0	0.0	0.0	108.8	0.0
c_6	-0.03913	0.0	0.0	0.0	3.997	0.0
a_7	0.0	0.0	0.0	0.0	0.0112	0.0
b_7	0.0	0.0	0.0	0.0	297.9	0.0
c_7	0.0	0.0	0.0	0.0	-1.922	0.0

Table 5. 2 List of correlation showing the adjustment between original and modeled curves with their errors for 256 data samples

Emotional states	R-square	Adjusted R-square	SSE	RMSE
Relax	0.868	0.7849	0.02007	0.02726
MA	0.8007	0.7718	0.03713	0.02598
Memory	0.9461	0.9327	0.01556	0.01881
Pleasant	0.9669	0.9559	0.001742	0.004063
EM	0.9719	0.9771	0.00213	0.00659
Fear	0.9407	0.9149	0.00192	0.006461

5.4 Performance evaluation of our proposed model

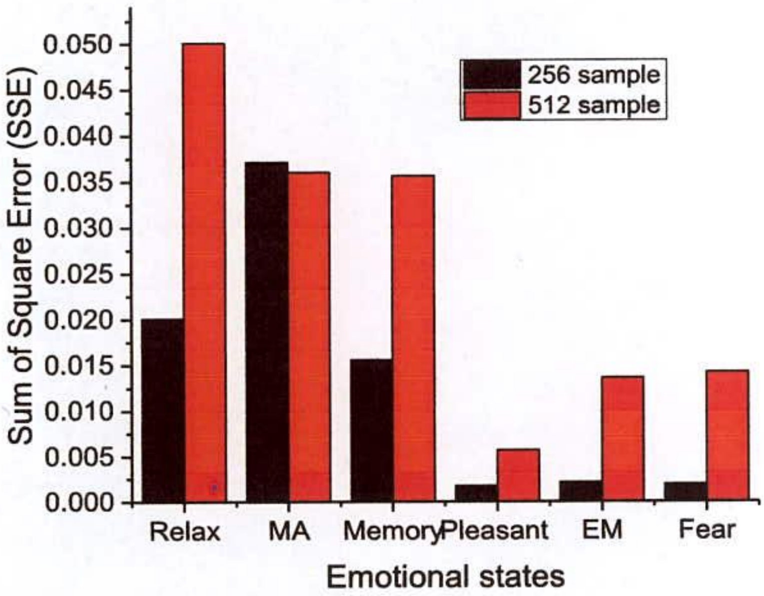
This mathematical model is for 256 data samples of each state. The raw EEG signals are analyzed with different time and frequency window and transformed in to 256 data samples. If 512 data samples are taken the coefficients can be obtained according to the trust region algorithm and applied with the sum of sinusoidal series expressions and can be verified from their R-square and Adjusted R-square value. Table 5.3 shows the result of correlation for 512 data samples which verify our proposed model with reference one for the 256 samples of data. The sum of square error (SSE) and root mean square error (RMSE) shows the effectiveness of our proposed mathematical model as shown in Fig. 5.8(a) & (b) for 256 and 512 data samples of different emotional states respectively. Table 5.4 shows the value of adjusted R-square and errors for 128 number of data samples. Figure 5.9(a) and (b) shows the plot of SSE and RMSE for 256 and 128 data samples respectively.

Table 5. 3 List of correlation showing the adjustment between original and modeled curves with their errors for 512 data samples

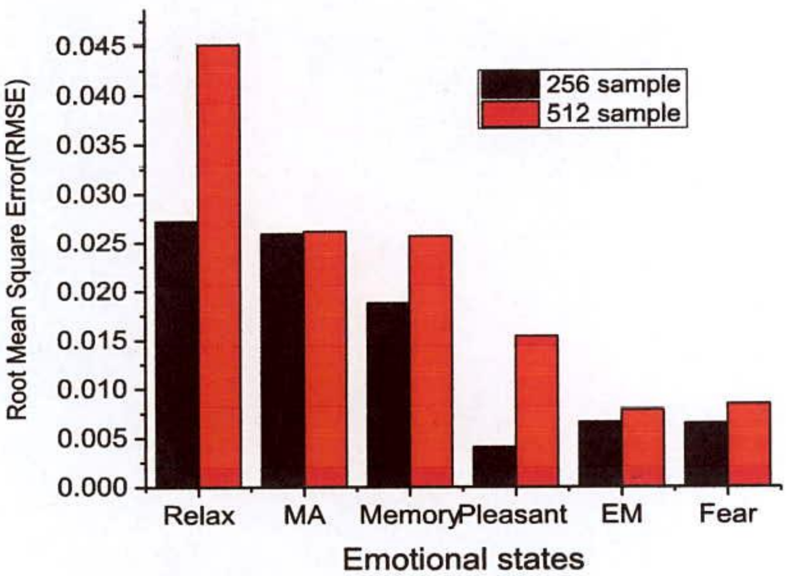
Emotional states	R-square	Adjusted R-square	SSE	RMSE
Relax	0.766	0.724	0.0501	0.0451
MA	0.821	0.794	0.036	0.0262
Memory	0.853	0.785	0.0356	0.0257
Pleasant	0.945	0.872	0.0057	0.0154
EM	0.913	0.887	0.0136	0.00784
Fear	0.924	0.902	0.0142	0.00847

Table 5. 4 List of correlation showing the adjustment between original and modeled curves with their errors for 128 data samples

Emotional states	R-square	Adjusted R-square	SSE	RMSE
Relax	0.826	0.801	0.0432	0.034
MA	0.785	0.773	0.054	0.0432
Memory	0.975	0.946	0.0031	0.0047
Pleasant	0.924	0.912	0.0211	0.0256
EM	0.966	0.946	0.0048	0.0035
Fear	0.975	0.962	0.00293	0.00245

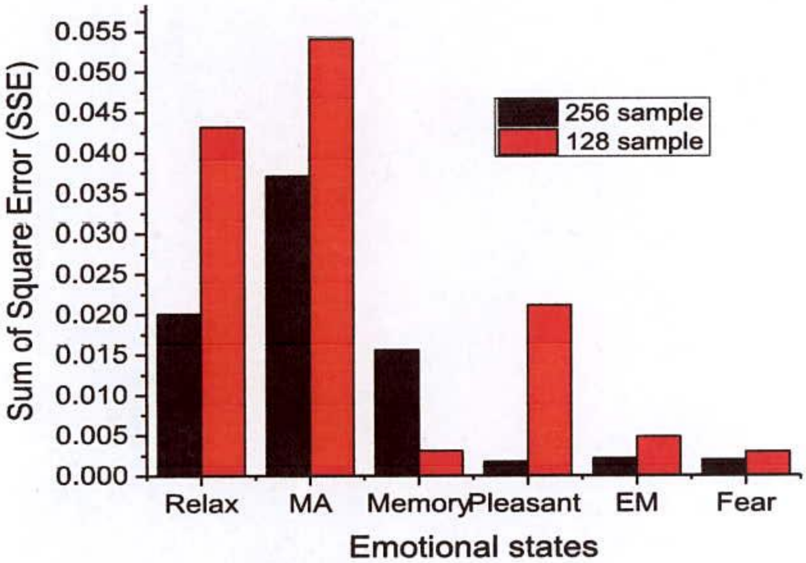


(a)

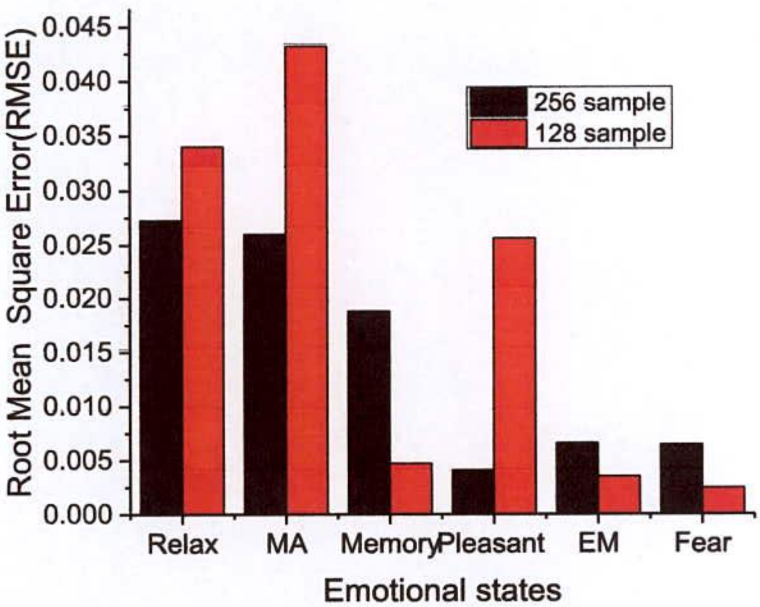


(b)

Figure 5. 8 (a) Plot showing the SSE value for 256 and 512 data samples, (b) Plot showing the RMSE value for 256 and 512 data samples



(a)



(b)

Figure 5. 9 (a) Plot showing the SSE value for 256 and 128 data samples, (b) Plot showing the RMSE value for 256 and 128 data samples

5.5 Emotion modeling with effective frequency band of EEG signal

Modeling of human emotion with the effective frequency band of EEG signal plays a significant role in brain signal analysis and physiological research area. In this work we have proposed an approach to model human emotion with the variations of different effective frequency bands of EEG signal during a test when subjected to sustained mental task.

A cognitive model while attending a test will support and facilitate the development of affective systems in emotion studies and act as a unifying platform in physiological research area. Sustained attention is the skill of maintaining a high degree of vigilance on physical events during a long period of time [72]. During a test or mental task performed human mind may feel relief or get tensed according to their performances of answering the questions. Human being suffers from stress which affects their lifestyle making them feel tension, anxious, angry and frustrated [73]. Oscillations of cortical activity in different frequency bands play an important role in the functional activity of human brain that underlies cognitive processing and attentive performances. For example, stress makes change the frequency band of EEG to high [74] and the low frequency indicate the state of relax. Therefore, our objective is to detect human's mental state during a test or sustained attention or while performing mental task. Modeling any emotional state with mathematics is really complex because the functional activity of brain is related with time, environments, mental activities which primarily related with emotional activity. So, for expressing of emotional states time associated with its frequency information is the most feasible which have made more interest to model the states with different mathematical expressions and functions based on the discrete wavelet transformation and different time-frequency based coefficients [75].

5.5.1 State of art

Many works have been done in this emerging area to find the relation between the changes in signals and emotional states with their mental behavior. Some researchers in [3]-[4] categorized the emotional states and extracted different features using time-frequency analysis to correlate and estimate the emotional states efficiently. In [1] authors tried to structure a model according to the strength and actual need of human behavior to predict emotions and support Human-Computer-Interaction (HCI). The mental behavior detection from the EEG signal was proposed with the findings of effective data recording from physiological signals, feature extraction through wavelet transform, data reduction and feature classification using various classification methods [8]. In [76] Klimesch suggests that synchronized alpha rhythms, when associated with mental inactivity or idling condition, can be crucial for the onset of strong inhibitory effect and the variations of gamma band while performing the mental task is noteworthy [77]. Authors in [16] propose an emotion recognition system with five levels of workload during a certain amount of time limit. From the scale of valence-arousal-dominance the emotional activities are classified using SVM. The different research techniques, specifications and results limit their applications in real time monitoring system. So, a mathematical model is essential to monitor the emotion related activity in a unifying frame.

5.5.2 Proposed approach of emotion modeling during sustained mental task

Some important aspects are held in this research, (i) to propose a technique for extracting some salient statistical and time-frequency analysis based features according to the variation of effective frequency band during a test of sustained attention, (ii) to evaluate and compare the efficiency of the extracted features for different bands to detect the emotional states and effective frequency bands using support vector machine, (iii) to model the states with mathematical functions and expressions with their effective frequency bands. In this research, the BIOPAC data acquisition unit MP36, C++ source code, MATLAB file and AcqKnowledge®4.1 software are used for data acquisition, analysis, storage, and retrieval to propose a mathematical model [17].

In this research EEG is used to verify the influence of mental task on human brain activity. The effect of different types of test on brain functions rate based on subject's preference or performances of answering the questions or solving the problems. They were given fixed time to answer the questions during test. EEG band waves were affected with the mental activities and changes the signal characteristics. To estimate the emotional states different features are extracted using statistical, frequency and time-frequency analysis techniques during attentive mental task to identify the variation of brain activities in different frequency band of EEG signal which are particularly important for recognition of human cognitive states when performing different mental activities. Furthermore, a mathematical model will be developed using DWT analysis and Trust-Region algorithm for real time monitoring system with the effective frequency band.

5.5.3 Emotion estimation according to the effective frequency band

The classification rate in different frequency band indicates which band is much effective for which type of mental task. The effectiveness of the bands of EEG signal mentions the emotional state of the subject while performing the test with great attention. Table 5.5 indicates the classification rate at different bands using SVM. From Table 5.5 it is shown that during performing test the most effective frequency bands are alpha and beta. Fig. 5.10 shows the classification rate at alpha and beta bands which mention that during test when the subjects were reading text the higher classification rate is found for alpha band which mentions the relax state. During reading and solving problems the higher accuracy is found for beta band which indicate the state of stress.

5.6 Modeling of emotional states during test

To model the emotional states, the time-frequency transformation is applied on the 1024 samples of EEG signal because of the nonstationarity of EEG data. In this paper Daubechies4 wavelet function D_4 band is used to model the classified states. Each 64-point of EEG samples which is extracted as the sub-band coefficients (D_4) of EEG data.The actual wave shape of the wavelet coefficients for alpha band is shown in Fig. 5.11(a) and (b) shows the wave shape of the mathematical expression which has modeled this state based on the coefficients as shown in Table 5.6. This state represents the relax state during the time of test of sustained attention. So in the present context of this research it is obtained that when the subject was reading the text he was in relax state.Figure5.12(a) and 5.13(a) show the plot of actual D_4 band and 5.12(b) and 5.13(b) the modeled plot of beta band for problem reading and problem sloving state respectively. Beta band is the comparatively high frequency band which mention stress. The mathematicall expression of relax and stress state during test is shown in Eq 5.11- 5.13.

$$f_R(x) = \sum_{i=1}^{6} a_i \sin(b_i x + c_i), \text{ } where\, x \in N \tag{5.11}$$

$$f_{PR}(x) = \sum_{i=1}^{7} a_i \sin(b_i x + c_i), \text{ where } x \in N \tag{5.12}$$

$$f_{PS}(x) = \sum_{i=1}^{8} a_i \sin(b_i x + c_i), \text{ where } x \in N \tag{5.13}$$

Table 5. 5 Classification accuracy at different effective busing SVM during test

Mental Tasks	EEG frequency band	Train dataset for SVM	Test dataset for SVM	Classification accuracy
Text reading (TR)	Alpha(α)	120	86	84.58%
	Beta(β)	120	85	10.2%
	Delta(δ)	120	76	16.15%
	Theta(θ)	120	87	36.25%
Problem reading (PR)	Alpha(α)	108	65	21.18%
	Beta(β)	108	66	83.68%
	Delta(δ)	108	62	23.22%
	Theta(θ)	108	65	21.15%
Problem solving (PS)	Alpha(α)	116	62	1.5%
	Beta(β)	116	73	95.5%
	Delta(δ)	116	62	25.18%
	Theta(θ)	116	74	32.47%

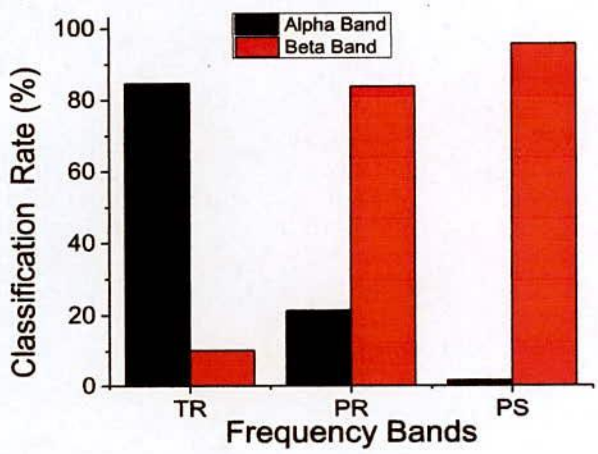


Figure 5. 10 Classification accuracy for alpha and beta frequency band during test

Equation (5.11)-(5.13) represent the mathematical expressions which can model the emotional state during the time of text reading, problem reading and problem solving respectively. Here, a_i, b_i, c_i represents the coefficient of the summation of sinusoidal series which represents the amplitude, frequency and phase constants respectively in which i is the iteration of sine series for different EEG bands and N is a set of 64 real numbers of the sub-band coefficients.

Table 5.7 presents the adjustment percentage with the actual and model state. It is shown that in case of reading simple text the effective band was found alpha as its classification rate was 84.58%. On the contrary, the effective band was beta for problem reading and problem solving and the classification accuracy were 83.38% and 95.5% respectively. So mathematical model was developed with the alpha and beta frequency band for relax and stress state respectively. The R-square percentage of the modeled emotional state was found 87.57% for text reading and 82.58% for problem solving task.

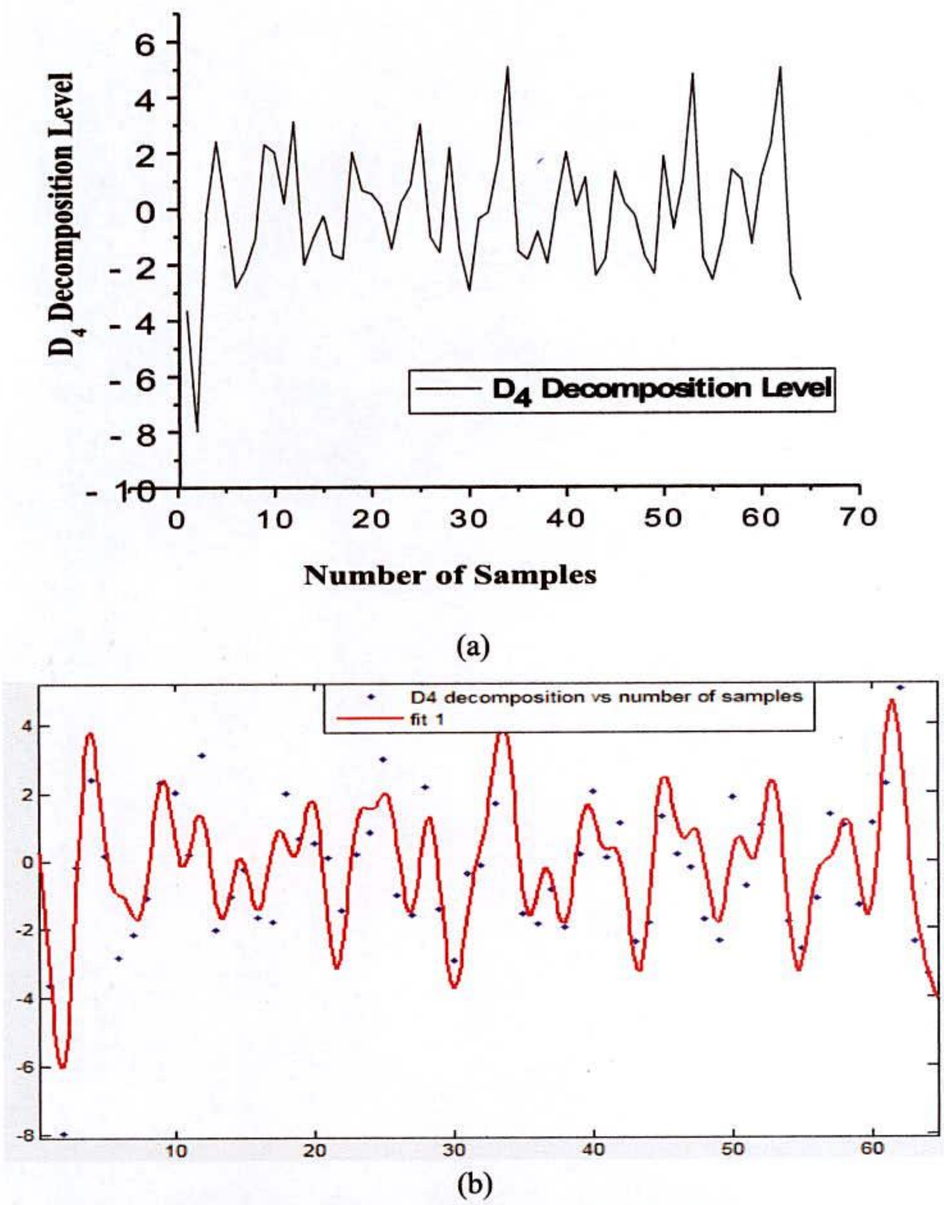
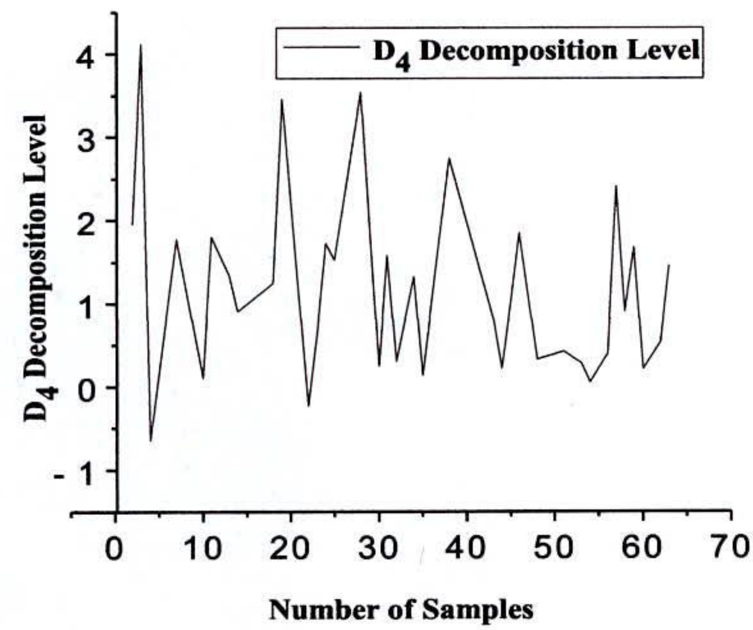
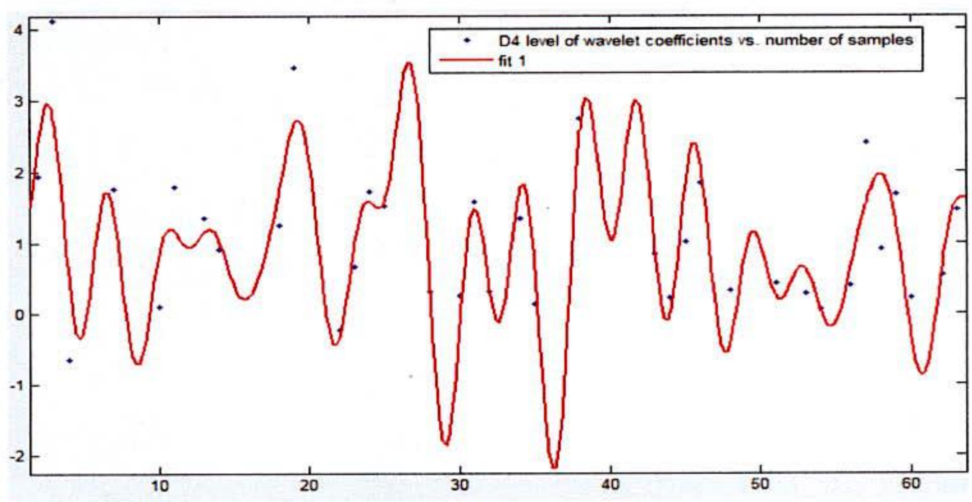


Figure 5. 11 (a) Plot of D_4 coefficients for alpha band during text reading; (b) Plot of mathematical expressions which has modeled the relax state

From this analysis it can be determined that for emotion modeling, alpha band is effective during the time of simple workload. When workload or pressure on human brain is increased like problem solving task then the effectiveness of beta band is vital. So to model the state of stress beta band is more effective band than the others.

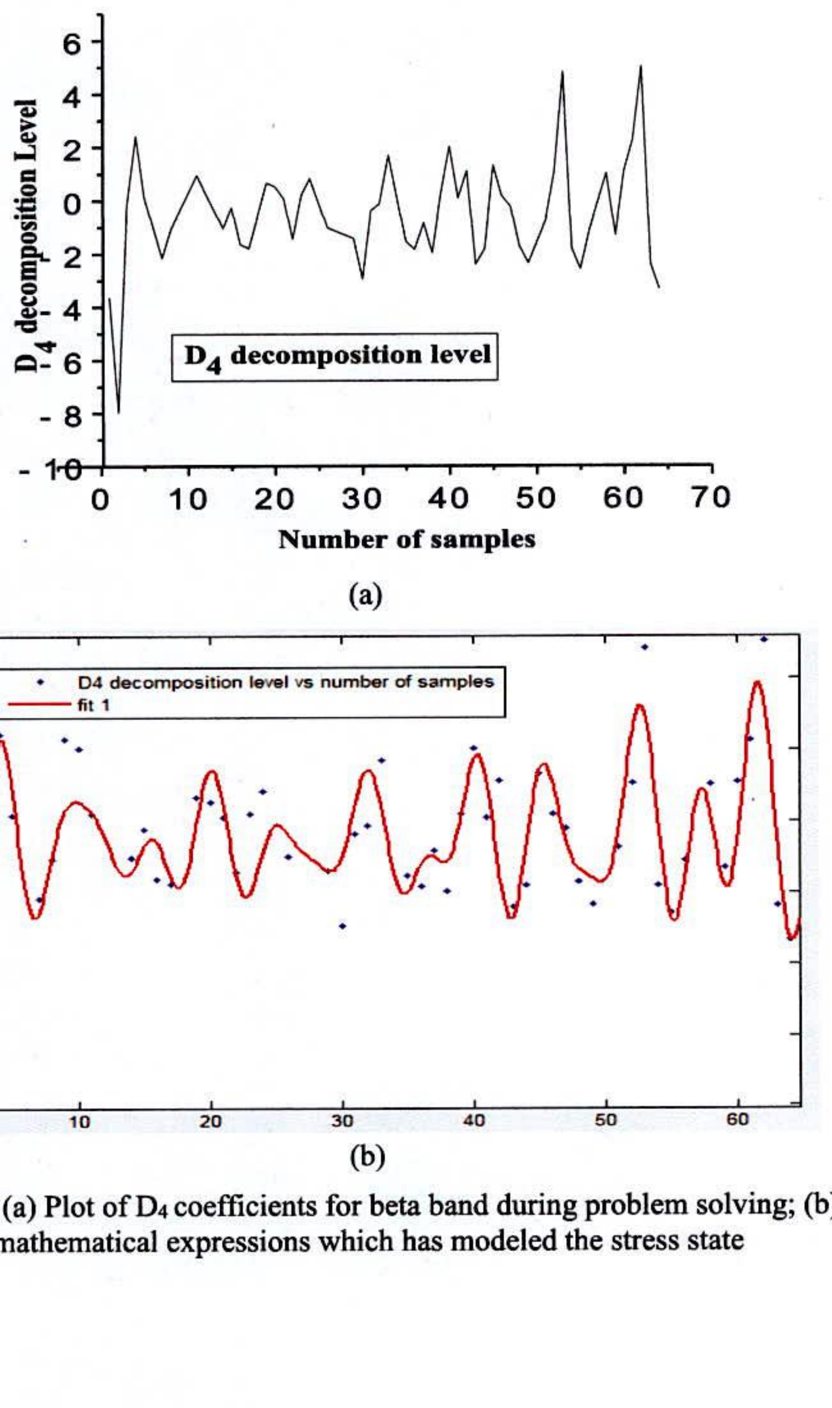


(a)



(b)

Figure 5. 12 (a) Plot of D_4 coefficients for beta band during problem reading; (b) Plot of mathematical expressions which has modeled the stress state



(a)

(b)

Figure 5. 13 (a) Plot of D_4 coefficients for beta band during problem solving; (b) Plot of mathematical expressions which has modeled the stress state

Table 5. 6 Coefficients of the mathematical expressions required for modeling the emotional states during test

Coefficients for modeling emotional states with effective band	Mental Task During Test		
	Text Reading	Problem Reading	Problem Solving
	Alpha Band (Relax State)	Beta Band (Stress State)	Beta Band (Stress State)
a_1	1.245	5.001	247.8
b_1	0.9036	0.001046	0.8811
c_1	2.822	2.92	-5.467
a_2	0.8768	0.6147	248.6
b_2	1.086	0.2993	0.8813
c_2	2.495	-4.923	-2.33
a_3	111.1	0.7048	215.1
b_3	1.253	1.766	1.136
c_3	-5.141	-2.858	1.46
a_4	111.2	0.841	7.328
b_4	1.254	0.9703	1.492
c_4	4.26	1.533	-3.29
a_5	0.9944	0.6823	0.5685
b_5	2.29	0.8156	0.5989
c_5	-0.5688	-0.5484	1.903
a_6	0.5523	0.8536	6.852
b_6	0.5016	1.611	1.487
c_6	2.823	2.72	-0.03275
a_7	0.0	0.4015	215.3
b_7	0.0	0.4621	1.136
c_7	0.0	1.558	4.59
a_8	0.0	0.0	0.6933
b_8	0.0	0.0	0.04012
c_8	0.0	0.0	-2.321

Table 5. 7 List of correlation showing the adjustment between actual and modeled curves with their errors

Mental Task	R-square (%)	Adjusted R-square (%)	RMSE
Text Reading	87.57	81.52	0.6389
Problem Reading	81.03	75.08	0.8556
Problem Solving	82.58	66.32	0.5226

5.7 Summary

This chapter focuses on the impact of emotional states on EEG signals in different environmental conditions using different wavelet functions, spectral components and statistical measures. The emotional states are modeled with the coefficients of sine functions based on amplitude, frequency and phase constants. The proposed model has been compared with the D_4 subband coefficients values in terms of SSE and RMSE values. The sum of square error percentage of the predicted model are 2%, 3.7%, 1.5%, 0.17%, 0.2% and 0.19% for the relax, MA, memory, pleasant, EM and fear state respectively for 256 data samples and also verified with 512 and 128 data samples. These percentage errors of different states and the graphical representation of the modeled emotional states justify the efficacy of the proposed model.

Chapter 6

6.1 Conclusion

This thesis describes a framework in order to classify human emotional sates and model the classified states based on EEG signal. In this thesis, proper channel or effective EEG bands are selected to alleviate the dimensionality reduction problem and the efficient features are extracted in order to classify the emotional states effectively. To evaluate the performance of channel selection, different kinds of temporal and spectral features and SVM classifier were used to demonstrate the efficacy of cognitive states. The results of this approach could help for selecting proper channel and estimate the emotional states using different transformation technique and machine learning algorithms. Considering the classification accuracy it is determined that power spectral density is the most efficient feature than the other frequency based features and the alpha channel is the most significant channel in case of cognitive state estimation. Therefore, such types of extraction of effective feature as well as the selection of proper channel of EEG signal may contributes much to a significant decrease in computation time and identify the characteristics of the signals for cognitive states estimation. This work proposes an approach of modeling of emotional states with mathematical functions using trust region algorithm. This algorithm modeled the emotional states in different environmental conditions in terms of sinusoidal series based on the amplitude, frequency and phase constants. The adjusted R-square percentage determines the effectiveness of our proposed model and the SSE and RMSE determine how much our approach is deviated with the actual data of the EEG signal. The error percentage of the predicted model are 2%, 3.7%, 1.5%, 0.17%, 0.2% and 0.19% for the relax, MA, memory, pleasant, EM and fear state respectively for 256 data samples and also verified with 512 and 128 data samples which validates our proposed system. These percentage errors of different states and the graphical representation of the modeled emotional states justify the efficacy of our proposed approach. Finally, this work developed an approach for the modeling of human emotional states with proper mathematical expressions which is applicable for practical implementation of emotion based systems.

6.2 Future Work

In this work there is little bit difficulty to collect the EEG data due to lack of 10-20 international data acquisition unit. In future much more data should be collected to get better and much more reliable inferences for the classification. We can also apply more machine learning algorithms to show the efficacy of the proposed approach as well as to show the significant features of emotion classification This work plays an effective way to find out the efficient coefficients of the classified emotional states which can be further extended to develop an emotion engine architecture for hardware implementation of low power emotion based systems.

In case of pattern recognition, diagnostic decision making with lower computational complexity and low cost patient monitoring system this work can be further extended which will be much effective for real time application.

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