

P300 Detection and Characterization for brain computer Interface

Thesis submitted in partial fulfillment
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In

Electronics and Communication Engineering

Submitted by

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DECLARATION

I hereby declare that the work presented in the thesis entitled “*P300 detection and characterization for brain computer interface*” is a bonafide record of the research work done by me under the supervision of Dr. Samit Ari, Department of Electronics & Communication Engineering, National Institute of Technology, Rourkela, India and that this thesis work has not been presented for the award of any other degree.

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CERTIFICATE

Certified that this project thesis on “**P300 DETECTION AND CHARACTERIZATION FOR BRAIN COMPUTER INTERFACE**” is a bonafide work of “**SAURADIPTA MISHRA**” who carried out the research project under my supervision and guidance during Aug 2013-May 2014(7th & 8th Semester). This thesis has not been submitted for any degree or academic award elsewhere.

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ABSTRACT

Advances in cognitive neuroscience and brain imaging technologies have enabled the brain to directly interface with the computer. This technique is called as Brain Computer Interface (BCI). This ability is made possible through use of sensors that can monitor some of the physical processes that occur inside the brain. Researchers have used these kinds of technologies to build brain-computer interfaces (BCIs). Computers or communication devices can be controlled by using the signals produced in the brain. This can be a real boon for all those who are not able to communicate with the outside world directly. They can easily forecast their emotions or feelings using this technology. In BCI we use oddball paradigms to generate event-related potentials (ERPs), like the P300 wave, on targets which have been selected by the user. The basic principle of a P300 speller is detection of P300 waves that allows the user to write characters. Two classification problems are encountered in the P300 speller. The first is to detect the presence of a P300 in the electroencephalogram (EEG). The second one refers to the combination of different P300 signals for determining the right character to spell. In this thesis both parts i.e., the classification as well as characterization part are presented in a simple and lucid way. First data is obtained using data set 2 of the third BCI competition. The raw data was processed through matlab software and the corresponding feature matrices were obtained. Several techniques such as normalization, feature extraction and feature reduction of the data are explained through the contents of this thesis. Then ANN algorithm is used to classify the data into P300 and no-P300 waves. Finally character recognition is carried out through the use of multiclass classifiers that enable the user to determine the right character to spell.

KEYWORDS: - Brain Computer Interface (BCI), Electroencephalography (EEG), Event Related Potential (ERP), P300, Artificial Neural Network (ANN), Multiclass classification

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CHAPTER-1

INTRODUCTION

Peripheral nerves and muscles are required to control any natural form of communication. It gets started with the user's intent. This intent triggers a process by which certain areas of the brain are activated. Signals generated by this trigger are sent through the peripheral nervous system (specifically, the motor pathways) to corresponding muscles. These muscles in turn perform the required movements which are necessary for performing communication or control task. Motor output is the result of this process. An alternative way to perform natural communication and control is by using a brain computer interface (BCI). The neuromuscular output channels i.e, the body's normal efferent pathways are bypassed by a BCI. A BCI directly measures brain activity without depending on peripheral nerves and muscles. It then transforms the recorded brain signals into corresponding control signals for different applications. This transformation requires signal processing and pattern recognition. These two works are done by a computer.

1.1 Brain Computer Interface

Brain-computer interface (BCI) or Mind Machine Interface (MMI) is basically a collaboration between a brain and a device. This device enables signals produced from the brain to direct some kind of an external activity, such as controlling a cursor or a prosthetic limb[1]. This interface creates a direct communications pathway between the brain and the object which is to be controlled by the brain. For example, in cursor control, the signals are directly transmitted from the brain to the mechanism which controls the cursor. It doesn't take the normal route i.e, using our finger to control a mouse, after the neuromuscular part of our body has been directed by the brain signals to act correspondingly. BCIs are often used for assisting, augmenting, or repairing human cognitive or sensory-motor functions. The basic working principle of any BCI system is that, it detects P300 signals and converts neurophysiologic signals into basic actions[2]. These actions are then displayed through a computer screen. For example in the case of P300 speller diagram the basic purpose of the BCI system is to map the P300 signals into the right character to spell. Even when we are sitting idle the brain generates lots and lots of signals. This is because the brain is doing some kind of work like controlling heart rate, respiration, etc. These signals produced by the brain in response to vital functions are called as Non-P300 signals whereas the signals produced by the brain in response to some kind of thinking or reasoning skills are known

as P300 signals [3]. So first these two kinds of signals need to be separated so that we can combine the P300 signals to generate the right character. Finally this character can be displayed on a screen[4][5].

1.1.1 Application of BCI

Brain-computer interfacing (BCI) is one of the latest developments in the field of science and technology. This technology has a huge number of applications. Some of these are as follows:

- A BCI provides disabled people with an opportunity of communication, a chance to control environment and movement restoration
- It assists the control of devices such as wheelchairs, vehicles or assistance robots for disabled people
- It provides additional channel of control in computer games
- It can be used to monitor the attention of long distance drivers like pilots
- Intelligent relaxation devices can be developed using BCI

1.2 Event Related Potential

Small voltages that are generated in the brain structure in response to a specific event or stimuli are called as event related potential (ERPs) (Blackwood and Muir, 1990). They are basically EEG changes which are time locked to measure sensory, motor or cognitive events. Event-related potentials can be generated by varieties of sensory, cognitive or motor events. They are assumed to reflect the summed activity of postsynaptic potentials. These postsynaptic signals are produced when a huge number of similarly oriented cortical pyramidal neurons produce synchronously while processing information (Peterson et al., 1995). ERPs can be basically divided into 2 categories. One is termed as ‘sensory’ or ‘exogenous’ as the components peak roughly around 100 milliseconds after the stimulus is produced. The other is termed as ‘cognitive’ or ‘endogenous’ as they examine information processing in which the subject evaluates various stimulus.

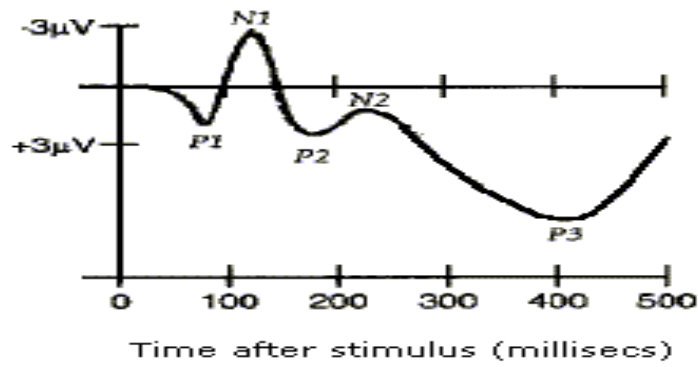


Fig 1.1: Typical Event related potential [6]

1.3 P300 Signal

Sutton *et al.* in 1965 discovered the P300 signal. Since then researchers in the field of ERP have analyzed it thoroughly. P300 signal is an endogenous ERP. For most adults in between the age of 20 and 70 the latency range is 250-400 ms for auditory stimuli. The latency is defined as the speed of stimulus classification that results from discrimination of one event from another. Shorter latencies indicate superior mental performance as compared to longer latencies. P3 amplitude reflects stimulus information. It indicates that greater attention produces larger P3 waves. Different paradigms have been used to generate the P300, of which the “oddball” paradigm is the most common. In this method different stimuli are presented in order to make one of them occur relatively infrequently. Reduced P300 amplitude is an indication of the broad neurobiological vulnerability that determines disorders within the externalizing spectrum [7].

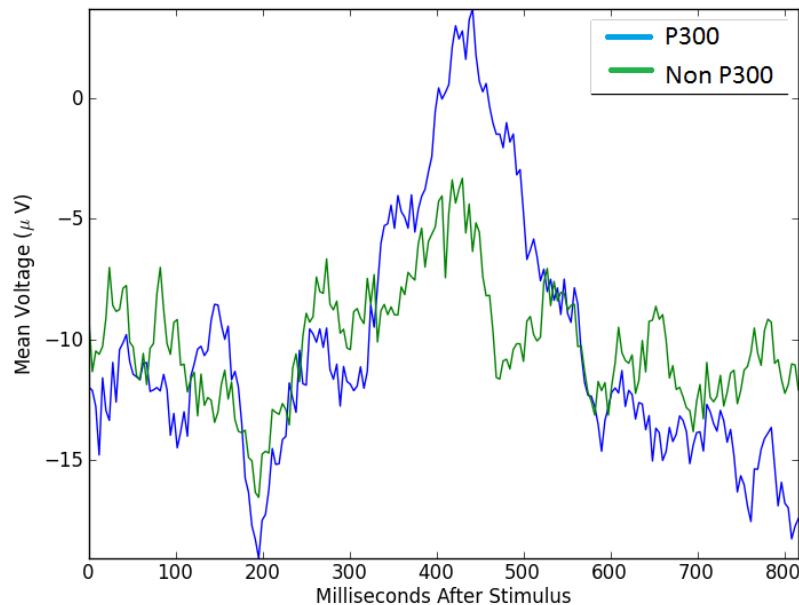


Fig 1.2: P300 and Non-P300 Signal [7]

1.4 Electroencephalogram (EEG)

In EEG technology electrodes are placed directly on the scalp to measure weak (5–100 μV) electrical potentials generated by different activities in the brain. Electrodes are separated from the actual electrical activity because of the fluids, bone and skin of the scalp. So, the signals tend to be smoothed and are rather noisy. Hence, it is clear that EEG measurements have good temporal resolution with delays being less than tens of milliseconds but spatial resolution tends to be really poor. Spatial resolution has accuracy of about 2-3 cm at best, but usually it is worse than that. Two centimeters on the cerebral cortex can produce catastrophic results. We could infer that the user is reading when actually he is watching TV [8][9][10].

1.5 LITERATURE SURVEY

Ben H. Jansen *et al.* proposed a threshold detector for single-trial P300 detection which operates on the 0–4 Hz band, isolated from the raw electroencephalogram using low-pass filtering, wavelet transforms, or the piecewise prony method (PPM). A detection rate around 70% was found, irregardless of stimulus type, inter-stimulus interval (ISI), probability of occurrence of the target stimuli, intra session and intersession effects, or filtering method [14]. Min Ki Kim *et al.* [15] and Rosas-Cholula [16] presented wavelet analysis and PCA preprocessing for detection of P300 rhythm using 14 channels which is further applied to input to classifier.

Matthias Kaper *et al.* [17] proposed support vector machine approach to analyze the P300 speller paradigm. In this classification they found correct solution after five repetitions using only 10 electrode positions .

Hubert Cecotti *et al.* [18] presented an approach of convolution neural network for detection of P300 waves. The topology of the network is adapted to the detection of P300 waves in the time domain. Seven classifiers based on the CNN are proposed: four single classifiers with different features set and three multi-classifiers

Vladimir Bostanov presented the t-CWT method for feature extraction, a simple and fast CWT computation algorithm for the transformation of large data sets and single trials P300 detection .

Alain Rakotomamonjy and Vincent Guigue proposed ensemble of SVM approach for BCI P300 speller. They addresses the problem of signal responses variability within a single subject and copes with such variability's through an ensemble of classifiers approach [19]. Kaper *et al.* [20]

investigated the application of Support Vector Machines (SVM's) using Gaussian kernel transformation but using only a few number of EEG channels. They have been elected as one of the winners in BCI Competition II [21] because of the success of the method they have proposed. SVM has also been applied in numerous studies for the classification of P300 responses [22], [23] and in other BCI applications [24], [25], [26].

1.6 Objective

Raw EEG signal was acquired using P300 speller paradigm. The main objective of our research is to correctly detect and characterize the P300 signals. In order to achieve this following processes are carried out in a systematic manner. The processes are as follows:

- 1) To detect the P300 Signals. For this process the following are implemented:
 - i) To filter the EEG signal and normalize the data within the pre-processing stage.
 - (i) To reduce the size of the feature matrix by using feature extraction.
 - (ii) To reduce the feature matrix by using Principal Component Analysis technique.
 - (iii) To separate the data into P300 and No-P300 waves using Artificial Neural Network.
- 2) To characterize the P300 waves for brain computer interface using multiclass classification.

1.7 Thesis outline

Chapter 1 of the thesis explains about brain compute interface. Next a brief insight is provided about event related potential and P300 waves. Finally the literature survey and objective are presented in a lucid and simple manner.

Chapter 2 of this thesis provide informal about the data collection, experimental setup used for the project. Next the raw EEG data is normalized in the preprocessing stage. Feature extraction and feature reduction techniques are used for reducing the size of the feature matrix and to reduce the computational complexity. Finally ANN classifier is to detect the P300 waves.

Chapter 3 of this thesis provides firsthand information about multiclass classification. The characterization problem is explained in this part of the thesis and finally the P300 signals detected in chapter 2 are used to generate the right character to spell.

Chapter 4 provides a concluding paragraph about the thesis. It also explains the future work that can be carried out in this field.

1.8 Data Base

Data was acquired from the Data set II of the third BCI competition [27]. This dataset represents a complete record of P300 evoked potentials recorded with BCI2000 using a paradigm described by Donchin et al., 2000, and originally by Farwell and Donchin, 1988. In these experiments, a user focused on one out of 36 different characters. The objective is to predict the correct characters in one of the three provided sessions.

CHAPTER-2

DETECTION OF P300

WAVES

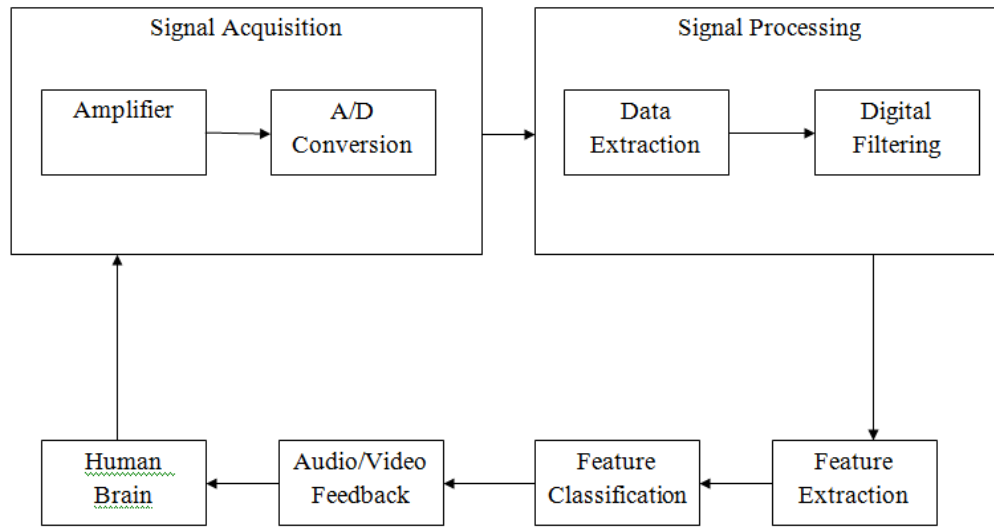


Fig 2.1: Basic Design and Operation of a BCI System [28]

There has been a lot of work in the field of BCI over the last two decades. Various methodologies have been used for analyzing applications in the field of BCI by researchers. To improve the quality of the BCI systems is the main goal of various researches. Thus, the most important task of any BCI research is to develop new algorithms that can improve the speed and accurately predict mechanisms in BCI applications. The applications of BCI are considered to be pattern recognition problems. Thus various feature extraction, pattern classification and signal processing techniques are used in these systems. This thesis work deals with two areas of BCI which are based on P300 signal classification and characterization by making use of the spelling paradigm (P300 speller). This enables paralyzed people to communicate with the external world and express their feeling through the use of a computer screen. The first part of this project deals with distinguishing the P300 and Non-P300 signals, so that we can get the appropriate signals for processing. The data is acquired using Electroencephalography (EEG) and analyzed with complex signal processing and classification methods. Finally the P300 signals obtained by classification are used for characterization i.e, to generate a character on which the user is focusing. Furthermore the output of the classifier can be fed as input to a computer which can display the identified character. In this way a brain signal can be translated into a character which can be displayed on a screen.

2.1 METHODOLOGY

2.1.1 Experimental Setup

The P300 speller paradigm which is described by Dolchin *et al*, and originally Farewell and Dolchin, 1988 is used for complete recording of P300 evoked potential [28]. The user is asked to concentrate on a 6×6 matrix of alphanumeric characters. This matrix is displayed on a computer screen. The instructor asks the user to concentrate on a particular character of the matrix. Some specific duration and inter-stimulus interval are used to intensify the rows and columns of the matrix randomly. The number of target stimulus is very less compared to non target stimulus i.e, the number of P300 waves is about one-fifth of the No-P300 waves. For example, in the 6×6 matrix of alphanumeric characters, only 2 out of 12 intensifications are target intensifications, one representing the row and other representing the column. These two intensifications provide us information about the desired character. Rests of the 10 intensifications are the non-target stimulus. A user's mind responds differently to target and non-target intensification. The basic principle of this spelling paradigm is that the subject produces different response to the target intensification and non target ones. This target intensification generates a P300 potential which basically a class of event related potential.

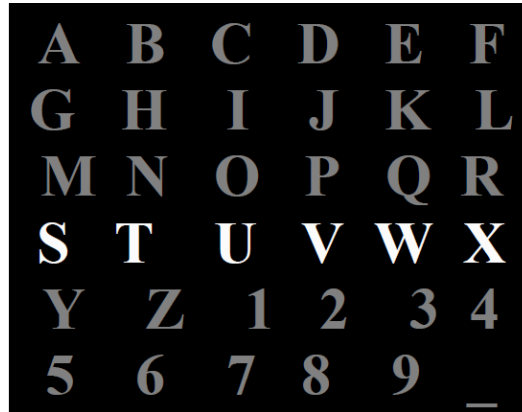


Fig 2.2: Speller Matrix used for data collection [29]

In order to predict the target character it is highly essential that the target intensification stimulus response defined by P300 wave can be clearly distinguished from the non-target ones defined by no-P300. But, it is generally quite difficult to distinguish this in a single trial i.e. by intensifying the row and column major's only ones. The very reason behind this is that EEG signal being

highly sensitive to noise makes it a tough task to distinguish the target response from the non-target ones. Henceforth, in order to increase the prediction accuracy several trials are required for identifying a single target character.

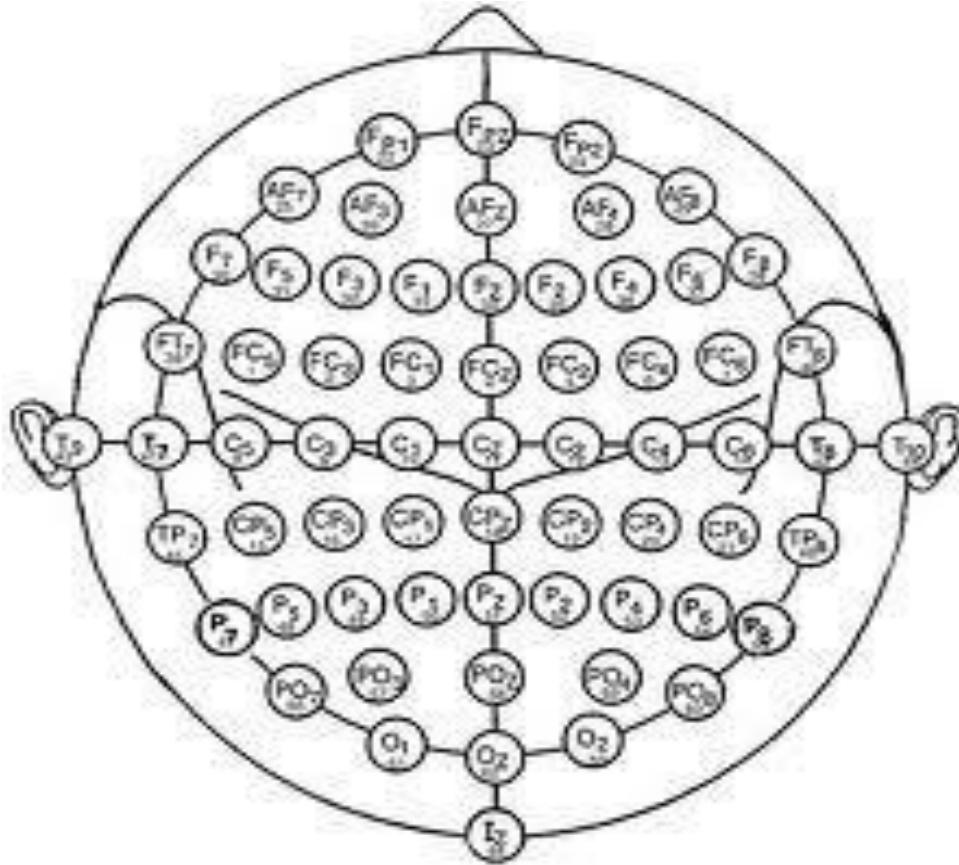


Fig 2.3: Electrode designations and channel assignment numbers for EEG measurement [29]

After data is obtained using the above described format, the flowchart below is implemented to achieve the required objective.

FLOWCHART

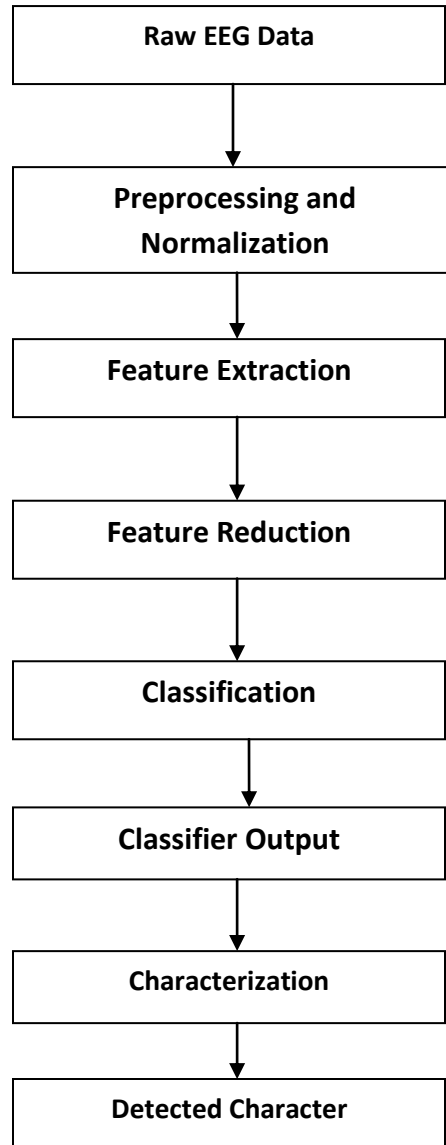


Fig 2.4: Flowchart of P300 classification and characterization

2.1.2 Data Extraction

First the data is collected from the data set 2 of the third BCI competition. Then it is required to be processed and extracted. This is done using matlab software. First a struct is extracted from the data and then it is converted to a cell. Then a matrix from the cell using the command

cell2mat. Once we have obtained the data in a matrix form we are set to begin the processing of the data.

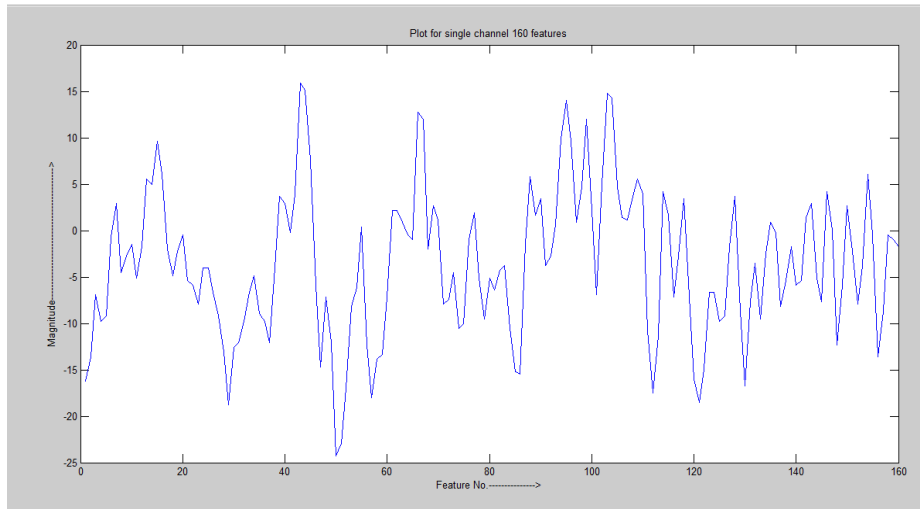


Fig 2.5: Plot for single channel 160 features

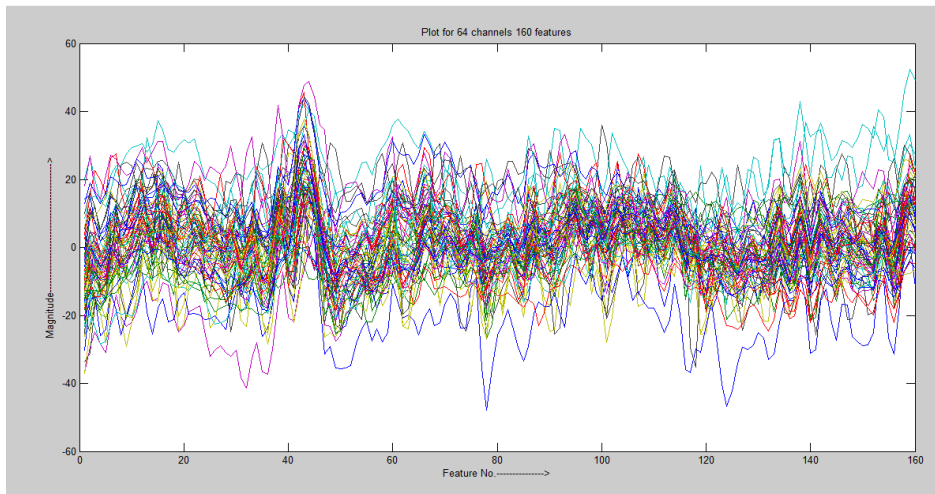


Fig 2.6: Plot for 64 channels 160 features

2.2 Pre-Processing and Normalization

We only require the part of the EEG signal that occurs after a particular intensification. Thus for each channel i.e, data collected from a single electrode we extract all data samples lying between 0 to 667 ms at the beginning of an intensification. We consider the window to be large enough to acquire all P300 signals as the P300 occurs about 300 ms after each stimulus. Thus a total of 160 features are extracted for each intensification, which correspond to the 667 ms EEG signals, each have a sampling rate of 240 Hz. The EEG signals have a magnitude lying between +15 and -15. In order to limit the value of each recorded EEG signal, it is normalized to a value lying in between -1 and +1. This is called as normalization and is done by dividing each sample with the absolute maximum value in the matrix.

$$\text{Normalize}(k) = \text{Signal}(k) / \|\text{Signal}(k)\|_{\max} \quad 2.1$$

2.3 Feature Extraction

Feature extraction is the method of extracting essentials features from the feature matrix while ignoring the irrelevant ones. This is done by using 'wrcoef'. This gives 160 wavelet coefficients for a single visual stimuli i.e, for a single channel. In order to reduce the size of the feature matrix the length of the entire matrix was divided into 5 equal segments. After that two very essential statistical parameters are calculated. These are as follows:

- (i) In each sub band calculate the maximum of wallet coefficient.
- (ii) In each sub band calculate the maximum of wallet coefficient.

Thus after wavelet transformation we get 10 features for a single channel. Thus total no. of features extracted = $64 * 10 = 640$ for 64 channels.

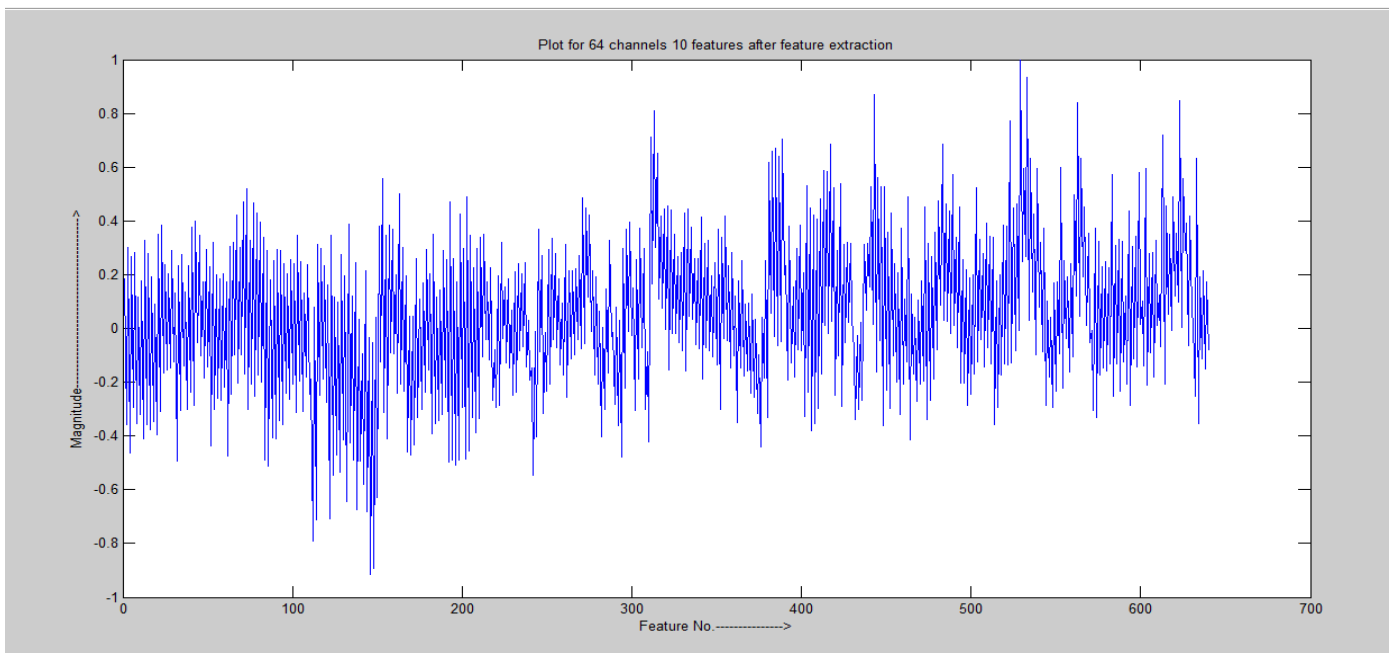


Fig 2.7: Plot for 64 channels 10 features after feature extraction

2.4 Feature Reduction

A common problem encountered in machine learning algorithm is feature selection. Transforming the data space into a feature space with exactly the same dimension as the original data is called as feature selection. The transformation is designed in a way to reduce the dimension of the data. One of the well known techniques for feature extraction and dimensionality reduction is Principal Component Analysis (PCA). The directions along which the variations are the maximum provide most information about classes. This is the underlying assumption of PCA. PCA algorithm reduces the number of dimensions of the feature space without losing a lot of information [29]. So, it is a pretty essential tool for data compression.

PCA operation can be operated by following the steps which are mentioned below:

Step1: The input data to be processed is acquired

Step2: The mean of the input data is obtained.

Step3: The mean is subtracted from each of the input data dimension.

Step4: The covariance matrix is calculated. The covariance matrix gives the value of the required covariance. The required Covariance can be calculated from the equation mentioned below as:

$$\text{cov}(x, y) = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{n - 1} \quad 2.2$$

Where \bar{X} is the mean of data set.

Step5: The Eigen Vectors and Eigen Values of the Covariance matrix obtained in above step are calculated.

Step6: The components to form the feature vector are chosen. W is calculated from the transformation matrix

$$\text{Transformed data} = w * \text{Row Data} \quad 2.3$$

Where w is the matrix having eigenvectors in the columns transpose and the Row data is the mean adjusted transpose.

In this case the feature vector obtained from discrete wavelet transform is of 1×640 dimension which is quite large input dimension for classifier. So here PCA is applied to reduce the feature dimension up to 1×100 for each stimulus response. An assumption is made for dimensionality reduction by PCA. The assumption is that the subspace spanned by the first m principal axes contains most information of the observation vectors, where $m < p$ for a p-dimensional data space.

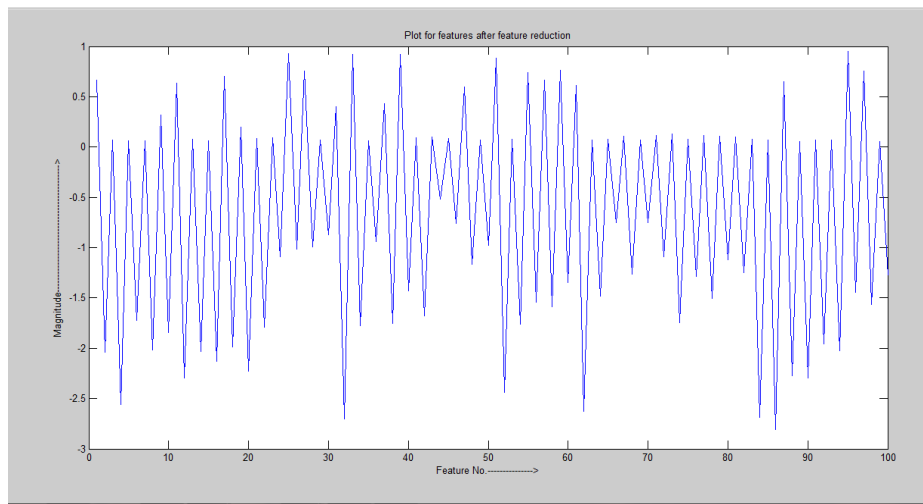


Fig 2.8: Plot for features after feature reduction

2.5 Classification

Neurophysiologic signals need to be mapped to basic actions. This is the main aim of any BCI application. To perform this we need to design a machine learning algorithm. This algorithm can be designed by any method of classification using a classical model. Classification methods can be divided into two categories. These are parametric or non-parametric methods. The common method used in BCI problems is to train the network with a set of training data which is already known to the instructor and then go for the testing part. This is called as supervised learning method.

2.5.1 Classification Problem

In order to detect the target character in P300 speller matrix, we first need to determine the row and column intensifications of the target character. The speller matrix is characterized by 12 classes i.e, 6 rows and 6 columns. Since the target character intersects at one row and column, there are basically 6 classes. So, in each classification group there are 6 classes. The problem seems to be a 6 class but since the aim is to classify the signals as target (P300) or non-target (no-P300), the task is just a binary classification problem.

2.6 ARTIFICIAL NEURAL NETWORK

Artificial neural networks are mathematical models. These are inspired by the functional aspect of Neurons' biological structure and are commonly known as neural networks. ANN is mainly useful in the classification of EEG signal because of its properties like: its structure is distributed massively in parallel compared to the other available artificial intelligence method in which sequential information processing takes place. Generalization property of the ANN makes itself useful for pattern recognition. Generalization can be defined as the ability to learn from surrounding and experience it and make it useful in future which will produce an adequate response to the unknown stimulus that is related to knowledge acquiring. Due to this property some other property like self-organization, adaptive learning, fault-tolerance are produced. This entire feature makes Artificial Neural Network so that it will be able to give a proper solution to complex problem which is normally difficult to solve using traditional approximation. Neuron is

the basic processing unit of brain and it works identically inside ANN. The fundamental unit , neurons, are interconnected with each other through synaptic weights . In learning phase it is used to acquire knowledge. The number of neurons and their respective synaptic weights can be changed in accordance with desired design perspective [31], basically a neuron processes information and that is fundamental to the operation inside a neural network.

2.6.1 Models of neuron

From the above explanations we got to know that a neuron is a fundamental information processing unit of a neural network. Figure given below shows the model of neuron. The basic elements shown are

- (i) Set of connecting link which are also known as synapses and they are characterized by its weight. A signal x_j which is at input of synapse j that is connected to neuron k and multiplied by weight w_{kj} .
- (ii) An adder which will sum the input signals which are multiplied by its synaptic weight and this is a linear combination.

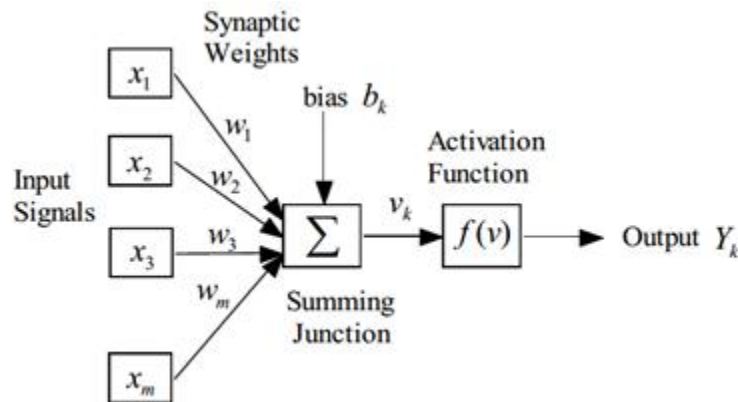


Fig 2.9: Non-linear model of a neuron

- (iii) An activation function which will put limit to the output of neuron. Generally, the normalized amplitude range of the neuron output is represented as the $[0, 1]$ or sometimes alternatively $[-1, 1]$.

(iv) Bias is denoted by b_k and it has effect of increasing and lowering the net input given to the activation function.

In mathematical term we can write the neuron k by following equations:

$$v_k = \sum_{j=0}^m w_{kj} x_j \quad , \text{where } v_k \text{ is the induced local field} \quad 2.4$$

$$y_k = \varphi(v_k) \quad , \text{where } y_k \text{ is the output} \quad 2.5$$

$$v_k = [w_{k0} \ w_{k1} \dots w_{kp}] \begin{bmatrix} x_0 \\ x_1 \\ \cdot \\ \cdot \\ x_p \end{bmatrix} = w_k^T x \quad 2.6$$

2.6.2 NETWORK ARCHITECTURE

Network architecture can be defined as the way in which the fundamental unit i.e. neuron is structured and directly linked to the learning algorithm which is responsible to train the network. Generally there exists three types of ANN architecture:

- 1) Single layer feedforward network
- 2) Multilayer feedforward network
- 3) Recurrent network

2.6.2.1 Multi layer feed forward network

Multi layered feed forward network is another type of feed forward structure in which there are no feedback loops. It distinguishes itself from the single layer feed forward network because of the presence of hidden layers. The purpose of the hidden layer is to intervene between the input and output and produce a desired result. The number of hidden layers can be one or many depending on the type and purpose of classification. These hidden layers increase the efficiency of the neural network by providing an additional layer of neurons. Though the computational complexity increases through the use of multi layer feed forward network, but accuracy increases by manifold [32][33].

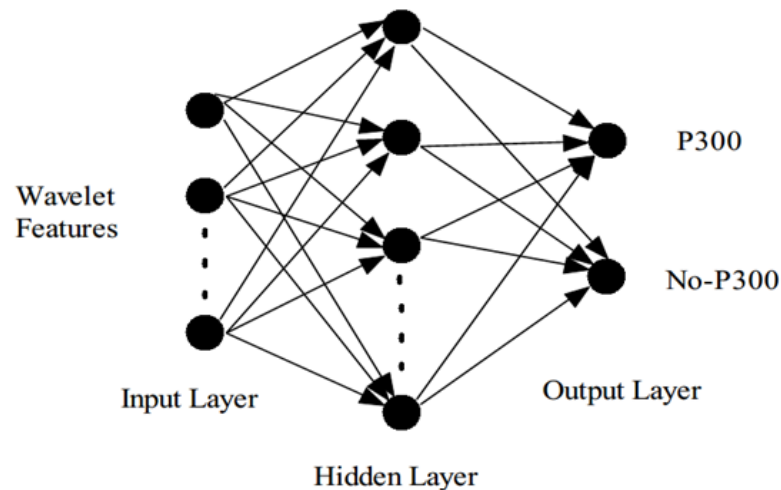


Fig 2.10 Multi layer feed forward network [33]

2.7 Multilayer Perceptron

Multi Layer perceptron is a feed forward neural network having one or more hidden layers lying between input and output layer. It can be described as feed forward because data flows in one direction i.e. in forward direction from input to output layer. This type of network is trained using the back propagation algorithm. MLPs are widely used for pattern classification, recognition, prediction and approximation. Multi Layer Perceptron can solve problems which are not linearly separable[34]. To create and train Multi Layer Perceptron neural network following steps are followed:

1. A Multi Layer perceptron network is created.
2. Using back propagation algorithm training set is created.
3. The network is trained.
4. The network is tested.

A MLP has single layer of neurons neuron synaptic weights can be adjusted and a bias is also provided. Generally Multilayer perceptron are being applied successfully to solve some difficult problems by training them in a supervised manner or supervising them with a highly popular algorithm which is also known as the “error back-propagation algorithm”. This algorithm can be elaborated as the rule for error-correction learning. This back propagation training with delta learning rule is a gradient algorithm specifically designed to minimize the root mean square error calculated between the actual output of a multilayered feed-forward Neural Network and the desired output. It reduces the root square error iteratively. Here each layer is fully connected to the previous layer (means no connection is missing), and has no other connection other than that.

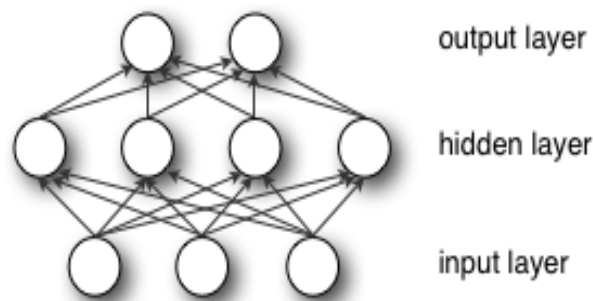


Fig 2.11 Multi layer Perceptron [34]

2.8 Back propagation algorithm

This algorithm is implemented to find the training signal in a multilayer perceptron. Steps followed in this algorithm are:-

- 1) The weight and biases are initialized to some real number chosen randomly
- 2) The input vectors $x(1), x(2), \dots, x(N)$ and their corresponding output vectors $d(1), d(2), \dots, d(N)$ are specified.

3) The actual output y_1, y_2, \dots, y_{NM} are calculated.

These are calculated by using the equation

$$\left(\sum_{j=1}^{N_{M-1}} w_{ij}^{(M-1)} x_j^{M-1} + b_i^{M-1} \right), \quad i = 1, \dots, N_{M-1}$$

4) Weight (W_{ij}) and bias(b_i) are changed adaptively during each iteration using the equations:

$$\Delta w_{ij}^{l-1}(n) = \mu \cdot x_j(n) \cdot \delta_i^{l-1}(n)$$

$$\Delta b_i^{l-1}(n) = \mu \cdot \delta_i^{l-1}(n)$$

Where

$$\delta_i^{l-1}(n) = \begin{cases} \varphi'(net_i^{l-1}) [d_i - y_i(n)], & l = M \\ \varphi'(net_i^{l-1}) \sum_k w_{ki} \cdot \delta_k^{(l)}(n), & 1 \leq l \leq M \end{cases}$$

In which $x_j(n)$ is the output of node j at iteration n , l denotes layer, k defines the number of output node, M indicates output layer and φ stands for the activation function and μ represent the learning rate. In order to achieve faster convergence with minimum no of oscillation, each time a momentum term is added to the updating equation which updates the basic weight. After completion of the training procedure of a neural network, the weights of MLP are frozen (can't be changed further means decided) and then ready for use in the testing mode. Then the values are used in testing mode [35].

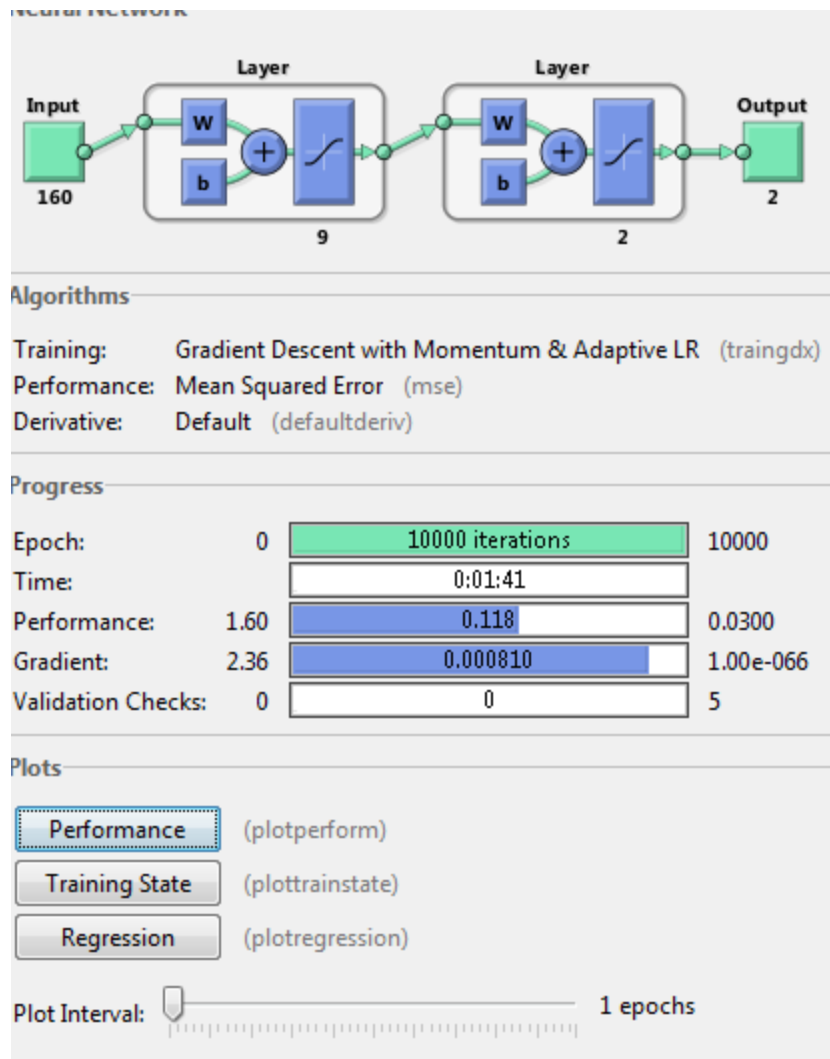


Fig 2.12: Implementation of ANN

ANN algorithm was implemented using MATLAB R2013. We have selected the number of hidden layers as 9 and number of output layers as 2. The number of iteration was chosen as 10000. Performance was chosen to be 0.3. Learning rate was chosen as 1.01 and the gradient was fixed at e-06. Finally the training sequence was given as input. The output was obtained when the testing sequence was initialized. Experimental result obtained is shown in a tabular format below.

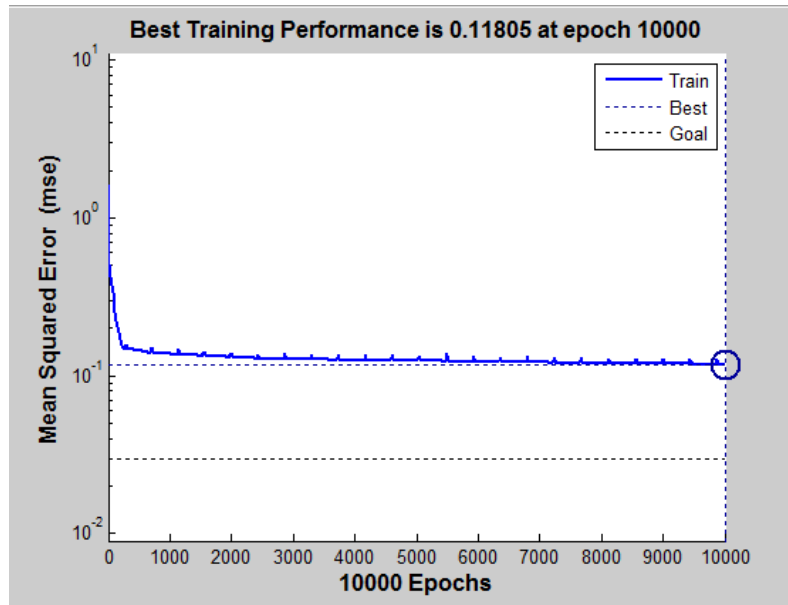


Fig 2.13: Performance Plot of ANN

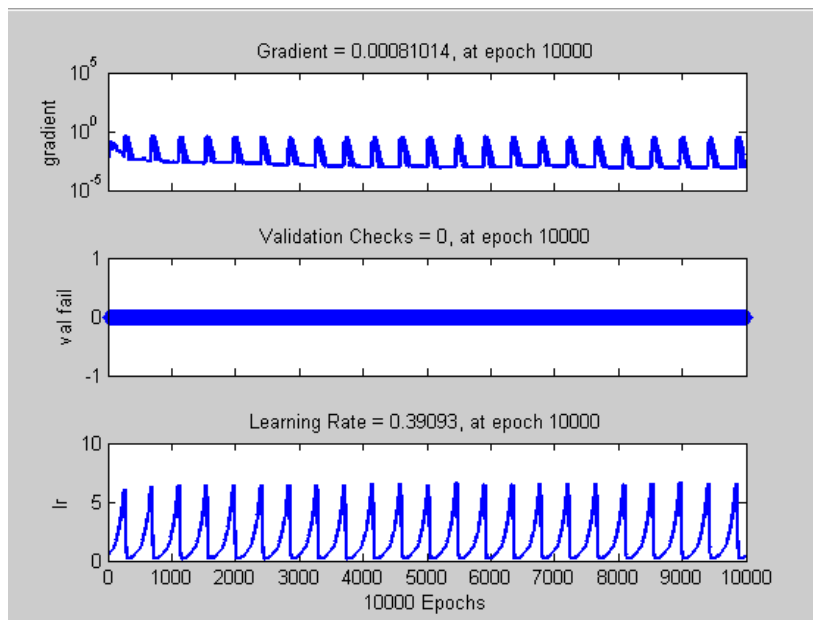


Fig 2.14: Plot for training state of ANN

2.9 EXPERIMENTAL RESULT

One of the objectives of the project is to classify brain signals into two classes i.e, P300 and No-P300 signals. The data collected from data set II of the third BCI competition is used for this purpose as already stated. Total no. of P300 signals in one sample is equal to 462 and total no. of No-P300 signals in one sample is equal to 2226. Thus this data was used for training purpose and during testing the results were obtained. These results are shown in Table 4.1. The result was analyzed and accuracy was calculated.

Classifier	Subject	Desired Result		Output	
		P300	No-P300	P300	No-P300
ANN	SUBJECT-A	462	2226	326	2185

Table 2.1: Output of ANN classifier

Accuracy for P300 detection= $(\text{Output}/\text{Desired Result}) \times 100$

$$=326/462 \times 100$$

$$=70.56\%$$

Accuracy for No-P300 detection= $(\text{Output}/\text{Desired Result}) \times 100$

$$=2185/2226 \times 100$$

$$=98.15\%$$

2.10 Conclusion

In this section first the data was normalized during the pre-processing stage. To reduce the size of the feature matrix feature extraction was done. Feature reduction was carried out with the help of PCA analysis to reduce the computational complexity and finally ANN was used to detect the P300 waves. The plot for training state of ANN and performance plot was obtained.

CHAPTER-3

**CHARACTERIZATION OF
P300 WAVES FOR BRAIN
COMPUTER INTERFACE**

3.1 Multi class classification

In neural network, multiclass or multiple classification is the method of classifying variables into two or more classes. Some algorithms are by default binary classification algorithms whereas others allow multiclass classification. The binary classification algorithms can be converted to multi class classification by using a wide range of strategies. The training points belong to any one of the M classes used for classification. The basic aim of multiclass classification is to find a function that can classify the data or variables into different classes when used for testing [36]

3.2 Types of multiclass classification

3.2.1 One-vs-All Classification

A good technique needs to be picked for building binary classifiers (e.g., RLSC, SVM). N different binary classifiers are to be built. For the i th classifier, let the positive examples be all the points in class i , and let the negative examples be all the points not in class i . Let f_i be the i th classifier. It is classified with

$$f(\mathbf{x}) = \arg \max_i f_i(\mathbf{x}). \quad 3.1$$

3.2.2 All-vs-All Classification

$N(N-1)$ classifiers are to be built, one classifier for distinguishing each pair of classes i and j . Let f_{ij} be the classifier where class i are positive examples and class j are negative. $f_{ji} = -f_{ij}$. It is classified using

$$f(\mathbf{x}) = \arg \max_i \left(\sum_j f_{ij}(\mathbf{x}) \right). \quad 3.2$$

3.3 Characterization Problem

The detection of the target character in P300 Speller requires the determination of the target row and column intensifications. There are 12 classes for a 6x6 speller matrix (6 row and 6 column

intensification classes). Thus it becomes a multiclass classification problem where we need to identify the target character. There are 36 characters in totals and we need to identify the right character which the user has focused on. This is done by detecting the P300 signals and then combining the P300 signals to generate the right character to spell.

3.4 Steps Used for Multiclass classification

- ▶ Load the data
- ▶ Find the time used for classification
- ▶ Set the electrode number
- ▶ Get all samples where PhaseInSequence == 3 i.e, end period after one character
- ▶ Get exactly the samples at which the trials end i.e, i.e., the ones where the next value of PhaseInSequence equals 1 (starting period of next character)
- ▶ This determines the first and last intensification to be used
- ▶ Go through all intensifications and calculate classification results after each trial
- ▶ Get the indices of the samples of the current intensification
- ▶ Get the data for these samples i.e., starting at time of stimulation and trial length samples
- ▶ Calculate average responses for each of the stimuli
- ▶ Plot averaged responses for each of the 36 grid positions
- ▶ Show the character with the highest classification result in the matrix

3.5 EXPERIMENTAL RESULT

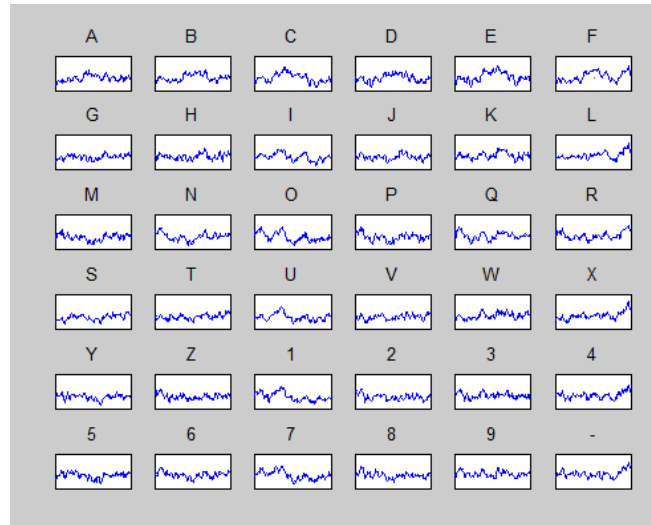


Fig 3.1: Signal representation of various characters used in the matrix

In the characterization part the detected P300 signals are combined to generate the right character to spell. The classification is done using multiclass classifier by comparing the average of signal generated with the existing signals. The one with best result is selected as the identified character.

Data	Identified character
1p.mat	F
2p.mat	R

Table 5.2: Characterization Output

3.6 Conclusion

This part of the thesis deals with the characterization part i.e, the detected P300 signals in stage 2 are combined to generate the right character to spell. First the signal representation of various characters used in the speller matrix are generated. Then the average response of each of the stimulus is calculated and plotted. This plot is compared with the signal representation of various characters. The one which provides the most accurate result is chosen as the output character.

CHAPTER-4

CONCLUSION AND

FUTURE WORK

CONCLUSION

In this world of cut-throat competition where the sky's the limit, man has crossed all boundaries in the field of technology and Brain Computer Interface is just another example of it. This technology has indeed been a boon for mankind, helping those who are not able to help themselves i.e, people with physical disability. It helps them to express their thoughts and imagination by interfacing their brain with a computer and when used in full proof mode it can indeed display what they are thinking through a screen. But the major challenge that lies ahead of this technology is to distinguish between P300 and Non-P300 signals. P300 signals are actually the ones used for generating characters and Non-p300 signals are just random signals generated in the brain. The central theme of this project is to distinguish these signals so that they can be used for further processing. This process is called as classification. The classification of signals requires feature extraction which has been implemented in this project using discrete wavelet transform. To reduce the burden of complexity feature reduction technology has been implemented using Principal Component Analysis (PCA). After this Artificial neural Network (ANN) classifier is used to distinguish the P300 and Non-P300 signals. The result obtained is shown in a tabular format and the accuracy is also calculated. Finally using multiclass classifier characterization is performed which identifies the right character to spell. So, in short this project report is a short hand representation of brain computer interface, which with little bit of modification can be used in real life for practical purpose.

FUTURE WORK

A lot of research can be done in the field of brain computer interface. It is a huge field with a lot of scope for development. Some of the important works that can be carried out in future in this field are as follows

[1] P300 detection varies with the data used from subject to subject. So, the neural network can be trained on a larger set of data so that accurate detection of P300 signals can be made which is the first step of any BCI system

[2] Better algorithms can be used to characterize the data set.

[3] Development of hardware circuit to implement BCI i.e, interfacing circuits can be designed so that the system becomes a real time system that acquires signal from the brain and directly displays characters on the screen.

[4] An overall operating protocol can be designed, so that the user can control how the system works. The how includes, for example, switching the system on or off, controlling what kind of feedback is to be provide and how fast, controlling the speed of implementation of commands, and switching between the device outputs.

BIBLIOGRAPHY

- [1] Bernhard Graimann, Brendan Allison, and Gert Pfurtscheller, “Brain–computer interfaces: A gentle introduction,” *The Frontiers Collection Springer Berlin Heidelberg*, pp.1-27, 2010.
- [2] J.R Wolpaw, D.J. McFarland., T.M. Vaughan, G. Schalk, “The Wadsworth Center Brain-Computer Interface (BCI) Research and Development Program,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 11, no. 2, pp. 1-4, June 2003.
- [3] S.G. Mason, G.E Birch, “A General Framework for Brain-Computer Interface Design”, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 11, no. 1, pp. 70-85, Mar 2003.
- [4] F. Cincotti, L. Bianchi, G. Birch, C. Guger, J. Mellinger, R. Scherer, R.N. Schmidt, O.Y. Suarez, G. Schalk, “BCI Meeting 2005 – Workshop on Technology: Hardware and Software,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 14, no.2, pp. 128-31, June 2006.
- [5] F. Lotte, M. Congedo, A. Lecuyer, F. Lamarche, B. Arnaldi, “A Review of Classification Algorithms for EEG-Based Brain-Computer Interfaces,” *Journal of Neural Engineering*, vol. 4, pp. 1-13, Jan 2007.
- [6] Hasan Balkar Erdoğan “A Design And Implementation Of P300 Based Brain-Computer Interface” Ph.D. thesis, The Graduate School Of Natural And Applied Sciences of Middle East Technical University, 2009.
- [7] Hubert Cecotti, Axel Graser, “Convolutional neural networks for P300 detection with application to brain-computer interfaces,” *IEEE transactions on communications*, vol. 33, no. 3, pp. 433-445, Mar 2011.
- [8] Saeid Sanei, and A. Jonathon Chambers. *EEG signal processing*. Wiley-Interscience, 2008.
- [9] Michal Teplan, “Fundamentals of EEG measurement,” *Measurement science review*, vol. 2, no. 2, pp 1-11, 2002.
- [10] Towle, L. Vernon, Bolanose Jose, Suarez Diane, Tan Kim, Robert Grzeszczuk "The spatial location of EEG electrodes: locating the best-fitting sphere relative to cortical anatomy." *Electroencephalography and clinical neurophysiology*, vol. 86, no. 1, pp. 1- 6, Jan 1993.
- [11] Nicolas-Alonso, Luis Fernando, and Jaime Gomez-Gil, “Brain computer interfaces, a review”, *Sensors*, vol. 12, no. 2, pp. 1211-1279, Jan 2012,

- [12] Dean J Krusienski, E. W. Sellers, D. J. McFarland, T. M. Vaughan, J. R. Wolpaw, "Toward enhanced P300 speller performance," *Journal of neuroscience methods*, vol. 167, no. 1, pp. 15–21, Jan 2008
- [13] L. Maggi, S. Parini, L. Piccini, G Panfili, G. Andreoni, "A four command BCI system based on the SSVEP protocol" *IEEE International Conference on Engineering in Medicine and Biology Society*, pp. 1264-1267, 2006.
- [14] Ben H. Jansen, A. Allam, P. Kota, K. Lachance, "An exploratory study of factors affecting single trial P300 detection," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 6, pp. 975-978, June 2004.
- [15] Min Ki Kim, and Sung-Phil, "Detection of P300 components using the Wiener filter for BCI-based spellers," *8th Asian IEEE conference on Control (ASCC)*, pp. 892-896, sep. 15-18, 2011.
- [16] Gerardo Rosas-Cholula, "On signal P-300 detection for BCI applications based on wavelet analysis and ICA preprocessing," *IEEE conference on Electronics, Robotics and Automotive Mechanics Conference (CERMA)*, pp.360-365, 2010.
- [17] Matthias Kaper, M. Meinicke, U. Grosse-kathoefer, "BCI competition 2003-data set IIb: Support vector machines for the P300 speller paradigm," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 6, pp. 1073-1076, June 2004.
- [18] Vladimir Bostanov, "BCI competition 2003-data sets Ib and IIb: feature extraction from event-related brain potentials with the continuous wavelet transform and the t-value scalogram," *IEEE Transactions on Biomedical Engineering*, vol. 51, no.6, pp. 1057- 1061, June 2004.
- [19] Alain Rakotomamonjy and Vincent Guigue, "BCI competition III: dataset II-ensemble of SVMs for BCI P300 speller," *IEEE Transactions on Biomedical Engineering*, vol. 55, no. 3, pp. 1147-1154, Mar 2008.
- [20] M. Kaper, P. Meinicke, U. Grosse-kathoefer, T. Lingner, H. Ritter, "BCI Competition 2003 – Dataset IIb: Support Vector Machines for the P300 Speller Paradigm," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 6, pp. 1073 – 1076, June 2004.
- [21] B. Blankertz, K.R. Müller, G. Curio, T.M. Vaughan, G. Schalk, J.R. Wolpaw, A. Schlögl, C. Neuper, G. Pfurtscheller, T. Hinterberger, M. Schröder, N. Birbaumer, "The BCI Competition 2003: Progress and Perspectives in Detection and Discrimination of EEG Single Trials," *IEEE Transactions on Biomedical Engineering*, vol.51, no.6, pp. 1044 – 1051, June 2004.

- [22] Z.L. Lin, C.S. Zhang, "Enhancing Classification by Perceptual Characteristics for the P300 Speller Paradigm," *Proceedings of the 2nd International IEEE EMBS Conference on Neural Engineering – Arlington/Virginia*, March 16-19, 2005.
- [23] M. Thulasidas, C. Guan, J. Wu, "Robust Classification of EEG Signals for Brain- Computer Interface," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 14, no. 1, pp. 24-29, Mar 2006.
- [24] D. Garrett, D.A. Peterson, C.W. Anderson, M.H. Thaut, "Comparison of Linear, Nonlinear, and Feature Selection Methods for EEG Signal Classification," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 11, no. 2, pp. 141-144, June 2003.
- [25] B. Blankertz, G. Curio, K.R. Müller, "Classifying Single Trial EEG: Towards Brain Computer Interfacing," *Advanced. Neural Information Processing Systems*, vol. 14, pp. 157-64, 2002
- [26] A. Schlögl, F. Lee, H. Bischof, G. Pfurtscheller, "Characterization of Four-Class Motor Imagery EEG Data for the BCI-competition 2005," *Journal of Neural Engineering*, vol. 2, no. 4, pp. 14-22, Dec. 2005.
- [27] B. Blankertz, BCI Competition III Webpage. [Online]. Available: http://ida.first.fraunhofer.de/projects/bci/competition_iii
- [28] L.A. Farwell, E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalography & Clinical Neurophysiology*, vol. 70, no. 6, pp. 510-523, Dec. 1988.
- [29] Dipti Patra, Manab Kumar Das, and Smita Pradhan, "Integration of FCM, PCA and Neural networks for classification of ECG Arrhythmias," *IAENG International Journal of Computer Science*. vol. 36, no. 3, pp. 24-62, Feb 2010.
- [30] Travis C. Collier and Charles Taylor, "Self-organization in sensor networks," *Journal of Parallel and Distributed Computing*, vol. 64, no. 7, pp. 866-873, July 2004.
- [31] Shang-Ming Zhou, Q. Gan John and Francisco Sepulveda, "Classifying mental tasks based on features of higher-order statistics from EEG signals in brain-computer interface," *Information Sciences*, vol. 178, no. 6, pp. 1629-1640, Mar. 2008.
- [32] Daniel Svozil, Vladimir Kvasnicka, and Jiri Pospichal, "Introduction to multi-layer feed-forward neural networks", *Chemometrics and intelligent laboratory systems*, vol. 39, no. 1, pp. 43-62, Nov. 1997.

- [33] Elif Derya Übeyli, “Least squares support vector machine employing model-based methods coefficients for analysis of EEG signals,” *Expert Systems with Applications*, vol. 37, no. 1, pp. 233-239, Jan. 2010.
- [34] Burges, JC. Christopher, “A tutorial on support vector machines for pattern recognition,” *Data mining and knowledge discovery*. vol. 2, no. 2, pp. 121-167, 1998.
- [35] Simon S. Haykin, *Neural networks and learning machines*. New Delhi: Pearson Education Asia, 2002.
- [36] Corinna Cortes and Vladimir Vapnik, “Support-vector networks,” *Machine learning*, vol. 20, no. 3, pp. 273-297, 1995.