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Design of Tri-channel Active Electrode EEG Device for Classification of Motor Imagery Brainwaves

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Abstract
This paper presents a cost effective method to design a three channel active electrode EEG (Electroencephalogram) device for recording brainwaves. The designed EEG device is tested for the classification of brainwaves related to motor imagery (MI) left and right hand movement. The designed EEG device could be used for various Brain Computer Interface (BCI) applications. The goal of this paper 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 Average power of the signal with MAF (MAP) 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 training accuracy of 88.6% for training data set and testing accuracy of 80% for testing data set. 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

1. Introduction

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[1, p. 347]. 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.

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, 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[2]. The Delta Waves are the slowest brainwaves with frequency ranging from 0.5 Hz to 4 Hz, the Theta Waves ranging from 4 Hz to 8 Hz are associated with sleep and also dominant in deep meditation. Alpha Waves (8 Hz - 13 Hz) are dominant during quietly flowing thoughts, Beta Waves (13 Hz - 38 Hz) are dominant in our normal waking state when out attention is towards cognitive tasks. Similarly, the Gamma Waves

(38 Hz- 90 Hz) are the fastest brainwaves and are highly active when in states of universal love, altruism, and 'higher virtues'. The different types of brainwaves that can be recorded using EEG devices are shown in Figure 1.

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 to their intent to control a device are measured[2]. These features are then translated to control commands that are used to control the device. 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. 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[4]. Non-physiological artifacts and 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.

2. Related Work

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 research work are mentioned here.

Schlogl *et al.* in [5], Kumar *et al.* in [6], and Daly *et al.* in [7] explains various methods (online as well as offline) to remove artifacts from the recorded raw brainwave signals. Kumar *et al.* in [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, Gandhi *et al.* in [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 brain–computer interface where the objective was to filter electroencephalogram (EEG) signals before feature extraction and classification to increase signal separability.

Campisi *et al.* in [9], Cecotti *et al.* in [10], and Iwasa *et al.* in [11] had explained the various methods to use brainwave 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), preprocessing technique, features extracted from EEG signals and the classification scheme.

Xu *et al.* in [12], Chai *et al.* in [13], and Steyrl *et al.* in [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. Xu *et al.* in [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.

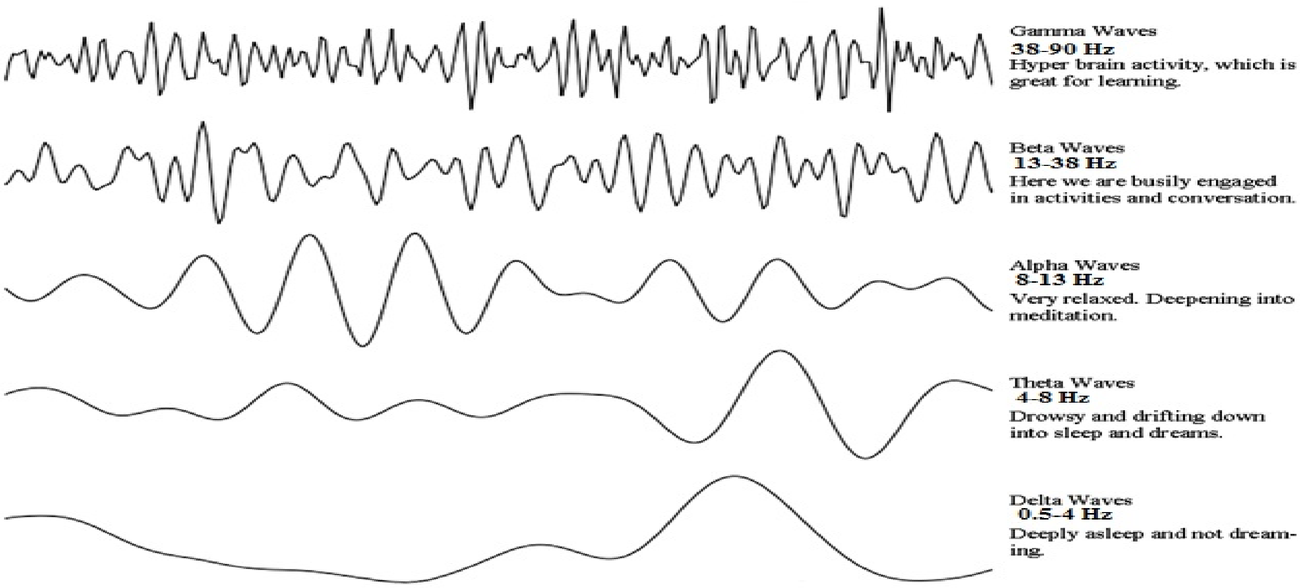

Figure 1: Different types of brainwaves[3]

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, Chai *et al.* in [13] 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.

In this paper, a method to design a tri-channel active electrode EEG device has been presented. The designed EEG device could be used to record EEG signals of different subjects under different experimental setups. This paper deals with the classification of brainwaves related to imagined left-hand and right-hand movement by a subject.

3. Methodology

3.1 Block Diagram of Self Made EEG Device

The general block diagram for the system implementation in shown in Figure 2. Active electrodes, amplifiers and signal recording tools combined forms the EEG data Acquisition system.

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.

3.1.3 Amplifiers

After the detection of the brain wave signals by the active electrodes, the signal is amplified by using

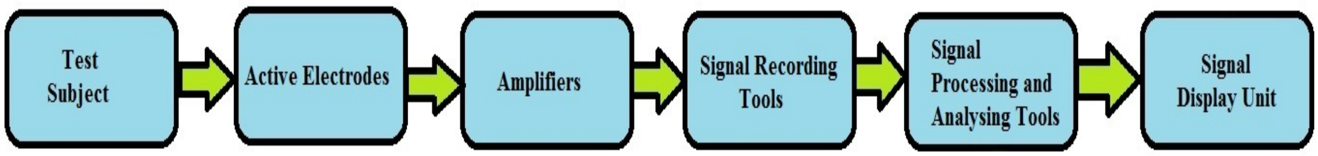

Figure 2: System Block Diagram

amplifiers. The brain wave signals are very low voltage signals with magnitude ranging form 50 to 500 microvolts, so for further processing of the 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.

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 user interface for the signal processing and analysis.

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.

3.2 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.

The raw EEG signals of a Subject recorded using designed three channel active electrode EEG device is shown in Figure 3.

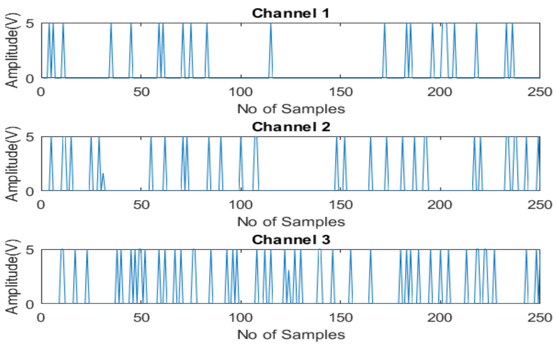

Figure 3: Raw EEG signals recorded from three channel EEG device

3.3 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 1.

$$D_V = \frac{D_B}{255} * 5V \tag{1}$$

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

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.

3.4 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 raw EEG signal shown in Figure 3 was filtered using 50 Hz notch filter. The filtered signal is shown in Figure 4, which is free from power-line noise.

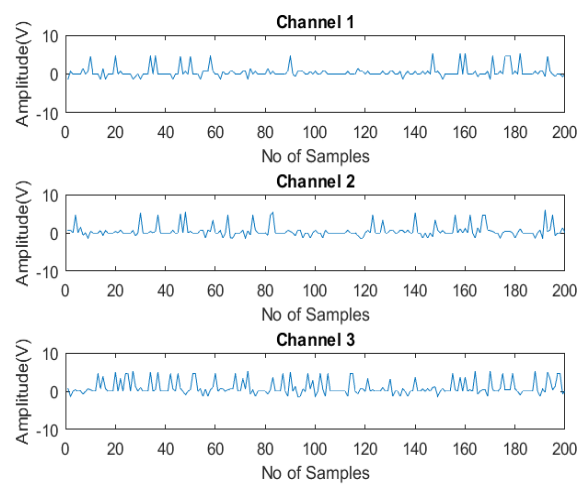

Figure 4: EEG signals after removing 50Hz power line artifacts using Notch Filter

The ICA removes the EOG and EMG artifacts from the recorded brainwave signals. 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].
The ICA process can be mathematically defined by

Equation 2.

$$x = Ws \quad (2)$$

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.

Before applying an ICA algorithm on the data, it is usually very useful to do some preprocessing. Some 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 as defined in Equation 3.

  $$E\{\tilde{x}\tilde{x}^T\} = I \quad (3)$$

  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, $D = diag(d_1, ..., d_n)$. $E\{xx^T\}$ can be estimated in a standard way from the available sample $x(1), ..., x(T)$. Whitening can now be done by using Equation 4.

  $$\tilde{x} = ED^{-1/2}E^T x \quad (4)$$

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

After ICA of the three channel EEG signal, three independent components (IC1, IC2, IC3) are generated as shown in Figure 5 . Among these there independent 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. Among three independent components shown in Figure 5, the chosen independent component is shown in Figure 6.

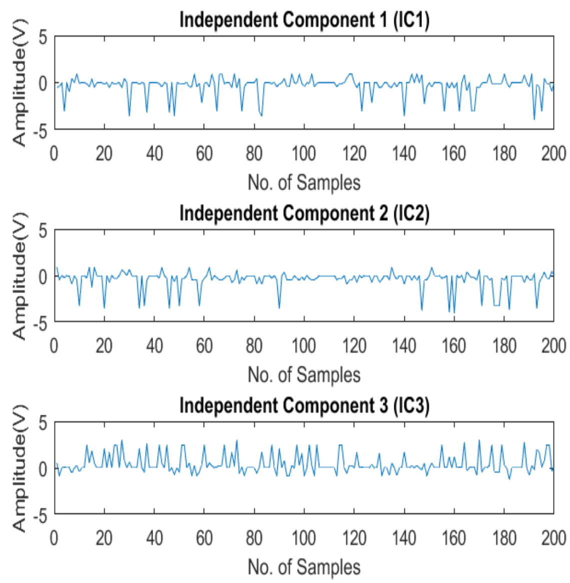

Figure 5: EEG signals after Independent Component Analysis

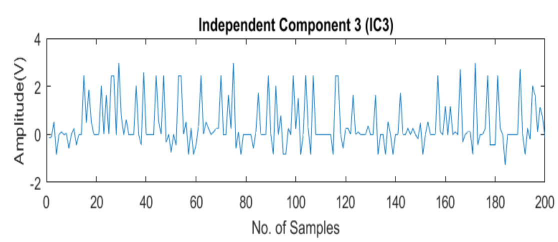

Figure 6: Independent Component chosen for Wavelet Decomposition

4. Data Analysis

4.1 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[17].
The wavelet decomposition can be defined mathematically by Equations 5 and Equation 6.

$$\omega(t,f) = \int_{-\infty}^{+\infty} x(t)\psi^{*}_{s,\tau}(t)dt \tag{5}$$

with

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi(\frac{t-\tau}{s}) \tag{6}$$

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, eight features are extracted from the wavelet decomposed signals. The extracted features from the signal are Maximum Amplitude (MA), Minimum Amplitude (mA), Average Amplitude (AA), Approximate Frequency (AF), Maximum Power (MP), Minimum Power (mP), Average Power (AP), and Power Variance (PV). 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 1. 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 1 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 2 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.

From Table 2 , it is clear that not all features of chosen decomposed signal can be used for the classification of MI Left Hand and MI Right Hand Classification. Among the eight features computed, the three features; Approximate Frequency (MAF) of chosen decomposed signal, Maximum Power (MMP) of chosen decomposed signal, and Average Power (MAP) of chosen decomposed signal are selected as input for classification algorithm.

4.2 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 paper, 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. Since, the EEG signals are highly non-stationary, dynamic and unpredictable signals, so for their classification, probabilistic methods such as LDA can outperform the other classifiers for two class classification problems [18]. In addition to that LDA makes some simplifying

Table 1: 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

assumptions about our data:

- 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, 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 as shown in Equation 7.

$$\mu_k = \frac{1}{n_k} \sum x \tag{7}$$

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 as shown in Equation 8.

$$\sigma^2 = \frac{1}{n-k} \sum (x-\mu)^2 \tag{8}$$

Table 2: 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

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 as shown in Equation 9.

$$P(Y=k|X=x) = \frac{P_k * f_k(x)}{\sum P_k * f_k(x)} \tag{9}$$

where, P_k defined in Equation 10, 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.

$$P_k = \frac{n_k}{n} \tag{10}$$

The $f_k(x)$ in Equation 9 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 9 and simplifying we end up with the Equation 11. This is called a discriminate function and the class is calculated as having the largest value will be the output classification (y):

$$D_k(x) = x * \frac{\mu_k}{\sigma^2} - \frac{\mu_k^2}{2*\sigma^2} + ln(P_k) \tag{11}$$

$D_k(x)$ is the discriminate function for class k given input x, the μ_k, σ^2 and P_k are all estimated from our data.
In this work, three features (MMP, MAP, MAF) and two classes (MI Left Hand, MI Right Hand) are used. So, the Equation 11 can be modified to generate discriminant function for two classes as shown in Equation 12 and Equation 13.
Discriminant Function for Class MI Left Hand:

$$D_{LH} = C_1 + L_{11} * MMP + L_{12} * MAP + L_{13} * MAF \tag{12}$$

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

Discriminant Function for Class MI Right Hand:

$$D_{RH} = C_2 + L_{21} * MMP + L_{22} * MAP + L_{23} * MAF \tag{13}$$

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

After training of LDA classifier using training dataset, the constants and linear coefficients are obtained as:
$C1 = 1.0449$ $L_{11} = 0.2237$ $L_{12} = 0.3265$ $L_{13} = -0.3137$
$C2 = -1.0449$ $L_{21} = -0.2237$ $L_{22} = -0.3265$ $L_{23} = 0.3137$

5. Conclusion

A 3-channel active electrode EEG device was designed and total of 100 data has been recorded from 10 different subjects. For each subject, 5 data corresponds to MI Left Hand and 5 data corresponds to MI Right Hand. A set of 70 randomly selected data (36 from MI Left Hand Class and 34 from MI Right Hand Class) was used as training set and the remaining 30 data set was used as test set. Training LDA classifier with training data set gave the training accuracy of 88.6% . When the trained classifier was tested with test data set, the accuracy of 80% was obtained.
To increase the classification accuracy, the EEG device with more than three channels could be used for more robust data recording and the other non-linear classification methods could also be used.

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