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INSTITUTE OF ENGINEERING
PULCHOWK CAMPUS**

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**A 3-channel Active Electrode EEG Device for the Classification of
Motor Imagery Brainwaves for Brain Computer Interface**

**by
Saroj Bista**

**A THESIS
SUBMITTED TO THE DEPARTMENT OF ELECTRONICS AND
COMPUTER ENGINEERING IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN
INFORMATION AND COMMUNICATION ENGINEERING**

**DEPARTMENT OF ELECTRONICS AND COMPUTER ENGINEERING
LALITPUR, NEPAL**

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Brainwaves for Brain Computer Interface**

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Thesis Supervisor

Dr. Nanda Bikram Adhikari

A thesis submitted in partial fulfillment of the requirements for the
degree of Masters of Science in Information and Communication
Engineering

Department of Electronics and Computer Engineering
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November, 2017

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RECOMMENDATION

The undersigned certify that they have read and recommended to the Department of Electronics and Computer Engineering for acceptance, a thesis entitled “**A 3-channel Active Electrode EEG Device for Classification of Motor Imagery Brainwaves for Brain Computer Interface**”, submitted by **Saroj Bista** in partial fulfillment of the requirement for the award of the degree of “**Master of Science in Information and Communication Engineering**”.

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The thesis entitled “**A 3-chanel Active Electrode EEG Device for Classification of Motor Imagery Brainwaves for Brain Computer Interface**”, submitted by **Saroj Bista** in partial fulfillment of the requirement for the award of the degree of “**Master of Science in Information and Communication Engineering**” has been accepted as a bonafide record of work independently carried out by him in the department.

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ABSTRACT

This thesis work presents a cost effective method to record brainwave signals using three channel active electrode EEG device and classify brainwaves related to motor imagery (MI) left and right hand movement, based on electroencephalography (EEG) measured from the central lobe, that could be used for the Brain Computer Interface (BCI) systems . The goal of this thesis is to use Independent Component Analysis (ICA) for the removal of EEG artifacts, and then extract the brainwaves features for MI left hand and MI right hand movement using Wavelet Decomposition (WD). The ‘Morlet’ mother wavelet is used for wavelet decomposition as it shows better performance for analysis of non-stationary biomedical signals like EEG. The brainwave features like Maximum Power among all decomposition level (MMP), Frequency corresponding to MMP (MAF), and Maximum Amplitude of the signal with MAF (MMA) is chosen as the classification features for the classification of MI brainwaves. The classification of MI brainwave signals is done using Linear Discriminant Analysis (LDA) which showed the accuracy of 81.6%. Thus, the designed three channel active electrode EEG device used showed good performance for recording EEG signals. Furthermore, signal preprocessing algorithm ICA, feature extraction method Wavelet Decomposition, and classification method LDA showed good performance for the classification of MI left hand and MI right hand activities.

Keywords: BCI, EEG, LDA, ICA, Wavelet Decomposition, Morlet, MI

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LIST OF ABBREVIATION

AA	: Average Amplitude
AF	: Approximate Frequency
AP	: Average Power
AUC	: Area Under Curve
BCI	: Brain Computer Interface
CMRR	: Common Mode Rejection Ratio
DIP	: Dual In-line Package
DWT	: Discrete Wavelet Transform
EEG	: Electroencephalogram
EMG	: Electromyography
EOG	: Electrooculography
FFT	: Fast Fourier Transform
GA-ANN	: Genetic Algorithm and Artificial Neural Networks
HHT	: Hilbert-Hung Transform
IC	: Integrated Circuits
ICA	: Independent Component Analysis
LDA	: Linear Discriminant Analysis
LH	: Left Hand
mA	: Minimum Amplitude
mP	: Minimum Power
MA	: Maximum Amplitude
MI	: Motor Imagery
MP	: Maximum Power
PCB	: Printed Circuit Board
PV	: Power Variance
RH	: Right Hand
ROC	: Receiver Operating Characteristics
SVM	: Support Vector Machines
WD	: Wavelet Decomposition

CHAPTER 1

INTRODUCTION

1.1 Background of Study

Brain is composed of billions of brain cells called neurons, which are interconnected to each other through synapses to form a neural network (10^{11} neurons and 10^4 connections in human brain). When brain cells (neurons) are activated, the electrical activity occurs in brain. The electrical activity in brain is due to Na^+ , K^+ , Ca^+ , and Cl^- ions that are pumped through channels in neuron membrane in the direction governed by membrane potential[2]. Brainwaves are produced by electrical activities from masses of neurons communicating with each other. The brain waves can be detected using sensitive medical equipment (such as EEG), which measures the electrical activity generated by brain structure over areas of the scalp.

1.1.1 Brain Anatomy

For the recording of brain wave signals, the knowledge of brain anatomy is required. The brain consists of different regions like frontal lobe, occipital lobe, temporal lobe, central lobe, parietal lobe responsible for processing of different types of human senses and activities. Different types of brain waves are dominant in different regions of brain. So, for the recording of the brain waves it is must to know that what kinds of brain waves are dominant in which brain region, so that we can place the electrodes in the scalp over those brain regions. The functions of different brain regions and the position for electrode placement is shown in Table 1.1 and Figure 1.1 respectively.

1.1.2 Brain Waves

Our brainwaves change according to what we are doing and feeling. For instance, the brain waves of a sleeping person are vastly different than the brainwaves of someone wide awake. When slower brainwaves are dominant we can feel tired, slow, sluggish,

Table 1.1: Functions of different Brain Regions

Brain Regions	Functions
Frontal Lobe	associated with reasoning, planning, parts of speech, movement, emotions, and problem solving
Occipital Lobe	associated with visual processing
Temporal Lobe	associated with perception and recognition of auditory stimuli, memory, and speech
Parietal Lobe	associated with movement, orientation, recognition, perception of stimuli
Cerebellum	balance, muscular co-ordination

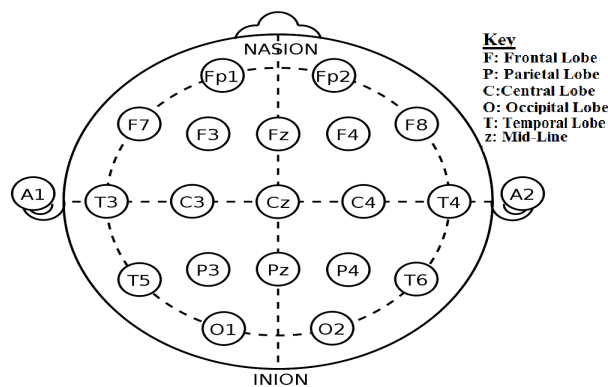


Figure 1.1: Brain regions for electrode placement for EEG recording[1]

or dreamy. The higher frequencies are dominant when we feel wired. or hyper-alert. Brainwave speed is measured in Hertz (cycles per second) and they are divided into bands delineating slow, moderate and fast waves[1].

- **Delta Waves (0.5 to 4 Hz)**

Delta brainwaves are the slowest but loudest brainwaves (low frequency and deeply penetrating, like a drum beat). They are generated in deepest meditation and in dreamless sleep. Healing and regeneration are stimulated in this state, and that is why deep restorative sleep is so essential to the healing process.

- **Theta Waves (4 to 8 Hz)**

Theta brain waves are considered brain waves that oscillate between the frequencies of 4 Hz to 8 Hz (cycles per second). Theta brainwaves occur most often in sleep but are also dominant in the deep meditation. In theta, our senses are withdrawn from the external world and focused on signals originating from within. It is that twilight state which we normally only experience fleetingly as we wake or

drift off to sleep.

- **Alpha Waves (8 to 13 Hz)**

Alpha brain waves are brain wave activity with oscillations that range from 8 Hz to 13 Hz (cycles per second). Alpha brain waves are dominant during quietly flowing thoughts, and in some meditative states. Alpha is the power of now, being here, in the present. Alpha is the resting state for the brain. Alpha waves aid overall mental co-ordination, calmness, mind/body integration and learning.

- **Beta Waves (13 to 38)**

Beta brainwaves dominate our normal waking state of consciousness when attention is directed towards cognitive tasks and the outside world. Beta is a fast activity, present when we are alert, attentive, engaged in problem solving, judgment, decision making, and engaged in focused mental activity.

Beta brainwaves are further divided into three bands-

Low Beta (13-15Hz)- focused thinking, or musing.

Mid Beta (15-22Hz) - states of high engagement.

High Beta (22-38Hz) - highly complex thought, integrating new experiences, high anxiety, or excitement.

- **Gamma Waves (38 to 90 Hz)**

Gamma brainwaves are the fastest brain waves and relate to simultaneous processing of information from different brain areas. The mind has to be quiet to access gamma brainwave frequencies. Gamma was traditionally dismissed as 'spare brain noise' until researchers discovered it was highly active when in states of universal love, altruism, and the higher virtues.

1.1.3 BCI Systems

A brain computer interface (BCI) system provides a communication channel between a user's brain and a device the user intends to control. A successful BCI system enables a person to control some aspects of his or her environment (such as lights in the room, a television, a neural prosthesis or a computer) by analyzing his or her brainwave signals. Specific features of the user's brain activity (or "neurological phenomenon") that relate

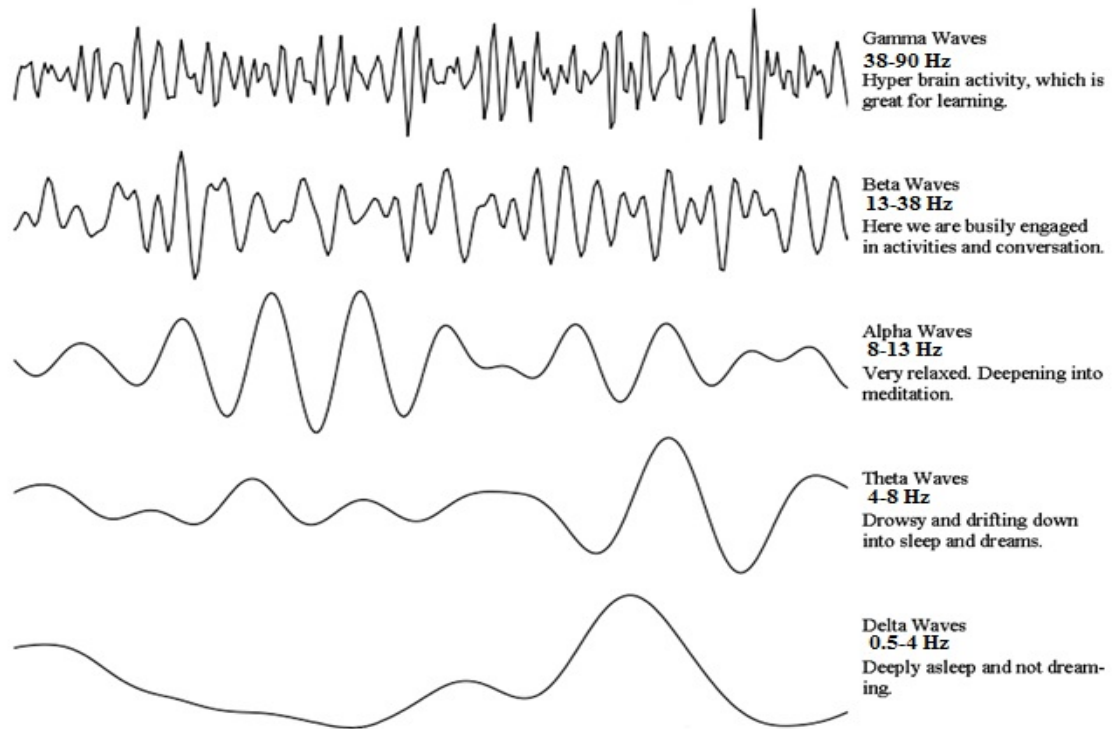


Figure 1.2: Different types of brainwaves[1]

to their intent to control a device are measured[3]. These features are then translated to control commands that are used to control the device.

1.1.4 Artifacts in BCI Systems

The EEG has a very poor spatial resolution due to the effects of volume conduction over the cortical surface [8]. More importantly, the amplitude of the EEG is often contaminated with other electrical activity, which may be observed in the signal but is not related to brain activity. Such additional signals are referred to as artifacts and may arise from external sources of noise, such as power lines and electrical equipment, or internally from the participant using the BCI. Artifacts are undesired signals that can introduce significant changes in brain signals and ultimately affect the neurological phenomenon[4]. There is a need to remove each of these artifact types prior to analysis of the EEG and its use in BCI control, to ensure that any control achieved may be genuinely attributed to the participants brain activity. However, this is a nontrivial task. Artifacts, particularly participant generated artifacts, occupy overlapping spectral bands with the neurological activity of interest, may occur on many or all channels, and often

have a larger amplitude than the EEG signal components of interest.

Artifacts are attributed either to non-physiological sources (such as 50/60 Hz power-line noise, changes in electrode impedances, etc.) or physiological sources, such as potentials introduced by eye or body movements. Non-physiological artifacts are usually avoided by proper filtering, shielding, etc. Physiological artifacts such as EOG and EMG artifacts are much more challenging to handle than non-physiological ones. Moreover, controlling them during signal acquisition is not easy. There are different ways of handling these types of artifacts in BCI systems.

1.2 Problem Statements

The brain is the control unit of the body; it controls each and every action of the body like senses, movement, emotions and many more. But sometimes due to various disabilities and diseases, people are unable to control their body functions, for example: a person in coma (a state of unconsciousness in which a person cannot be awakened; fails to respond normally to painful stimuli, light, or sound; lacks a normal wake-sleep cycle; and does not initiate voluntary actions) has some parts of brain working , a person with paralysis cannot move his/her paralyzed body part. In these cases, the brain of the persons are working but the information cannot be relayed to the body parts. In such medical conditions, by recording the brainwaves activities and analyzing them, we can know the medical status of the person and find out the way to get them out of it. Not only this, but also we can use the brainwave activities to perform various regular task using BCI which can be of great help for the handicapped people to live regular life.

1.3 Objective of Study

The objective of this thesis work is to design three channel active electrode EEG device, record the motor imagery brainwaves and classify the brainwaves for motor imagery actions (imagined left hand and right hand movement) of a person.

CHAPTER 2

LITERATURE REVIEW

In this section, we describe the related work on brainwaves and the application of the brain waves on various fields. In past few decades, many authors and researchers have contributed in brainwaves, their significance and their applications. Some of the honorable works in the field of brainwaves related to this thesis work are mentioned here.

Brainwaves are subjected to various noise signals called artifacts. A large number of research has been carried out to remove these artifacts from the EEG signal so the further processing of the EEG signals becomes easy and accurate. The authors in papers [5], [6], and [7] explains various methods (online as well as offline) to remove artifacts from the recorded raw brainwave signals. The authors in paper [6] proposed a fully automated and online artifact removal method for the electroencephalogram (EEG) for use in brain-computer interfacing (BCI). The method (FORCe) was based upon a novel combination of wavelet decomposition, independent component analysis, and thresholding. FORCe was able to operate on a small channel set during online EEG acquisition and did not required additional signals (e.g., electrooculogram signals). The method was able to remove a wide range of artifact types including blink, electromyogram (EMG), and electrooculogram (EOG) artifacts. Similarly, authors in paper [8] had explained a Quantum Neural Network based EEG filtering techniques for the removal of artifacts from EEG signals. According to authors, it is a novel neural information processing architecture inspired by quantum mechanics and incorporating the well known Schrodinger wave equation. The architecture proposed by the authors referred to as recurrent quantum neural network (RQNN) could characterize a nonstationary stochastic signal as time-varying wave packets. The RQNN filtering procedure was applied in a two-class motor imagery-based braincomputer interface where the objective was to filter electroencephalogram (EEG) signals before feature extraction and classification to increase signal separability.

The brainwaves signals has also been used for biometric authentication systems. Brain signals has some peculiarities, not shared by the most commonly used biometrics, such

as face, iris, and fingerprints, with reference to privacy compliance, robustness against spoofing attacks, possibility to perform continuous identification, intrinsic liveness detection, and universality. These peculiarities make the use of brain signals appealing. The authors in papers [9], [10], and [11] had explained the various methods to use brain-wave signals for biometric user authentication. According to these papers, EEG-based authentication systems mainly composed of four primary modules: data acquisition, pre-processing, feature extraction and finally classification. Usually EEG biometric authentication systems are evaluated in two modes; identification and verification. The accuracy of the system is usually evaluated in identification mode using average correct recognition rate (CRR) or genuine acceptance rate (GAR). The performance of EEG biometric authentication systems depends on four important factors: namely, the acquisition protocol of EEG (the protocol followed in recording EEG signals), pre-processing technique, features extracted from EEG signals and the classification scheme.

The authors in papers [12], [13], and [14] had explained various feature extraction methods like DWT, FFT, HHT and classification algorithms like LDA, SVM, GA-ANN, Random Forest etc. for the classification of motor imagery brainwave signals. The authors in paper [12] presented a method for classifying the off-line experimental electroencephalogram (EEG) signals from the BCI Competition 2003 and achieved higher accuracy. The method had three main steps. First, wavelet coefficient was reconstructed by using wavelet transform in order to extract feature of EEG for mental tasks. At the same time, in frequency extraction, they used the AR model power spectral density as the frequency feature. Second, they combine the power spectral density feature and the wavelet coefficient feature as the final feature vector. Finally, linear algorithm was introduced to classify the feature vector based on iteration to obtain weight of the vector's components. The classified result showed that the effect using feature vector is better than just using one feature. Similarly, the paper [13] paper presents the classification of a three-class mental task-based brain computer interface (BCI) that used the Hilbert-Huang transform (HHT) for the features extractor and fuzzy particle swarm optimization with cross mutated-based artificial neural network (FPSOCM-ANN) for the classifier. The experiments were conducted on five able-bodied subjects and five patients with tetraplegia using electroencephalography (EEG) signals from six channels, and different time-windows of data were examined to find the highest accuracy.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Block Diagram of Self Made EEG Device

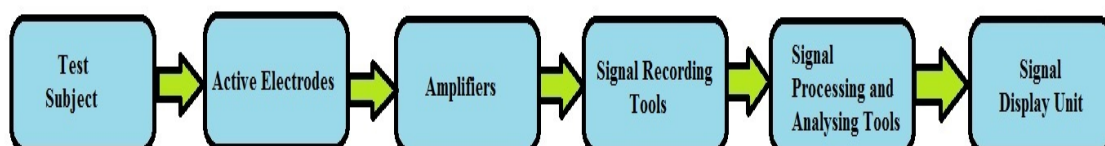


Figure 3.1: System Block Diagram

3.1.1 Test Subject

Any person whose brainwaves are to be recorded and detected by using the active electrodes of EEG device are called test subject.

3.1.2 Active Electrodes

Active Electrodes are the electronic circuit with filters and amplifier that are placed in the frontal regions of test subject's head for the detection of the brainwaves. These are the sensors used for the conversion of brain signals into electronic signals. The active electrodes are constructed using operational amplifier which consists of the circuit that implements a low-pass filter of cutoff frequency around 100Hz and a unity gain amplifier. The circuit diagram for the construction of active electrode is shown in Figure 3.2.

3.1.3 Amplifiers

After the detection of the brain wave signals by the active electrodes, the signal is amplified by using amplifiers. The brain wave signals are very low voltage signals with magnitude ranging from 50 to 500 microvolts, so for further processing of the

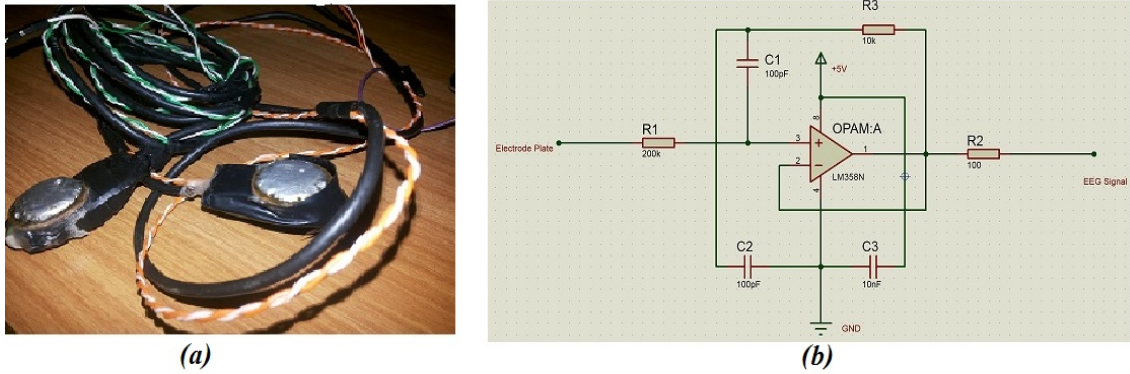


Figure 3.2: (a) Active Electrodes (b) Internal Schematic of Active Electrode

signals these low voltage signals are amplified by using amplifiers. For the propose of amplification, an Instrumental Amplifier is used as they have better CMRR (Common Mode Rejection Ratio). The gain of the instrumentation amplifier can be set by using a single resistor. The circuit diagram for the construction of the amplifier circuit using instrumentation amplifier is shown in Figure 3.3.

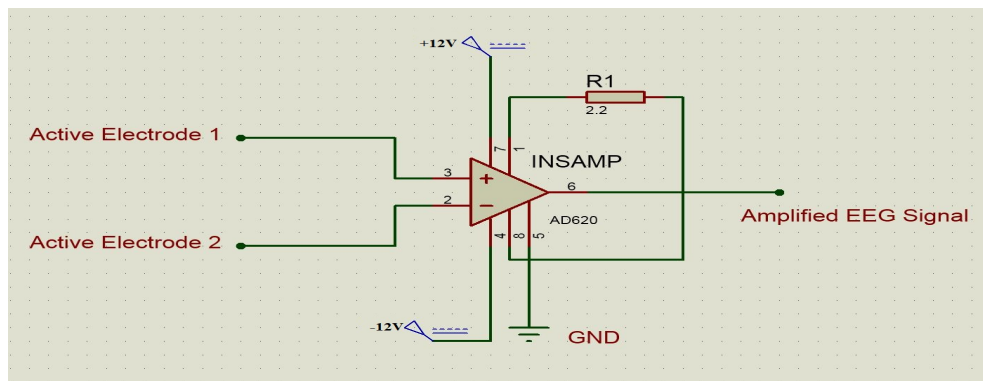


Figure 3.3: Schematic Diagram of Amplifier

3.1.4 Signal Recording Tools

After amplification of a low voltage brain waves signals, they are send to the signal recording tools to record for the further processing. The signal recording tools consists of an Arduino Hardware and Matlab Software communicating via USB connection. The eeg signal from the amplifier are measured using analog input pin of the Arduino with the help of MATLAB. Thus, the eeg signals are recorded and displayed in MATLAB with the help of Arduino. For interfacing and enable communication of Arduino with Matlab, we need to install Hardware Support Package for Arduino in Matlab. A portion

of an application designed in MATLAB is used as user interface to record and store the brainwave signals from three channels of the eeg recording device.

3.1.5 Signal Processing and Analysis Tools

The recorded brain wave signal contains all types of brain wave signals with frequency ranging from 1Hz to 100Hz along with the line frequency and other artifacts. A notch filter of 50Hz is used to remove the line frequency artifacts from the recorded eeg signal. Since, the brain wave signals are recorded using MATLAB, the recorded signals are pre-processed for classification in MATLAB. The pre-processing is done by using Fast ICA algorithm, which removes the ocular artifacts from the brainwaves. Further, each independent component is subjected to a mean-filtering before using the components for feature extraction. The feature extraction is done by using wavelet transform with 'morlet' as mother wavelet. After feature extraction, the brainwave signals are classified using linear discriminant analysis. For all these steps, a MATLAB application has been designed which provides better UI for the signal processing and analysis as shown in Figure 3.4.

3.1.6 Signal Display Unit

The resulting brainwave signals and the intermediate signals obtained during the course of signal processing and analyzing will be displayed on the Monitor.

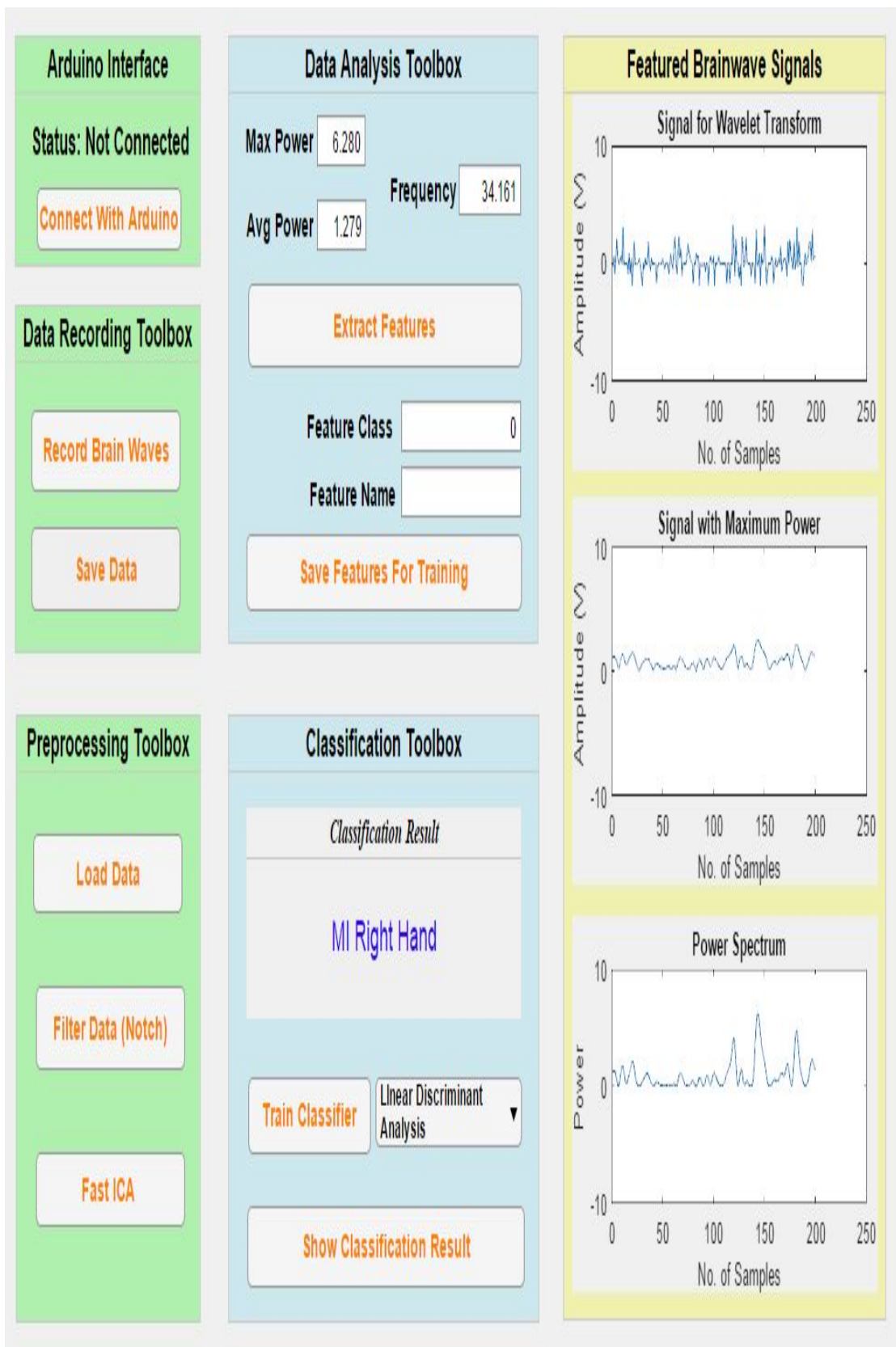


Figure 3.4: MATLAB Application used as signal recording, signal processing, and signal analysis tool

3.2 System Flowchart

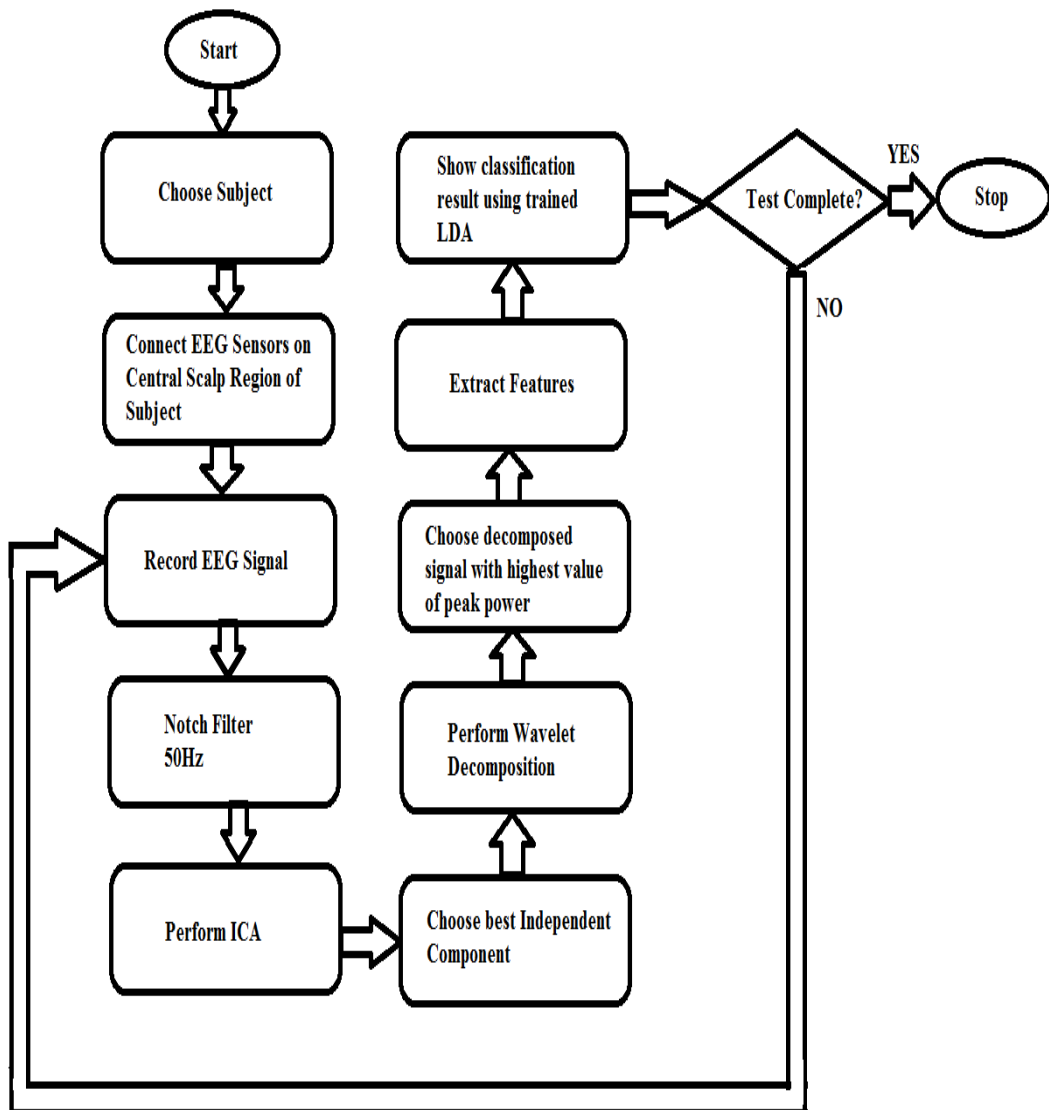


Figure 3.5: Flow Chart

The procedure starts with choosing a subject whose brainwaves needs to be classified. The EEG sensors of the proposed design must be connected to the specified scalp region of the subject for the recording of the EEG signal. The recorded signal should be filtered to remove power line noise followed by independent component analysis. The procedure continues with choosing best independent component which is subjected to wavelet decomposition using. A decomposed signal with highest value of peak power is chosen for feature extraction. The trained linear discriminant algorithm finally classify the signal on the basis of extracted features.

CHAPTER 4

SYSTEM IMPLEMENTATION AND ANALYSIS

4.1 System Implementation

4.1.1 Hardware Requirements

The hardware and major electronic components required for the implementation of the project are:

- **Arduino Uno:** It is the hardware development platform which consists of AT-MEGA32 micro-controller. It is used to convert analog brain wave signal into digital and feed the digital signal to computer for further processing in MATLAB. The active electrode sensor output are supplied to the non-inverting input pin of instrumentation amplifier. The output of each amplifier is supplied to the analog pins of the Arduino Uno.



Figure 4.1: Arduino Uno (Source: arduino.org)

- **LM358:** It is the 8 pin DIP operational amplifier IC used to design Active Electrodes. It consists of two operational amplifiers. Among two op-amp of LM358 only one has been used for the detection of brainwave signals.

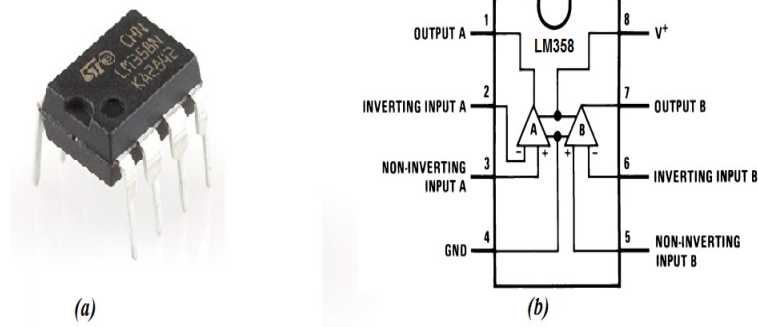


Figure 4.2: (a) LM358 DIP (b) LM358 Internal Schematic and Pin Diagram (Source: sparkfun.com)

- **AD620:** It is the 8 pin DIP instrumentation amplifier IC used for the amplification of low voltage brain wave signals. It requires only one external resistor to set gains of 1 to 100,000. A resistor of 2.2 ohms has been used to provide a gain of about 22,000.

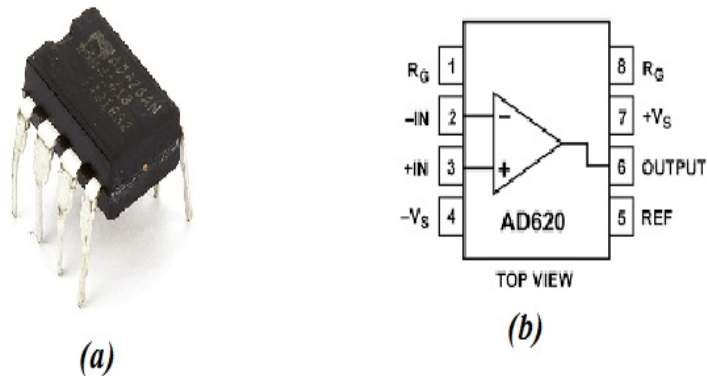


Figure 4.3: (a) AD620 DIP (b) AD620 Pin Diagram (Source: rhydolabz.com)

- **Insulated Cables:** The insulated cables are used to connect the active electrodes to the Arduino. They will help to reduce the external noise that may be coupled with the actual brain wave signals.
- **Power Supply:** The DC power supplies of 5V, 12V and -12V are required to power the electronic circuits and devices like Arduino, Amplifiers and Active Electrodes.

4.1.2 Software Requirements

The software used for the implementation of the thesis work are:

- **Arduino IDE:** It is used to program Arduino Uno hardware for the implementation of conversion of detected analog alpha brain wave signals to digital and send the signal to MATLAB .
- **MATLAB:** MATLAB has been used to receive the three channel brainwave signals, process it further, and display the signals, and perform all the analysis and classification of the brainwaves. All the algorithm used for signal filtering, analysis, and classification has been implemented in MATLAB.
- **Eagle:** This PCB design tool has been used to design the PCB (printed circuit board) layout for the various hardware circuits (active electrodes, amplifiers) used in the thesis work.
- **TeXstudio:** This software tool has been used for proper documentation of thesis work using LATEX.

4.1.3 Hardware Cost

The cost required for the development of 3-channel active electrode hardware eeg device is in Table 3.1.

Table 4.1: Hardware Cost

S.N	Item/Component	Quantity	Rate(NRS)	Cost(NRS)
1	Arduino Uno	1	2000	2000
2	Operational Amplifier (LM358)	4	50	200
3	Instrumentation Amplifier (AD620)	3	750	2250
6	Power Supply (5V, 12V, -12V)	1	3500	3500
8	Copper Clad Board	2	250	500
9	Insulated Cables	5 mtrs	200/mtr	1000
11	Electronic Components (Resistors, Capacitors)	-	-	1000
12	Jumper Wires	20	10	200
13	Miscellaneous	-	-	2500
	Total			13150

4.1.4 Data Recording

The brainwaves signals are recorded using MATLAB. The analog brainwaves signals are converted to digital using Arduino and the digital signal are send to MATLB for recording. The brainwave signals of the test subject will be recorded according to following experimental paradigm:

- Three bipolar recordings (C3, Cz, and C4) will be recorded with a sampling frequency of 150 Hz. The electrode position Fz served as EEG ground.
- Each subject was participated in ten sessions on two different days within a week. Each session was about 30 seconds long in which the subject was asked to close his/her eyes and imagine movement of his/her left hand or right hand. In each session 250 samples of brainwave voltage was recorded for a MI action. Therefore, a total of 10 MI data (5 for MI left hand and 5 for MI right hand) was obtained from each subject.

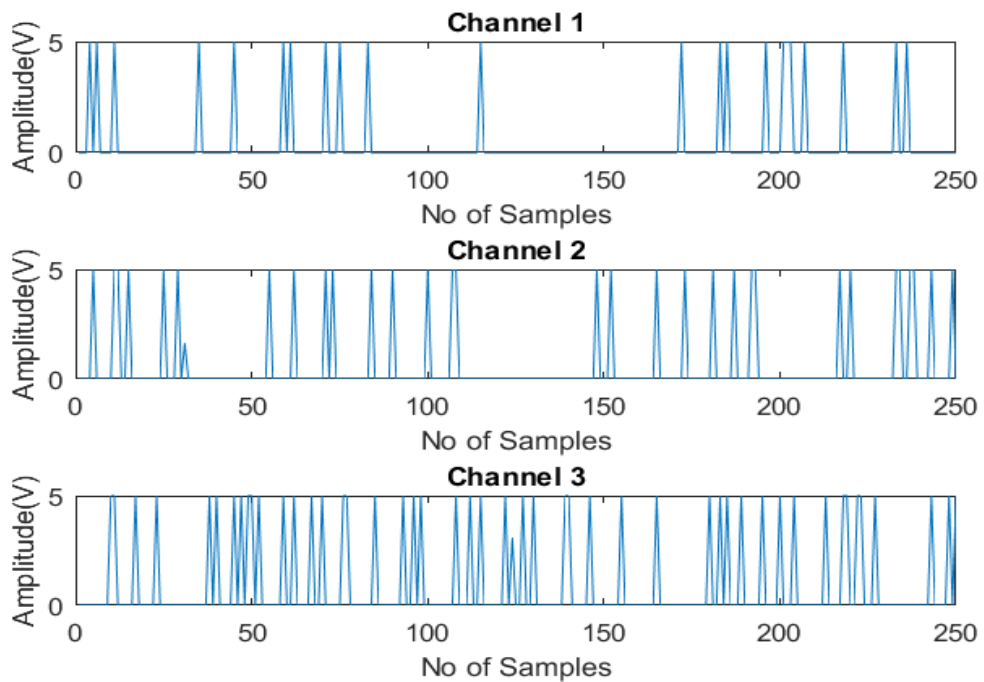


Figure 4.4: Raw EEG signals recorded from three channel EEG device

4.1.5 Data Calibration

The raw EEG data recorded from self made EEG device is calibrated by comparing the raw data recorded from MindWave headset of NeuroSky. The MindWave headset of NeuroSky is a bluetooth powered device which can record EEG data from its sensor attached to the forehead of the Subject. The data from the MindWave headset are stored in the internal device buffer of size 512 Bytes which can be read from the bluetooth interface. This headset records EEG data in continuous asynchronous mode by overwriting the previous data after the buffer becomes full. The data from Mind Wave headset is 8 bit data in the range of 0 to 255, which can be converted into voltage of range 0 to 5 Volts by using simple formula as shown in Equation 3.1.

$$D_V = \frac{D_B}{255} * 5V \quad (4.1)$$

where D_V is data obtained in Volts and D_B is data recorded in bits.



Figure 4.5: MindWave Headset of NeuroSky used for data calibration (*Source: neurosky.com*)

For the calibration of data recorded from self made EEG device, 200 samples of data each are recorded from both the devices from same Subject under same conditions. The data calibration is done by using Simple Moving Average Filter (SMAF). The data recorded from the self made EEG device is filtered using SMAF and the filtered data and the data from the MindWave headset were compared in terms of variance:

Variance of data recorded from MindWave headset of NeuroSky= 2.92

Variance of Uncalibrated data from self made EEG device=6.20

Variance of Calibrated data from self made EEG device= 2.27

It showed that calibrated data from self made EEG device was more similar to the data recorded by MindWave headset . Thus, the calibrated data was obtained for the further processing of the signal. The signal comparison between uncalibrated data and calibrated data with MindWave data is shown in Figure 3.11 and Figure 3.12 respectively.

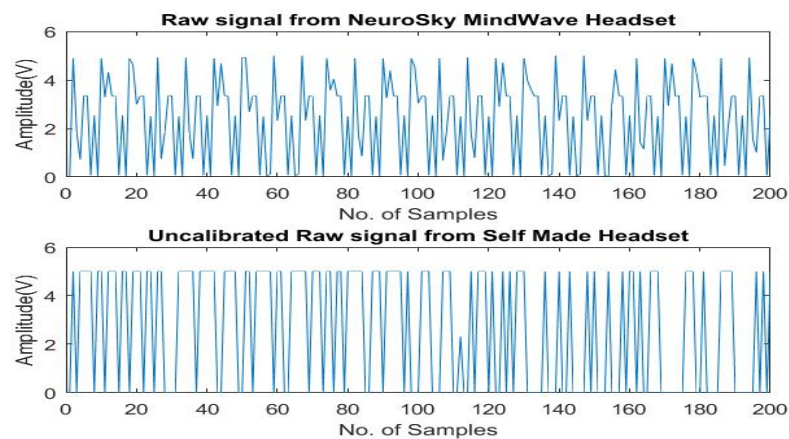


Figure 4.6: Signal comparison between uncalibrated raw EEG signal from self made EEG device and raw EEG signal from MindWave headset

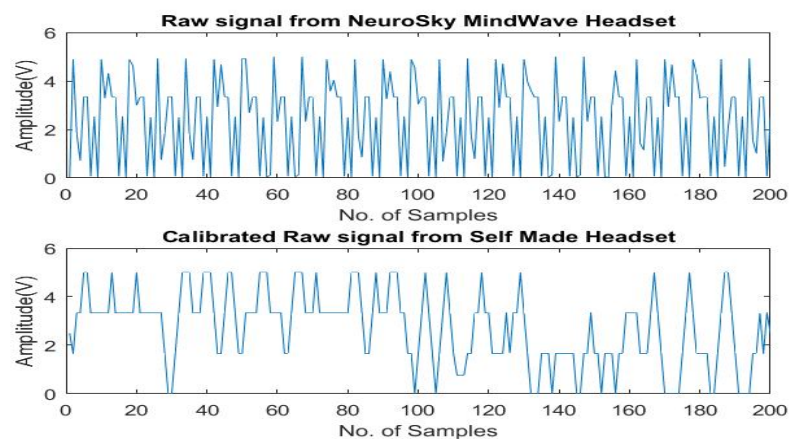


Figure 4.7: Signal comparison between calibrated raw EEG signal from self made EEG device and raw EEG signal from MindWave headset

4.1.6 Preprocessing

For the removal of artifacts, the recorded data is preprocessed. The preprocessing has been done by using a notch filter (50Hz) to remove power-line noise followed by ICA. The ICA removes the EOG and EMG artifacts from the recorded brainwave signals.

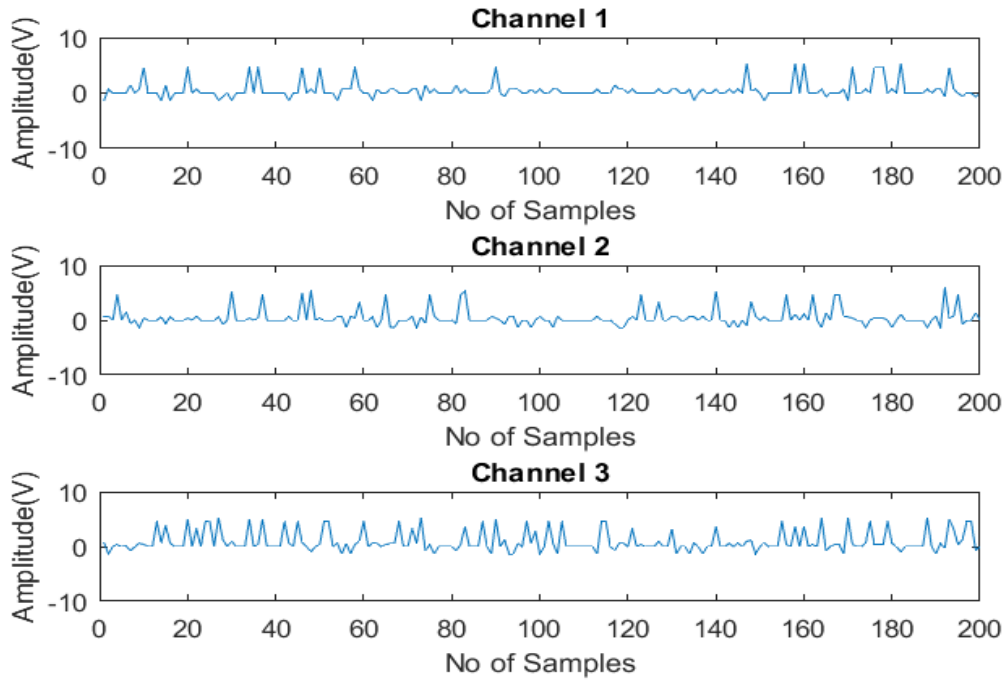


Figure 4.8: EEG signals after removing 50Hz power line artifacts using Notch Filter

Independent component analysis (ICA) attempts to separate multivariate signals into subcomponents which are maximally statistically independent from one another. The EEG is assumed to arise from the summed electrical activity generated from multiple independent sources. ICA attempts to estimate the mixing process which gave rise to the EEG from these sources and then, by inverting the mixing matrix, to attempt to reconstruct the sources[7].

Formally, this may be defined as

$$x = Ws \quad (4.2)$$

where x denotes the EEG signals recorded from the scalp, s the original dipole sources from which the EEG originates, and W the linear mixing matrix.

The data preprocessing was done before applying ICA algorithm to the filtered data.

The preprocessing techniques that make the problem of ICA estimation simpler and better conditioned are as follows[15]:

- **Centering**

The most basic and necessary preprocessing is to center x , i.e. subtract its mean vector $m = E\{x\}$ so as to make x a zero-mean variable. This implies that s is also zero-mean.

This preprocessing is done to simplify the ICA algorithms. After estimating the mixing matrix W with centered data, we can complete the estimation by adding the mean vector of s back to the centered estimates of s . The mean vector of s is given by $A^{-1}m$, where m is the mean that was subtracted in the preprocessing.

- **Whitening**

Another useful preprocessing strategy in ICA is to first whiten the observed variables. This means that before the application of the ICA algorithm (and after centering), we transform the observed vector x linearly so that we obtain a new vector \tilde{x} which is white, i.e. its components are uncorrelated and their variances equal unity. In other words, the covariance matrix of \tilde{x} equals the identity matrix:

$$E\{\tilde{x}\tilde{x}^T\} = I \quad (4.3)$$

One popular method for whitening is to use the eigen-value decomposition (EVD) of the covariance matrix $E\{xx^T\} = EDE^T$, where E is the orthogonal matrix of eigen vectors of $E\{xx^T\}$ and D is the diagonal matrix of its eigenvalues, $D = \text{diag}(d_1, \dots, d_n)$. $E\{xx^T\}$ can be estimated in a standard way from the available sample $x(1), \dots, x(T)$. Whitening can now be done by:

$$\tilde{x} = ED^{-1/2}E^T x \quad (4.4)$$

where, the matrix $D^{-1/2}$ is computed by a simple component-wise operation as $D^{-1/2} = \text{diag}(d_1^{-1/2}, \dots, d_n^{-1/2})$.

The application of ICA method on three channel EEG signals, three independent components (IC1, IC2, IC3) are generated as shown in Figure 4.9. Among these there inde-

pendent components, only one component with low artifacts is chosen for the wavelet decomposition. For the selection of independent component, mean amplitude and maximum amplitude of each component is calculated. The component with positive value of mean amplitude having lowest value of maximum amplitude is chosen for the further processing.

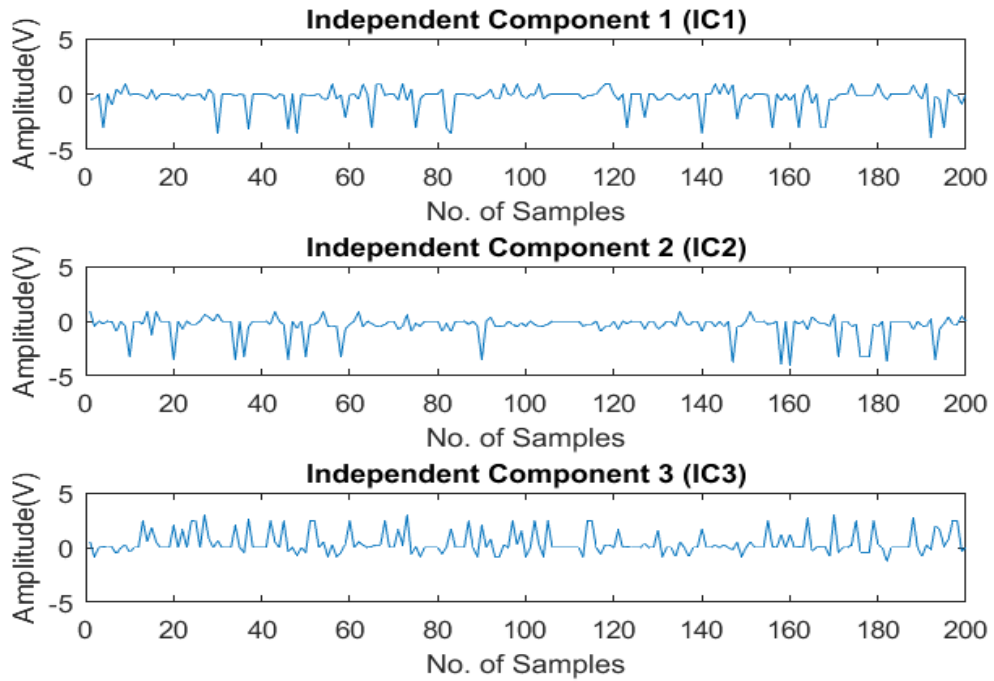


Figure 4.9: EEG signals after Independent Component Analysis

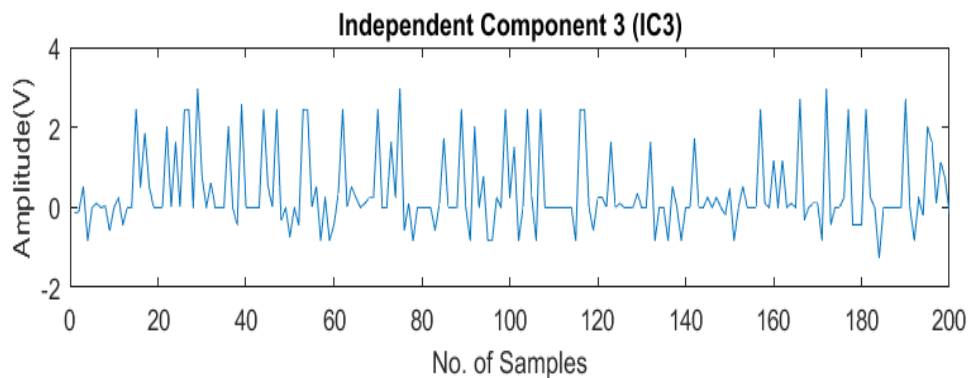


Figure 4.10: Independent Component chosen for Wavelet Decomposition

4.2 Data Analysis

4.2.1 Feature Extraction and Selection

Once the EEG signals are preprocessed, we need to determine features from the signals by the use of signal processing techniques. This process is named feature extraction. Feature extraction is a special form of dimensionality reduction. Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. Since not all features that can be extracted from EEG signals for a given classification problem need to be used, due to their redundancy, a further process is needed for redundancy reduction by retaining only an informative subset of them[16]. This stage of processing is called ‘feature selection’.

After removing the artifacts from EEG signals, the features are extracted by using Wavelet Decomposition (WD). Wavelets attempt to decompose a signal by convolving it with a mother wavelet function at a range of different time and frequency locations and measuring the strength of the signal as a coefficient of the wavelet function[11].

The wavelet decomposition may be defined as:

$$\omega(t, f) = \int_{-\infty}^{+\infty} x(t)\psi_{s,\tau}^*(t)dt \quad (4.5)$$

with

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \quad (4.6)$$

where $x(t)$ is the original signal and *denotes the complex conjugation. $\omega(t, f)$ shows how the signal $x(t)$ is translated into a set of wavelet basis functions $\psi_{s,\tau}(t)$ at scale and translation dimensions s and τ . ψ is the mother wavelet function with which the signal is convolved.

The ‘Morlet’ mother wavelet is used in this work.

The basic feature extraction procedure consists of[17]:

- Decomposing the signal using WD into N levels using daughter wavelets generated by scaling mother wavelet at N different scales.
- Extracting the features from the decomposed signals.

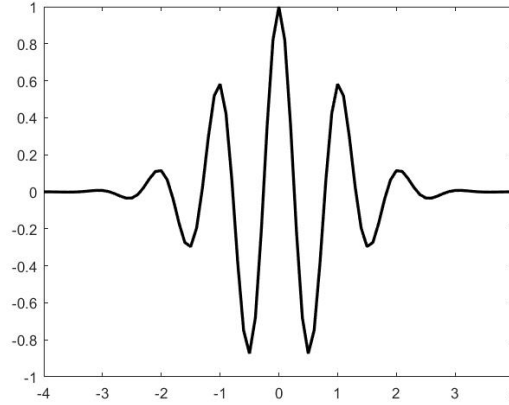


Figure 4.11: Morlet Mother Wavelet Signal

The features extracted from the Wavelet Decomposition of EEG signals are considered useful features for input into classifiers due to their effective time-frequency representation of non-stationary signals.

In this work, eight features are extracted from the wavelet decomposed signals. The extracted features from the signal are as below:

1. **Maximum Amplitude(MA):** It is the peak value of amplitude of the decomposed signal. Its unit is Volts.
2. **Minimum Amplitude(mA):** It is the lowest value of amplitude of the decomposed signal. Its unit is Volts.
3. **Average Amplitude(AA):** It is the mean value of the amplitude of the decomposed signal. Its unit is Volts. It is given by:

$$AA = \frac{1}{n} \sum_{i=1}^n x_i \quad (4.7)$$

where, $n =$ no. of samples in the decomposed signal x .

4. **Approximate Frequency(AF):** It is the approximate value of frequency for a decomposition level. It depends on the scale of the daughter wavelet used in signal decomposition. Its unit is Hertz. It is given by:

$$AF = \frac{F_c}{a.\Delta} \quad (4.8)$$

where, a is a scale, Δ is the sampling period, and F_c is the center frequency of a wavelet in Hz.

5. **Maximum Power(MP):** It is the peak value in power spectrum of decomposed signal. Its unit is Square Volts.
6. **Minimum Power(mP):** It is the lowest value in power spectrum of decomposed signal. Its unit is Square Volts.
7. **Average Power(AP):** It is the mean value of power of the decomposed signal. Its unit is Square Volts. It is given by:

$$AP = \frac{1}{n} \sum_{i=1}^n x_i^2 \quad (4.9)$$

where, n = no. of samples in the decomposed signal x .

8. **Power Variance(PV):** It is the sum of square of difference between sample power (P_i) and average power (AP) divided by the number of samples (n) in the power spectrum of decomposed signal. Its unit is Square Volts. It is given by:

$$PV = \frac{1}{n-1} \sum_{i=1}^n (P_i - AP)^2 \quad (4.10)$$

These features of 27 decomposed signals generated from WD of a EEG signal recorded under MI Left Hand of Subject S01 is shown in Table 4.2. Since all these eight features of all the 27 decomposition levels cannot be used for the purpose of classification, only the features of decomposed signal with highest value of Maximum Power is chosen. In the Table 4.2 the signal with decomposition level N=16 has the highest value of Maximum Power (MP).

For the chosen decomposed signal, these eight features Maximum Amplitude, Minimum Amplitude, Average Amplitude, Approximate Frequency, Maximum Power, Minimum Power, Average Power, and Power Variance are designated as MAM, MmA, MAA MAF, MMP, MmP, MAA, and MPV respectively. Table 4.3 shows the values of all these features for the chosen decomposed signals (from 27 decomposed signals) for MI Left Hand (LH) and MI Right Hand (RH) of five different subjects.

Before classification of the data it is important to reduce the dimension of the data

Table 4.2: Features of WD signals for 27 decomposition levels (N) for MI Left Hand of Subject S01

N	Scale	MA (V)	mA (V)	AA (V)	AF (Hz)	MP (V ²)	mP (V ²)	AP (V ²)	PV (V ²)
1	0.20	1.68	0.02	0.68	40.62	2.82	0.00045	0.58	0.25
2	0.23	1.80	0.04	0.87	34.16	3.25	0.00184	0.92	0.54
3	0.28	1.91	0.01	0.84	28.72	3.67	0.00024	0.93	0.77
4	0.33	2.00	0.02	0.84	24.15	4.01	0.00079	0.89	0.61
5	0.40	1.99	0.06	0.87	20.31	3.97	0.00361	0.99	1.01
6	0.47	2.17	0.01	0.78	17.08	4.72	0.00035	0.91	1.15
7	0.56	1.69	0.01	0.75	14.36	2.86	0.00010	0.75	0.48
8	0.67	1.84	0.01	0.76	12.07	3.41	0.00019	0.74	0.50
9	0.80	1.65	0.14	0.88	10.15	2.75	0.02000	0.92	0.50
10	0.95	1.93	0.01	0.83	8.54	3.73	0.00001	0.92	0.86
11	1.13	2.27	0.09	1.24	7.18	5.15	0.00942	1.90	2.46
12	1.34	1.96	0.66	1.19	6.23	3.84	0.44591	1.55	0.92
13	1.60	1.21	0.19	0.70	5.07	1.47	0.03991	0.56	0.16
14	1.90	1.84	0.22	0.90	4.27	3.41	0.05233	1.02	0.92
15	2.26	2.44	0.45	1.30	3.59	5.97	0.20508	2.02	2.90
16	2.69	2.54	0.18	1.36	3.01	6.46	0.03294	2.41	4.77
17	3.20	1.87	0.58	1.19	2.53	3.52	0.34610	1.64	1.31
18	3.80	1.35	0.23	0.82	2.13	1.83	0.05585	0.78	0.33
19	4.52	1.24	0.66	0.93	1.79	1.54	0.43705	0.91	0.12
20	5.38	1.26	0.19	0.86	1.50	1.59	0.03755	0.86	0.29
21	6.40	1.10	0.80	0.94	1.26	1.22	0.65531	0.91	0.03
22	7.61	1.23	0.23	0.82	1.06	1.53	0.05332	0.79	0.27
23	9.05	1.64	1.56	1.60	0.89	2.69	2.46223	2.58	0.01
24	10.76	1.41	1.33	1.37	0.75	2.00	1.77782	1.89	0.01
25	12.80	0.44	0.05	0.29	0.63	0.19	0.00262	0.10	0.01
26	15.22	0.73	0.72	0.72	0.53	0.53	0.52478	0.53	0.00
27	18.10	1.58	1.58	1.58	0.44	2.52	2.52007	2.52	0.00

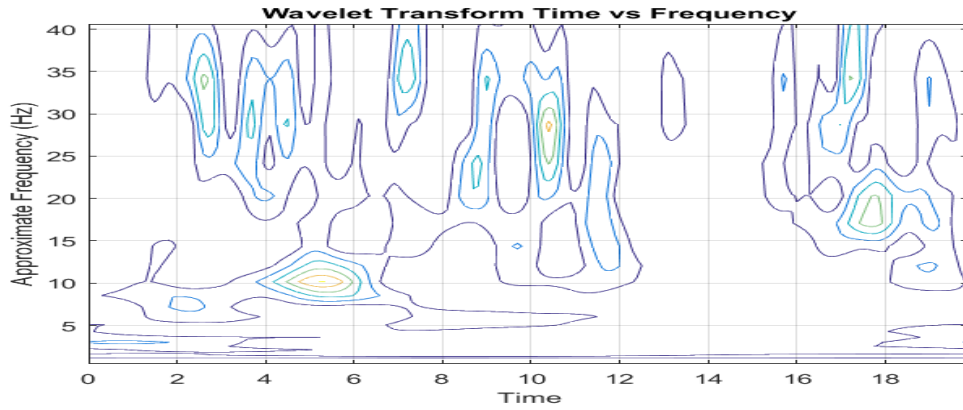


Figure 4.12: Frequency vs Time contour plot of wavelet decomposed EEG signal

Table 4.3: Features of chosen WD signal of MI Left Hand and MI Right Hand for five different subjects

Subject	MI-Class	MMA (V)	MmA (V)	MAA (V)	MAF (Hz)	MMP (V ²)	MmP (V ²)	MAP (V ²)	MPV (V ²)
S01	LH	2.54	0.18	1.36	3.01	6.46	0.0329	2.41	4.77
S02	LH	2.78	2.78	2.78	0.44	7.76	7.7655	7.76	0.00
S03	LH	2.77	0.07	0.94	17.08	7.69	0.0062	1.20	2.07
S04	LH	2.61	0.28	1.06	4.27	6.81	0.0793	1.56	3.86
S05	LH	3.21	0.02	0.68	24.15	10.35	0.0005	0.89	3.19
S01	RH	2.52	0.13	0.89	17.08	6.38	0.0193	1.05	1.78
S02	RH	2.37	0.03	0.85	12.07	5.63	0.0009	1.04	1.92
S03	RH	2.77	0.01	0.79	34.16	7.67	0.0001	0.99	2.14
S04	RH	2.21	0.03	1.03	20.31	4.92	0.0013	1.35	1.55
S05	RH	2.75	0.10	1.27	10.15	7.59	0.0118	2.10	3.76

by finding a small set of important features which can give good classification performance. This can be done by using appropriate feature selection algorithm. Feature selection algorithms can be roughly grouped into two categories: **filter methods** and **wrapper methods**[18]. Filter methods rely on general characteristics of the data to evaluate and to select the feature subsets without involving the chosen learning algorithm. Wrapper methods use the performance of the chosen learning algorithm to evaluate each candidate feature subset. Wrapper methods search for features better fit for the chosen learning algorithm, but they can be significantly slower than filter methods if the learning algorithm takes a long time to run.

In this thesis work, filter method has been used for the selection of the features for MI Left Hand and MI Right Hand signal classification. In this method t-test has been ap-

plied on each feature and p-values obtained from the t-test for each feature has been used as a measure of how effective it is at separating groups. Among the eight features computed, the three features; Approximate Frequency (MAF) of chosen decomposed signal, Maximum Power (MMP) of chosen decomposed signal, and Maximum Amplitude (MMA) of chosen decomposed signal are selected as input for classification algorithm on the basis of p-values.

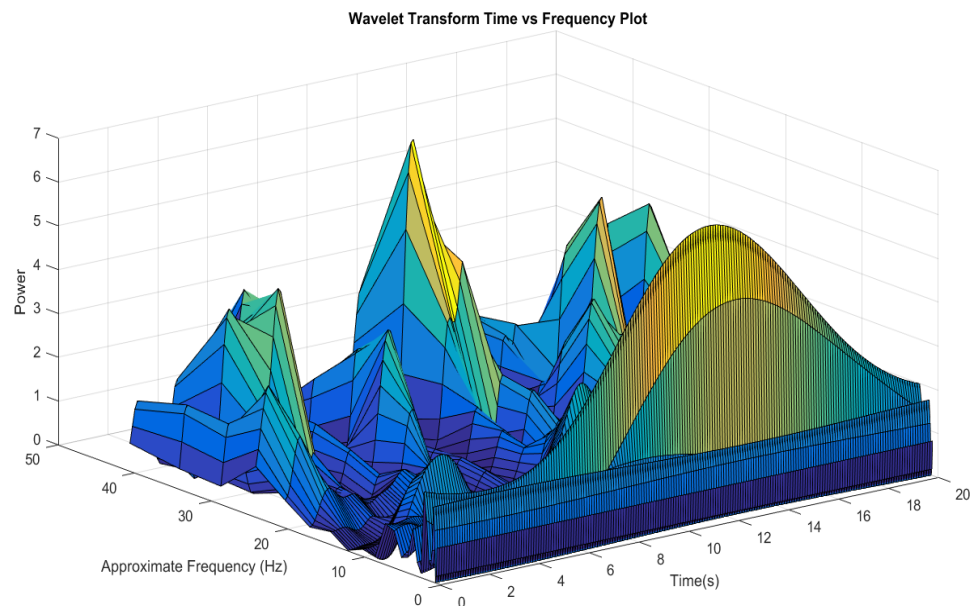


Figure 4.13: Frequency vs Time surface plot of wavelet decomposed EEG signal

4.2.2 Classification Method

Classification method has a direct and critical impact on classification performance. There are many ways for classification, such as Linear Discriminant, Common Space Models, Bayesian methods, Neural Networks, SVMs and so on. In this thesis work, Linear Discriminant Analysis (LDA) is used to classify the MI left-right hand movement classes on the basis of features extracted and selected from WD.

Linear discriminant analysis (LDA) is a generalization of Fisher's linear discriminant, a method used in statistics, pattern recognition and machine learning to find a linear combination of features that characterizes or separates two or more classes of objects or events. LDA makes some simplifying assumptions about our data[19]:

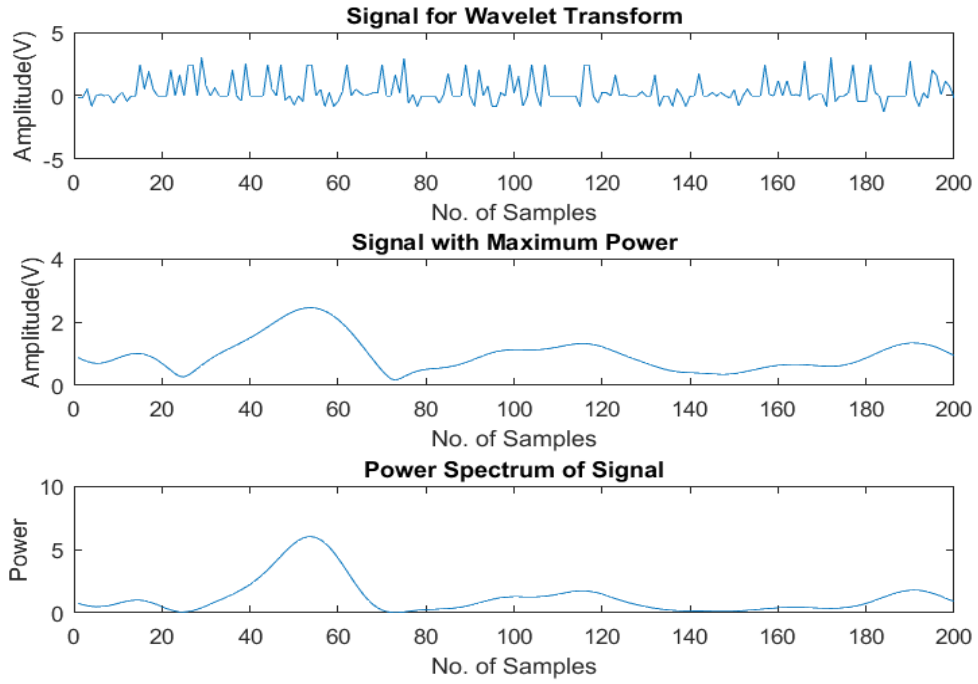


Figure 4.14: Signal features used for classification of MI brainwaves

- That our data is Gaussian, that each variable is is shaped like a bell curve when plotted.
- That each attribute has the same variance, that values of each variable vary around the mean by the same amount on average.

With these assumptions, the LDA model estimates the mean(μ) and variance(σ^2) from our data for each class. It is easy to think about this in the univariate (single input variable) case with two classes. The mean (μ) value of each input (x) for each class (k) can be estimated in the normal way by dividing the sum of values by the total number of values.

$$\mu_k = \frac{1}{n_k} \sum x \quad (4.11)$$

where μ_k is the mean value of x for the class k , n_k is the number of instances with class k .

The variance is calculated across all classes as the average squared difference of each value from the mean.

$$\sigma^2 = \frac{1}{n - k} \sum (x - \mu)^2 \quad (4.12)$$

where σ^2 is the variance across all inputs x , n is the number of instances, k is the number of classes and μ is the mean for input x .

LDA makes predictions by estimating the probability that a new set of inputs belongs to each class. The class that gets the highest probability is the output class and a prediction is made. The model uses Bayes Theorem to estimate the probabilities. Briefly Bayes Theorem can be used to estimate the probability of the output class (k) given the input (x) using the probability of each class and the probability of the data belonging to each class:

$$P(Y = k|X = x) = \frac{P_k * f_k(x)}{\sum P_k * f_k(x)} \quad (4.13)$$

where P_k refers to the base probability of each class k observed in our training data (i.e 0.5 for a 50-50 split in a two class problem). In Bayes Theorem this is called the prior probability.

$$P_k = \frac{n_k}{n} \quad (4.14)$$

The $f_k(x)$ in Equation 4.13 is the estimated probability of x belonging to the class k . A Gaussian distribution function is used for $f_k(x)$. Plugging the Gaussian into the Equation 4.13 and simplifying we end up with the Equation 4.15. This is called a discriminate function and the class is calculated as having the largest value will be the output classification (y):

$$D_k(x) = x * \frac{\mu_k}{\sigma^2} - \frac{\mu_k^2}{2 * \sigma^2} + \ln(P_k) \quad (4.15)$$

$D_k(x)$ is the discriminate function for class k given input x , the μ_k , σ^2 and P_k are all estimated from our data.

For the classification of MI brainwaves, three features (MMA, MMP, MAF) and two classes (MI Left Hand, MI Right Hand) are used. So, the Equation 4.15 can be modified to generate discriminant function for two classes as shown in Equation 4.16 and Equation 4.17.

Discriminant Function for Class MI Left Hand:

$$D_{LH} = C_1 + L_{11} * MAF + L_{12} * MMP + L_{13} * MMA \quad (4.16)$$

where, C_1 is constant, L_{11} , L_{12} and L_{13} are linear coefficients that corresponds to three features MF, MMP, and MAF respectively for class MI Left Hand.

Discriminant Function for Class MI Right Hand:

$$D_{RH} = C_2 + L_{21} * MAF + L_{22} * MMP + L_{23} * MMA \quad (4.17)$$

where, C_2 is constant, L_{21} , L_{22} and L_{23} are linear coefficients that corresponds to three features MF, MMP, and MAF respectively for class MI Right Hand.

After training of LDA classifier using training dataset 'trainingData', the constants and linear coefficients are obtained as:

$$\begin{aligned} C_1 &= 2.6415 & L_{11} &= -0.3392 & L_{12} &= 0.2338 & L_{13} &= 0.0036 \\ C_2 &= -2.6415 & L_{21} &= 0.3392 & L_{22} &= -0.2338 & L_{23} &= -0.0036 \end{aligned}$$

Since, the coefficient for the third feature MMA is very small in comparison to the coefficient of other two features, it has very low contribution towards classification result. The scatter plot shown in Figure 4.15 shows the training data related to MI LH and MI RH along with the trained linear classifier which separate these two classes.

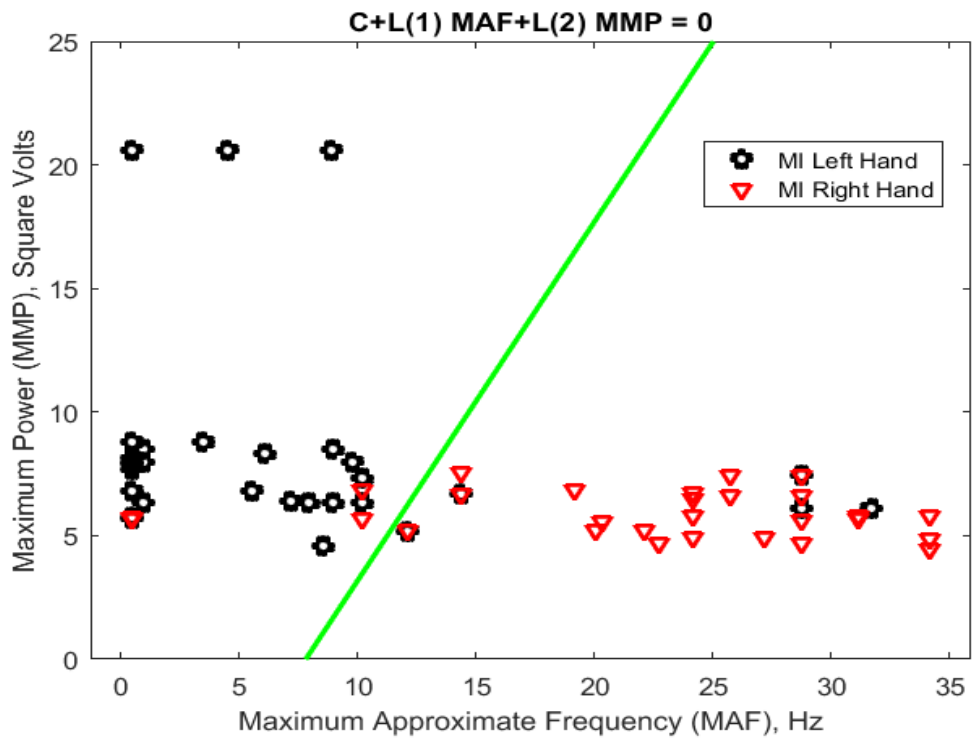


Figure 4.15: Scatter plot showing two class (MI LH and MI RH) data along with the liner discriminant function

CHAPTER 5

RESULT AND DISCUSSION

A total of 200 data has been recorded from 20 different subjects. For each subject, 5 data corresponds to MI Left Hand and 5 data corresponds to MI Right Hand. A set of 140 randomly selected data (70 from MI Left Hand Class and 70 from MI Right Hand Class) named as 'trainingData.mat' was used as training set and the remaining 60 data set named as 'testingData.mat' was used as test set. Training LDA classifier with 'trainingData' gave the training accuracy of 88.5% . The ROC curve for training is shown in Figure 5.1. In ROC curve, the value of AUC is 0.97, which indicates that the trained classification model is good representation for the training data set.

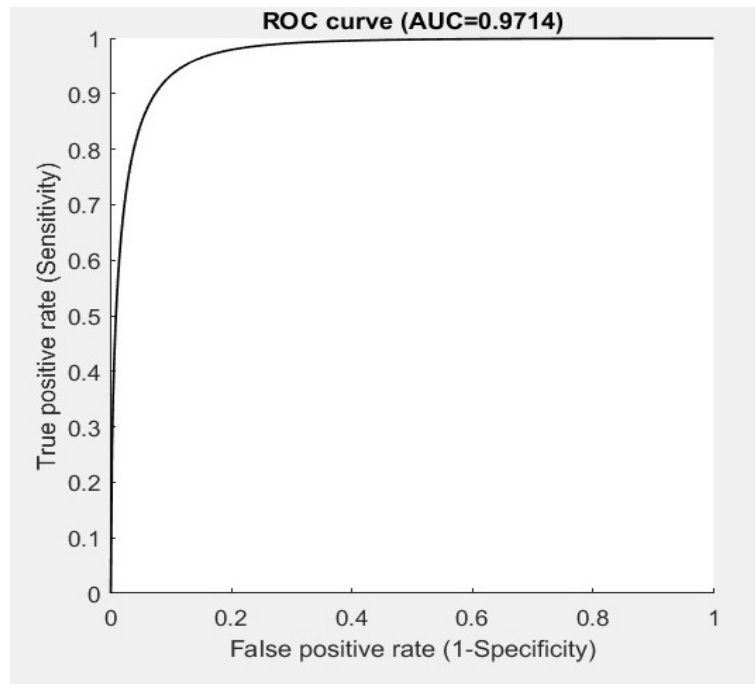


Figure 5.1: ROC curve for training data set

When the trained classifier was tested with test data set 'testingData', the accuracy of 81.6% was obtained. The confusion matrix for testing is shown in Figure 5.2 which shows that the true positive rate (TPR) of classifier for test data is 0.66 whereas the true negative rate (TNR) is 0.93.

Similarly, when the histogram was plotted for the approximate frequencies feature of

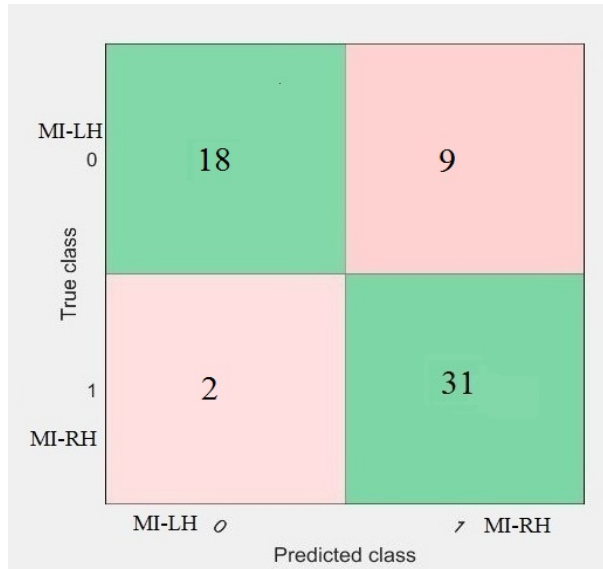


Figure 5.2: Confusion matrix for testing data set

the all the data recorded from self designed EEG device, it showed a some what bi-modal nature. From the histogram shown in Figure 5.3 it can be implied that there is clear distinction between the frequencies for MI Left Hand and MI Right Hand Classes. The MI Left Hand class showed dominance in the frequency range of about 3 to 14 Hz, whereas the MI Right Hand class showed dominance in the frequency range of about 19 to 34 Hz. So, it can be said that imagination of left hand movement showed lower frequency brain activity in comparison to imagination of right hand movement.

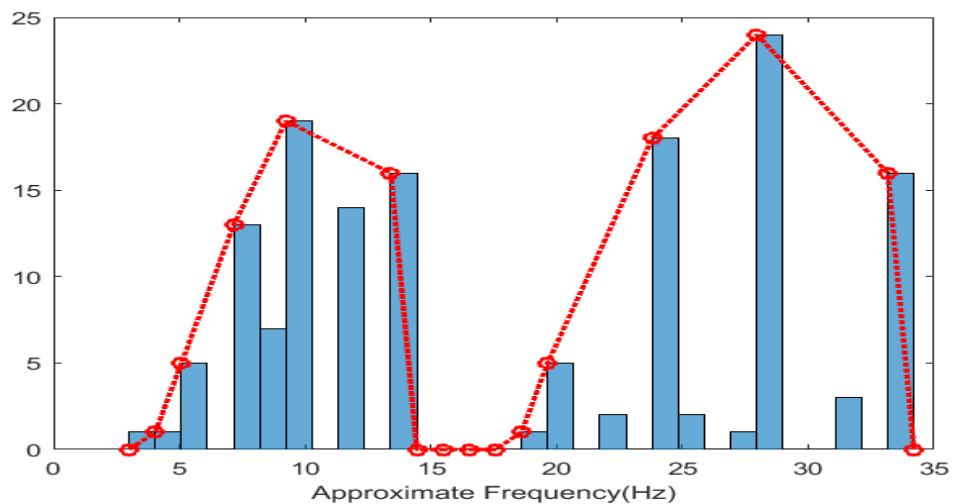


Figure 5.3: Histogram of Approximate frequency for data recorded from designed EEG device

CHAPTER 6

VERIFICATION AND VALIDATION

The validation of data recorded from the designed 3-channel EEG device has been done by comparing with the data recorded from the Mindwave EEG Headset of NeuroSky. At first, MI data for RH and LH was recorded for a subject by using the designed EEG device and then the MI data for RH and LH was recorded by using NeuroSky Mindwave Headset for the same subject. From both of these data, three brainwave signals (theta wave, alpha wave and beta wave) were extracted by using Butterworth bandpass filters of order 20. The correlation coefficients of the extracted brainwaves signals was calculated for each channel of the designed EEG device with respect to the channels of the NeuroSky Headset for both MI LH and MI RH data as shown in Table 6.1. The average correlation coefficient for 40 data (20 MI LH and 20 MI RH)

Table 6.1: Correlation coefficients for a data of designed EEG device when compared with a NeuroSky Headset data for different types of brainwave signals

Brainwaves Types	MI Left Hand			MI Right Hand		
	Ch1 (r)	Ch2 (r)	Ch3 (r)	Ch1 (r)	Ch2 (r)	Ch3 (r)
Theta Waves	0.9798	0.9762	0.9569	0.9656	0.9650	0.9659
Alpha Waves	0.9404	0.8920	0.8247	0.9020	0.9055	0.8963
Beta Waves	0.2880	0.3696	0.2484	0.5246	0.5498	0.6231

recorded from designed EEG device and 40 data (20 MI LH and 20 MI RH) recorded from NeuroSky Headset for same subject is shown in Table 6.2 and Figure 6.1. From Table 6.2, the correlation coefficients of all channels for theta, alpha and beta waves is greater than 0.5 ($r > 0.5$). This showed that there is high correlation between the brainwave signals recorded from designed EEG device and the data recorded from the NeuroSky Headset.

Table 6.2: Average correlation coefficients for 40 data samples of designed EEG device when compared with 40 data samples of NeuroSky Headset for different types of brainwave signals

Brainwaves Types	Channel 1 (r)	Channel 2 (r)	Channel 3 (r)
Theta Waves	0.9685	0.9669	0.9675
Alpha Waves	0.8958	0.9117	0.9023
Beta Waves	0.5414	0.5300	0.5638

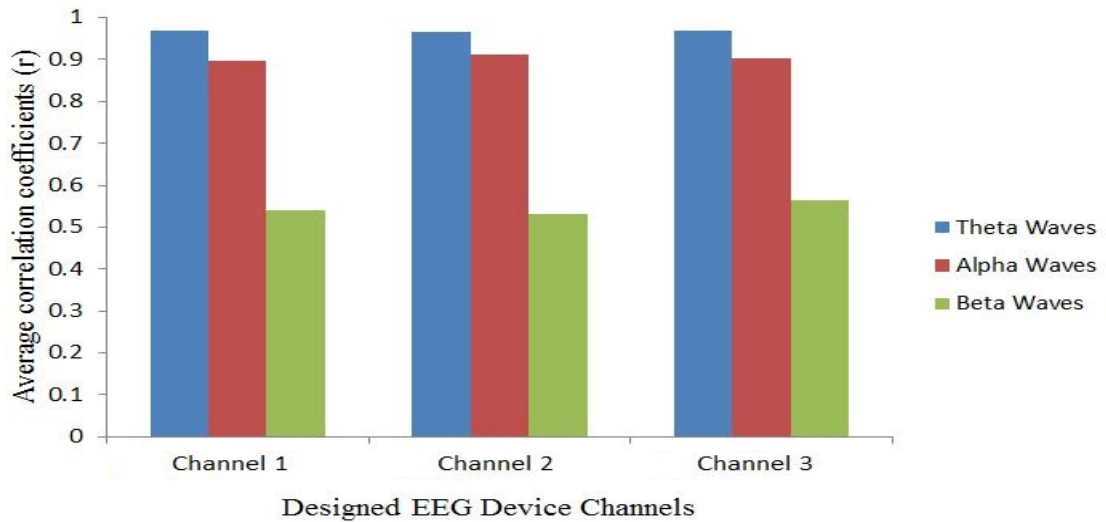


Figure 6.1: Average correlation coefficients for channels of designed EEG device when compared with NeuroSky Headset channel for different types of brainwave signals

Furthermore, for the verification of the classification algorithm, it was trained with standard brainwave data (25 MI LH and 25 MI RH) recorded from NeuroSky Headset. The trained classifier was then tested with 200 brainwave data (100 MI LH and 100 MI RH) recorded from the proposed 3-channel EEG device. The accuracy of 78.5% was obtained when the classifier trained with standard dataset was tested with the data from the proposed EEG Device .

CHAPTER 7

CONCLUSION AND RECOMMENDATION

7.1 Conclusion

The 3-channel active electrode hardware EEG device designed and developed is capable of recording the brainwave activities of different subjects under different circumstances. This work shows that the active electrode EEG device can be used for recording EEG data without skin preparation and conductive gels and the low cost home made EEG device can be used to record EEG data for research works and BCI development. In this thesis work, the preprocessing methods (filtering and ICA) used removed power line noise and EOG artifacts from raw EEG signals. The feature extraction of EEG signals is done using Wavelet Decomposition. The classification method (LDA) was implemented which classified the recorded brainwave activities for imagined left hand-right hand movement of a subject with accuracy of 81.6%. Thus, the designed 3-channel active electrode EEG device can be used to record EEG data with fewer limitations.

7.2 Limitation

The classification of MI data from the designed EEG device using model trained using the standard MI data from NeuroSky headset showed the accuracy of 78.5% which is slightly less than that of the classification accuracy of data recorded from designed 3-channel active electrode EEG device. The decrease in accuracy may be due to the EEG artifacts like EMG and ECG that has not been considered in this thesis work. The scalp impedance of the subject has also not been considered which might have introduce some noise in the EEG signal recorded from the designed 3-channel EEG device.

7.3 Recommendation

Furthermore, the accuracy of the design can be increased by adding more than three channels in the EEG device. Since, this thesis work focused on the classification of

motor imagery brainwaves using LDA, other linear and non-linear classification method could increase the classification performance. The classification performance could also be increased by using methods to remove EMG and ECG artifacts.

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APPENDIX A

A 3-channel EEG Device for recording brainwaves



Figure A.1: Different components of a 3-channel EEG Device for recording brainwaves which includes a power supply, an EEG headset and an amplifier.

APPENDIX B

Experimental setup for recording brainwaves



Figure B.1: A subject wearing designed EEG headset for recording brainwaves.