Motor Imagery Movement and Neurological Disorder Classification using Salient Features of EEG Signal

By

(Md. Mamun Or Rashid)

A thesis submitted in partial fulfillment of the requirement for the degree of
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Khulna 9203, Bangladesh
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Declaration

This is to certify that the thesis work entitled "**Motor Imagery Movement and Neurological Disorder Classification using Salient Features of EEG Signal**" has been carried out by **Md. Mamun Or Rashid** in the Department of Biomedical Engineering, Khulna University of Engineering & Technology, Khulna, 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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Dedicated to-

My Parents and Honourable Supervisor

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Abstract

Electroencephalography (EEG) measurement plays a significant role in the clinical and scientific research of brain studies. EEG signals are very important, particularly for classification and treatment of neurological diseases and brain computer interface (BCI) applications. The aim of this dissertation is to develop methods for the analysis and classification of different categories of motor imagery (MI) movements, epileptic EEG signals, and human alertness states. A novel method is also developed for continuous alertness monitoring.

EEG signals of MI movements are classified for right hand and left hand (two class) and right hand, left hand, and feet (three class) movements. Nowadays, MI is a highly prescribed method for the disabled patients to give them hope to control machine or computer by interfacing with brain or mind. This dissertation proposes a classification method between imagery left and right hands movement using Daubechies wavelet of discrete wavelet transform (DWT) and Levenberg-Marquardt back propagation training algorithm of artificial neural network (ANN). DWT decomposes the raw EEG data to extract significant features that provide feature vectors precisely. ANN classifies the two class and three class trials data. Classification accuracy varies with respect to the subject. This method can be used to design a well-organized BCI system with better accuracy. Results from classifier can be used to design brain machine interface (BMI) for better performance that requires high precision and accuracy scheme.

Neurological disorder i.e. epilepsy detection is enough time consuming and requires thorough observation to determine epilepsy type and locate the responsible area of the cerebral cortex. The dissertation proposes an effortless epilepsy classification method for epilepsy detection and investigates the classification accuracy of multiclass EEG signal during epilepsy. For accomplishing the proposed research work we use DWT to obtain responsible features to accumulate feature vectors. Afterward feature vectors are given in the input layer of the ANN classifiers to differentiate normal, interictal, and ictal EEG periods. Accuracy rate is calculated based on the confusion matrix. Proposed method can be utilized to monitor and detect epilepsy type incorporating with an alarm system.

It is tiresome for human to concentrate constantly, though several works require continuous alertness like efficient driving, learning, etc. A practical method is applied to investigate the concentration state of human brain by EEG acquisition. This research work proposes continuous alertness state classification method based on two different types of mental tasks with respect to the resting state (resting with eyes open and eyes close). To conduct this research work, some participants were involved and they performed several tasks such as alphabet counting, virtual motor driving, resting with eyes open and eyes close. During the performances of the tasks, 9 channel EEG data has been acquired from their scalps. The data acquisition is performed by B-Alert (BIOPAC) system. The acquired data are filtered by IIR filter and responsible channels are selected by the statistical method. The features of the signals were extracted by using principal component analysis (PCA) and DWT algorithms. The alert states of our brain are classified by ANN. In addition, the specific relative power (RP) of the responsible frequency band of EEG signals is calculated for alertness monitoring. Within the RP range of resting and active state, a threshold value is proposed for monitoring the alertness state of the participants.

This work will be helpful to classify the epileptic states with more accuracy as well as this works is also a well guide to classify the motor imagery movements. In addition, the proposed method based on continuous alertness monitoring will be remarkable approach to design machines for monitoring driving or learning.

Contents

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List of Abbreviations

Abbreviated Form	Elaboration
ANOVA	Analysis of Variance
BSS	Blind Source Separation
CNS	Central Nervous System
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
EEG	Electroencephalogram
FFT	Fast Fourier Transform
ICA	Independent Component Analysis
KNN	K-Nearest Neighbor
LDA	Linear Discriminant Analysis
PCA	Principal Component Analysis
PNS	Peripheral Nervous System
SVM	Support Vector Machine
WT	Wavelet Transform
WPT	Wavelet Packet Transform
BCI	Brain Computer Interface
MI	Motor Imagery
BMI	Brain Machine Interface
RP	Relative Power
PSD	Power Spectral Density
fMRI	Functional Magnetic Resonance Imaging
MRI	Magnetic Resonance Imaging
PET	Positron Emission Tomography
SPECT	Single Photon Emission Computed Tomography
ECoG	Electrocorticography
MNDs	Motor Neuron Diseases
ADHD	Attention Deficit Hyperactivity Disorder
ALS	Amyotrophic Lateral Sclerosis
ERD	Event Related Desynchronization
ERS	Event Related Synchronization
MMI	Mind Machine Interface

DNI	Direct Neural Interface
CC	Cross Correlation
ST	Stockwell Transform
LMA	Levenberg Marquardt Algorithm
TN	True Negative
FN	False Negative
TP	True Positive
FP	False Positive
CSP	Common Spatial Pattern
NEWFM	Neural Network with Weighted Fuzzy Membership Functions
SODP	Second-Order Difference Plot
EMD	Empirical Mode Decomposition
WPT	Wavelet Packet Tree
DWPT	Discrete Wavelet Packet Transform
MAD	Mean Absolute Deviation
MSE	Mean Squared Error

CHAPTER I

Introduction

1.1 Motivation

Human brain generates different rhythmic electrical signals when a person thinks, reads, watches or does something. It is correlated with work load, memory reservation and other activities. Brain function can be recorded by different functional neuroimaging techniques to understand the change of brain activity in certain brain areas with specific mental task. Common methods of such functional neuroimaging methods include: functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIR or fNIRS), positron emission tomography (PET), single photon emission computed tomography (SPECT), multichannel electroencephalography (EEG) and magnetoencephalography (MEG). PET, fMRI and fNIR measures localized changes in cerebral blood flow related to neural activity. EEG and MEG methods of neuroimaging involve recording of electrical currents and magnetic fields, respectively. Electrocorticography (ECoG) is an invasive electrophysiological monitoring method. Electrical activity is recorded from the cerebral cortex using electrodes placed directly on the exposed surface of the brain. All these techniques are widely accepted for different medical and research uses. In our research work we use EEG signal, it is easier to use for many reasons (low cost, portable, wireless system etc.) and recently modern science made it possible to monitor person’s behavior by analyzing EEG. Consequently the use of EEG is increasing in the brain machine interface (BMI) and in diagnosis and treatment of different neurological diseases.

Motor imagery (MI) movement is the simulation of executing voluntary motor activity in which a person imagines of doing any voluntary motor act but in reality he does not. Research has shown that human brain generates electrical impulses while doing imagery motor act. Brain computer interface (BCI) is an application of EEG signal and MI movement can be used to design BCI to control prosthetic limbs [1-4]. For the physically disabled person, various physiological signal based rehabilitation systems can be used in BCI for differentiating among various mental tasks [5-8]. MI movement is also used to treat neurological disorders such as motor neuron diseases (MNDs) that affect mostly motor neurons; that command over the voluntary muscles of the body [9]. But for that purpose an efficient algorithm needed which can differentiate between right hand and left hand or among hands and feet also with great classification accuracy.

Epilepsy is a severe neurological disorder, characterizes by seizures that is an abrupt changes in brain electrical activity causes the patient to lose control over the extremities and behavior. Types of epilepsy vary with the brain location responsible for the seizures. In the treatment and diagnosis of epilepsy, EEG is widely used but an effective detection method is necessary for long term monitoring of the epilepsy patient which will reduce the number of the wrong alarm [10-12].

Remain conscious is very important, especially while doing important or risky works but keeping constant attention is not easy. Mental workload or mental fatigue will reduce our alertness. Attention deficit hyperactivity disorder (ADHD) is a neurological disorder that characterizes by certain symptoms such as inattention, impulsivity and hyperactivity that is responsible for creating problems for patients to remember information, to concentrate, to arrange tasks etc. Worldwide 5.9–7.1% school going children suffer from ADHD and show symptoms into adulthood [13]. Human alertness can be determined by monitoring EEG signal of the person. Consciousness monitoring can be introduced to monitor the alertness level of the drivers, pilots, students in the classroom and for surveillance purpose, also for medical purposes to keep eyes on the patient [14-16]. So it is very crucial to develop an algorithm with perfect accuracy to monitor human alertness.

Since EEG signals is widely used and very significant in the field of biomedical engineering research so it is necessary to carefully analysis EEG signal to understand the signal very well. Several research works have been done but need more methods which propose better classification accuracy to use it without error. To use EEG signal in the arena of BCI or detection of epilepsy or detection of alertness, an adequate neuroscience research is still needed to reach this aim. Consequently in this dissertation we aim to develop and propose methods that successfully classify MI movements, epilepsy and mental alertness and monitor the human attention level.

1.2 Problem Statements

After recording EEG signals it becomes huge amount data to analyze, particularly when recorded over long time such as for epilepsy detection or mental consciousness monitoring. Analyzing all data manually is not possible so an automatic technique is require to extract responsible information from the signals and to make difference with the reference or standard data or between multiple class [17-18]. For an error free automated system it is necessary to classify with an acceptable accuracy rate.

In BCI application to use MI successfully several research works [19-22] have been done, but still several factors are needed to be improved. BCI system needs to recognize the patterns of the subject's intention to move the prosthetic limbs or to establish the communication with the machine by utilizing neural activity. So finding responsible information or the feature from the signal is very important for respective activity to make the classification method more efficient [20, 23-25]. For epilepsy detection and mental alertness monitoring wrong alarm is irritating and features may vary with the responsible activity [10, 26-27]. Again for alertness monitoring a perfect method is very much needed to prevent accident or to avoid damages [28]. So a perfect classification method with least error is very significant. Alertness monitoring method is very much needed to control the alertness so that can be remain alert during surveillance or driving vehicles etc. [15-16, 29-30].

To solve these problems, an effective method is proposed for the MI movement classification, epilepsy detection and monitoring of mental alertness of the subject with acceptable accuracy rate.

1.3 Objectives

The objectives of this research work are to classify motor imagery movement, epilepsy and mental alertness of the participants and develop a method to monitor alertness. This research work also aims to compare the outcome with related accomplished research work.

The specific objectives of the proposed research work are summarized below:

- To develop a motor imagery (MI) movement classification (both hands and feet) method by using the statistical features of EEG signal.
- To investigate the classification accuracy of the inter-ictal and ictal EEG period of the patient with epilepsy in comparison with the normal subject EEG period.
- To develop an efficient method to monitor mental alertness and classify active mental state and inactive mental state and determine the classification accuracy.

1.4 Contributions

The main contribution of the research work can be stated shortly as given below:

- **Developed a method to classify motor imagery (MI) right, left hand (2 class) and MI right hand, left hand and feet (3 class) movement:** This research work efficiently classifies MI right, left hand (2 class) and right hand, left hand and feet (3 class) movement with acceptable accuracy by selecting responsible channels with a set of features for BCI application where higher accuracy is crucial. Selection of the significant channels and features are the main contribution of this objective.

- **A method is developed to detect epilepsy accurately:** This research work devise a method with a set of features to continuously monitor epilepsy with alarming system by classifying the normal, ictal and inter-ictal EEG period efficiently. Selection of the significant features is the main contribution of this objective.

- **A noble technique is developed to efficiently monitor mental alertness continuously:** This research work introduces a mental consciousness monitoring system in comparison of resting state of the person which can be promising to reduce the number of accident that occur due to attention deficit hyperactivity disorder (ADHD) or mental fatigue. The noble method of continuous monitoring of alertness is the principal contribution of this part of the dissertation.

1.5 Potential Applications of this Research

The applicable scope of this research is quite wide-ranging. Some of them are:

- To design a BCI system MI movement classification can be used. High accuracy rate would provide advantage.
- This research outcome can be used to treat neuromuscular diseases because MI movement now widely used.
- The feature set the MI movement research can be adopted to establish MMI for automation.

- Epilepsy detection method can be applied to effectively detect epilepsy as well as to continuously monitor the patient with epilepsy with less error.
- Mental alertness monitoring has wide range of use such as to monitor the student's attention in the classroom, monitor the attention of the drivers and pilots and also for the vigilance purpose.

1.6 Thesis Outlines

Chapter 1: The first chapter includes the motivation, problems, objectives and contribution of this research. Besides, this chapter noted some important applications of this research work.

Chapter 2: Includes the background knowledge of the structure of human brain with nerve cell and Electroencephalography (EEG). Besides this chapter provide important information regarding the MI movement classification, BCI system, epilepsy and importance of mental alertness monitoring.

Chapter 3: This chapter describes the right hand and left hand (two class) and right hand, left hand and feet (three class) motor imagery (MI) classification methodology and analyze the classification accuracy.

Chapter 4: This chapter contains the epilepsy detection method by classifying ictal, inter-ictal and normal EEG period and discusses the significance of the results by comparing with the previous accomplished works.

Chapter 5: A method of mental alertness monitoring system is proposed in this chapter which is convenient for monitoring alertness of the students and drivers or pilot by using wireless EEG acquisition system.

Chapter 6: This chapter concludes the dissertation by discussing the further research opportunities.

CHAPTER II

Introduction of Human Brain and Electroencephalography

The aim of this dissertation is to develop three categories (motor imagery, epilepsy and alertness) of EEG signal classification to improve the diagnosis and treatment process of neurological diseases and monitoring the human attention level. This chapter provides the background knowledge of EEG and classification concept with the introduction of different methods commonly used.

Before providing the overview of the classification, this chapter introduces the general concepts and background knowledge about EEG, epilepsy and BCIs. A brief description of structure of brain is discussed in Section 2.1. Section 2.2 presents nerve cell and 2.3 and 2.4 elaborately illustrates the Electroencephalography (EEG) and its rhythms. Section 2.5 gives a brief summary of the motor imagery, epilepsy and alertness to improve the diagnosis and treatment of neurological diseases. Finally, section 2.6 describes the introduction of EEG signal classification and algorithms.

2.1 Structure of Human Brain

The central nervous system is consisting of brain and spinal cord that controls over the most of the functions of the body [31-32]. The brain collects sensory information from the nerves that transmit through the spinal cord and other nerves. Spinal cord is the chief path for the passage of sensory information to and from the brain. Information flows to the central nervous system from the peripheral nervous system. In the Fig. 2.1 shows that CNS and PNS forms the human nervous system where brain and spinal cord forms the CNS and cranial and spinal nerves forms PNS.

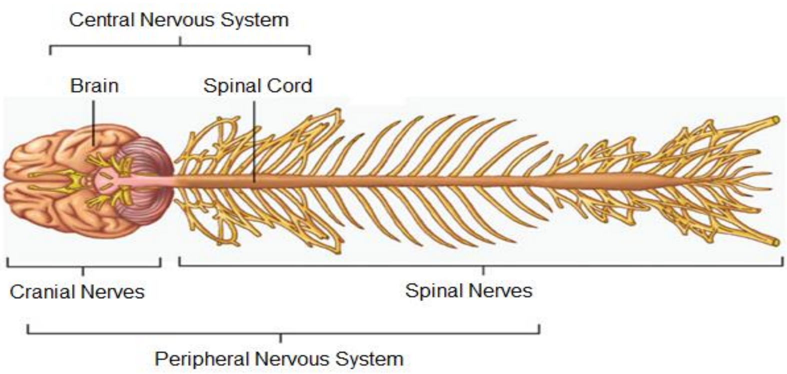

Fig. 2.1: CNS and PNS of the human nervous system.

Anatomically human brain consists of three main parts which are the cerebrum, cerebellum and brainstem [33] as illustrated in Fig.2.2. Detail explanations of these parts of the brain are given.

(1) Cerebrum: The cerebrum is the biggest part of the human brain and divided into nearly symmetrical two (left and right) hemispheres, is generally associated with brain functions related to thoughts, movements, emotions and motor functions. The most outer part of the cerebrum is made up of grey matter known as the cerebral cortex.

Each hemisphere can be divided into four lobes: frontal, parietal, occipital and temporal [34]. These lobes perform various bodily functions.

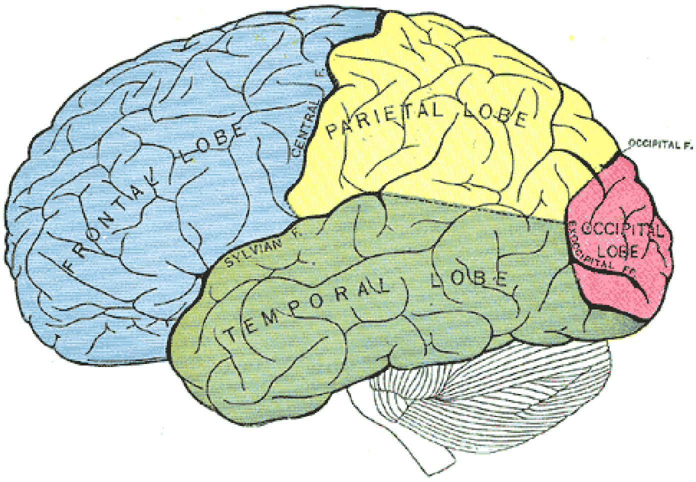

Fig. 2.2: Different lobes of human brain [33].

• Frontal lobe is located at the front of the brain and contains most of the dopamine sensitive neurons in the cerebral cortex. This lobe is greatly related with the voluntary movement and center of the primary motor cortex that controls movement or walking. Also responsible for personality, emotions, problem solving, motor development, reasoning, planning [35].

• Parietal lobe is sandwiched between two lobs and mainly responsible for sensation (pain, touch) or sensory comprehension. Also it processes recognition, orientation and movement etc. related information [35-36].

• Temporal lobe is located beneath the both cerebral hemispheres of the mammalian brain and responsible for processing auditory and visual sensory input stimuli and language recognition [37-38].

• Occipital lobes are the smallest of four lobes in the human brain and located in the rearmost areas of the skull.It is the prime visual stimuli processing unit and deals with the recognition of auditory stimuli, speech, perception and memory.

(2) Cerebellum: The cerebellum is positioned at the lower back of the head and also separated into two hemispheres. It is the second largest structure of the brain and holds more than half of the brain neurons. The cerebellum is one of the sensory areas of the brain that performs motor control, sensory perception and coordination. The cerebellum is also associated with voluntary muscle movements, posture and balance regulation [39-40].

(3) Brainstem: The brainstem is situated at the bottom of the brain and links the cerebrum to the spinal cord. The brainstem is works as a hard drive of a computer and it is the main control panel of the body. It controls important functions of the body, including breathing, consciousness, movements of the eyes and mouth etc. [39-41].

2.2 Nerve Cell

Nerve cell or neuron is called the processing unit of nervous system. Human brain contains 100 billion neurons which controls the electrical activity of the brain. Maintaining electrochemical balance it interchanges electrical signal and transfer messages to each other. In Fig. 2.3 a nerve cell is shown with the basic parts. Cell body is the heart of the cell, process the information receives by dendrite from neighboring neuron. Axon transfers the processed information to another neuron and performs all functions by creating a commanding network. Synapses are kind of junction permits a nerve cell to communicate with other neuron by transferring electrical or chemical signals.

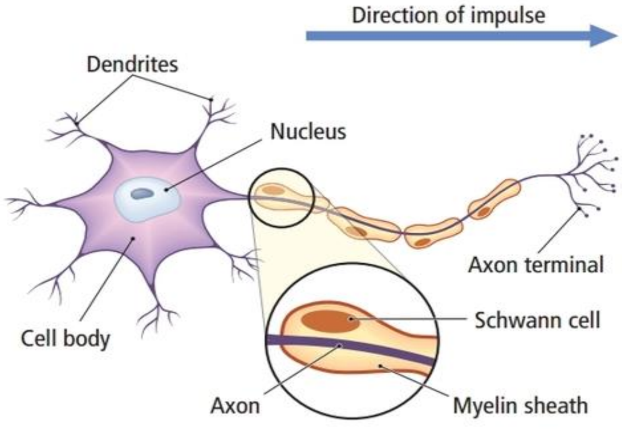

Fig. 2.3: Basic parts of a nerve cell [42].

2.3 Electroencephalography (EEG)

EEG is the recording of the change of electrical potentials that is generated by activation or inhibition of neurons in the cerebral cortex. The EEG is broadly used by researchers, scientist and psychologist to diagnosis and treats different brain disorders (autism, attention disorder, sleep disorder, dementia, epilepsy etc.) and automation using BCI technique etc.

Hans Berger, a neuropsychiatrist in 1929 first introduces EEG recording system to the world [43]. To define the graphical presentation of the electric currents produced in the brain, he used a German name 'elektrenkephalogramm' and suggested that brain's electrical activity varies with functional status (sleep, alert, and epilepsy) of the brain. The first recording of EEG signals made by Hans Berger is the first published Electroencephalogram of a human.

For measuring EEG signal electrode placement is very important. Two types (scalp or surface electrode and intracranial electrode) of electrodes are used primarily. Most of the scenario of using surface electrode (noninvasive) according to world recognized 10-20 technique. Fig.2.4 shows the outer circle was drawn at the level of the nasion and inion. The inner circle represents the temporal line of electrodes. This diagram provides a useful stamp for the indication of electrode placements in routine recording.The "10" and "20" is the actual distances between inter-electrodes are either 10% or 20% of the total font-back or right-left distance of the skull depending on the number of the electrodes.Electrodes are named based region of the lobe of the brain and counting starts from the left side of the cortex. This electrode placement procedure is known as montage and currently four different types (Bipolar montage, Referential montage, Average reference montage and Laplacian montage) of montage are used.

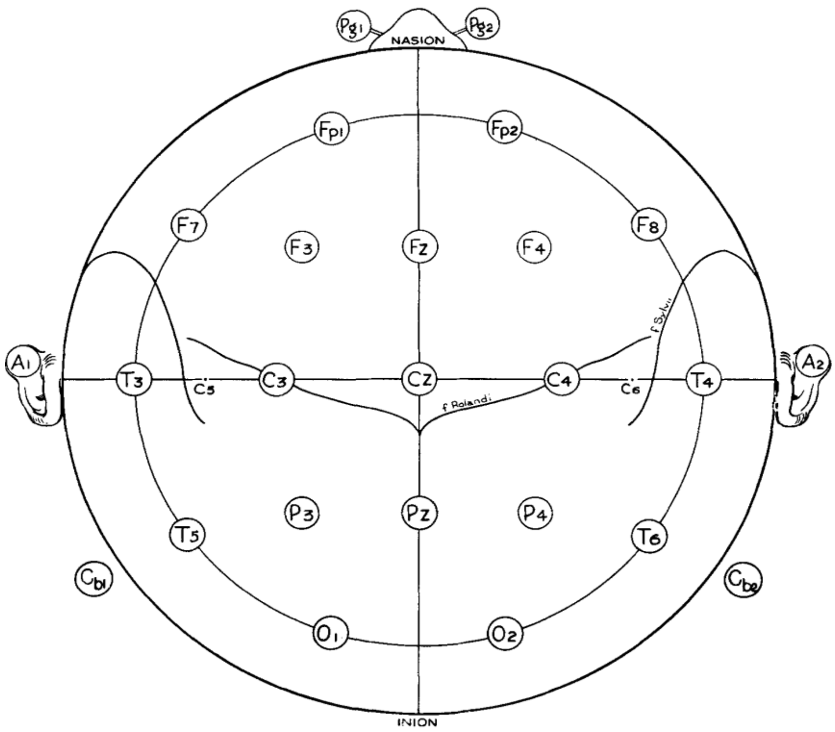

Fig. 2.4: A single plane projection of the head, showing all standard positions and the location of the Rolandic and Sylvian fissures [44].

2.4 EEG Signal Rhythms: EEG signals are characterize as random or unpredictable signal so its information varies with time and frequency domain. But frequency is very crucial for assessing EEG signal for research purpose Fig. 2.5 shows a segment of an EEG signal of a participant during resting state with different frequency bands. EEG frequency bands are describes as:

Delta (δ): This wave has frequency ranges between 0.5 to 3 Hz and between 100 and 200 μV in amplitude. The shape is known as the highest in amplitude and the slowest in waves and located at the frontal lobe of the brain. It is primarily responsible for deep sleep, unconsciousness, serious brain disorder and in the waking state [45].

Theta (θ): Theta contains the frequency ranges between 4 to 7 Hz and with amplitude of less than 30 μV. Theta waves can be recorded from the central and temporal lobe and responsible for drowsiness, resting with eyes close, emotional stress or frustration, deep meditation etc. [45]. Gradual theta power increases with transition from resting state to sleeping state [46].

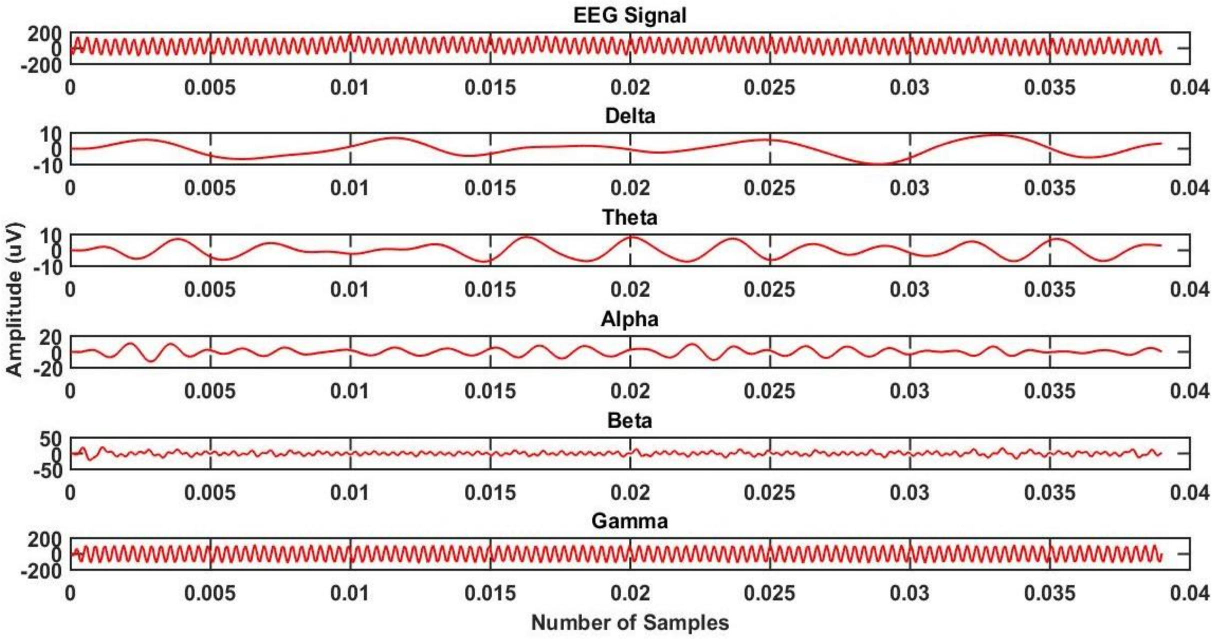

Fig. 2.5: EEG signal (F3 channel) of different bands of a subject.

Alpha (α): Frequency ranges from 8 to 13 Hz, with amplitude of 30-50 µV, which appears mainly in the occipital lobe but can be recorded from all over the cerebral cortex which is usually associated when the person is in a relax state or in stress and tension. When a person awake from the resting state and starts to think, blink then α waves disappear. This is called alpha block [45]. If a person is active with eyes open, α power remains low and in resting conditions with eyes closed, α power increases [46].

Beta (β): The frequency range is 14 Hz-30 Hz and has low amplitude (5-20µV). Beta band generated in the frontal area as well as in the parietal lobe also. When the brain is actively engaged with mental activities (concentrating, thinking, alert), it generates beta waves. Beta waves are responsible for strongly engaged behavior [45]. When a person goes to sleep stage 1 from wakefulness, beta activity decreases [47].

Gamma (γ): This electromagnetic wave has the frequency above 30 Hz with amplitude of between 5 to 10 µV. It is connected with several cognitive activities, perceptual task and motor functions [45].

2.5 Concepts of MI Movement and Neurological Diseases

Scientists and researchers are deeply engaged with the efficacious use of MI movement and complex mental disorders. MI movement is widely accepted for BCI application to command the machine. For disabled persons, engineers design a man machine interface (MMI) to communicate with the surroundings exploiting their neural activity. Physician and neuroscientist proposes it as an only via to energize the brain nerves that once damaged. Among innumerable neurological disorder some diseases are possible to monitor using EEG signal. A patient with epilepsy in a hospital and human alertness, while engaged with monotonous task but require attention is possible to monitor by analyzing the EEG signal.

2.5.1 MI Movement in Brain Computer Interfaces (BCIs) and Neurological Diseases

A brain computer interface (BCI) can be explained as a “communication and control channel that does not depend on the brain’s normal output channels of peripheral nerves and muscles” [48]. The information and commands transmitted through a BCI are encoded into the user’s brain activity. BCI technologies provide a direct interface between a brain and a computer [49]. The ultimate goal of a BCI is to offer humans an alternative communication channel that allows users to perform intended task.A structure of a BCI system with prime component is shown Fig. 2.6.

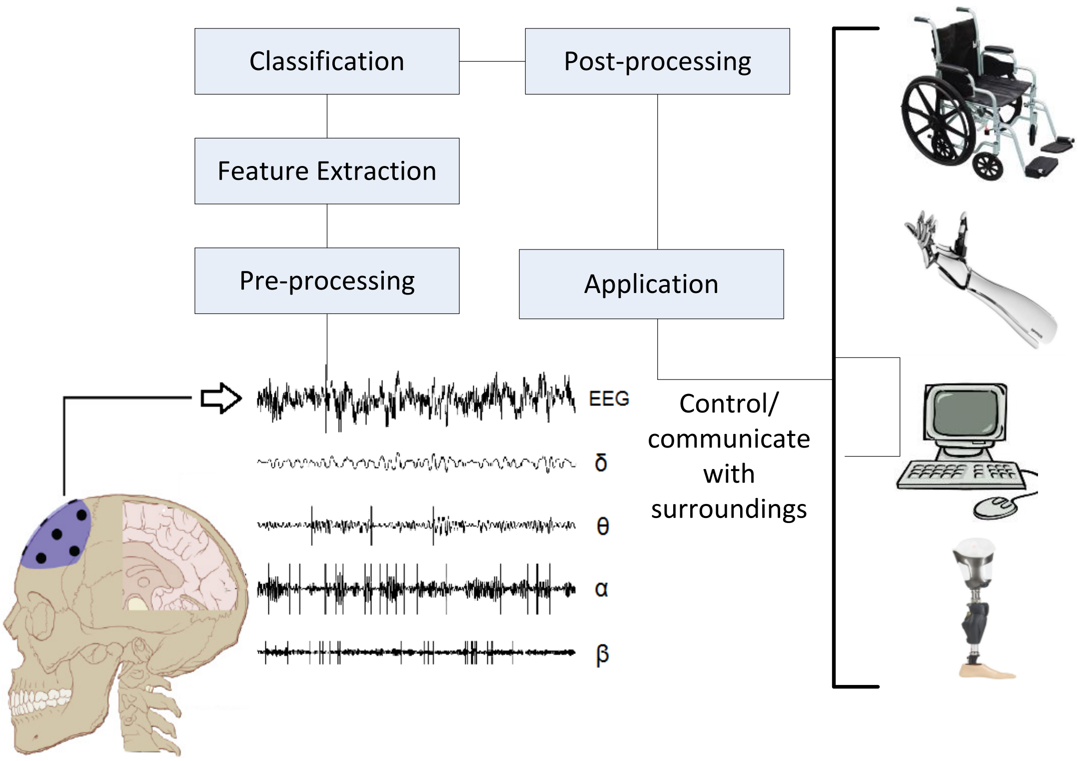

Fig. 2.6: A general architecture of a BCI system with prime component.

In the architecture of a BCI system some prime components are: the recording of brain activity, pre-processing, responsible feature collection, classification, post-processing and feedback [50]. Among these six steps first five steps can be accomplished by availing different algorithms but must be intended to get best results in the evaluation. Uncountable neurological diseases are present with their severe effect. Neuromuscular disease especially patients with five motor neuron diseases (MNDs) can be treated with practicing with MI movement to energize the affected neurons. These diseases affect the motor neurons, makes patient unable to move voluntary muscle and organ. Nerve fiber with MND disease affected a horse is shown in Fig. 2.7. Nowadays this method is the most promising technique to treat neuromuscular diseases.

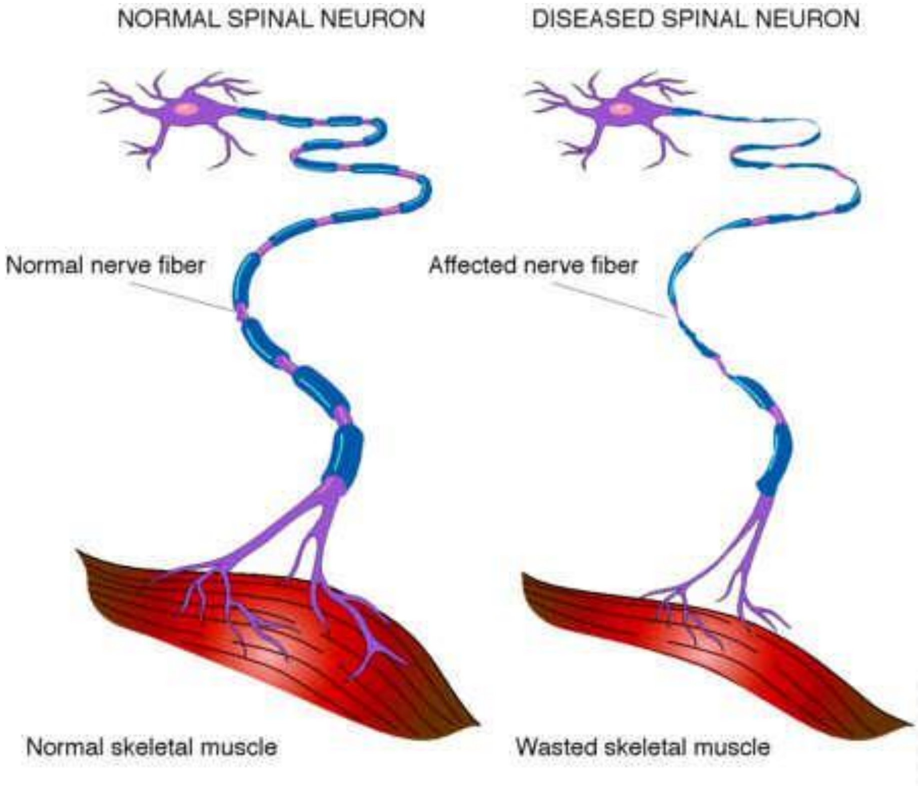

Fig 2.7: Comparative view of nerve cell with Equine Motor Neuron Disease (EMND) [51].

Amyotrophic lateral sclerosis (ALS) is the most common among the all motor neuron diseases. ALS is recognized by stiff muscles, muscle twitching and gradually loses power to move attached organ because of decreasing muscles size. That causes difficulty in speaking, swallowing and finally breathing [52-53]. Most of the cases (90% - 95%) reasons are unknown and around 5-10% of cases are inherited [54-55]. Differences betweenthe normal nerve cell, muscle and ALS affected nerve cell, muscleis easily noticeable from Fig. 2.8.

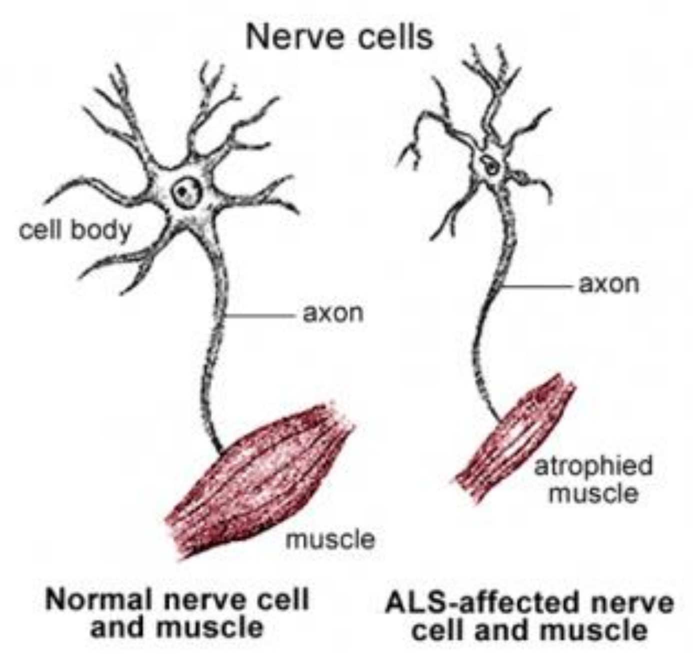

Fig. 2.8: Normal and ALS affected nerve cell and muscle [56].

2.5.2 Epilepsy and its Detection

Epilepsy is the most common neurological disease prevail in all countries. Epilepsy can be described as the periodic seizures where seizures are known as the rapid fluctuations in the recurrent electrical activity of the cerebral cortex. It makes the patient to lose conciousness, sudden change in behaviour, memory loss and sometimes it can triger other physical complications. During seizure period all neurons are activated together and makes a electrical storm. The reason in of most cases of epilepsy is unknown and some cases occur as the result of brain injury, stroke, brain tumors, infections of the brain, and birth defects, through a process known as epileptogenesis [57]. Seizures can be generated from a region of the cortex or from the all area of the brain. During the abnormal activity two class of EEG signals are noticed. One is ictal EEG period during an epileptic seizure and another is inter-ictal occur during between seizure. For making the diagnosis and treatment environment the dissertation propose a method to detect normal EEG period, ictal EEG period and inter-ictal EEG period based on the EEG signal of the patient with epilepsy. Ictal refers to a physiologic state or event such as a seizure, stroke, or headache. In electroencephalography (EEG), the recording during a seizure is said to be "ictal". Inter-ictal refers to the period between seizures, or convulsions that are characteristic of an epilepsy disorder. Fig. 2.9 shows the simultanious electrical stimulation of the neurons during epileptic seizure.

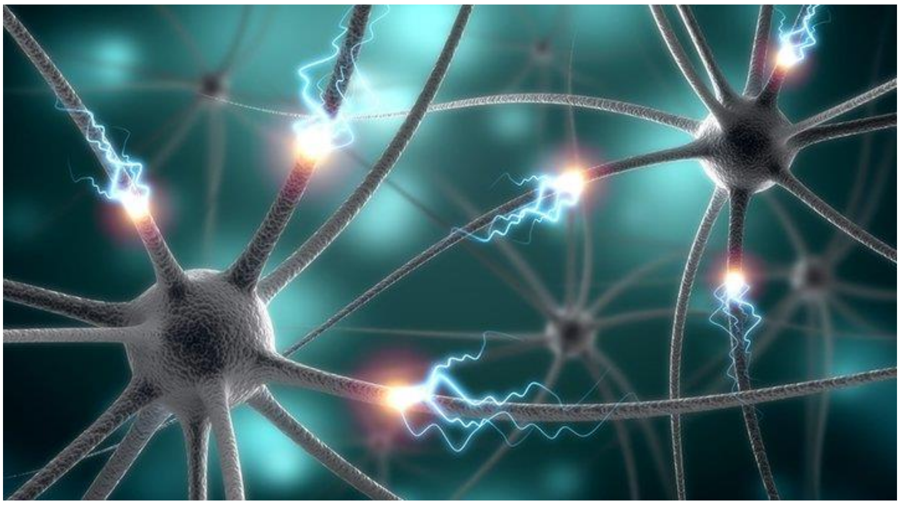

Fig. 2.9: Electrical storm of the patient during seizure in nuerons [58].

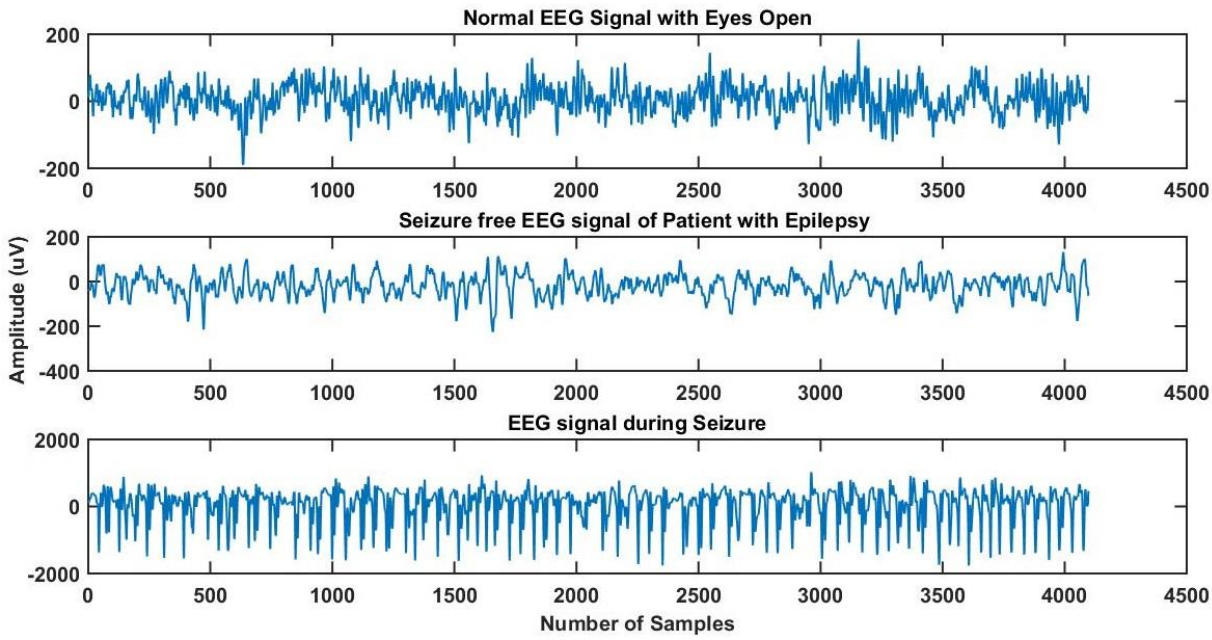

Fig. 2.10: Normal, seizure free and seizure EEG signal segment [59].

EEG presents important information for assessing the characteristics of epilepsy. In Fig. 2.10 visual shows the normal, inter-ictal and ictal EEG period.

2.5.3 Concept of Alertness Monitoring

Keeping constant attention to every specific task is crucial but because of mental fatigue it is not easy and after some hours we fail to concentrate. Analyzing the recorded EEG signal, student's alertness can be monitored to make the education system more effective. This principle can be adopted for the driver and pilots when driving for long time. A neurodegenerative disease is also responsible for losing attention known as Attention deficit hyperactivity disorder (ADHD). This mental disorder is noticed by problems paying attention, excessive activity, or difficulty controlling behavior and these symptoms begin by age six to twelve [60-61]. The World Health Organization (WHO) predicted that it affected nearly 39 million people as of 2013 [62]. About 30–50% of people diagnosed in childhood but continue to have symptoms into adulthood [63]. This dissertation aims to propose an improved method to monitor human alertness while executing a task to escape from error and accident.

2.6 Introduction of EEG Signal Classification and Algorithms

Classification task happens throughout our daily life by which we make decision to select or deselect depending on bunch of information. For this purpose, most of the cases, a reference point is selected for comparing with others to end the process.

EEG signal classification always attracts the scientist and researchers to make diagnosis and treatment delivery procedure easier in the branch of biomedical research. For monitoring the human behavior and neurological disease detection classification method is widely used. But significant research work is needed to ameliorate the classification procedure with promising accuracy rate. From large amount of EEG data it is necessary to select responsible information as a feature to gain better accuracy. In machine learning and pattern recognition algorithm, classification is the procedure for assigning a provided piece of input data into one of a given number of categories [64-65]. The piece of input data is termed as instance and the categories are called classes. The instance can be described as the feature vectors.

In this research work supervised classification method adopted between two main divisions (supervised classification and unsupervised classification). For MI movement classification (section 3) and epilepsy detection (section 4), a respective publicly available dataset is collected and DWT and ANN algorithms are used for feature extraction and classification, respectively. For the alertness monitoring (section 5), dataset is recorded in the Neuroimaging laboratory of the Department of Biomedical Engineering of Khulna University of Engineering & Technology (KUET). PCA and DWT are used for dimensionality reduction and feature extraction, respectively and ANN algorithm is used for classification.

2.6.1 Statistical Feature Extraction using DWT

Many research studies has been supported that DWT is an ideal tool for feature extraction from EEG signal and for biomedical signal processing [66-67]. It decomposes a signal into different sub band frequencies using continuous high pass and low pass filtering.

DWT decomposes each EEG segment into increasingly finer detail depending on the two sets of basic functions [68]. In equation (2.1), *A(t)* is the segment of a data which is decomposed based on the given function.

$$A(t) = \sum_k 2^{j_0/2} m_{j_0}(k)\varphi\left(2^{j_0 t-} k\right) + \sum_{j=j_0}^{\infty}\sum_k 2^{j/2} n_j(k)\psi\left(2^j t - k\right) \qquad (2.1)$$

Here *φ(t)* and *ψ(t)* are the basic scaling and mother wavelet function respectively. Scaling function and wavelet function of Daubechies-4 (db4) wavelet is shown in Fig. 2.11 which is used among different wavelets.

$$m_j(k) = \int_{-\infty}^{\infty} 2^{j/2} x(t)\varphi\left(2^j t - k\right)dt \qquad (2.2)$$

$$n_j(k) = \int_{-\infty}^{\infty} 2^{j/2} x(t)\psi\left(2^j t - k\right)dt \qquad (2.3)$$

Here $m_j(k)$ and $n_j(k)$ are the approximation and detail coefficients of wavelet, respectively.

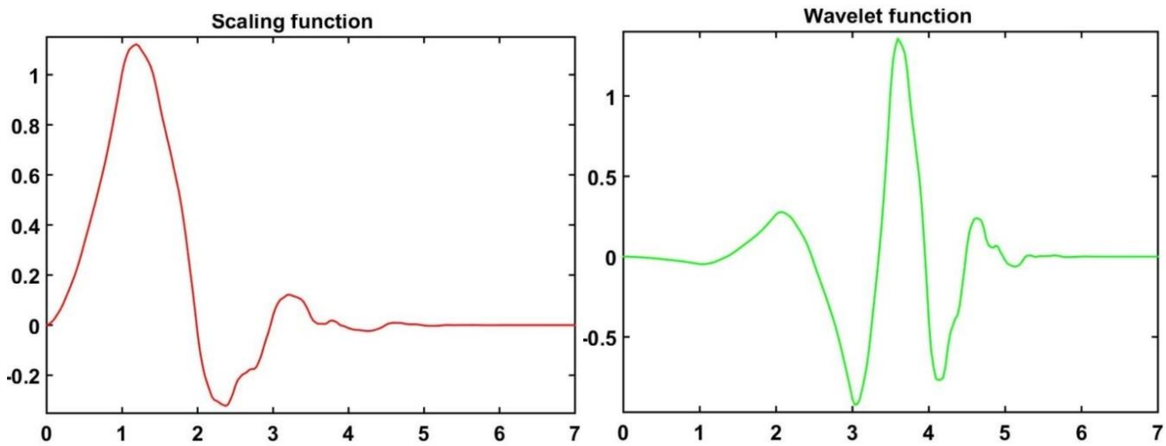

Fig. 2.11: Scaling and wavelet function of db wavelet.

The first part of the equation (2.1) adds summation is an approximation of *A(t)* and second term sums more detail component [26]. The down sampled signals through first filters are called first level approximation, A1 and detail coefficients, D1 of the original signal. Approximations are the high-scale, low-frequency components of the signal and details are the low-scale, high-frequency components. The two filters are related to each other and they are defined as a quadrature mirror filter. Approximation and detail coefficients of next level are obtained by using the approximation coefficient of the previous level. The number of decomposition levels is determined depending on the dominant frequency components of the signals [69]. After decomposition significant features are collected to make feature vector for further processing to classify imagery movement. Using MATLAB wavelet toolbox 10 features (mean, median, maximum, minimum, standard deviation, median absolute deviation, mean absolute deviation, l1 norm, l2 norm, max norm) are extracted and noted. Some of the features are described as:

Mean Absolute Deviation (MAD)

MAD of a data is defined as the average value of absolute distances from the mean of the data. It can be referred to a general form about some specified central position. Mean deviation and average absolute deviation terms are also represent the mean absolute deviation.

The formula for mean absolute deviation for an ungrouped data is given below

$$MAD = \frac{\sum_{i=1}^{n} \left| x_i - \bar{x} \right|}{n} \tag{2.4}$$

Where

x_i= Given values

n = Total number of observations

For Grouped Data the formula for mean absolute deviation is given below

$$MAD = \frac{\sum_{i=1}^{n} \left| x_i - \bar{x} \right| f_i}{n} \tag{2.5}$$

Where

x_i= Given values

n = Total number of observations

f_i =Frequencies corresponding to the given values or observations

Median Absolute Deviation (MAD)

MAD is a measure of the variability of a univariate sample. For a univariate data set a_1, a_2....... a_n, the MAD is defined as:

$$MAD = median(\left| a_i - median(a) \right|) \tag{2.6}$$

L1-Norm

$L1$-norm also known as mean norm or least absolute deviations (LAD) and defined as the sum of the absolute values of the dataset.

$$L1-norm=\sum_{i=1}^{n}|v_i| \tag{2.7}$$

L2-Norm

$L2$-norm also represented as mean-square norm or least-squares norm and illustrates as the square root of the sum of the absolute values of the dataset.

$$L2-norm=\sqrt{\sum_{i=1}^{n}|v_i|^2} \tag{2.8}$$

Max norm

Max norm also represented as infinity norm or uniform norm and describes as the maximum of the absolute values of the dataset.

$$L_\infty-norm=\max|v_i| \tag{2.9}$$

2.6.2 Classification using ANN

ANN is a prominent classifier for EEG signal classification in supervised learning technique. The knowledge lies in the interconnection weights between neurons to neurons used in the design. In Fig. 2.12, an ANN is designed with 10 input as 10 features are used and 3 output as our 3 class. In the hidden layer different neuron number are employed but better results within 10-14 neurons in our work. So in the hidden layer 10 neurons are used. Feature vectors and targets are feed to the ANN with feed forward network using pattern recognition algorithm of MATLAB NN toolbox. All trials are then randomly distributed for training (70%), testing (15%), and validation (15%).

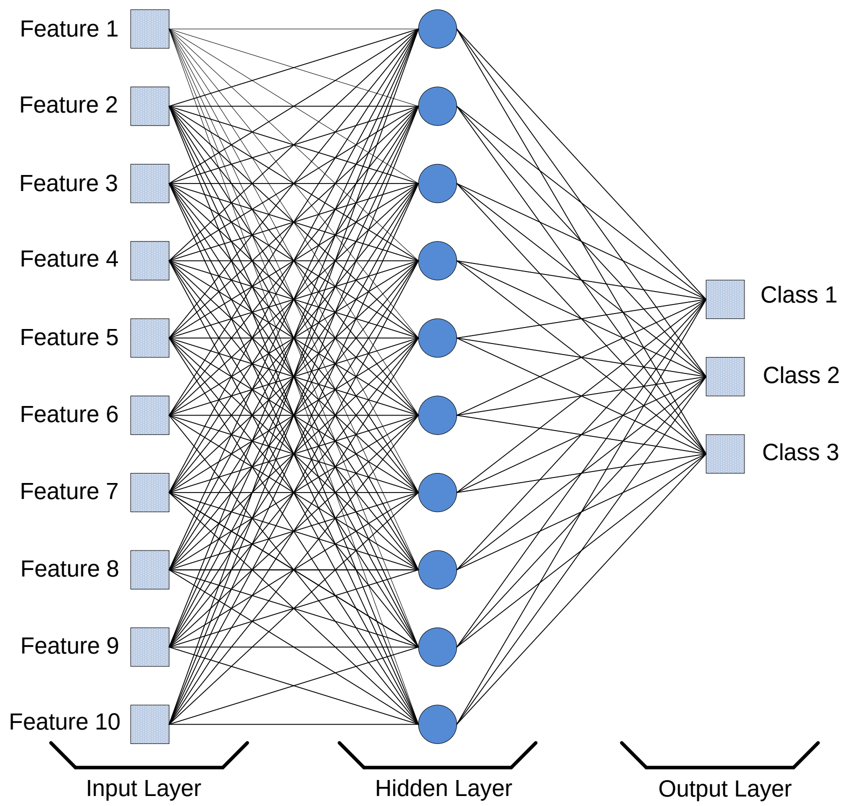

Fig. 2.12: ANN for classification with 10 neurons in hidden layer.

Levenberg Marquardt Algorithm (LMA) is a fast and efficient algorithm for EEG signal classification which uses the standard numerical optimization technique. It has both property of local convergence of the Gaussian-Newton method and the global of the Gradient descent method. LMA increases the training speed, decreases the training steps as well as improves classification accuracy, though it's better to use trial and error method for better accuracy.

CHAPTER III

Motor Imagery Movement Classification using Statistical Features of EEG

This chapter describes the 2 class (RH/LH) and 3 class (RH/LH/FT) Motor Imagery **(**MI) hands movement classification which is the first objective of this dissertation.

3.1 Introduction

MI is an efficient procedure for the patients who suffer from Motor neuron diseases (MNDs). MNDs are neurological disorders that affect mostly motor neurons; that command over the voluntary muscles of the body. Patients with severe neuromuscular disorders and paralyzed from higher level spinal cord injury or in a late stage of amyotrophic lateral sclerosis (ALS) are not able to produce any voluntary muscle movement [5]. Their sensory and cognitive functions become only way to communicative with surroundings. Such patients can be motivated, trained for MI movement to execute real movement by incorporating with brain computer interface (BCI) utilizing neural activity to do like cursor control, selection of letters or words, control of prosthesis, navigation of wheelchair etc. MI is also consulted for the paralyzed patients or if the motor neurons are dead because of disease or accident.

Imagery movement of two hands can be distinguished according to the change of the electrical (neural) activity. MI is the process by which humans experience sensations with or without external stimuli by using imagination. Motor imagery movements can be same as motor act without any overt motor output. Sensory stimulation, motor behavior and mental imagery change the functional connectivity within the cortex and results in amplitude suppression [event related desynchronization (ERD)] in amplitude enhancement [event related synchronization (ERS)]. Motor imagery movements dramatically change the neural activity in the primary sensorimotor areas in a very similar way as executed movements [1].

Practical implementation of mind machine interface (MMI), direct neural interface (DNI), or brain machine interface (BMI) system requires an efficient brain signal processing method to extract responsible features and to perform classifications with better accuracy. Several methods have been reported to extract features in different domains where wavelet transformation (WT) based features extraction method is highly effective, because it deals better with the non-stationary behavior of EEG signals than other methods. Wavelet-based features, including wavelet coefficients [69], wavelet entropy and wavelet statistical features (mean, median, and standard deviations) have been reported for normal EEG analysis, in clinical applications as well as in research areas also.

In literature, two new features, multifractalcumulants and predictive complexity measure in addition with band power feature are introduced [2]. Linear Discriminant Analysis (LDA) classifier is used to classify and compares classification accuracy with each other (features). Stockwell Transform (ST) based analysis of EEG dynamics introduced [5] during different mental tasks. KNN, LDA and SVM classifiers were employed to test the strength of the proposed features. Accuracy ranging between 84.72% and 98.95% was achieved for multi-class problems (five mental tasks). Wavelet pack entropy feature and SVM classifier have used [6] for discriminating a baseline task from a cognitive task with 87.5–93 % accuracy. This study has used a database where seven subjects performed five tasks—baseline (open eyes) task, multiplication, visual counting, mental letter composing and geometric object rotation task. In [23] authors combined time and frequency features approach for the classification of healthy and epileptic EEG signals. Time domain features are extracted using the cross correlation (CC) method. Frequency domain feature are extracted by calculating PSD. The combination of the cross correlation and power spectral density for EEG classification is very promising. A multilayer perceptron neural network (MLPNN) based classification model is [69] proposed using EEG signal. DWT and MLPNN outcomes classification accuracy for five different experiments are above 95% for individuals. Authors in [70] proposed a scheme to calculate relative wavelet energy in terms of detailed coefficients and approximation coefficients. Extracted features (relative wavelet energy) are provided to the SVM, multi-layer perceptron (MLP), K-nearest neighbor (K-NN) and Naïve Bayes classifiers with classification accuracy 98.75%, 98.21%, 98.21%, 83.57% respectively.

Many wavelet based research work accomplished [70] using different features except wavelet statistical features. This chapter of the dissertation proposes that wavelet statistical features can be used to classify EEG signal in addition with better classification accuracy. This dissertation also investigates the performance of the Levenberg-Marquardt algorithm to classify right and left hands imagery movement using Daubechies 4 wavelet.

In the research field of multiclass classification, among many accomplished research studies, authors in [3] classify left hand, right hand, feet and tongue, a multi-class imagery movement based on ERD and sample entropy using SVM classifier. Authors in [9] used CSP for feature extraction and FDA for dimension reduction of the feature vectors. Finally SVM classifies the four class motor imagery movement individually from the rest position. Researchers in [19] introduced a method to distinguish between simple and compound limb motor imagery with help of CSP and SVM. They adopted ERSP, PSE and spatial distribution coefficient method to prove the comparison. Researchers in [20] introduced a new technique to collect MRICs automatically and differentiate three class LH, RH and foot imagery data. In [21], authors used 22 electrodes over the scalp and multi-class discrimination accomplished using ICA and CSP algorithm. In [22] authors proposed Biomimetic Pattern Recognition (BPR) for 2 class motor imagery classification and compares performance between SVM and LDA. Authors [71] developed a method to decompose the EEG signal using short time Fourier transform with CSP and SVM for better classification accuracy. Results verified that single channel EEG signals taken from both sensorimotor and forehead areas can classify four class motor imagery movement. In [72] researchers used SVM, LDA and KNN classifiers to multiclass motor imagery using two different datasets. In [73] authors proposed FBCSP algorithm to separate multiclass motor imagery and evaluates performance in terms of kappa value. In [74], authors proposed wavelet-CSP algorithm with ICA to improve the classification rate of SVM in terms of kappa value.

3.2 Materials and Proposed Methodology

3.2.1 EEG Data Collection and Dataset Description

For two class classification the dataset is collected from internet [2] which is taken at INRIA Renne-Bretagne Atlantique using the OpenVIBE, an open-source and free software [2]. This data set contains EEG signals of each subject who performed left hand and right hand motor imagery. Five hundred sixty trials of motor imagery (280 trials per class) were recorded over a 2 week period.

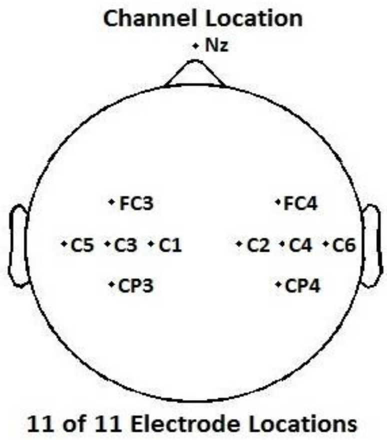

Fig. 3.1 Electrode placement system of the subject [2].

During data acquisition same experimental protocol is used as Graz BCI protocol [1-2] for the discrimination of two mental states. The experimental task was to imagine either right-hand or left-hand movement. Each trial lasts for 8 seconds including resting, imagery movements of either left or right hand and for feedback. EEG data was sampled at 512 Hz and recorded from frontal, central and central frontal lobe using the following electrodes: C3, C4, FC3, FC4, C5, C1, C2, C6, CP3, and CP4, with a nose reference electrode [2]. Such electrodes enables to apply a discrete Laplacian spatial filter [75] over C3 and C4 obtains better signals, as recommended in [2]. All electrodes placement are depicted in Fig. 3.1, where, Nz is the reference electrode. Six electrodes from ear to ear band are very crucial for MI.

For three class classification, a publicly available dataset is exploited [76]. Many subjects perform two class and three class motor imagery functions during data acquisition. In our works three class data for three subjects (A, B, C) are used. Fourteen electrodes have been placed over the subject's sensorimotor area for data acquisition as shown in Fig. 1. All three subjects imagine left hand (LH), right hand (RH) and both feet (FT) movement on different days for several sessions. Subjects are requested to sit in front of a computer desk and to imagine as the cue indicated. Motor imagery task starts after the trigger and continuous to 3-10 seconds and ends each trial followed by 2 seconds of short break.

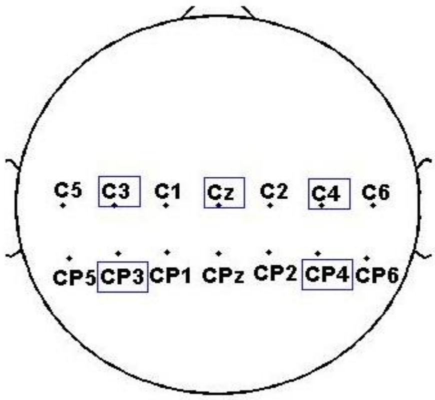

Fig. 3.2: Electrode placement (14-channel) for data acquisition [76].

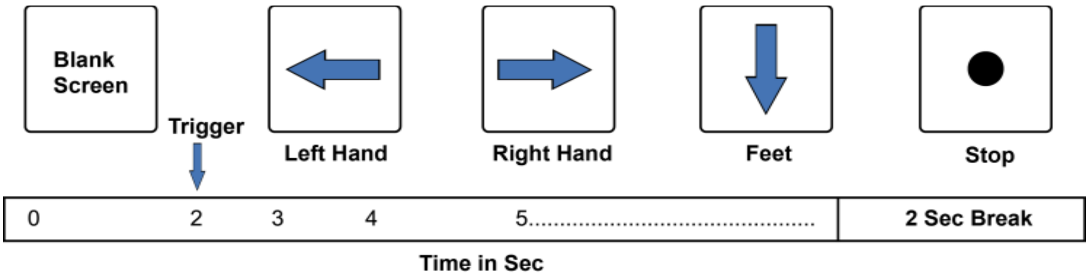

Fig. 3.3: Block diagram of the experimental paradigm for data acquisition [76].

The whole experimental procedure with corresponding time is shown in Fig. 3.3 above as given in [76].

3.2.2 Channel Selection and Experimental Flowchart

For two class classification eleven channels have been used including reference electrode for data collection but our interested channels are above the sensorimotor cortex region. The motor imagery EEG signal is predominant in sensorimotor cortex, corresponding to electrode positions C3 and C4 [2]. In our dataset each electrode collects data of both L/R hands data. Based on the universal truth that left hemisphere controls our right side of the body and right hemisphere powers over left part of the body, we selected C3 channel data for right hand imagery movement and C4 channel data for left hand imagery movement.

For three class classification, EEG signals from the subjects are recorded using two devices of g. tec and Neuroscan devices. Among the 14 electrodes 5 electrodes data are recorded for 3 class motor imagery movement. Those 5 electrodes are indicated in Fig. 3.2 in square box. But further for our research purpose most significant channels, channels C3 and C4 are taken from both hemispheres.

The complete experimental working flow is shown in Fig. 3.4. First and foremost is to record the motor imagery data from subjects and all subjects are required to perform imagery task well for better results. Recorded signal then segmented according trials and decomposed using DWT to collect statistical characteristics for each signal. These feature vectors afterwards provided to ANN to evaluate the classification accuracy of the proposed method.

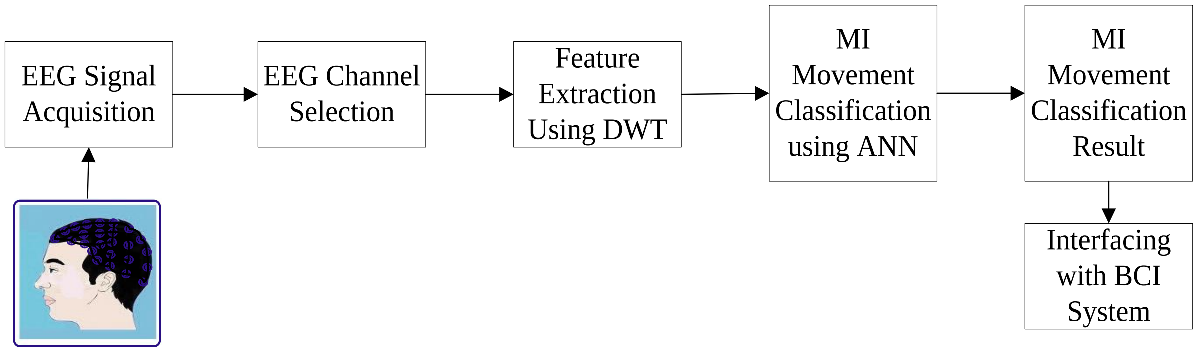

Fig. 3.4 Block diagram of the classification of motor imagery (MI) movement.

3.3 Results and Discussions

3.3.1 Feature Extraction using DWT

Decomposition of LH, RH and FT segmented EEG signal up to level 5 using Daubechies 4 wavelet (db4) is shown in Fig. 3.5, 3.6 and 3.7 respectively to extract the statistical features. In both figures signal S decomposes into 6 sub-signals according to their frequencies and amplitudes. Sum of all the detail coefficients and approximation coefficient will be the equivalent of the S signal.

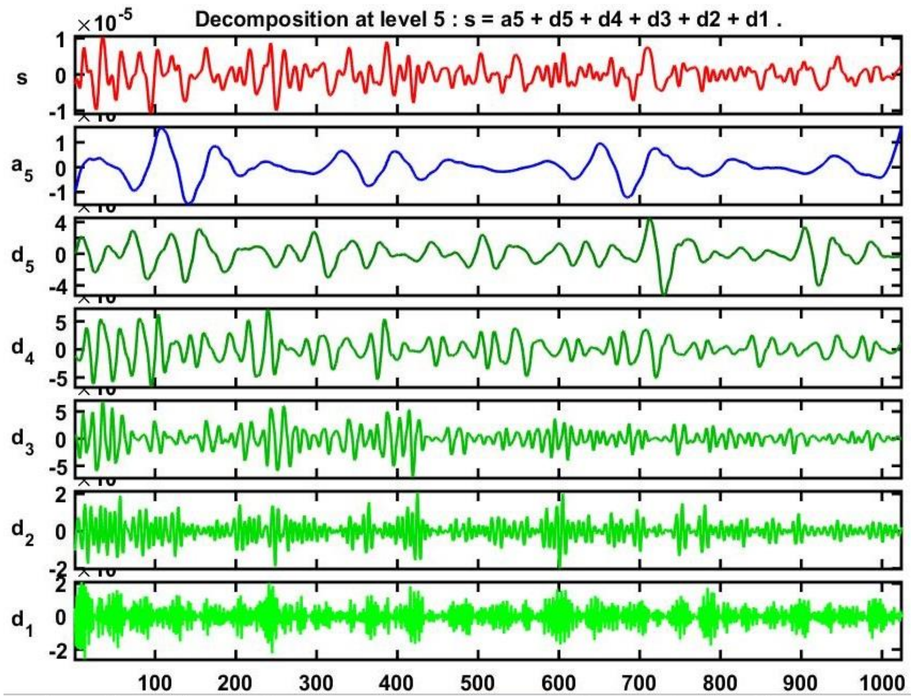

Fig. 3.5: Decomposition of LH imagery signal of subject A.

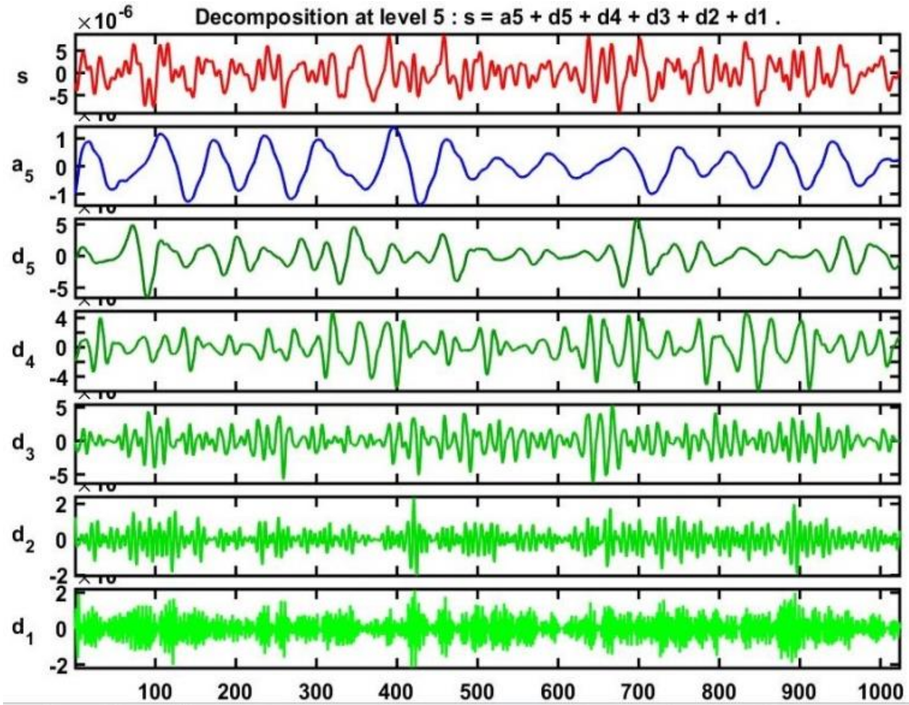

Fig. 3.6: Decomposition of RH imagery signal of subject A.

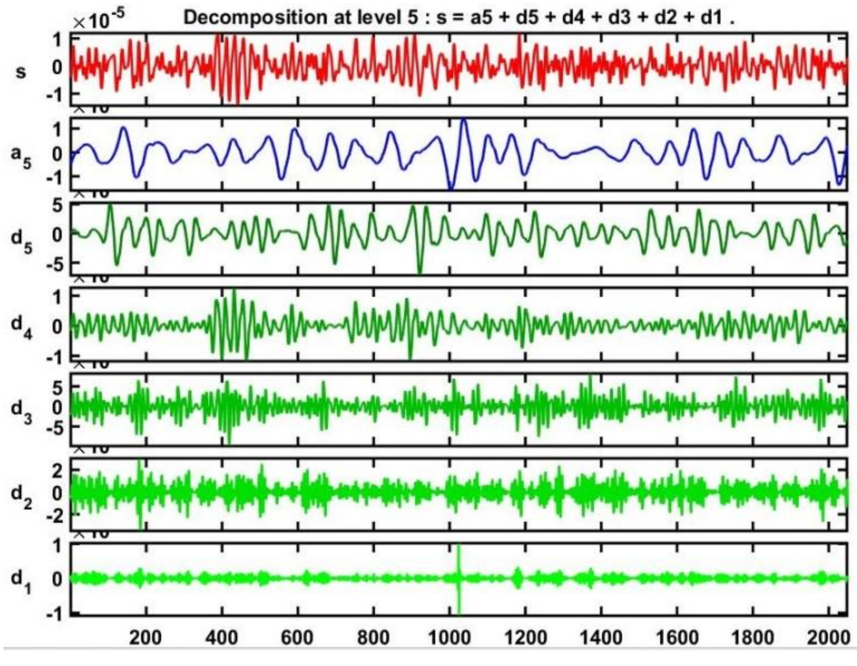

Fig. 3.7: Decomposition of FT imagery signal of subject A.

Features for each segment data are mean, median, maximum, minimum, standard deviation, median absolute deviation, mean absolute deviation, L1 norm, L2 norm, max norm. For a segmented EEG data of left and right hand imagery movement taken from right hemisphere and left hemisphere are given in Table 3.1.

Table 3.1: Extracted Features for Imagery LH/RH Movements

Features	Left Hand (µV)	Right Hand (µV)
Mean	9263	4706
Median	9263	4706
Maximum	9275	4714
Minimum	9249	4697
Standard Dev.	4.514	2.865
Median Abs. Dev.	2.929	2.065
Mean Abs. Dev.	3.574	2.293
L1 Norm	7.123	3.619
L2 Norm	2.569	1.305

3.3.2 LH and RH Classification

Features collected from left and right hemisphere definitely assure differences for the imagery movement of the two hands. Now for the classification between two imagery hands movement (two classes), among 500 both hands trials, 450 trials (both hands) randomly has been used for classification. For training purposes 314 trials for training, 68 validation trials for and 68 trials for testing (both left and right) randomly used. Levenberg-Marquardt back-propagation training algorithm used in this network because of its training consumes less time. After classification confusion matrix of LMA based ANN is shown in Table 3.2. Among 100% (450) trials, for LH imagery 50% (225) trial, 42.7 % (192) trials are correctly classified. Same happens for RH trials where 49.3 % (222) trials are correctly classified from 225 trials (50%) of the total trials.

Table 3.2: Confusion Matrix of ANN

Confusion Matrix		
Output/Desired	**Left Hand Imagery Movement**	**Right Hand Imagery Movement**
Left Hand Imagery Movement	192 42.7%	3 0.7%
Right Hand Imagery Movement	33 7.3%	222 49.3%

The performance of the classifiers was determined by the calculation of sensitivity, specificity and total classification accuracy are defined below and results shown in Table 3.2.

$$\text{Sensitivity (True positive rate)} = \frac{TP}{TP + FN} \tag{3.1}$$

$$\text{Specificity (False positive rate)} = \frac{TN}{TN + FP} \tag{3.2}$$

Total classification accuracy (Percentage of all samples correctly classified) =

$$\frac{TN + TP}{TN + FN + TP + FP} \tag{3.3}$$

Where,

Total number of correctly classified positive patterns = TP,

Total number of actual positive patterns = $TP+FN$

Total number of correctly classified negative patterns = TN

Total number of actual negative patterns = $TN + FP$

Total number of correctly classified patterns = $TN + TP$

Total number of applied patterns = $TN + FN + TP + FP$.

Table 3.3: Calculation of Statistical Parameter

Statistical Parameters		
Sensitivity (%)	**Specificity (%)**	**Accuracy (%)**
87.06	98.46	92.00

Performance curve represents the relationship among validation performance, train and test performance of a neural network with respect to the best. Validation curve measures network generalization, and to halt training when generalization stops improving.

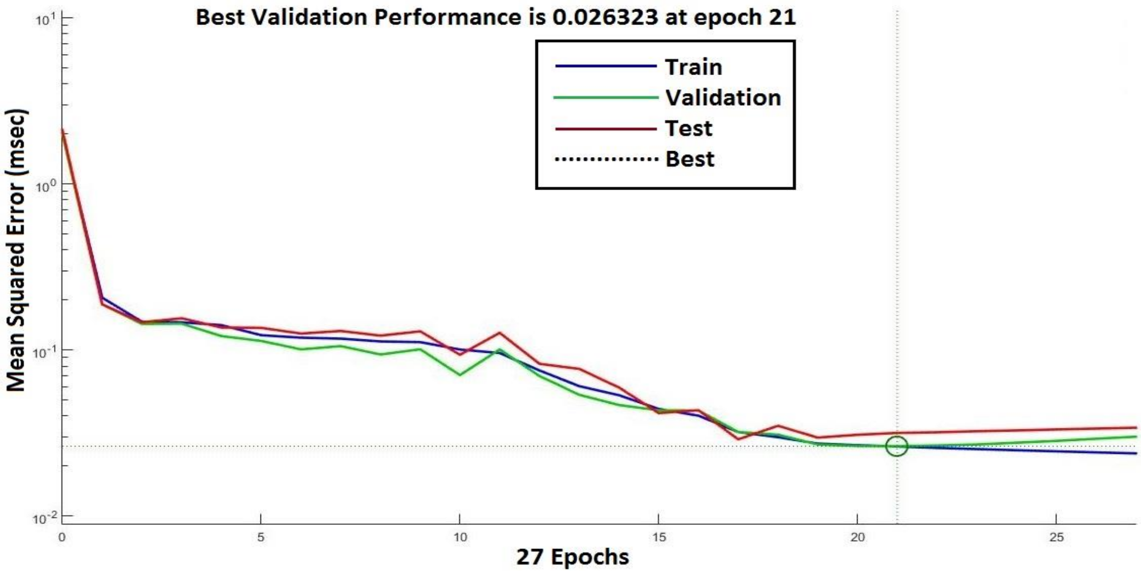

Fig. 3.8: Relation between train, validation and test curve.

The validation and test curves are very similar. If the test curve had increased significantly before the validation curve increases, then it is possible that some over fitting might have happened. Mean Squared Error is the average squared difference between outputs and targets used in the network from the feature vectors. Lower values are better. Zero means no error. In the proposed method, validation performance is 0.026323 at epoch 27 as shown in Fig. 3.8.

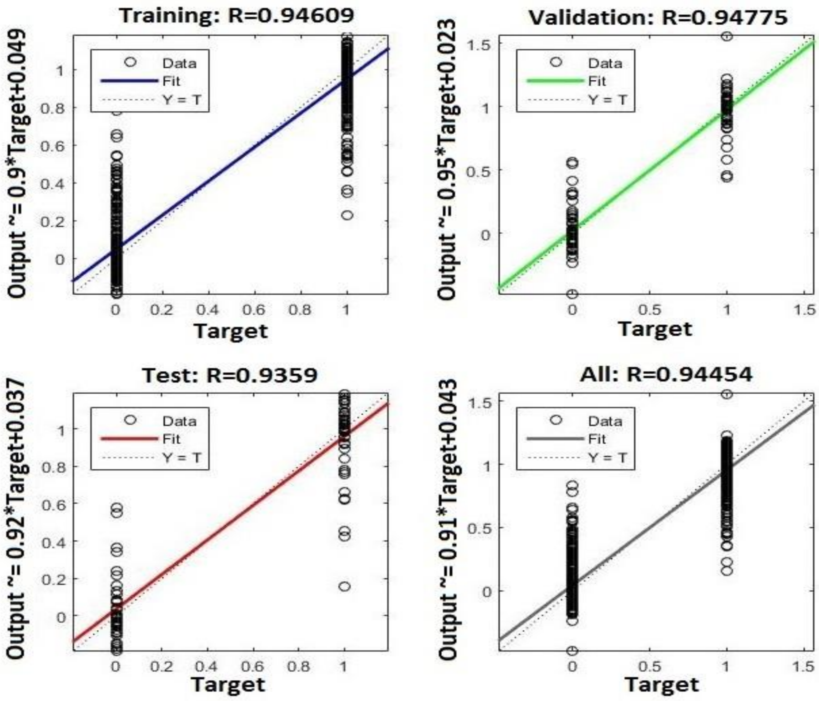

Fig. 3.9: Regression curve of train, validation, test with 'R' value.

The four plots in Fig. 3.9 represent the regression, R values of training, validation, testing for all data and this pictorial view depicts the accuracy of the features vectors for train, test and validation data. The dashed line represents the perfect result – outputs = targets. The solid line represents the best fit linear regression line between outputs vectors and targets vectors. The R value indicates the relationship of the outputs and targets. If R = 1, this represents that there is an exact linear relationship between outputs and targets feature vectors. If R is close to zero or zero, then there is no linear relationship between outputs and targets. Here in the portrait of training, test and all data indicates a good fit. The validation results also show R values greater than 0.9. If the network performance on the validation vectors fails to improve or remains same validation vectors are used to stop training early. Training stops when the maximum number of epochs (repetitions) is reached or the maximum amount of time is exceeded or even if the performance is minimized to the goal. Test vectors check that the network is generalizing well but do not have any influence on training.

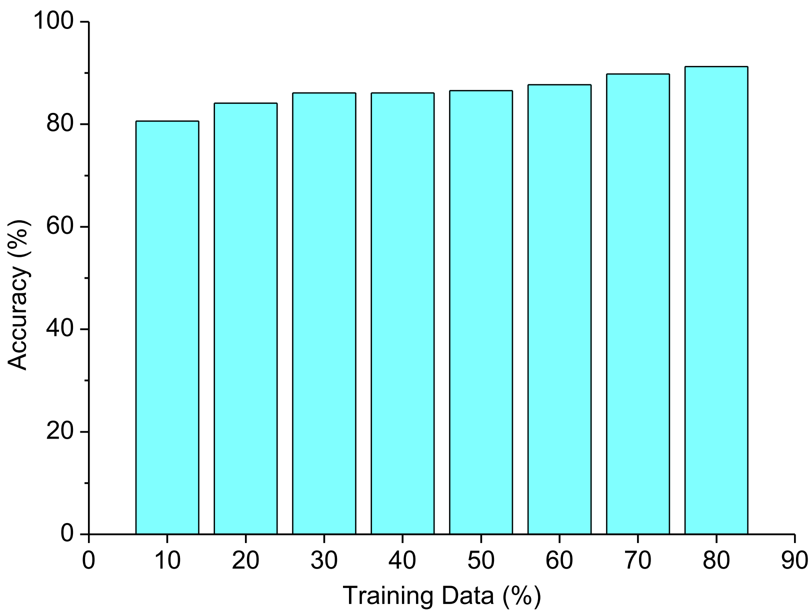

Fig. 3.10: Classification accuracy distribution with training data variation.

By remaining validation data 10% constant, training and testing data are interchanged to 10-80%. Increasing training data 10% gradually from 10% to 80% training data Fig. 3.10 depicted. While 10% training data and 80 % testing data are used then 80% accuracy assured and to the end while 80% training data and 10 % testing data are used then classification accuracy reaches to around 90%. From the graph it is easily noticeable that the percentage of classification accuracy between right and left hands is increasing as percentage of training data increases.

Difference between the electrical activities in comparison with one hemisphere to another is expected because right half of our cerebrum controls the left side of the body and vice-versa. This assumption makes this study feasible. We make a comparison list of some previous researches with our proposed method by comparing setup, methodology, and classification accuracy as shown in Table 3.4. By selecting responsible channels and features, the overall classification accuracy can be increased which is the main contribution of this part of the dissertation. That’s why features and channels used in various previous research works are also included. From many methods when using ANN methods, this proposed method with db4 and LMA promises satisfactory classification accuracy. This study proves that statistical parameters (features) can be used to differentiate two imagery hands movement with accuracy for BCI and other application.

Table 3.4: Comparison of Methods and Classification Accuracy with Proposed Method

Researchers	Setup and Database	Features and Channels	Algorithms	Classification Accuracy
M. Hariharan [5] et al.	Keirn and Aunon database Seven subjects (five mental tasks).	S-transform based MSR features	KNN, LDA and SVM	Between 84.72% and 98.95%
Solhjoo [7] et al.	Two EEG dataset	Mahalanobis distance and PSD	Gaussian classifiers, LDA classifiers using method	63.1%, 65.4% and 65.5% respectively
L. Zhang [8] et al.	Keirn and Aunon database Four subjects with five mental tasks	Asymmetry Ratio C3, P3, O1 and C4, P4, O2	High frequency power and Fischer's discriminant classifier	72.4–76.4 %
M. H. Alomari [17] et al.	The EEG dataset (Physio Net). http://www.physionet.org/pn4/eegmmidb/.	Mean, power, energy and ERD, ERS and movement-related cortical potentials (MRCP). C3, Cz and C4	NN and SVM	89.8% and 97.1% respectively
S. M. Zhou [24] et al.	Graz BCI data set	12 temporal and frequency features. C3, Cz and C4	ANN and LDA	90.00% and 89.29% respectively
Y. Chen [62 77] et al.	Graz data set B, BCI competition 2008	---	LMA with Multilayer feed forward neural network	78.2% and 87.1% respectively
J. Z. Xue [78] et al.	Six-channel EEG data of four subjects, performing three different mental tasks	---	Wavelet packet transform and RBF classifier	85.3 %
Proposed Method	OpenViBE / INRIA data, recorded by OpenViBE software.	10 Wavelet statistical features. C3, C4	Db4 wavelet and LMA based NN	92%

3.3.3 LH, RH and FT Classification

In 3 class classification, depending on the input feature vectors and on the number of class of the classifier ANN is designed. So 5 input and 3 output for the corresponding input and output class respectively is used in the NN. While using 2 classes, 2 target vectors are used for the corresponding 2 class classification. 5-45 neurons in the hidden layer are tried, but better results using 10-15 neurons. Trials number varies with respect to the subject; subject A completes 270 trials, 90 trials for each class. Subject B performs 174 trials, 58 for each class and subject C imagines 180 trials, 60 trials for each class.Feature vectors are given to NN subject wise and 70% of them are counted for training, 15% for testing and 15% are for validation. Resulting, such as for subject A; 188, 41 and 41 trials are for 3 class and 126, 27, 27 trials for 2 class are randomly distributed for training, testing and validation respectively. Confusion matrixes are listed in Table 3.5 and Table 3.6, and classification accuracies are shown in Table 3.7.

Table 3.5: Confusion Matrix for LH and RH Classification

Subject A		**Subject B**		**Subject C**	
LH	**RH**	**LH**	**RH**	**LH**	**RH**
61 33.9%	20 11.1%	39 33.6%	21 18.1%	60 50.0%	0 0.0%
29 16.1%	70 38.9%	19 16.4%	37 31.9%	0 0.0%	60 50.0%

Table 3.6: Confusion Matrix for LH, RH and FT Classification

Subject A			**Subject B**			**Subject C**		
LH	**RH**	**FT**	**LH**	**RH**	**FT**	**LH**	**RH**	**FT**
57 21.1%	18 6.7%	0 0.0%	37 21.3%	21 12.1%	21 12.1%	60 33.3%	0 0.0%	2 1.1%
32 11.9%	55 20.4%	2 0.7%	15 8.6%	29 16.7%	2 1.1%	0 0.0%	57 31.7%	2 1.1%
1 0.4%	17 6.3%	88 32.6%	6 3.4%	8 4.6%	35 20.1%	0 0.0%	3 1.7%	56 31.1%

Table 3.7: LH-RH and LH-RH-FT Classification Results

Subject	**LH-RH Classification**		**LH-RH-FT Classification**	
	Accurately classified	**Misclassified**	**Accurately classified**	**Misclassified**
A	72.8%	27.2%	74.1%	25.9%
B	65.5%	34.5%	58.0%	42.0%
C	100.0%	0.0%	96.1%	3.9%

Table 3.5 and 3.6 represent the confusion matrix for two and three classes, respectively for all subjects. In two class classification, trials are divided as class wise to 50% and for three class to 33.3%. So in Table 3.5for subject A, 33.9% (61) trials are correctly classified from 50% (90) trials for LH and 38.9% (70) trials are accurately discriminate from 50% (90) trials for

RH. Best results come for subject C with 50% (60) trials out of 50% (60). In Table 3.6 for subject A, from 33.3% (90) trials, correctly separated 21.1% (57), 20.4% (55) and 32.6% (88) trials for LH, RH and FT, respectively.

Regression plot illustrates the connection between outputsand targets. In Fig. 3.11, Fig. 3.12 and Fig. 3.13, regression plot for individual subjects are depicted with their corresponding R values. R value indicates that how closely related outputs and targets. If the value is 1 proves they are closely related or if 0 then randomly related. In the figure inside the square box, the dash line represents the best fit position and solid line as in Fig. 3.11, the blow line shows the original fits of the data. Circles portray the distribution of the data. Subject C indicates the best regression value for all R=0.94, nearly 1 and subject B shows regression value for all R=0.45, close to 0.50. So subject C's data best fits and finally results maximum classification accuracy. Here regression plots are drawn for LF, RH and FT (3 class data) feature vectors for subject A, B and C.

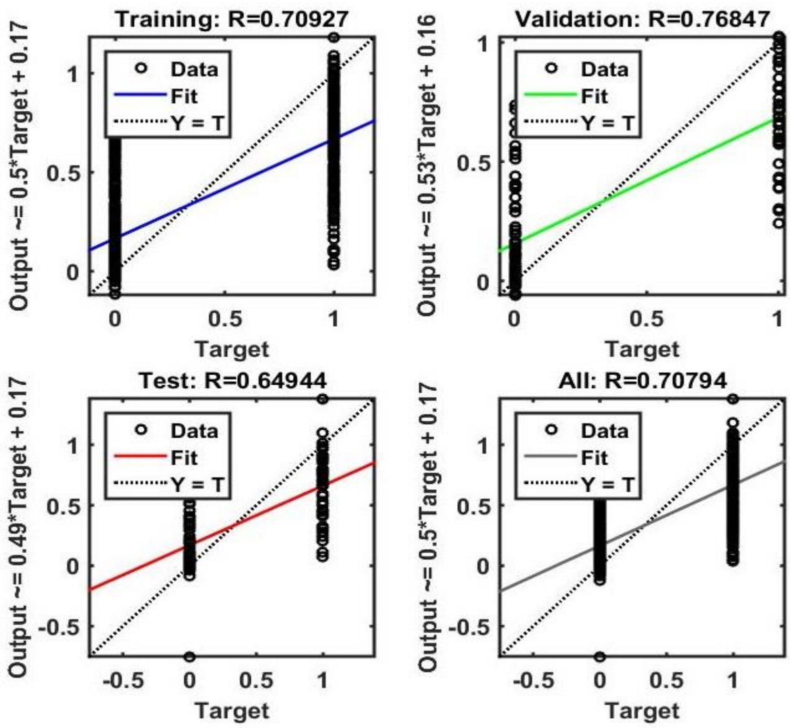

Fig. 3.11: Regression curve of a random trial of subject A.

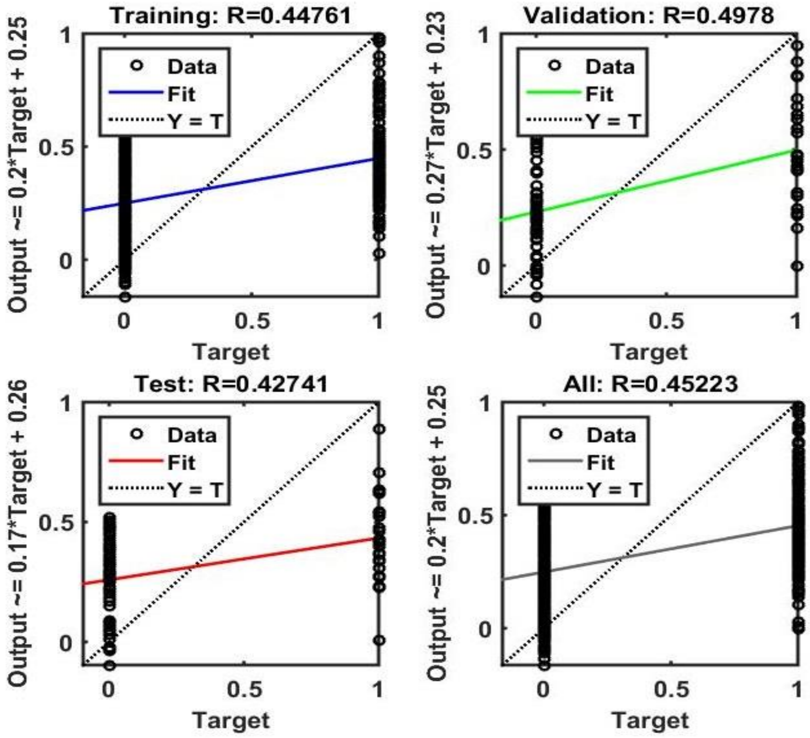

Fig. 3.12: Regression curve of a random trial of subject B.

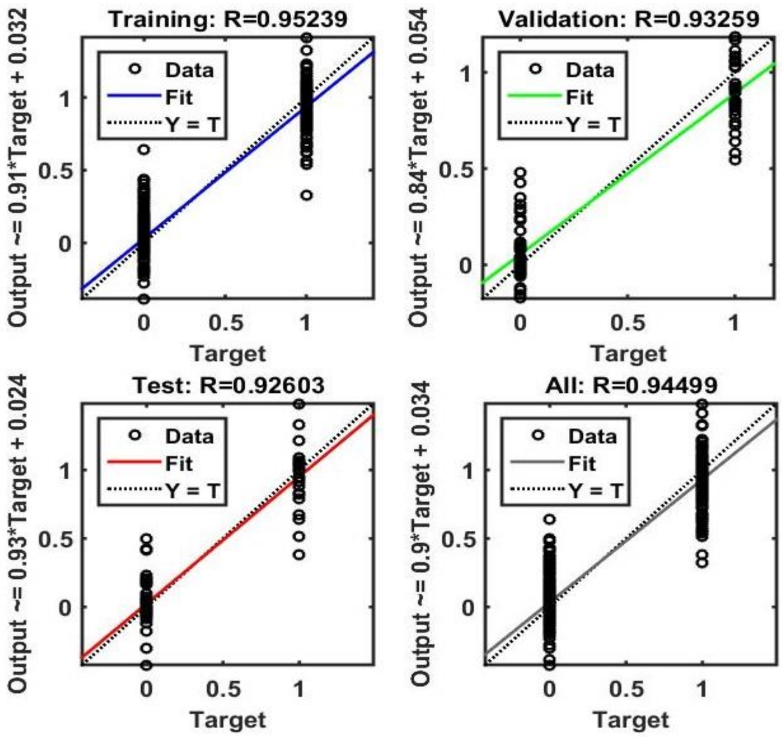

Fig. 3.13: Regression curve of a random trial of subject C.

Classification results show that proposed methodology effectively classifies 3 class motor imagery movement (LH/RH/FT) utilizing statistical features of the EEG signal. Among three subject's classification results, dataset for subject C showsbest separation accuracy, for 2 class (LH/RH) and 3 class accuracy is 100% and 96% respectively. But dataset of subject B shows average accuracy results for both 2 and 3 classes. Now after analyzing and comparing the regression plot and R value of the subject B's and C's dataset, plots shows data unfitted for B's dataset and well fitted for subject C's dataset. R values for B's is 0.50 (approximately) and for subject C's is above 0.90. So if the datasets of subject's B and A fits well as subject's C then classification results would be better for all subjects. However our proposed method can be used to classify 3 class motor imagery movement with precise accuracy as subject C for various BCI application. Accuracy rate varies ± 4% for all class except subject C's 2 class accuracy rate which shows 100 % always.

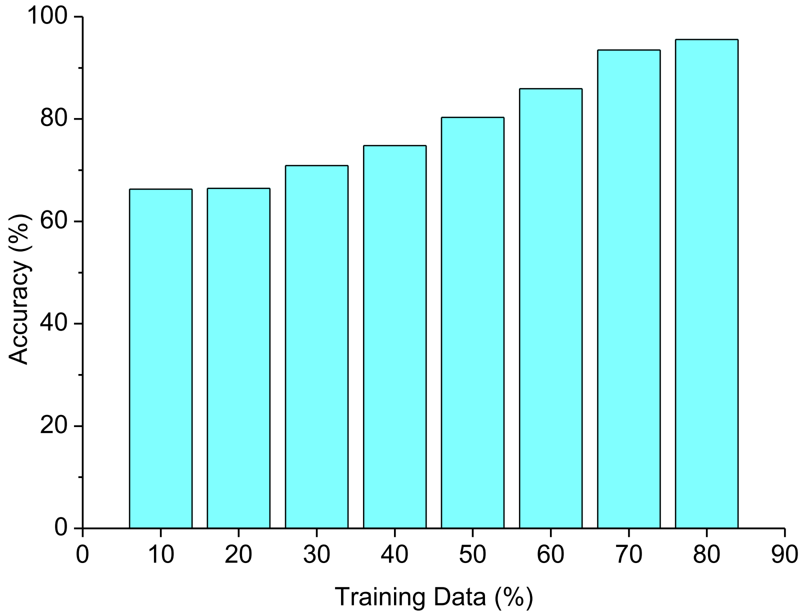

Fig. 3.14: Classification accuracy distribution with training data variation of subject C

Validation data is remained 10% constant, training and testing data are interchanged to 10-80%. Increasing training data 10% gradually from 10% to 80% training data Fig. 3.14 depicted. While 10% training data and 80 % testing data are used then approximately 68% accuracy assured and to the end while 80% training data and 10 % testing data are used then classification accuracy reaches to around approximately 98%. From the graph it is easily noticeable that the percentage of classification accuracy among right hand, left hand and feet is increasing as percentage of training data increases.

In Table 3.8, we have presented a comparison table where we juxtapose our research work with other relevant studies and research works with related important information. By selecting responsible channels and features, the overall classification accuracy can be increased which is the main contribution of the classification of MI movement. That's why channels and features used in various previous research works are also included.

Table 3.8: Comparison with Methods and Performance of Relevant Studies

Authors	**Data Set**	**Channels and Features**	**Methods**	**Performance**
D. Wang [3] et. al.	Dataset IIa BCI IV	C3, Cz , C4 ERD/ERS analysis	ICA and SVM	Highest accuracy 87.86
Y. Wang [4] et. al.	---	C3, C4 Spatial patterns of ERD	CSP and LDA Classifier	Average online 79.48% and offline 85.00%
A. Kumar [9] et. al.	BCI IV	---	CSP and SVM	Overall accuracy 91.11%.
W. Yi [19] et. al.	Author's	C3, Cz, C4 Event-related spectral perturbation, Power spectral entropy and spatial distribution coefficient	CSP and SVM	Highest accuracy 84% Mean accuracy 70%.
B. Zhou [20] et. al.	Dataset IIa BCI IV	---	ICA and SVM	Highest accuracy 86.96% and average accuracy 67.64%.
M. Naeem [21] et. al.	---	C3, C4, Cz, CP1, CP2, CPz	ICA and CSP	Classification accuracies between 33% and 84%
Y. Wu [22] et. al.	Five datasets, BCI and Author's	C3, Cz, C4 ERD/ERS features	CSP and Biomimetic Pattern Recognition, LIBSVM	SVM – average 82.33 % LDA – average 80.43 % BPR – average 85.56 %
S. Ge [71] et. al.	Dataset IIIa, BCI	C3, Cz, C4, Fp1, Fpz, Fp2, Temporal and Frequency features	CSP and STFT, SVM	Fp2 - 73.4, 78.3, 75.2 C4 - 71.3, 88.1, 71.2
R. Djemal [72] et. al.	IIa, BCI IV IVa, BCI III	C3, Cz, C4 2-21 features	FFT, AR and SVM, LDA and	For IIa: 86.06%; For IVa: 93.3%

			KNN Classifier	
Z. Y. Chin [73] et. al.	Dataset IIa BCI IV	---	FBCSP	Mean Kappa values ranges 0.31-0.57
B. Xiaoping [74] et. al.	Data sets of BCI IV	C3, Cz, C4 ERD and ERS	Wavelet-CSP with ICA and SVM	Average kappa coefficient of 0.68
Proposed Method	Data sets provided by the Dr. Cichocki's Lab [76]	C3, C4 10 Wavelet statistical features	DWT and ANN	2 class: Highest 100% and average: 79.43%. 3 class: Highest 96.1% and average: 76.06%.

3.4 Summary

This study proved that statistical parameters (features) can be used to differentiate two imagery hands movement and left hand, right hand and feet classification is the mostly used in the BCI application to execute primary command using neural activity with standard accuracy. To perform elementary task with perfectness it is very necessary to discriminate between those orders from cerebral cortex. So this procedure can be applied to design an efficient BCI system to differentiate multiclass or three class neural activities.

CHAPTER IV

Epileptic Seizure Classification using Statistical Features of EEG Signal

This chapter describes the epileptic seizure classification that is a severe neurological disorder and it is the second objective of this dissertation.

4.1 Introduction

Human brain is a complex structure engineered and among innumerable neurological disease, epilepsy holds the second place after stroke where 50 million people suffer globally [79]. Temporal, sudden and irregular cerebral electrical discharge characterizes epilepsy that compelled patient to shake their extremities and lose consciousness. Depending on the affected neuron cell area of the cortex, epilepsy categorized as partial and generalized epileptic seizures [18]. It is crucial to differentiate the normal EEG period, interictal EEG period and ictal EEG period signal to classify the types of epileptic seizures. Interictal period is EEG signal during a seizure-free interval of an epileptic subject and ictal period is EEG signal during a seizure of an epileptic subject.

Many researches have been accomplished. In [10] authors used DWTs for preprocessing of EEG signal and enquires the efficacy of the WNNs for the detection of epileptic seizure. The performance varies according different wavelets, features. Authors in [11] applied immune clonal algorithm (ICA) to organize feature vectors incorporating DWT and three classifiers used to differentiate epilepsy types. In [12], authors embraced ANFIS classifier to differentiate between ictal and inter-ictal EEG signal. In [25], authors proposed time-frequency analysis and extracts PSD as feature for each EEG segment. Further ANN used to calculate the classification rate of epileptic seizures. In [26], researchers developed an epilepsy detection method where WT is used for feature collection and quadratic classifier classifies the three class EEG signal. In [27] researchers adopted nonlinear analysis of time, frequency and time-frequency domain to collect responsible features and a quadratic classifier calculates classification accuracy. Authors in [69] adopted DWT and MLPNN based technique that resulted promising accuracy rate for five different experiments. Researchers in [80] adopted a combined method using neural network with weighted fuzzy membership functions (NEWFM) to classify epileptic and normal EEG. Performance results in terms of accuracy, sensitivity and specificity. In [81], authors proposed a method based on the empirical mode decomposition (EMD) and the second-order difference plot (SODP) to classify ictal and seizure-free EEG signals using the artificial neural network (ANN) classifier. Authors [82] proposed a focal and non-focal EEG signals classification method using EMD method and entropy measures. Several entropy features are used for LS-SVM classifier and outcomes average 87% classification accuracy. Authors in [83] proposed an automatic detection process using WT and ANN. Outputs average specificity of 99.19%, sensitivity of 91.29% and selectivity of 91.14% are obtained. In [84], authors proposed empirical mode decomposition (EMD) based method to classify focal and non-focal EEG signals. The average Renyi entropy and the average negentropy of IMFs for EEG signals are computed as features and set to input in ANN.

Long term monitoring of epileptic EEG signal and manual visual inspection results inaccuracy. As a result many algorithms have been exploited for efficient epilepsy detection. In our research work we adopted DWT MATLAB toolbox for feature extraction and ANN to classify different epileptic EEG signal.

4.2 Materials and Methods

4.2.1 Data Collection and Description

The In our research purpose we utilized a dataset made publicly available by Dr. Ralph Andrzejak [85]. This EEG dataset contains five subsets (A, B, C, D, E) of EEG data from both normal and epileptic subjects. Set A and B contain normal EEG data during eyes open and eyes closed respectively from 5 subjects. Data acquisition performed by using 19 surface electrodes placed according to the international 10-20 system. Set C, D and E carries data from epileptic patients. But set C and D contain interictal activity and EEG signals recorded from hippocampal formation and epileptogenic zone respectively of the brain. Only set E carries ictal activity. Set C, D and E signals recorded using implanted intracranial electrodes from five subjects. Each subset of this dataset contains 100 text file of segmented EEG signals. Each signal is 23.6 seconds long and total 4097 samples at a 173.61 Hz sampling rate. Nineteen surface electrode positions are shown in Fig. 4.1.

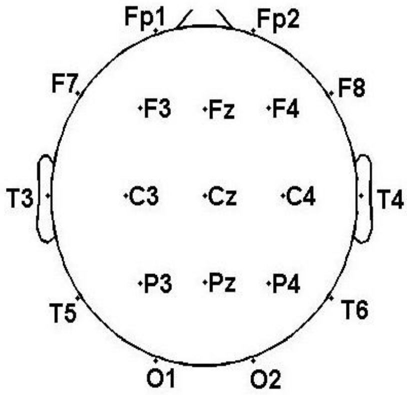

Fig. 4.1: Nineteen surface electrodes placement position.

4.2.2 Experimental Flowchart

Data acquisition from the normal and epileptic is the elementary step to accomplish this study. To use an exact dataset we utilize a well-known dataset sot that we can compare the results. After dataset collection it is necessary to perform preprocessing steps for artifacts removing and data segmentation. In this dataset signals are already segmented and processed. Each subset contains 100 trials for every class. We decompose all five subsets using DWT MATLAB toolbox. This toolbox after decomposition provides 10 most significant features are collected to organize the feature vectors. Consequently for each class feature vectors will be 100×10. This set of feature vectors provided to the designed NN to show the classification accuracy. It is very important to classify EEG signal during epileptic seizure, seizure free EEG signal and normal EEG signal (either eyes are open or close) to detect ictal and interictal period during seizure. So feature vectors are arranged according to interest of class. The complete working procedure is shown in block diagram in Fig. 4.2.

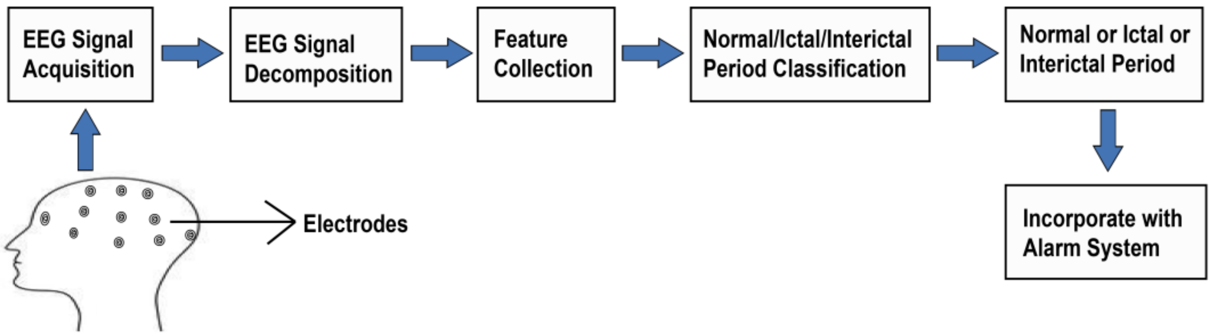

Fig. 4.2: Block diagram of the working procedure of epilepsy classification.

4.3 Experimental Results

4.3.1 DWT Decomposition and Feature Collection

All trials from all subsets are decomposed (500 signals) using Daubechies 4 wavelet (db4) and 10 features are recorded. The decomposition of an EEG signal from A, C and E subsets of normal, interictal and ictal EEG period are shown in Fig. 4.3, Fig. 4.4 and Fig. 4.5, respectively into different coefficients. The recorded statistical parameters are mean, median, maximum, minimum, range, standard deviation, median absolute deviation, mean absolute deviation, l2 norm and max norm. So for a 2 class feature vector structure is 200×10 and for 3 class is 300×10 according its class.

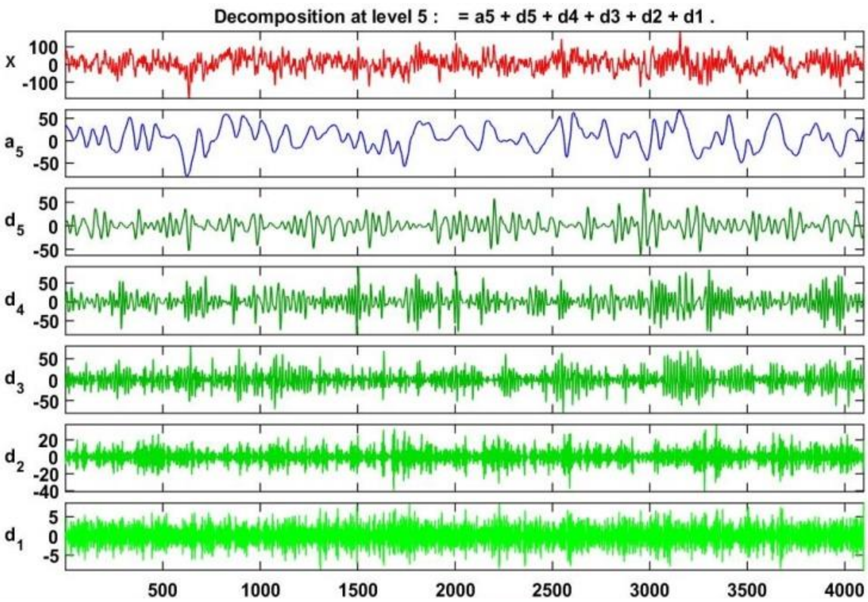

Fig. 4.3: EEG signals decomposition from data subset A.

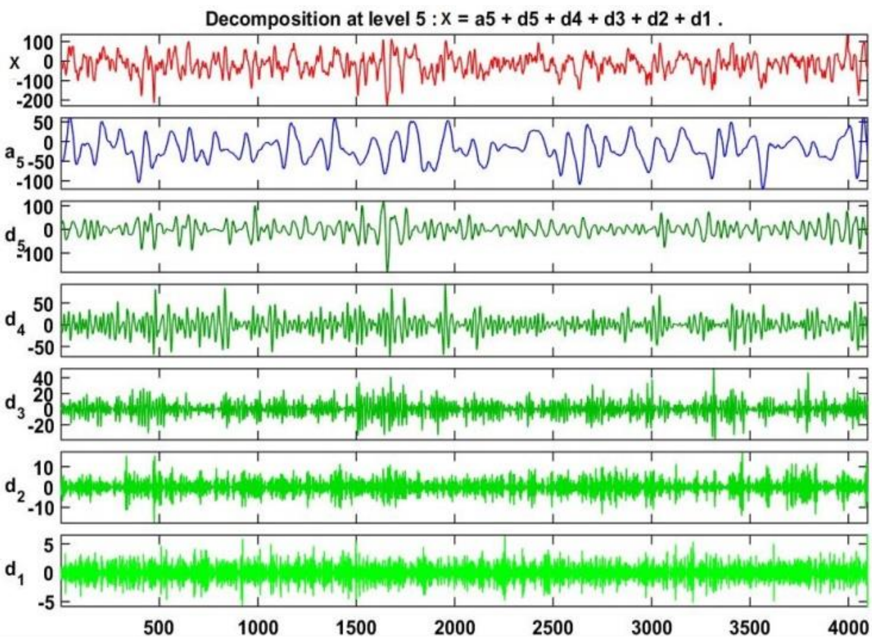

Fig. 4.4: EEG signals decomposition from data subset C.

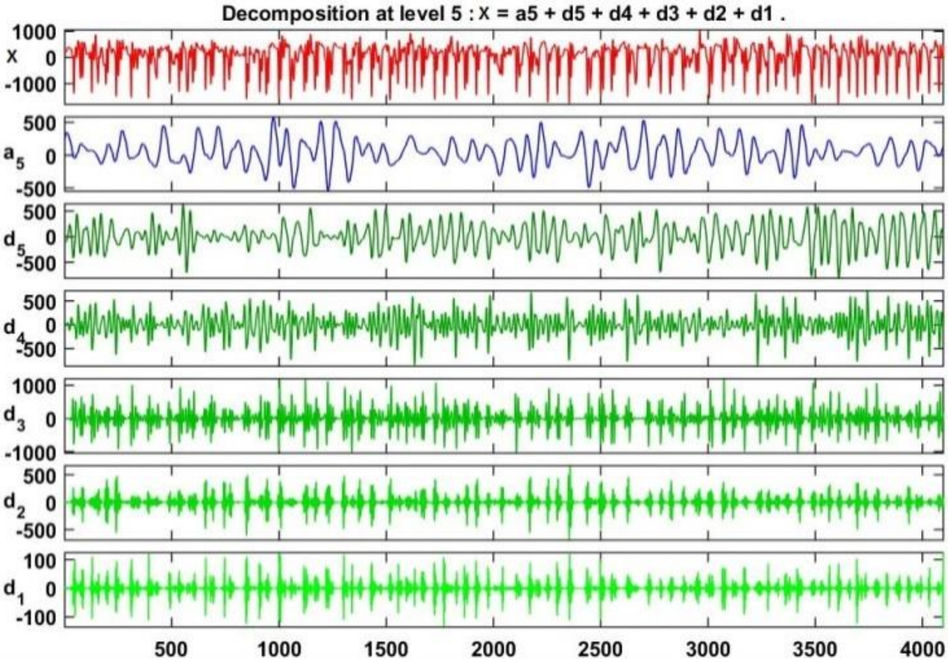

Fig. 4.5: EEG signals decomposition from data subset E.

4.3.2 NN Classification

When feature vectors are given to the NN, NN randomly divides total signals or trials as follows: 70% for training, 15% for testing and rest 15% for validation. So finally for 2 class classification, among 200 feature vectors 140, 30 and 30 feature vectors are randomly selected for training, testing and validation, respectively. For 3 class, among 300 feature vectors, 210, 45 and 45 feature vectors are randomly differentiate for classification. In Table 4.1 and Table 4.2 confusion matrix of the NN are given for 2 class and 3 class classification respectively. Table 4.3 represents the overall performance of the methodology for both classes.

Table 4.1: Confusion Matrix of 2 Class Classification of Subset A, B, C, D, & E

Subset A & E		Subset B & E		Subset C & E		Subset D & E	
A	**E**	**B**	**E**	**C**	**E**	**D**	**E**
100 50.0%	0 0.0%	99 49.5%	0 0.0%	100 50.0%	1 0.5%	99 49.5%	1 0.5%
0 0.0%	100 50.0%	1 0.5%	100 50.0%	0 0.0%	99 49.5%	1 0.5%	99 49.5%

Table 4.2: Confusion Matrix of 3 Class Classification of Subset A, B, C, D, & E

Subset ACE			**Subset BCE**			**Subset ADE**			**Subset BDE**		
A	**C**	**E**	**B**	**C**	**E**	**A**	**D**	**E**	**B**	**D**	**E**
93 31.0%	50 16.7%	0 0.0%	71 23.7%	28 9.3%	5 1.7%	93 31.0%	49 16.3%	0 0.0%	81 27.0%	33 11.0%	1 0.3%
7 2.3%	47 15.7%	0 0.0%	28 9.3%	70 23.3%	0 0.0%	7 2.3%	47 15.7%	0 0.0%	17 5.7%	60 20.0%	2 0.7%
0 0.0%	3 1.0%	100 33.3%	1 0.3%	2 0.7%	95 31.7%	0 0.0%	4 1.3%	100 33.3%	2 0.7%	7 2.3%	97 32.3%

Table 4.3: Two & Three Class Classification Accuracy Results

	2 Class Classification Accuracy				**3 Class Classification Accuracy**			
Data Subset	**AE**	**BE**	**CE**	**DE**	**ACE**	**BCE**	**ADE**	**BDE**
Accurately Classified	100.0%	99.5%	99.5%	99.0%	80.0%	78.7%	80.0%	79.3%
Misclassified	0.0%	0.5%	0.5%	1.0%	20.0%	21.3%	20.0%	20.7%

From the classification results Table 4.3 shows that for 2 class classification, subset E i.e. ictal period shows best classification accuracy with normal EEG periods and interictal EEG periods (both subset C and D). For 3 class classification all subsets show less accuracy (average 79.5%) than 3 class but acceptable for epilepsy detection.

4.3.3 Regression Plots

Regression plot establishes relationship between input and output of the NN. Fig. 4.6 and Fig. 4.7 illustrate the regression plot of the data subsets of the highest (AE) accuracy rate of the 2 class and lowest (BCE) accuracy rate of the 3 class classification to analyze the interconnection and distribution of the data. In Fig. 4.6, the solid line completely fits with the dashed line. In Fig. 4.7 depicts that solid line did not fully matched with dashed line. So both lines are not well fitted. The regression value R should be 1 or nearly 1 that represents good fit. In these figures R values are 1and 0.80 for best and lowest accuracy rate for AE and BCE, respectively.

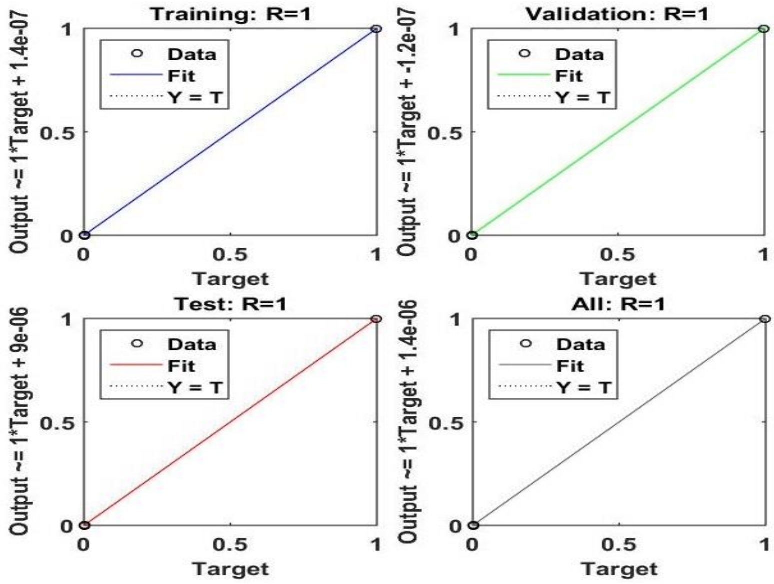

Fig. 4.6: Regression plot of AE subsets.

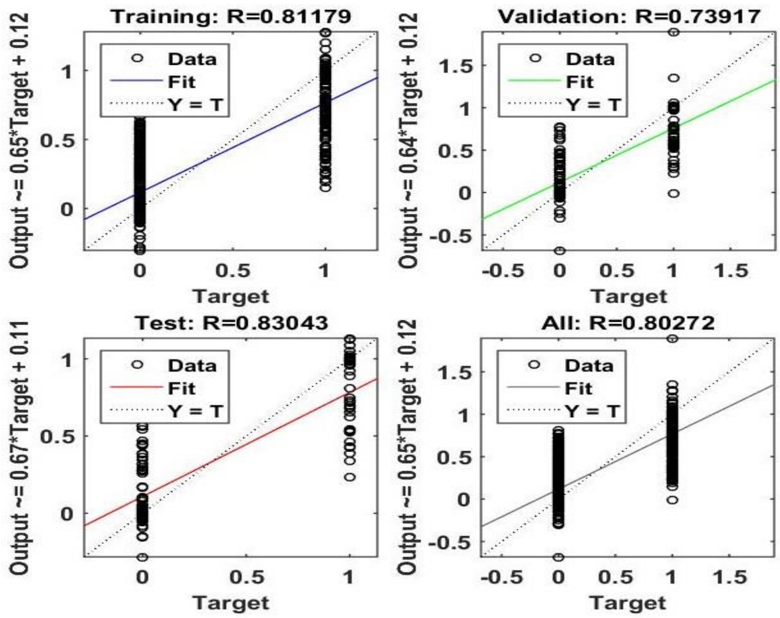

Fig. 4.7: Regression plot of BCE subsets.

Validation data remained constant (10%), training and testing data are interchanged to 10-80%. Increasing training data 10% gradually from 10% to 80% training data Fig. 4.8is illustrated. While 10% training data and 80 % testing data are used then approximately 65% accuracy assured and to the end while 80% training data and 10 % testing data are used then classification accuracy reaches to around approximately 80%. From the graph it is easily visible that the percentage of classification accuracy among normal, inter-ictal and ictal EEG signal period of an epileptic patient is increasing as percentage of training data increases.Though for 40% training data and 50% testing unpredictable classification accuracy showing which is higher than the next two increments of training data (50%, 60%).

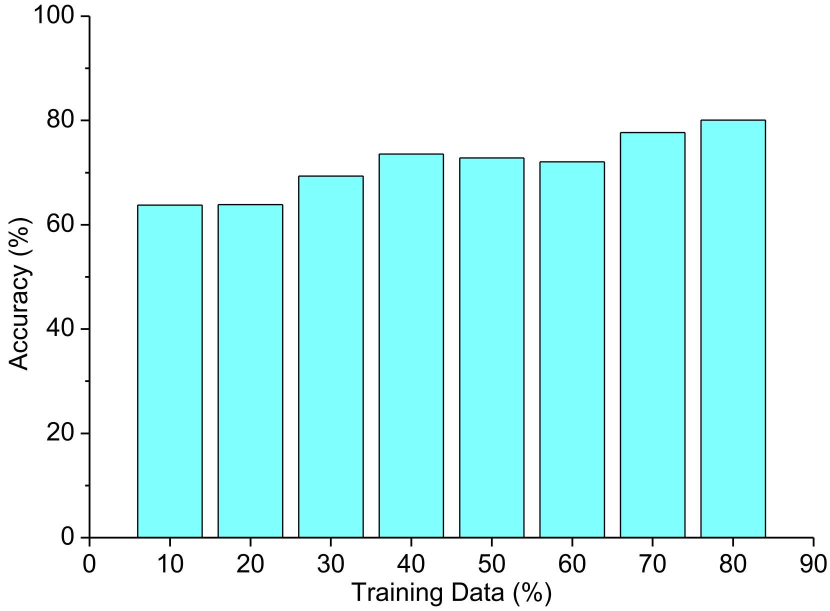

Fig. 4.8: Classification accuracy distribution with training data variation of data subset ACE.

4.4 Experimental Discussions

The proposed method shows 100 % (average 99.5%) classification accuracy for epileptic EEG signal (ictal period) detection corresponding to normal EEG (both eyes open and close), epileptic patient's EEG signal but seizure free (interictal periods). For 3 class classification accuracy rate is 80.0% (average 79.0%) and classifies all 5 subsets of data. This method shows constant accuracy rate for all classes. Selection of the responsible features increases the overall classification accuracy for detection of the epilepsy is the main contribution of this part of the dissertation. That's why features used in various previous research works are also included. However, In Table 4.4 we present current research work accomplished on these same dataset for better understanding.

Table 4.4: Methods and Performance of Research Work on the Same Dataset

Authors	Data Subset	Methods	Features	Performance
Z. Zainuddin [10] et. al.	-----	DWT, WNN	Max, min, mean, and SD	96.56% to 98.66%
Y. Peng [11] et. al.	A, C and E. (A, B), (C, D) and (E).	Immune Clonal Algorithm (ICA) and SVM, KNN and LDA.	Mean Energy SD Fluctuation	Seizure & Seizure free 97.51% Normal,

			coefficient Skewness	Interictal & Ictal 95.04%.
S. A. Hosseini [12] et. al.	Normal & Inter-Ictal. Normal & Ictal, Inter-Ictal & Ictal.	Chaos-ANFIS (Adaptive Neuro-Fuzzy Inference System).	Hurst exponent Lyapunov exponent	97.4%, 96.9% & 96.5%.
A. T. Tzallas [25] et. al.	Z,S & Z,F,S & Z,O,N,F,S.	Time–Frequency (T-F) Analysis and ANN.	12 time–frequency distributions	100%, 100% & 89%.
D. Gajic [26] et. al.	Normal EEG, Interictal EEG & Ictal EEG	DWT, PCA and Quadratic Classifier.	Energy, entropy, and standard deviation	99%.
D. Gajic [27] et. al.	Non-Epileptic & Epileptic.	DWT, Quadratic Classifier.	30 time, frequency and t-f features	98.7%.
U. Orhan [69] et. al.	ABCD-E, A-E, AB-CDE. AB-CD-E, A-D-E.	DWT and MLPNN.	Average power, mean, entropy and standard deviation	99.60%, 100%, 98.80%, 95.60% 96.67%.
S-H. Lee [80] et. al.	Normal and Epileptic Seizure.	WT, PSR, and ED and NN with Weighted Fuzzy Membership Functions (NEWFM).	Max, min, mean and Standard deviation	98.17%.
M. S. Mercy [86] et. al.	Normal and Seizure Signals.	DWT & ICA, SVM & NN.	Approximate Entropy (ApEn)	99.5%.
Proposed Method	AE, BE, CE, DE, AC and BC ACE, BCE, ADE and BDE.	DWT and ANN.	10 wavelet statistical features	100.0% 99.5% 99.5% 99.0% & 80.0%, 78.7%, 80.0% and 79.3%.

4.5 Summary

Epilepsy is a severe life threatening neurological disease. Taking EEGs of the patient it can be monitored and decide whether it is a generalized or partial epilepsy. This research work using proposed method investigates the classification accuracy of every EEG subset data in a 2 class and 3 class order and shows epilepsy detection with 100% and 80% accuracy respectively which can increase the detection accuracy of epileptic seizure in comparison with normal and interictal EEG signal period, specially to detect ictal periods of an epileptic patient. This will reduce the wrong alarm and increase the long-term epilepsy monitoring ability of the hospital.

CHAPTER V

Brain Alertness Classification and Monitoring

This chapter describes the brain alertness classification and monitoring methods to facilitate the real driving environment to avoid accident and the educational environment to make more effective. This is also the last objective of this dissertation.

5.1 Introduction

Temporal resolution of EEG signal benefits scientific arena to exploit it in research and engineering. Recent development [87-89] proves human behavior can be represented by their brain signal. Besides vast application and implementation of EEG signal in various field (biomedical instrumentation, neuroscience, brain computer interface etc.), EEG signal can be utilized to detect alertness state with respect to resting state.

According to neurophysiological methodology, drowsiness is defined as the transition from awaking state into the sleeping state or deep relaxation state, marked by reduces alertness and slow movements. Sleeping state begins with the neurons activation and inhibition of the brain. The transformation of awaking or alertness state to unconscious or drowsiness state is described by certain rhythmic changes [90-91]:

(i) decreased activity of beta rhythm (13-30 Hz);
(ii) increase and subsequent reduction of alpha rhythm activity (8-13 Hz); and
(iii) increased theta rhythm activity (4-8 Hz)

This work presents two important virtual ambivalence where keeping constant alertness mandatory, which are monitoring of students alertness to force the students to pay attention on their studies and monitoring of driver or pilot alertness for safe driving. Classrooms can be modernized introducing wireless EEG acquisition system to monitor the attention level of the students to make classes more effective. More importance is given for the drivers or pilots, still now on average 3,287 people die each day by road crush worldwide which can be largely reduced with the attention level monitoring system [28]. An alarm unit can be integrated for better result. This implementation of EEG signal cannot be overlooked to reduce the accident number consequently innumerable lives.

Attention deficit hyperactivity disorder (ADHD) is a neurological disorder that characterizes by certain symptoms such as inattention, impulsivity and hyperactivity that create problems for patients to remember information, to concentrate, to arrange tasks etc. Worldwide 5.9–7.1% school going children suffer from ADHD [13]. 30–50% of them diagnosed in childhood continue to exhibit symptoms into adulthood [92-93]. So monitoring constant consciousness of ADHD patient is very crucial to prevent error.

Countable research works have been accomplished, though accuracy level still unsatisfactory. Ning-H. L. [14] proposes a method to make the learning process of students more effective by distinguishing attentive and inattentive state. Authors employed a portable brainwave sensor to collect the EEG data from the participants. Support vector machine (SVM) classifier is used after extracting various features to arrange a feature set to identify student's attentive state and provides 76.82% as highest classification accuracy. Zahra M. [15] introduces a method of separating alertness and sleepiness state for riskless driving using EEG signal as a reliable source. After collecting data from 10 volunteers and necessary preprocessing, authors separated logarithm of energy, Petrosian's fractal dimension and Higuchi's fractal dimension as chaotic features of signal. ANN is used to evaluate the effectiveness of each feature and results 83.3% classification accuracy with all features. M. Kemal Kiymik [16] proposed an automatic alertness detection system from three states (alert, drowsy and sleep). For that purpose EEG signals are recorded from 12 subjects and PSD as feature is extracted using DWT. Features are feed to ANN which results 96 ± 3%, 95 ± 4% and 94 ± 5% accuracy rates for alert, drowsy and sleep, respectively. Mousa K.W. [29] developed a driver distraction level measurement method using different wavelets of discrete wavelet packet transform (DWPT) depending 4 distraction stimuli. Analyzing results from 3 classifiers, subtractive fuzzy inference system classifier and sym8 wavelet provides best accuracy of 79.21% based on PSD feature. Abdulhamit S. [30] classifies participant's 3 state (alert, drowsy and sleep) DWT and MLPNN classifier which results satisfactory accuracy rate. Tiago da S. [91] describes a drowsiness detection system where feature are selected based on the most responsible m terms approximation of the DWT expansion. Authors argue this method alleviates the use of complex techniques. Agustina G. C. [94] proposed another work to detect the drowsiness of the driver as the prime factor of road accident. Using wavelet, spectral and time analysis, authors collects 19 features and select 7 features to detect drowsiness and alertness and ANN results 83.6% and 87.4% of correct rates respectively. R. Kianzad [95] proposed deferent sleep stage classification method for diagnosis purpose in psychiatry and neurology. Physionet database exploited for data collection and wavelet packet tree (WPT) used to extracts features. Three classifiers are used to evaluate the accuracy rate and outcomes 70% of overall accuracy. D. Begum [96] presented a BCI application of patient monitoring using EEG signal of mental alertness. After preprocessing, Wavelet features are extracted and feed to adaptive neuro fuzzy interface system (ANFIS) classifier is used for evaluation. Leonard J. T. [97] proposed a method of assessing mental fatigue or workload comparing with alertness. PSD coefficients of EEG segments from alert or fatigued task periods are classified using a kernel partial least squares classifier. Akshansh G. [98] introduces a feature extraction method for mental multitask classification. Empirical wavelet transform (EWT) with fuzzy clustering method is employed for feature extraction. After feature selection, vectors are feed to support vector classifier (SVC). Akshansh G. [99] in another research article proposes a method to increase performance of mental task using WT and EMD feature extraction method. Uses 4 classifiers to make a combination with 6 selection method and finally proves that the combination of WT and linear regression (LR) performs best. Naiyana B. [100] classifies drowsiness with respect to alertness extracting energy coefficients from WT. to train NN authors used this feature and classifies drowsy and alert state with 90.27 % accuracy. Nikita G. [101] introduces a drowsy driving monitoring technique by extracting statistical features adopting DWT from recorded EEG signals and classifying using K-means clustering technique. Gang L. [102] proposes a drowsiness detection method of the driver due to mental fatigued using heart rate differences. WT and fast Fourier transform (FFT) based features are selected and classified using SVM and finally compares accuracy which shows that WT based features provide better accuracy rate (95%) than FFT based features.

5.2. Materials and Mathematical Description of the Algorithms

5.2.1 Experiment and Dataset Description

This experiment is arranged in such order so that we can mimic the environment for students concentration monitoring, can be used for distance learning or where requires constant concentration. And another virtual ambient where the alertness of a driver or pilot can be monitored which can also be adopted to reduce the possibility accident occurrence. Each volunteer are requested to be focused on their assigned test work during testing. Besides experiments related information is given and shown for once by doing practically. Afterwards for being accustomed with experiment procedure single trial data is taken before data recording for experimental purpose. To have a wide screen, volunteers are requested to sit on a comfortable armchair in front of a projected screen on a Starboard screen which is 8 feet away from the participants as shown in Fig. 5.1.

1. Finding specific word: this experiment is organized to compel the each volunteer to pay full constant attention during the test. All volunteers are requested to find an exact word from a given paragraph as soon as possible. So that they remain focused during the test time. Five alphabets (A, E, R, S, T) are requested to count as each counted as one trial.

Fig. 5.1: Pictorial view of data acquisition from several participants.

2. Participate in virtual driving: To simulate the driving environment and remain alert during test time a virtual driving (bike) game is supervised to play to all the volunteers. In the game 12 other competitors will be presents and hard level three so that driving environment can be copied and the volunteers are forced to remain concentrated during test time. They are requested to not fall and stay their track.

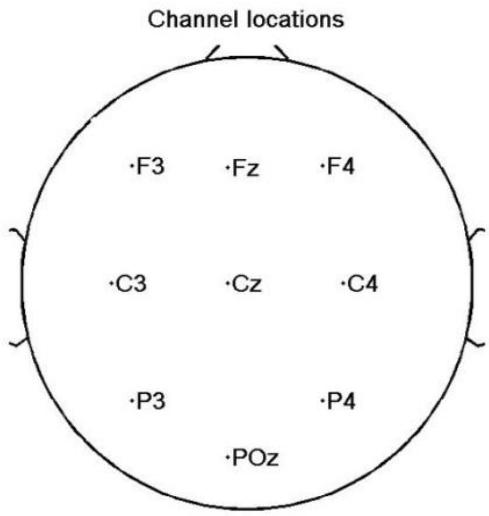

Fig. 5.2: Channel placement according to the 10-20 system

Electrode placement is shown in Fig. 5.2 where 9 electrodes are positioned according to the 10-20 system. In our research work we use B-Alert X10 wireless EEG acquisition system and 9 electrodes placed over the frontal, central and parietal region of cerebral cortex. This device is highly suitable for long time monitoring the cognitive state, such as engagement, workload, stress, confusion, drowsiness. Data recorded with the sampling rate of 252 Hz and the impedance of the electrodes is checked frequently to confirm their conductivity.

5.2.2 Filtering and Channel Selection

All data are filtered using a 3 order Butterworth filter after data recording. Bands limits are chosen based on the responsible frequency bands of the EEG signal generated due to the given task. Alpha (8-13) and theta (4-8) rhythms are responsible for relaxation and drowsiness, respectively. So for inactive state (relaxation and drowsiness) signals are filtered within 4-13 frequency. Beta (13-30) rhythm results for concentration and thinking state of the person. Consequently for active state (alphabet counting and virtual driving) monitoring signals are filtered within 13-30 frequency range for further preprocessing. Among the 9 channels only the responsible channels are selected based on the previous researches. For inactive state (relaxation and drowsiness) frontal 3 electrodes (F3, FZ, and F4) are preferable and for active state (alphabet counting and virtual driving) central 3 electrodes (C3, CZ, and C4) are better [103].

5.2.3 Dimensionality Reduction using PCA

Principal Component Analysis is a statistical transformation procedure to identify the patterns existed in data and expressing the data highlighting their similarities and differences. PCA is probably the most popular multivariate statistical technique that is used by almost all branches of scientific analysis. PCA can be applied in different purposes such as, to extract the most important information from the data set, to compress the size of the data set by preserving only important information, tosimplify the description of the data set, to analyze the structure of the observations and the variables, etc. [104]. In this paper, PCA is used to reduce the dimensionality of EEG Signal. Since, EEG signal does not have good spatial resolution (~10cm) multiple signals of same region can be treated as multiple variables with slight variation to each other. Therefore, for classifying purpose, three or more channels can be transformed into single signal by PCA. In this work, the frontal area of the brain is covered by three channels, Fp1, Fp2, and Fz. If a matrix Λ consists of the data of Fp1, Fp2, and Fz which means the data matrix, Λ is of three dimensional. Now, a matrix U can be calculated which represents the eigenvectors sorted as the eigenvalues of the covariance matrix of Λ. In that case, we can get the PCA transformation of the data Λ in the form of Y as,

$$Y = U^T \Lambda \tag{5.1}$$

The eigenvectors are also termed as the principal components. If only first r rows of Y are selected to project the data, the data becomes of r dimensional from d dimensions. This transformation is performed by singular value decomposition (SVD). The procedure to perform PCA by SVD can be described by matrix decomposition. Suppose, the matrix, Λ can be decomposed using SVD as [105],

$$\Lambda = \Omega \Gamma \Psi^T \tag{5.2}$$

Here, Ω is n×m matrix with orthonormal columns ($\Omega^T \Omega = I$), Ψ is a m×m orthonormal matrix ($\Psi^T \Psi = I$), and Γ is a m×m diagonal matrix with positive or zero element which is also known as singular value. Besides, we can calculate the covariance matrix, C of Λ as,

$$C = \frac{1}{N} \Lambda \Lambda^T = \frac{1}{N} \Omega \Gamma^2 \Omega^T \tag{5.3}$$

As the singular values are sorted in descending order and if n<m, the first n columns in Ω corresponds to the sorted eigenvalues of matrix C and if m≥n, the first m corresponds to the sorted non-zero eigenvalues of C. Therefore, eventually the transformed data can be written as,

$$Y = U^T \Lambda = U^T U \Gamma \Psi^T \tag{5.4}$$

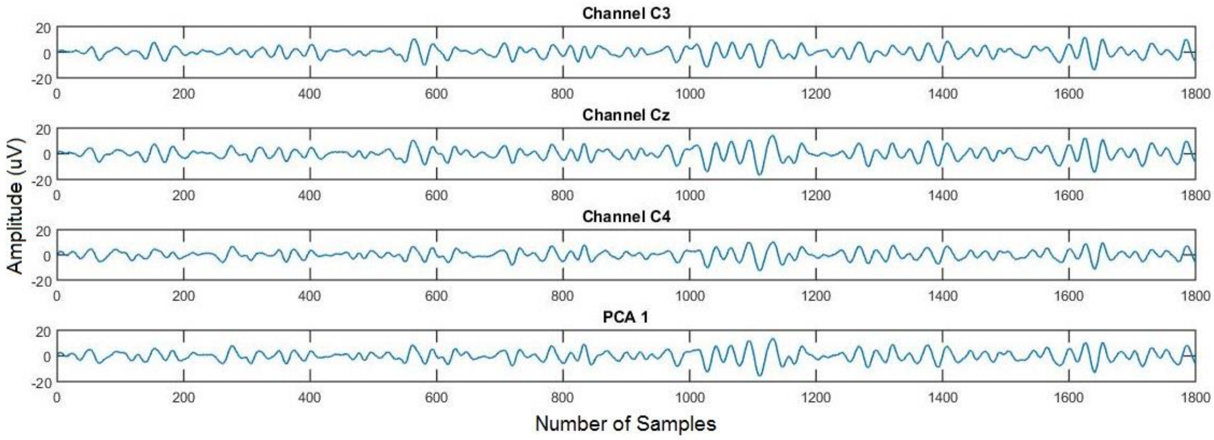

Fig. 5.3: PCA of three channels of EEG signal.

In Fig. 5.3 shows the PCA of three channel EEG data, C3, Cz, C4 and their first PCA which will contain the characteristics from all of the three signals.

5.2.4 PSD Estimation using Welch Method

For random signals it is only possible to propose probabilistic reports about the dissimilarity of the signals based on probability of occurrence. To assess EEG signal PSD as a frequency domain feature provides crucial information about the distribution of power. Power spectrum or spectral analysis of the signal x(t) is the distribution of power over its frequency components. In this research work beta PSD is calculated from each to point out the variation of PSD (μV2/Hz) according to the different tasks using FFT algorithm. A random signal usually contains finite average power which is characterized as average power spectral density. The average power *P* of a signal *x(t)*over all time is therefore given by the following time average:

$$P = \lim_{T\to\infty} \int_{-T}^{T} |x(t)|^2 \, dt \tag{5.5}$$

For analyzing the frequency content of the signal *x(t)*, PSD is the Fourier transform of the auto-correlation function which is written as,

$$P_x(e^{j\omega}) = \sum_{k=-\infty}^{\infty} r_x(k) e^{-jk\omega} \tag{5.6}$$

In (5.15), $r_x(k)$ means autocorrelation for periodic signal. But for ergodic process,

$$r_x(k) = \underset{N\to\infty}{Lim} \left\{ \frac{1}{2N+1} \sum_{n=-N}^{N} x(n+k)\, x \otimes (n) \right\} \tag{5.7}$$

Where, ‘$\otimes$’ denotes the analysis of convolution [106].

PSD calculation adopting windowing method is very important for nonparametric such as EEG signal. For nonparametric power spectral density estimation, Welch method is most renowned method than the other methods (Periodogram and Bartlett). Let's suppose that the successive sequences are offset by D points and that each sequences are L point long, then the i^{th} sequence is,

$$x_i(n) = x(n+iD) \tag{5.8}$$

Thus the overlap is L-D points and if K sequences cover the entire U data points then,

$$N = L + D(K-1) \tag{5.9}$$

According to the previous conditions, Welch's method can be written in terms of the data record as,

$$\hat{P}_W(e^{j\omega}) = \frac{1}{KLU}\sum_{i=0}^{K-1}\left|\sum_{n=0}^{L-1} w(n)x(n+iD)e^{-jn\omega}\right|^2 \tag{5.10}$$

Therefore the expected value of Welch's estimate [106] is,

$$\begin{aligned} E\left\{\hat{P}_w(e^{j\omega})\right\} &= E\left\{\hat{P}_M(e^{j\omega})\right\} \\ &= \frac{1}{2\pi LU} P_x(e^{j\omega}) * \left|W\left(e^{j\omega}\right)\right|^2 \end{aligned} \tag{5.11}$$

5.2.5 Relative Power Index Estimation

The absolute power of a frequency band is the summation of all of the power values within its frequency range. Relative Power (RP) indices for each band were derived by expressing absolute power in each frequency band as a percent of the absolute power (AP) over the two frequency bands. In this research work, Relative Power of each given band/sum of power from 1 to 49 Hz was calculated by,

$$RP(\varphi_1,\varphi_2) = \frac{P(\varphi_1,\varphi_2)}{P(1,49)} \times 100\% \tag{5.12}$$

Here, P indicates the power, RP represents the Relative Power, and φ_1 &φ_2 is the low and high frequency, respectively [107]. The RP for each band and the ratios of power for beta frequency bands were averaged in each region.

5.3. Proposed Methodology

This research work proposes a methodology for alertness classification and alertness monitoring in comparison with resting state (both eyes open and close). In classification, EEG signals of alphabet counting, virtual driving and resting state (both eyes open and close) are classified. And alertness level are detected and monitored by comparing with resting state (both eyes open and close). All data acquisition procedures are accomplished in Neuroimaging Laboratory of the department of Biomedical Engineering of Khulna University of Engineering & Technology (KUET). In preprocessing step all the signals are filtered with band pass filtered according to their (delta, theta, alpha and beta) respective band frequency limit of the responsible channel. For classification, PCA technique is adopted to find the principle component of the 3 channels from respective (frontal or central) lobe. Among the 3 principle component first signal is selected for feature vector arrangement after doing necessary segmentation. Afterwards each segmented EEG signal is provided to DWT for statistical feature extraction and arranged as a feature vector. This feature vectors are feed to the ANN to evaluate the accuracy of the alertness detection of every participants. The block diagram for alertness classification and alertness detection using EEG signal of the volunteers is shown in Fig. 5.4.

For alertness monitoring beta relative power (RP) is calculated and based on the mathematical analysis (ANOVA) it is confirmed that PSD as a feature is significant for monitoring alertness of the participants. Afterwards our algorithm is employed to test EEG signals for alertness monitoring. Results are described in results and discussions section. By using relative power as an indicator we can select a threshold value and since the relative power of each participants varies so it should check before selecting the threshold.

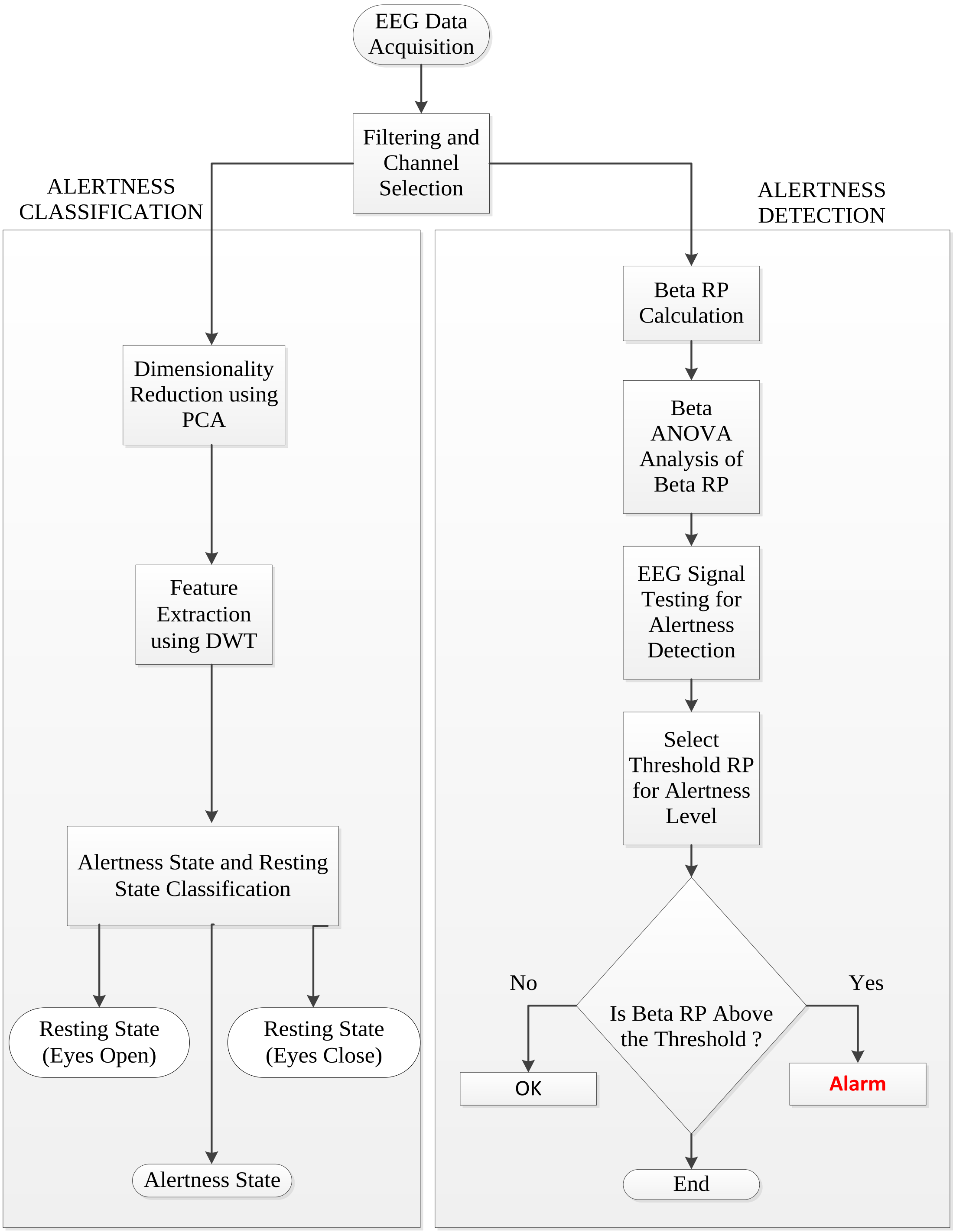

Fig. 5.4: Block diagram of the mental alertness classification and monitoring.

5.4. Experimental Results and Discussions

In this research work, data acquisitions have been performed based on four different mental states. Among them two mental states are protocoled to highlight the alertness of mental state or concentrated in any task. One of them was to count specific alphabet from a paragraph with full concentration and in another task, volunteers participated in virtual driving. The other two tasks are considered as mental control states and those are resting conditions with eyes open and eyes closed. The concentration level in some defined works like alphabet counting and virtual driving should have higher than the resting states (either at eyes open or eyes closed). Our goal of this work was to classify the alertness while being engaged of doing different task with respect to resting state and monitor this alertness state of brain from EEG signal and the level of alertness for different mental states of the brain.

5.4.1 Alertness Classification

Classification is accomplished according to three class classification by differing alphabet counting and virtual driving with resting state. For that purpose statistical features collected from DWT are organized according to 3×3 feature vector and feed to the ANN. The classification results are shown in Table 5.1 of the 14 volunteers. Average accuracy is calculated by taking 5 consecutive accuracies and highest accuracy is the highest accuracy among the 5 accuracies.

Table 5.1: Alertness Classification Results of the Participants.

Participants ID	**Alphabet counting and resting state (eyes close and open)**		**Virtual driving and resting state (eyes close and open)**	
	Average Accuracy (%)	**Highest Accuracy (%)**	**Average Accuracy (%)**	**Highest Accuracy (%)**
P1	78.66	100	90.64	100
P2	100	100	**76**	**93.3**
P3	94.66	100	100	100
P4	98.66	100	93.34	100
P5	80.02	**86.70**	93.34	100
P6	82.66	93.3	84	93.3
P7	98.66	100	93.32	100
P8	**72**	93.3	90.66	100
P9	100	100	89.34	100
P10	86.68	100	90.66	93.3
P11	100	100	82.68	100
P12	97.32	100	92	100
P13	94.66	100	98.66	100
P14	100	100	97.32	100

From the table it’s noticeable that 100% accuracy frequently reappears though lowest accuracies are also enlarged. After analyzing all those results we can conclude that without taking all channels, only taking responsible channels with corresponding lobes that represents rhythmic changes with specific task. Additionally PCA plays important role on depending on single signal by combining principal component of the all signals. However Table 5.2

represents all the accomplished research works as compare with our research work which shows the different methods and accuracy level.

Table 5.2: Comparison of the Relevant Accomplished Work with Method and Performance.

Authors	Different Class	Methods and Features	Performance
N. H. Liu [14]	Attention and Inattention	FFT and SVM PSD of different bands	Accuracy of up to 76.82%.
Z. Mardi [15]	Sleepiness and Alertness	ANN Chaotic features and logarithm of energy	83.3% and this accuracy
M. K. Kiymik [16]	Alert, Drowsy and Sleep	DWT and ANN Classifier. PSD of different bands	Accuracy of the ANN was 96 ±3% alert, 95 ± 4% drowsy and 94 ± 5% sleep.
M. K. Wali [29]	Driver Distraction Level	DWPT, FFT and PNN, *K*-Nearest Neighbor Classifier, Fuzzy Subtractive Clustering. Spectral Centroid, And Power Spectral	Best average accuracy subtractive fuzzy inference system classifier is 79.21%
A. Subasi [30]	Alert, Drowsy and Sleep	DWT and MLPNN Spectral features	Classification rate was 93.3% alert, 96.6% drowsy, and 90% sleep.
T. d. Silveira [91]	Awake or Drowsy States	DWT significant m-term approximation	PhysioNet Sleep Database tested Accuracy 98.7%
A. G. Correa [94]	Alertness and Drowsiness Stages	WT and ANN, LDA Features from time and spectral analysis	87.4% and 83.6% of alertness and drowsiness correct detections rates
R. Kianzad [95]	Five Sleep Stages	Wavelet packet tree (WPT) and Logistic Linear classifier, Gaussian classifier and Radial Basis Function classifier. statistical features	Highest for Slow Wave Sleep as 81.68%, lowest for NREM stage 1 as 43.68%. The overall accuracy is 70%.
L. J. Trejo1 [97]	Alert or Fatigued	Kernel Partial Least Squares classifier. PSD	89.53 to 98.89% (mean = 98.30%).
A. Gupta [99]	Mental Task	EMD, WT and LDC, QDC, KNN and SVM classifier.	Highest 95%
N. Boonnak [100]	Drowsy and Alert	WT and ANN. Energy-based features	90.27% of accuracy
Proposed Method	Alertness and resting state (eyes open and close)	DWT, PCA and ANN Statistical features	Highest Alertness Classification accuracy is 100%, Lowest Alertness Classification accuracy is 72%.

5.4.2 Alertness Monitoring

To achieve this goal, first of all it is necessary to find out one of the major feature of EEG signal that can be able to differentiate the mental states of different tasks. It is already mentioned that mental alertness significantly increases the power of beta band. Therefore, all the relative powers of beta band from all the participants for all the tasks are calculated from power spectral density (PSD) by Welch method. It can be noted that the relative power of beta or beta relative power is the ratio of PSD of beta band (13-30Hz) and PSD of total EEG signal (1-49Hz). Therefore, beta relative power is a unit less quantity. The beta relative power of 10 participants for four different tasks are calculated and tabulated as following below. Table 5.3 to Table 5.6 presents the beta relative power of the resting conditions (eyes close and open) and alert conditions (alphabet counting and virtual driving).

Table 5.3: Beta Relative Power for Resting Condition with Eyes Open

P.	Channel No and their corresponding beta relative power (Unit less)								
	1	2	3	4	5	6	7	8	9
P1	1.0476	0.4902	0.7719	0.8232	0.7351	0.5716	0.5512	1.4456	0.9409
P2	1.3989	1.4084	1.4257	6.2653	4.1449	4.8885	4.3706	2.1826	1.4765
P3	0.3427	0.3328	0.3825	0.4236	0.4456	0.2906	0.3103	0.4462	0.347
P4	0.4213	0.4178	0.4441	0.4984	0.5908	0.348	0.385	0.5543	0.451
P5	1.1342	0.9803	1.1601	3.677	3.6053	3.3989	2.3889	1.5635	1.5636
P6	1.3882	1.1782	1.2423	3.885	2.955	2.5713	2.1353	2.1727	1.3764
P7	0.3902	0.3827	0.4661	0.5764	0.3743	0.5062	0.4236	0.4881	0.3851
P8	0.4558	0.4512	0.4845	0.6306	0.4112	0.5636	0.466	0.5541	0.441
P9	0.1275	0.1314	0.1474	0.1498	0.2049	0.1554	0.2258	0.1134	0.1585
P10	0.1389	0.1463	0.1752	0.1638	0.1508	0.2777	0.3138	0.1284	0.1321

*P.=Participants

Table 5.4: Beta Relative Power for Resting Condition with Eyes Closed

P.	Channel No and their corresponding beta relative power (Unit less)								
	1	2	3	4	5	6	7	8	9
P1	1.5127	1.1171	0.9536	0.8689	0.7513	0.9247	0.7061	1.8218	1.2367
P2	0.5472	0.5786	0.6109	1.3484	0.9312	0.821	0.8609	0.7519	0.6947
P3	0.3538	0.3631	0.318	0.349	0.3642	0.2276	0.2424	0.4104	0.3451
P4	0.3763	0.3843	0.3618	0.3898	0.4069	0.265	0.2858	0.4424	0.3665
P5	0.7105	0.7426	0.9331	2.8111	1.4212	1.5013	1.1009	1.0637	0.859
P6	0.7173	0.7647	0.8211	2.2719	1.1071	1.8593	1.0097	1.0562	0.827
P7	0.414	0.4069	0.5653	0.6067	0.407	0.5438	0.4991	0.5206	0.3984
P8	0.449	0.4419	0.5438	0.5886	0.4176	0.5267	0.4844	0.5516	0.5169
P9	0.2682	0.2869	0.3048	0.2609	0.2357	0.2404	0.2216	0.2343	0.2648
P10	0.2841	0.305	0.3449	0.2844	0.2674	0.2464	0.2473	0.2426	0.2854

Table 5.5: Beta Relative Power for Alphabet Counting

P.	Channel No and their corresponding beta relative power (Unit less)								
	1	2	3	4	5	6	7	8	9
P1	1.31	0.8491	0.8473	0.8724	0.7141	0.9586	0.8339	1.8886	1.122
P2	0.3319	0.2091	0.2667	0.2462	0.5977	0.3659	0.2838	0.4281	0.3493
P3	0.2572	0.2536	0.2765	0.3307	0.3711	0.2089	0.2299	0.3335	0.2771
P4	0.389	0.3839	0.3892	0.4488	0.5362	0.307	0.3413	0.5056	0.4258
P5	1.2802	1.2989	0.6829	1.2513	0.8462	2.1024	4.3659	1.7514	0.8318
P6	1.2646	1.2471	0.7856	2.3043	1.265	2.5678	3.9286	2.01	0.9911
P7	0.5088	0.5072	0.5145	0.6749	0.4449	0.5464	0.5862	0.6097	0.4542
P8	0.3631	0.356	0.376	0.4443	0.3189	0.4025	0.3778	0.4068	0.3286
P9	0.1377	0.1461	0.1516	0.1355	0.1301	0.1599	0.2553	0.1209	0.1266
P10	0.1278	0.1352	0.1492	0.1994	0.1441	0.1759	0.227	0.1702	0.1382

Table 5.6: Beta Relative Power for Virtual Driving Condition

P.	Channel No and their corresponding beta relative power (Unit less)								
	1	2	3	4	5	6	7	8	9
P1	2.251	1.9514	1.9751	7.5528	8.0228	8.1846	7.5783	2.9996	3.4034
P2	2.331	2.0561	1.934	7.041	8.043	8.2161	6.705	3.1125	3.5047
P3	1.0344	0.9754	1.108	1.0955	1.1468	1.1388	1.11	1.2222	1.0751
P4	0.3238	0.3143	0.3546	0.3449	0.326	0.3442	0.3298	0.3768	0.311
P5	1.418	1.2387	1.4277	5.7396	6.21	7.7927	6.3758	1.7257	2.5142
P6	4.0364	3.2854	3.0219	10.4002	11.1556	11.8057	9.9355	4.3523	6.2898
P7	2.4402	2.0458	2.4622	3.0242	2.1095	2.6816	2.0946	2.91	2.2887
P8	2.5884	2.3845	2.7765	3.6069	2.3749	3.3815	2.6253	3.2633	2.3546
P9	0.2344	0.244	0.2976	0.3533	0.4474	0.5925	0.6733	0.241	0.2662
P10	0.1927	0.1936	0.2373	0.2479	0.2323	0.5493	0.7487	0.1836	0.1938

Based on the results of beta relative power of different functional brain states of different positions of EEG acquired signal from the brain were statistically analyzed by one way and two ways ANOVA considering 95% confidence interval. This result will help us to take decision on the feature we can trust.

Table 5.7: Results of one way ANOVA

Source of Variance	Degrees of Freedom	Factor	p-value	F Critical
Channel 1	3	5.206473586	0.004330514	2.866265551
Channel 2	3	5.399106146	0.003582388	2.866265551
Channel 3	3	7.225764165	0.000645253	2.866265551
Channel 4	3	4.643599552	0.007614366	2.866265551
Channel 5	3	5.665255929	0.002764523	2.866265551
Channel 6	3	6.019326235	0.001968346	2.866265551
Channel 7	3	5.074147715	0.004938149	2.866265551
Channel 8	3	4.104782628	0.013258564	2.866265551
Channel 9	3	6.361304704	0.001425527	2.866265551

From the Table 5.7 where one way ANOVA analysis is done for 4 tasks (resting condition with eyes open and eyes closed, virtual driving condition and alphabet counting) and for this reason degrees of freedom are 3. As the ANOVA is performed with 95% confidence interval and alpha = 0.05 so there is statistically significant differences between groups as p value is below the alpha value determined by one-way ANOVA. Table 5.8 where two ways ANOVA is performed with 95% confidence interval for 10 participants and 4 tasks so the degrees of freedom are (9, 3). Here also noticeable that the all the p values are below the alpha value (0.05). So there are statistically significant differences between groups that are among the mental states and among the participants. Consequently using PSD as the only feature, the four tasks representing the active state (alert) and inactive state can be significantly differentiated.

Table 5.8: Results of two ways ANOVA

Source of Variance (Participants, Tasks)	Degrees of Freedom	Factors	P values	F critical
Channel 1	(9,3)	4.058558, 9.187549	0.002207, 0.000235	2.250131, 2.960351
Channel 2	(9,3)	3.683019, 9.020583	0.004057, 0.000265	2.250131, 2.960351
Channel 3	(9,3)	3.387872, 11.53931	0.006646, 4.76E-05	2.250131, 2.960351
Channel 4	(9,3)	4.087633, 8.228033	0.002107, 0.000476	2.250131, 2.960351
Channel 5	(9,3)	2.692597, 8.062505	0.022374, 0.00054	2.250131, 2.960351
Channel 6	(9,3)	3.403446, 9.636107	0.006473, 0.000171	2.250131, 2.960351
Channel 7	(9,3)	3.538891, 8.294825	0.005154, 0.000453	2.250131, 2.960351
Channel 8	(9,3)	5.611496, 8.83708	0.000222, 0.000303	2.250131, 2.960351
Channel 9	(9,3)	3.045375, 9.614119	0.011982, 0.000173	2.250131, 2.960351

Since one way and two ways ANOVA results, Table 5.7 and Table 5.7are too convincing to work with the only feature beta relative power to differentiate mental alertness than the other two control states conditions. Due to check this feasibility of this feature to distinguish the mental alertness conditions from EEG signal we acquired signal from the participants with multiple task at a time like virtual driving, resting condition with eyes open and eyes closed.

This combined task EEG signals are tested with our proposed algorithm which is previously described. The results are shown in Fig. 5.5 for volunteer P1 for all channels. Graphs also depicts that electrodes placed over frontal and central area shown noticeable variation according to task. Our intention is to monitor alertness state, consequently focused on the frontal electrodes (F3, Fz, F4).

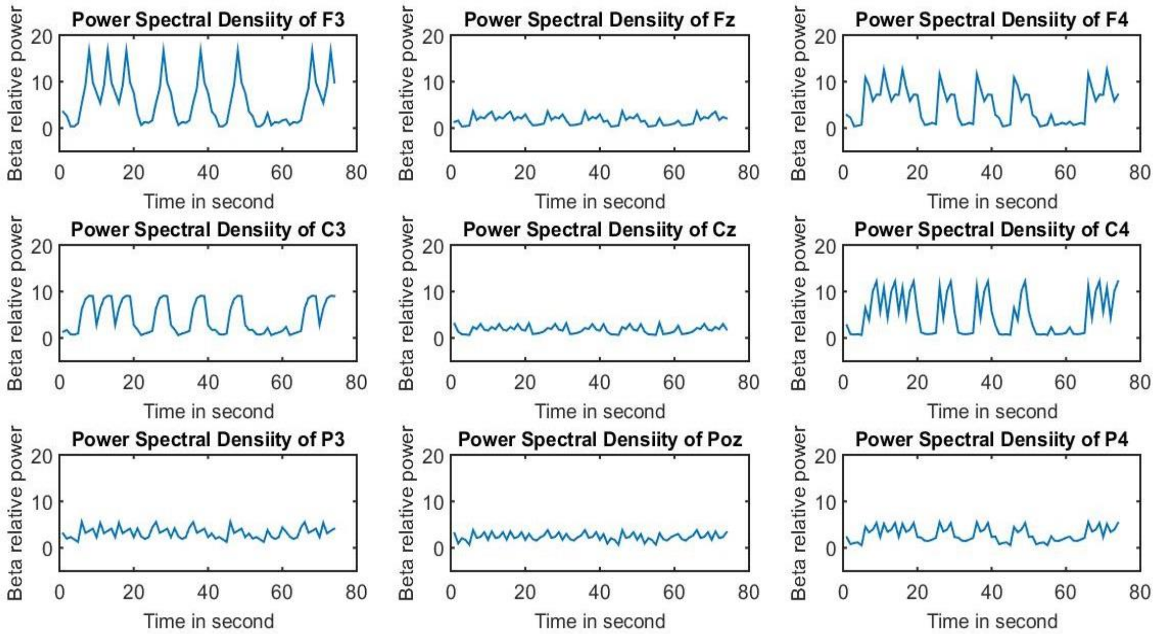

Fig. 5.5: Variation of PSD due to Transition of Alert and Resting State.

Among the three channels (F3, Fz, F4) for alertness monitoring we subsequently emphasize more on the F3 channel. So we proposes with supporting results that F3 channel is promising and shows responsible variation of the PSD for alertness detection for most of the volunteers participated in our research work. The signals used in this algorithm is combination of virtual driving, eyes open and eyes close with different frequency which is shown in Table 5.8.

Table 5.9: Task Arrangement and Duration for Testing.

Task	EO	VD	VD	VD	EC	VD	EC	VD	EO	VD	EO	EC	EC	VD
Duration (sec)	5	5	5	5	5	5	5	5	5	5	5	5	5	5

*EO = Eyes Open

**EC = Eyes Close

***VD = Virtual Driving

The distribution of the beta RP of the each participant is plotted in the Fig. 5.6 to Fig. 5.15 respectively of F3 channel. From the graphs it is clearly decipherable the transition of alert state in comparison with resting state and the value of RP varies with subject to subject.

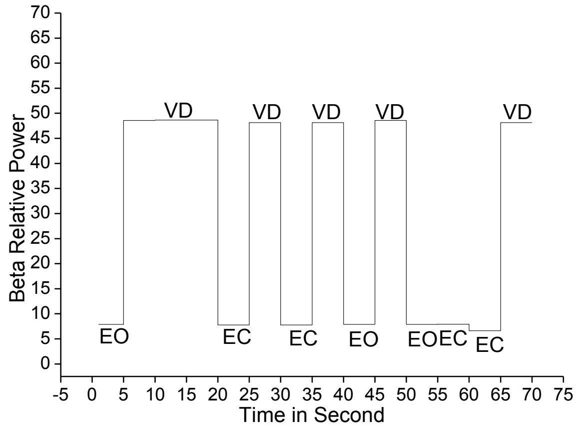

Fig. 5.6: Beta RP Variation of P1.

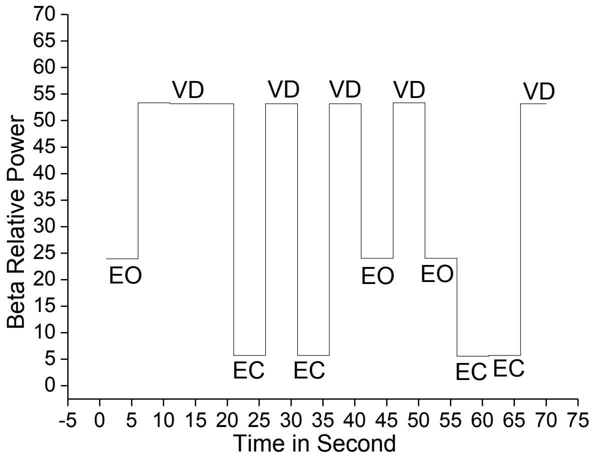

Fig. 5.7: Beta RP Variation of P2.

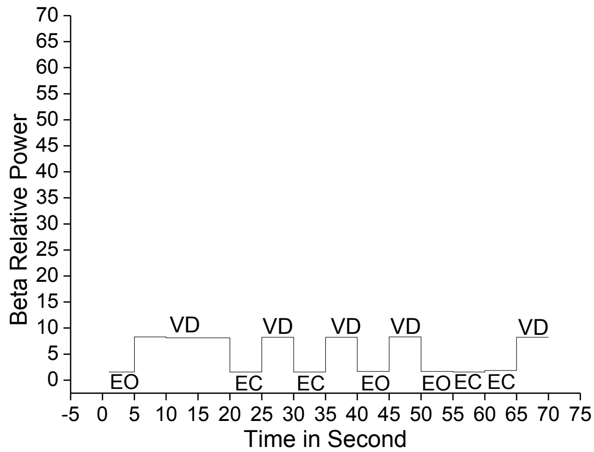

Fig. 5.8: Beta RP Variation of P3.

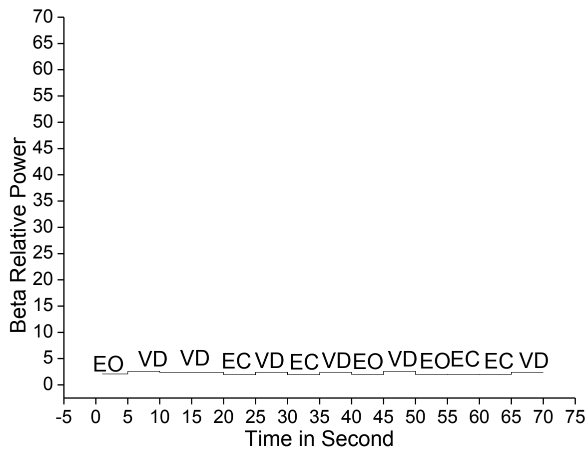

Fig. 5.9: Beta RP Variation of P4.

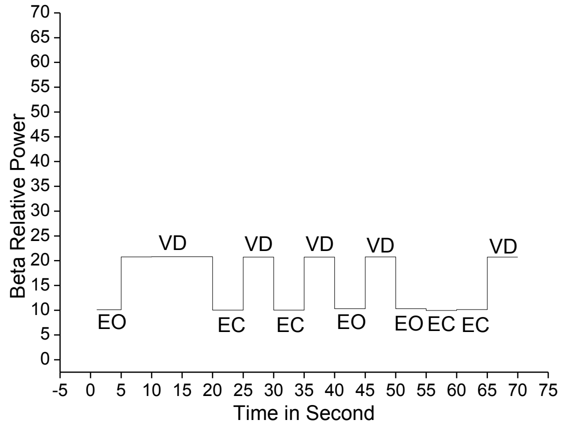

Fig. 5.10: Beta RP Variation of P5.

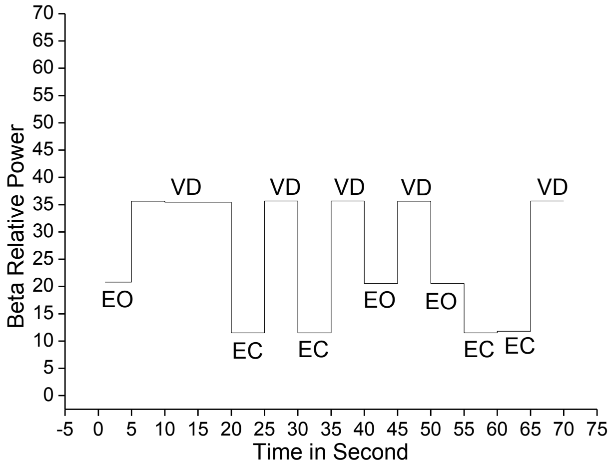

Fig. 5.11: Beta RP Variation of P6.

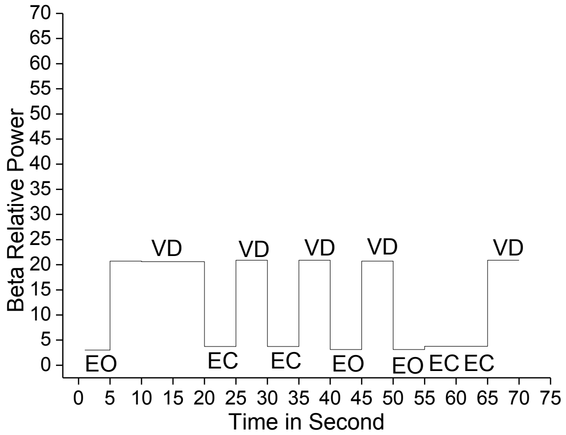

Fig. 5.12: Beta RP Variation of P7.

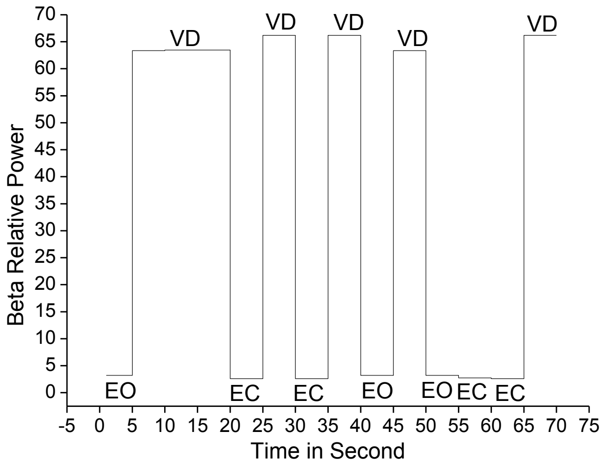

Fig. 5.13: Beta RP Variation of P8.

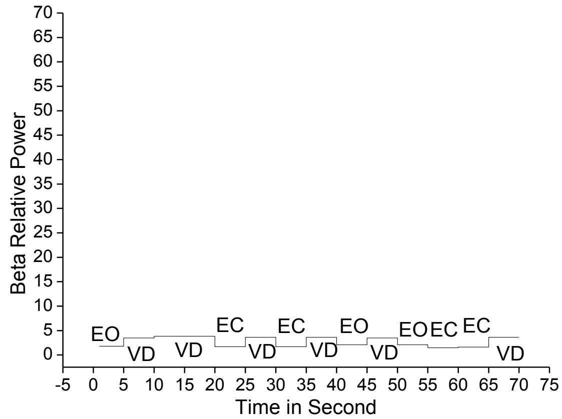

Fig. 5.14: Beta RP Variation of P9.

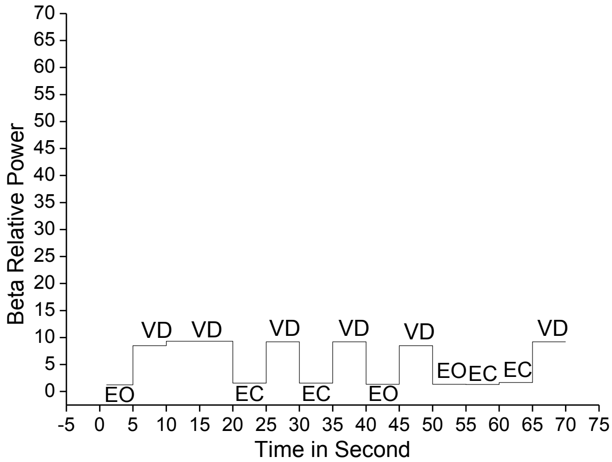

Fig. 5.15: Beta RP Variation of P10.

By selecting a threshold value between the intervals of the RP value of alertness state and resting state, it is possible to monitor the human concentration level. More difference in RP value will provide benefits like it will reduces the chances of making error decision. Table 5.10 shows the average relative power of eyes open (EO), eyes close (EC) and virtual driving (VD) and propose a threshold range for alertness monitoring of the individual participants.

Table 5.10: Proposed Threshold for Alertness Monitoring.

Subjects	Average RP of EO	Average RP of EC	Average RP of (VD)	Proposed Threshold Range (Average RP)
P1	5	7	52	20-40
P2	20	5	36	25-30
P3	5	1.5	10	7-8
P4	1.9	1.7	2.4	2.1-2.2
P5	7	10	36	15-30

P6	21	11	35	26-30
P7	2.5	2.5	18	10-15
P8	4	4	58	20-40
P9	1	1.25	5.5	3-4
P10	1	1.1	10	5-8

For classifying among alphabet counting and resting state (eyes close and open), the lowest average accuracy is 72% of five consecutive results and from the highest accuracy, 86.70% is the lowest. For virtual driving and resting state (eyes close and open), the lowest average accuracy is 76% of five consecutive results, from the highest accuracy, 93.3% is the lowest. By adopting this method alertness state can be classified effectively. From the Table 5.10 it is noticeable that P3, P4 and P9 have very limited range of threshold value with 1, 0.1 and 1, respectively. Being not attention for assigned task or electrode displacement or these participants could be BCI illiterate could result such low PSD variation. And P1 and P8 participants have wide range of threshold value of 20; can be because of performing the given task very well. This wide range of threshold value will support P1 and P8 for alertness monitoring without any almost any error as there is less chance of merging with EO and EC values. This proposed noble method for alertness monitoring is the main contribution of this part of the dissertation which has several scopes to practically implement.

5.5 Summary

EEG signals reflect the status of our mental state. Human alertness monitoring is very essential for performing governed task with efficiency. This research work provides effective methodology for alertness monitoring and classification. The classification results are very promising for alertness classification using the EEG signal. For monitoring alertness as threshold varies with respect to every user, to avoid or less error it is better to train user and after getting acceptance level of accuracy after several simulation then select the threshold value. Alertness monitoring for drivers or pilots may have unprecedented change by reducing the chances of road crushes that will save innumerable lives. Thus this proposed research work can be adopted during designing vehicles or in other sectors where alertness monitoring is out most important to reduce the degree of risk.

CHAPTER VI

Conclusion and Future Work

This section of the dissertation describes the summary of all the research works with objectives, methodologies and contributions. Finally provides some suggestions to improve these works to a higher level for future research.

6.1 Conclusion

EEG signal is very important to capture brain activity which in turn can represent the human behavior or neurological diseases. In our work we classified both two and three class MI movement EEG signal which can be adopted for MNDs treatment and also for BCI system. Our both methods show promising results that can be employed to design high accuracy system for the patients. Results also show that selected set of feature vectors is very effective for MI EEG signal classification.

Next part of this dissertation describes the epilepsy classification using EEG signal of patients with epilepsy and without epilepsy. In methodology, statistical features of the signals are extracted using DWT and selected features are used to classify normal, ictal and inter-ictal EEG data for epilepsy classification. Results show that our methods can classify the epilepsy with great accuracy.

In the last part illustrates the mental alertness classification and monitoring mythology for employing in working areas where alertness is very crucial. In our classification methodology we use PCA for extracting features more efficient way to get the highest accuracy. In alertness monitoring methodology PSD is used to determine user mental status. A threshold value can be proposed for individuals for monitoring alertness level.

All together if can be concluded that all these methods and techniques will help for further research as well as adopting in practical use for neurological disease treatment or in BCI design or even if require to monitor the alertness of the patients who suffer from ADHS or due to mental fatigue as they are successful and reliable methods.

6.2 Scopes for Future Work

This dissertation may create certain scopes for further research works which can be describe as:

- These research works can be inspiration for the researchers for investigating the most responsible feature selection method for classification or detecting neurological diseases or mental stats. Because it's cumbersome to take decision only having an eye view so it is very important for EEG signal analysis and implementation.

- Researchers may be motivated to make practical implementation of the described work.

- These methodologies can be employed for other neurological disease detection and human behavior monitoring.

- From the very beginning EEG signal is being used to find out changes of human behavior and mental status but most efficient method is still necessary so more research require to increase the efficiency.

- It can be a motivation to design a mental alertness monitoring device for using in surveillance or other sectors where needed.

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List of Publications

[1] **Md. Mamun or Rashid** and Mohiuddin Ahmad, "Classification of motor imagery hands movement using Levenberg-Marquardt Algorithm based on statistical features of EEG signal", Proceedings of the 3rd International Conference on Electrical Engineering and Information & Communication Technology (iCEEiCT 2016), MIST, 22-24 September 2016.

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[3] **Md. Mamun or Rashid** and Mohiuddin Ahmad, "Epileptic seizure classification using statistical features of EEG signal", Proceedings of the International Conference on Electrical, Computer and Communication Engineering (ECCE 2017), CUET, 16-18 February 2017.