CLASSIFICATION OF P300 SIGNALS IN BRAIN-COMPUTER INTERFACE USING NEURAL NETWORKS WITH ADJUSTABLE ACTIVATION FUNCTIONS

SEYED ALIAKBAR MOUSAVI ASLARZANAGH

UNIVERSITI SAINS MALAYSIA

2013

CLASSIFICATION OF P300 SIGNALS IN BRAIN-COMPUTER INTERFACE USING NEURAL NETWORKS WITH ADJUSTABLE ACTIVATION FUNCTIONS

by

SEYED ALIAKBAR MOUSAVI ASLARZANAGH

Thesis submitted in fulfilment of the requirements
for the degree of
Master of Science

November 2013

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to Professor Dr. Muhammad Rafie Hj. Mohd. Arshad and Ms. Hasimah Hj. Mohamed who encouraged and guided me through this interesting research journey. I appreciate their constant support from the first day I started my research program.

My best regards to Universiti Sains Malaysia, especially School of computer sciences for providing me this opportunity.

I am also grateful and thankful to my dear parents and brothers for their continuous support, understanding and care.

Last, but not least, my special thanks go to my dear wife Mina, without her support and companion, I could never finish this research. Your love, patience and sacrifice have made this dream come true.

DECLARATION

Name: Seyed Aliakbar Mousavi aslarzanagh

Matric No: P-COM0003/10(R)

School: School of Computer Science

Thesis Title: Classification of Brain‘s P300 ERP wave using Neural Networks with Adaptive Activation Function

I hereby declare that this thesis I have submitted to .... on .... is my own work. I have stated all references used for the completion of my thesis.

I agree to prepare electronic copies of the said thesis to the external examiner or internal examiner for the determination of amount of words used or to check on plagiarism should a request be made.

I make this declaration with the believe that what is stated in this declaration is true and the thesis as forwarded is free from plagiarism as provided under Rule 6 of the Universities and University Colleges (Amendment) Act 2008, University Science Malaysia Rules (Student Discipline) 1999.

I conscientiously believe and agree that the University can take disciplinary actions against me under Rule 48 of the Act should my thesis be found to be the work or ideas of other persons.

Students Signature: .... Date: ....

Acknowledgement of receipt by: .... Date: ....

TABLE OF CONTENTS

Acknowledgements ii

Declaration iii

Table of Contents iv

List of Tables viii

List of Figures ix

List of Abbreviations xi

Abstrak xii

Abstract xiv

CHAPTER 1 – INTRODUCTION

1.1 Overview 1

1.2 Research Background 2

1.3 Problem Statement 5

1.4 Objectives 6

1.5 Research Scope 6

1.6 Summarized Research Method 7

1.7 Contribution 7

1.8 Definition of Terms 8

1.9 Organization of Thesis 10

CHAPTER 2 – LITERATURE REVIEW

2.1 Introduction 11

2.2 The EEG and ERP Brain Signals 11

2.2.1 The Types of ERP Components 13

2.3 The ERP Classification 13

2.3.1 Issues in ERP Classification 17

2.4 Brain-Computer Interface (BCI) and P300 Detection in EEG Data 18

2.5 The P300 Speller Paradigm 20
2.5.1 P300 Detection 21
2.5.2 Database 21
2.5.3 Current Methods in P300 Speller Application 23
2.6 Artificial Neural Network 25
2.6.1 Back-Propagation Neural Networks 26
2.7 Activation Functions in Artificial Neural Network 28
2.7.1 Different Types of Activation Functions 30
2.7.2 Nguyen - Widrow Initialization Method 33
2.7.3 Validation of Classification Method 34
2.8 Chapter Summary 34

CHAPTER 3 – RESEARCH METHODOLOGY

3.1 Introduction 36
3.2 Software 36
3.3 Database 36
3.4 Framework 38
3.5 Preprocessing and Feature Extraction 39
3.5.1 Building Classifiers 40
3.6 Developing Neural Network Models 42
3.6.1 Pre-Experiment 43
3.6.2 Training Three Neural Networks Models 43
3.7 Testing the Trained Neural Networks Models 52
3.7.1 P300 Classification 52
3.7.2 Character Recognition 54
3.8 Chapter Summary 55

CHAPTER 4 – EXPERIMENTAL RESULTS OF MODELS AND CLASSIFIERS

4.1 Introduction 56

4.2 Result of Pre-Experiment 56

4.3 Results from P300 Classification 57

4.4 Results from Character Recognition 60

4.5 Comparison of Results with Previous Studies in BCI 63

4.6 Scalability Results 66

4.7 Limitations 67

4.8 Chapter Summary 67

CHAPTER 5 – CONCLUSION

5.1 Introduction 69

5.2 Discussion 69

5.3 Summary of Findings 70

5.4 Future Work 71

REFERENCES

APPENDICES 78

APPENDIX A – WADSWORTH BCI DATASET (P300 EVOKED POTENTIALS) DATA ACQUIRED USING BCI2000'S P3 SPELLER PARADIGM (HTTP://WWW.BCI2000.ORG) 79

A.1 Dataset Summary 79

A.2 The Paradigm 79

A.3 Data Collection 80

A.4 The Data-Set 81

A.5 Results of Pre-Processing 83

APPENDIX B – DATA SET IVA FROM THIRD BCI COMPETITION 86

B.1 Experimental Setup 86

B.2 Format of the Data 86

B.3 Technical Information 88

List of Publications 89

LIST OF TABLES

Page

Table 2.1 The size of dataset for each subject in BCI database **23**

Table 3.1 The size of dataset for each subject in BCI database **37**

Table 4.1 Accuracy of NN models with different number of nodes and learning rate (β) **57**

Table 4.2 Number of nodes and learning rate for each model **57**

Table 4.3 The result of EEG classification for either P300 or non-P300 signals **58**

Table 4.4 Character recognition percentage for the all classifiers of NN3 model **60**

Table 4.5 Comparison of results with current methods in BCI P300 speller **65**

Table 4.6 Comparison of results of NC2 classifier with current methods in BCI P300 speller **66**

Table 4.7 The mean accuracy of NN models in cued motor imagery **67**

LIST OF FIGURES

		Page
Figure 1.1	EEG recording process and the produced signals	**3**
Figure 1.2	ERPs are physiological signals which are created once the segments of EEG are averaged and sub-divided in time and event of interest	**3**
Figure 1.3	Summarized research method	**7**
Figure 2.1	ERP generation process and ERP components	**14**
Figure 2.2	NeuroElectroMagnetic Ontologies (NEMO) framwork to classify ERP components and building ERP domain Ontology	**16**
Figure 2.3	Encountered eye-muscle artifacts during experiment. The points of A and B are showing the effect of artifacts/noises on the EEG signals	**18**
Figure 2.4	B is showing P300 signal peak and A is the brain region that P300 peak is occurring, C is showing BCI P300 Speller application: the row/column paradigm (Donchin et al., 2000)	**21**
Figure 2.5	P3 or P300 occurs around 300 to 400 milliseconds time after presentation of stimulus and suggests the perception of stimulus by subject	**22**
Figure 2.6	Illustration of activation function in a neural network (White, 2009)	**30**
Figure 2.7	Architecture of neural network with adoptive activation function	**31**
Figure 3.1	Framework to classify P300 signals and recognize the characters	**39**
Figure 3.2	Feature extraction from all electrodes in a time window from flashing light (0 millisecond) to 650 milliseconds	**40**
Figure 3.3	Extracted P300 patterns from 8 electrodes for classifier NC2	**42**
Figure 3.4	The process of activation function in neural networks models (White, 2009)	**43**
Figure 3.5	Training flowchart	**52**
Figure 3.6	Each character trial contains an X and Y coordinates specifying the row and column of spelling board by flashing lights on each one	**54**
Figure 4.1	Accuracy of P300 classification for NN models and classifiers in Subject B	**59**

Figure 4.2	Mean character recognition rate from both Subject A and B for the classifiers in NN3 model	**61**
Figure 4.3	The changes in precision for the models and classifiers in P300 classification	**62**
Figure 4.4	The changes in sensitivity for the models and classifiers in P300 classification	**62**
Figure 4.5	Comparing the accuracy of NN3-MultiNC with CNN model in Subject B	**63**
Figure 4.6	Comparing mean character recognition rate with current BCI methods	**65**
Figure A.1	This figure illustrates the user display for this paradigm. In this example, the user's task is to spell the word "SEND" (one character at a time). For each character, all rows and columns in the matrix were intensified a number of times (e.g., the third row in this example) as described in the text	**80**
Figure A.2	This diagram illustrates electrode designations (Sharbrough, 1991) and channel assignment numbers as used in our experiments	**81**
Figure A.3	This figure illustrates the content of each Matlab file (The test data set does not contain StimulusType and TargetChar). Channel numbers in the variable Signal correspond to numbers in Figure A.2	**83**
Figure A.4	This figure illustrates the assignment of the variable StimulusCode to different row/column intensifications	**83**
Figure A.5	Feature extraction from all electrodes in a time window from flashing light (0 millisecond) to 650 milliseconds	**84**
Figure A.6	Extracted P300 patterns from 8 electrodes	**85**

LIST OF ABBREVIATIONS

EEG Electroencephalography

ERP Event-Related Potentials

NN Neural Networks

BCI Brain-Computer Interface

NN1 Neural networks model 1

NN2 Neural networks model 2

NN3 Neural networks model 3

NC1 Neural networks classifier 1

NC2 Neural networks classifier 2

MultiNC Neural networks multiclassifier

TP True Positive

TN True Negative

FP False Positive

FN False Negative

RE Recognition rate of P300 signals in the test

SE Sensitivity rate of statistical testing

SP Specificity rate of statistical testing

P Precision

PENGKELASAN ISYARAT OTAK P300 MENGGUNAKAN RANGKAIAN NEURAL DENGAN FUNGSI PENGAKTIFAN ADAPTIF

ABSTRAK

Antara muka Otak- Komputer (BCI) menggunakan isyarat otak 'electroencephalograms' (EEG) dan potensi acara-berkaitan (ERP) seperti P300 bagi menyediakan komunikasi secara langsung antara otak manusia dan komputer. Aplikasi pengeja P300 adalah BCI yang mencari lokasi aksara sasaran menggunakan isyarat P300. Aplikasi ini cuba mengklasifikasikan isyarat otak P300 untuk mencari aksara yang betul dari papan aksara. Aplikasi ini amat berguna untuk membantu orang-orang kurang upaya berkomunikasi dengan dunia luar. Paradigma pengeja P300 mempunyai dua masalah klasifikasi utama. Masalah pertama ialah pengesanan isyarat P300 daripada data EEG (klasifikasi isyarat P300). Pengesanan isyarat P300 adalah satu tugas yang mencabar kerana kehadiran bunyi dan artifak dalam data EEG. Masalah kedua adalah untuk mengenal pasti dengan betul aksara-aksara sasaran berdasarkan isyarat P300. Mengesan isyarat P300 adalah bersamaan dengan pengesanan satu aksara oleh seorang pengguna yang sedang melihat lebih kurang 300 milisaat sebelum pengesanan isyarat. Kajian ini bertujuan untuk mengklasifikasikan isyarat P300 dengan ketepatan yang lebih tinggi dan mengenal pasti aksara-aksara dengan cubaan aksara yang lebih rendah, demgan menggunakan rangkaian neural dengan fungsi pengaktifan boleh laras. Model rangkaian neural terbaik diperolehi dengan menjalankan tiga ujikaji ke atas tiga model NN yang berbeza mengikut fungsi pengaktifan dalam lapisan tersembunyi, dan tiga pengelas piawai. Prestasi bagi model NN terbaik dan pengelasnya juga dibandingkan dengan teknik klasifikasi lain seperti ESVM, CNN dan LDA dalam BCI. Hasil pembandingan menunjukkan bahawa model rangkaian neural NN3 dengan fungsi pengaktifan ‘Morelet Wavelet’ dan pengelas berbilang *MultiNC* telah mendapat ketepatan tertinggi dalam klasifikasi P300 dan pengesahan aksara. Hasil kajian juga menunjukkan bahawa kepekaan klasifikasi P300 dapat menggambarkan kedudukan model NN dan pengelas dalam masalah pengesahan aksara dengan lebih baik.

CLASSIFICATION OF P300 SIGNALS IN BRAIN-COMPUTER INTERFACE USING NEURAL NETWORKS WITH ADJUSTABLE ACTIVATION FUNCTIONS

ABSTRACT

Brain-Computer Interface (BCI) employs brain's Electroencephalograms (EEG) signals and Event-related potentials (ERP) such as P300 to provide a direct communication between human brain and computer. P300 speller application is a BCI that finds the location of target character using P300 signals. This application tries to classify brain‘s P300 signals to find the correct character from character board. P300 speller paradigm has two main classification problems. The first problem is the detection of P300 signals from EEG data (classification of P300 signals). Detection of P300 signals is a challenging task due to presence of noise and artifacts in EEG data. The second problem is to correctly recognize the target characters based on P300 signals. Detecting P300 signals is equivalent to detection of a character by a user who was looking about 300 milliseconds before the signal detection. This study aims to classify P300 signals with higher accuracy and recognize the characters with lower character trials by using neural networks with adjustable activation function. The best neural networks model is obtained by conducting three experiments on three NN models which differ based on the activation function in the hidden layers and three standard classifiers. The performance of the best NN model and its classifiers also compared with other classification techniques such as ESVM, CNN and LDA in BCI. The results shows that neural network model NN3 with Morelet Wavelet activation function and multi-classifier MultiNC have obtained highest accuracy in P300 classification and character recognition. It also shows that Sensitivity of P300 classification is better describing the ranking of NN models and classifiers in character recognition problem.

CHAPTER 1

INTRODUCTION

1.1 Overview

Brain has been a mysterious part of humans. Understanding how brain responds to the events occurring around it, is one of main goals in neuroscience and many other researches. Just like the heart, human brain also disperse signals from millions of interconnected cells. The signals are in form of electric currents called Electroencephalograms (EEG). EEG provides a direct measure of brain activities in milliseconds with temporal solution. By capturing and analyzing EEG signals, a communication between brain and outside device can be established. However, analyzing EEG signals are difficult task due to existence of artifacts and noise along with signals. In order to make a successful communication with brain, target signals in EEG currents need to be found and recognized by having advance tools and methods.

Brain computer interface (BCI) is a communicative infrastructure to make a pathway between brain and other external systems. BCI empowers alive subjects which have brain (such as humans) to communicate with external devices without having to use other means of communication such as sound, moving or any other actions. Disable people are mostly benefited from BCI systems. BCI uses non-invasive EEG method to read the brain signals. Some of BCI systems are designed to spot specific EEG signals (patterns) related to given tasks. Those signals called ERP components. ERP components are same EEG currents that are averaged and time locked to an event of interest. BCI systems use feature extraction techniques such as pattern recognition to classify specific brain's event-related potentials. On the other hand, P300 signals are reflection of brain perceptive respond to outside stimulus. By receiving the P300 signal on specific stimulus, we can assume that brain has perceived that event. P300 is a positive wave occurring about 300 milliseconds after flashing light. Receiving P300 signal is equivalent to detecting where user was looking about 300ms before the detection. P300 speller is a BCI paradigm and a famous application to detect the characters from screen. The main goal in this application is to identify the target characters with high accuracy and instantly. The other goal is to detect P300 signals in EEG data.

The detection of P300 signals is a challenging task due to presence of noise and artifacts in EEG data. The motivation of this research is to classify EEG data and detect P300 signals more accurately and instantly than other previous researches in BCI P300 speller paradigm. Detecting those signals leads to identification of corresponding characters in P300 speller paradigm. The accuracy of P300 detection in EEG classification will ensure better character recognition.

An enhanced back-propagation feed-forward neural networks with adjustable activation function models used for detection of P300 signals in EEG data and recognition of characters. These neural networks models use different electrode set and data size as classifiers. Each model have a different activation function with few free parameters. The significance of such adjustable activation function, can be expressed in network size reduction and the training become faster.

1.2 Research Background

Human Brain is continuously dispersing huge amount of EEG signals. The EEG signals are the actual carriers of conscious experience (McFadden, 2002). Figure 1.1 is an example of EEG recorded data. EEG signals are recorded using a set of sensors called electrodes (channels). EEG brain signals are important in the neurophysiology area (Cahn and Polich, 2006).

Furthermore, Event-related potentials (ERP) signals are physiological patterns created by averaging and sub-dividing the EEG signals base on time and events of interest (Coles and

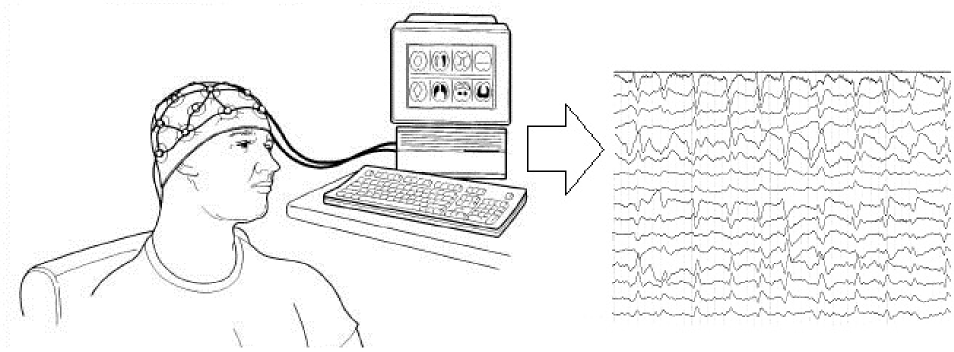

Figure 1.1: EEG recording process and the produced signals

Rugg, 1996). P300 is an ERP pattern extracted from EEG patterns. It is time-locked to light flashing stimulus and occurs around 300 milliseconds after flashing human eyes in positive value to show brain perceived on the event. The ERP components and P300 are presented in Figure 1.2.

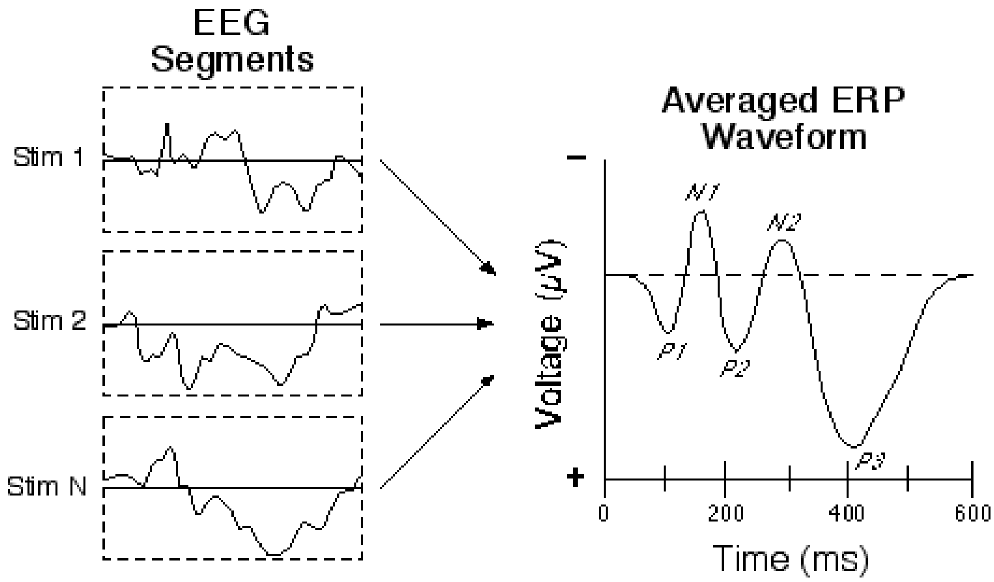

Figure 1.2: ERPs are physiological signals which are created once the segments of EEG are averaged and sub-divided in time and event of interest

On the other hand, BCI systems are trying to discover a new way of communication between the human brain and computers by analyzing and processing the signals extracted from the brain by a computer interface (Pasqualotto et al., 2012; Ebrahimi et al., 2003; Wolpaw et al., 2000). BCI is trying to establish robust computational analysis, machine learning and pattern recognition methods to correctly interpret (classifying) P300 signals and relate them to specific events (Rong et al., 2007). The P300 detection is used in BCI P300 speller application. Correctly detection of P300 signals in this application leads to better character recognition and increasing system accuracy.

The neural network (NN) can be used for prediction and classification. NN is consisted of input, output and hidden layers. Hidden layers have one or more than one layers. Each layer has more than one nodes that defines the complexity of NN. Other domains such as image processing have achieved best results using neural network methods. NN with three layers have been used before in BCI systems to classify EEG patterns. In the artificial neural network structure, the weighted sum of each neuron input is calculated and applied to sum a nonlinear transfer function (Yu et al., 2002; Solaui and Uncini, 2000). The NN models have function in nodes of hidden or output layers. This function called activation function. Many activation functions have been proposed to improve the performance of NN. In other word, the neural networks models with more utilized and optimized activation functions have shown more accurate results in pattern recognition tasks. In literature, the sigmoid function is often used as activation functions. The other derivations of sigmoid function are also used in neural networks models such as generalized sigmoid and the radial basis sigmoid. The common characteristics of those functions are the function parameters which usually are fixed. The neural networks performance depends on the performance of activation function. Therefore, those functions are so critical in process of learning (Xu and Zhang, 1999a, 2001, 2005).

The free parameters are adjusting along with other NN parameters such as weights and thresholds. The neural network with adjustable activation function has proved to have higher performance comparing to other types of NNs (Xu and Zhang, 1999a, 2001, 2005). The activation function is adjusted gradually during network‘s intervals. The process of adjusting free parameters leads to more accurate models and better performance in the training.

1.3 Problem Statement

Brain computer interface (BCI) is a direct communicative pathway between brain and external devices. BCI allows people to communicate without having to move by measuring brain activities. BCI uses EEG method to read brainwaves. BCI systems use feature extraction techniques such as pattern recognition for classification of brain's P300 signals. P300 signals are reflection of brain perceptive respond to outside stimulus. P300 is an averaged and positive EEG signal occurring about 300 milliseconds after flashing light stimulus. Receiving P300 signal is equivalent to detection where user was looking about 300ms before the detection. On the other hand, BCI P300 speller application is used to detect the characters from screen using EEG P300 signals.

The P300 speller has two main classification problems. The first problem is detection of P300 signals from EEG data. The detection of P300 signals is a challenging task due to presence of noise and artifacts in EEG data. Therefore finding best classification method to overcome the uncertainty in P300 detection has always been a challenge in BCI P300 speller application. The second problem is to recognize the characters more accurately and quickly. Many methods are proposed for character recognition in P300 speller in BCI community. Some of those techniques are support vector machines (SVMs), hidden Markov models and Covolutional Neural Networks (CNNs) (Cecotti and Graser, 2011). These techniques are used for detecting P300 wave and also determining the target characters. However, the challenge in second classification is to correctly recognize the characters in lower character trials. Furthermore, despite there is a connection between P300 detection and character recognition and the proposed methods provided various measurements in both classification attempts, but it is still challenging to find the relation between the first and second classification problem.

The motivation behind this research is to detect (classify) P300 patterns and identify the target characters in P300 speller paradigm more accurately by lower trials. The results of character recognition can be described by measuring the results of first classification attempt (EEG classification).

1.4 Objectives

The objectives of this research are to propose using neural networks with adjustable activation functions for classifying the EEG data into P300 and non-P300 signals and identifying target characters in the BCI P300 speller paradigm.

- To classify P300 signals in EEG data with higher accuracy by using three neural networks models with adjustable activation functions and classifiers.
- To recognize the target characters in P300 speller application using the trained neural networks with higher recognition rate and lower character trials.

1.5 Research Scope

The scope of this research is limited to EEG spectrum and P300 pattern discovery. As P300 is the signal reflecting brain's respond to outside stimulus, the present study focuses on detecting the presence of P300 signals in EEG data. This is done by using neural network models and default classifiers and relating the P300 signals to specific target characters.

1.6 Summarized Research Method

The Figure 1.3 illustrates the summarized research method in this study. The main approaches in this study are to train three neural networks models for classification of P300 signals and recognition of target characters. In this study, we use standard benchmark dataset to train the models and compare the results with previous methods in BCI P300 speller application.

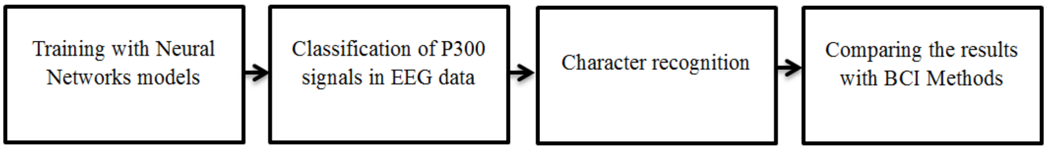

Figure 1.3: Summarized research method

1.7 Contribution

In BCI P300 speller paradigm, the main focus is to develop models to detect the characters from screen more quickly and accurately. The reason is to develop more efficient applications in P300 paradigm helping disabled people to spell the words and sentences by using only a board of characters without requiring any movement or speaking. This study proposes using three enhanced back-propagation feed-forward neural networks models with different adjustable activation functions to recognize the characters with higher accuracy and lower character trials in BCI P300 speller paradigm. The activation functions use few free parameters. Those parameters are gradually changing during the training process along with neuron weights and thresholds and trying to adopt to the present problem. The enhanced neural networks models also classify the EEG data into either P300 or non-P300 signals. Moreover, this research finds the relation between results generated in EEG classification and the results of character recognition by applying statistical measurements in EEG classification. In other word, this study analyzes the findings of first classification attempt (EEG classification) to discover the most relevant measurement describing the next classification attempt (character recognition).

1.8 Definition of Terms

The followings are definitions of terms which have been used in this thesis. The following definitions are to clear up and focus on the terms as they pertain to this research. By providing a fundamental approach at interpretation, I hope any potential confusion become apparent.

Activation Function: Activation function is a linear or non-linear function in the nodes of hidden layer and/or output layer of neural network. The activation function of a node determines the output of that node by giving the input or set of inputs. The activation function is usually an abstraction representing the rate of action potential firing in the node. In its simplest form, this function is binary that is, either the neuron is firing or not.

BCI P300 speller paradigm: P300 speller paradigm is a BCI application based on analysis of EEG measurements in Oddball paradigms to render event-related potentials (ERPs) such as P300 wave on target characters which selected by the user. P300 speller application shows a board of characters with the flashing light on the columns and rows to subjects. Each flashing on either row or column is associated with the waves coming from brain. The intensified characters are associated with P300 signals after flashing light.

Brain-Computer Interface (BCI): Brain-computer interface (BCI) is a communicative infrastructure to make a pathway between brain and other external systems. BCI empowers alive subjects which have brain (such as humans) to communicate with external devices without having to use other means of communication such as sound, moving or any other actions. Disable people are mostly benefited from BCI systems. BCI is using non-invasive EEG method to read the brain signals.

Classification: is a machine learning function that assigns items in data to classes. The goal is to accurately predict the target class for each case and extract the properties of classes.

Data mining: is the process of analyzing data from different perspectives and summarizing it into useful information. It is the process of searching large volumes of data for patterns that can be considered knowledge about the data.

Electroencephalography (EEG): is a technique for capturing, studying and analysis the electrical current in the brain cortex. Electrodes are attached to the scalp. Wires attach these electrodes to a machine which records the electrical impulses. Different patterns of electrical impulses can denote various problems in the brain.

Event-Related Potentials: is temporally/spatially measured brain response (might be measured by EEG or other brain signal formats) that is directly the result of a thought or perception to an internal or external stimulus.

Neural Network (NN): NN is a mathematical model inspired by biological neural networks. A neural network processes information using a connectionist approach to computate and consisted of an interconnected group of artificial neurons . The structure of a NN with an adaptive system changes based on external or internal information (weights) that flowed through the network during the learning phase. Multilayer perceptron (MLP) is kind of artificial neural network which has feed forward structure that maps groups of input on a group of suitable output.

Noise and Artifact: are the signals or electric currents that are not originated from the cortex or from region-of-interest (ROI) in the brain. Artifacts are normally overlapping the target cortex signals and need to be removed / decomposed in the process of studying brain functions.

1.9 Organization of Thesis

Briefly, this thesis is organized as follow:

- Chapter 1 is a general introduction to neuroscience and machine learning techniques such as neural network as well as BCI and its famous P300 speller application. In this chapter, an overview and background of this research are briefly explained. The aim is to express background knowledge of brainwaves and the usefulness of machine learning in processing of brain signals in BCI domain. Although the research problem and objectives are clearly mentioned as well as the main contribution of this research.
- In Chapter 2, literature of past and contemporary researches of EEG pattern recognition, P300 signal detection and machine learning processes will be reviewed and discussed. Important methods and terminologies will also be reviewed.
- In Chapter 3, the methodology and enhanced neural networks models are presented and discussed. In this chapter, the learning algorithm of neural networks models with adjusting activation functions along with the training and testing process are well discussed.
- In Chapter 4, the findings and results of neural networks models and classifiers are presented and discussed. The results are evaluated and compared with related methods in BCI P300 speller paradigm.
- In Chapter 5, the findings will be summarized with conclusion and discussion. The research will be finalized with recommendations for further researches.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In this chapter, the literature of past and contemporary researches are reviewed together with relevant works regarding to methods of machine learning in classification of brain signals. Latest literature in pattern recognition of brain electroencephalogram (EEG) signals are included and discussed. This chapter is arranged as follow; an introduction to EEG signals and types of ERP components are given to achieve better understanding of brain signals. In the next section, the current machine learning and pattern recognition methods in Brain Computer Interface (BCI) for classification of EEG and ERP signals are reviewed and discussed. The related researches in BCI P300 speller paradigm are also reviewed in the following sections. The BCI P300 speller application is reviewed as a benchmark for this research. Finally, a review of neural network models as a method in classification of brain signals is given in last sections. Furthermore, This chapter is finalized by reviewing different types of activation functions in the neural network.

2.2 The EEG and ERP Brain Signals

The indulgence of the fundamental neural processes in motivating the complex high order cognitive operations and functional domains are the basic objective of cognitive neuroscience. Electroencephalogram (EEG) is a non-invasive technique used in capturing and analyzing the electromagnetic signals in the brain cortex. Comparing to the Magnetoencephalogram (MEG), the EEG is an inexpensive technique measuring the neurophysiological activities inside brain. The electrical impulses are recorded by the electrodes placed around the scalp and attached to external device. The different patterns of produced electrical impulses would help in detecting various problems in the brain. The EEG functioned as a measuring tool in perceiving the electromagnetic activity of large numbers of neurons in the brain. On the other hand, event-related potential (ERP) are time-locked EEG patterns. ERPs are utilized in designing EEG-based experiments in a way that the time-locked EEG currents are measured using its average together based on each trial. This technique allowed researchers to investigate sensory, cognitive and perceptual processing in milliseconds. In other words, ERP is a temporally and spatially measured brain response. ERP is also a direct result of a thought or perception to an internal or external stimulus. Furthermore, ERP consisted of many components. Each component is defined by its latency (time of occurrence after stimulus), polarity (signal amplitude) and topography (the region of occurrence). Donchin et al. (1978) proposed these components could be classified into either exogenous or endogenous classes. The endogenous components such as N200 (latency 200, negative) and P300 (latency 300, positive) are linked to the inner properties of a stimulus and are connected to inner events and information processes. The exogenous components such as N100 (latency 100 milliseconds, Negative) and P100 (latency 100 milliseconds and positive) are controlled by the physical characteristics of the stimulus and are associated with the automatic processing of the stimulus besides being evoked by the events' extrinsic to the nervous system.

The reason of using EEG and ERP signals in brain researches is laid on the comparative advantages of these methods. These methods are relatively inexpensive way of recording brain signals. The continuous activities of brain can be recorded using EEG method for almost any type of researches. The other methods of recording brain signals are functional Magnetic Resonance (FMRI) Imaging and Position Emission Tomography (PET). FMRI and PET take more than 6 seconds to record a signal. However, in EEG all sensing and processing is done within a few hundred milliseconds. EEG provides a direct measure of neuronal activity and best temporal resolution of milliseconds. So it gives a good representation of temporal brain activity to control brain signals in time. ERP also bounds and divides EEG currents to the events of interest such as flashing light. So experiments are able to control the brain responds over time and events.

2.2.1 The Types of ERP Components

ERP signals consisted of different components such as P100, N200, P300 and etc (Coles and Rugg, 1996). Each component is elicited by different stimulus. The components are named using a letter that indicated the polarity, followed by a number indicating either the latency in milliseconds or the component's ordinal position in the waveform. Thus, for N100 or N1, the number 100 is indicating the latency in milliseconds and the letter N means negative peak. N100 represents a negative-going peak and often occurred about 100 milliseconds after a stimulus is presented. N1 is often followed by a positive peak that is called P200 (positive in 200 milliseconds). The stated latencies for ERP components are quite variable, for example, the P300 component (positive in 300 milliseconds) has the possibility to exhibit a peak anywhere between 250 milliseconds and 900 milliseconds. Figure 2.1 shows the different ERP components on the variable amplitude and time. As shown in Figure 2.1, P300 peak amplitude has occurred on 400 milliseconds after stimulus.

2.3 The ERP Classification

The Characteristics of ERP components are provided by neuroscience and discussed in previous section. The ERP components are inside the EEG currents and can be detected by classifying the EEG patterns base on those characteristics. ERP components are classified base on the peak amplitude and the expected time of occurrence. For example, P300 is an ERP component and can be detected by having EEG peak amplitude in between 250 to 650 milliseconds after

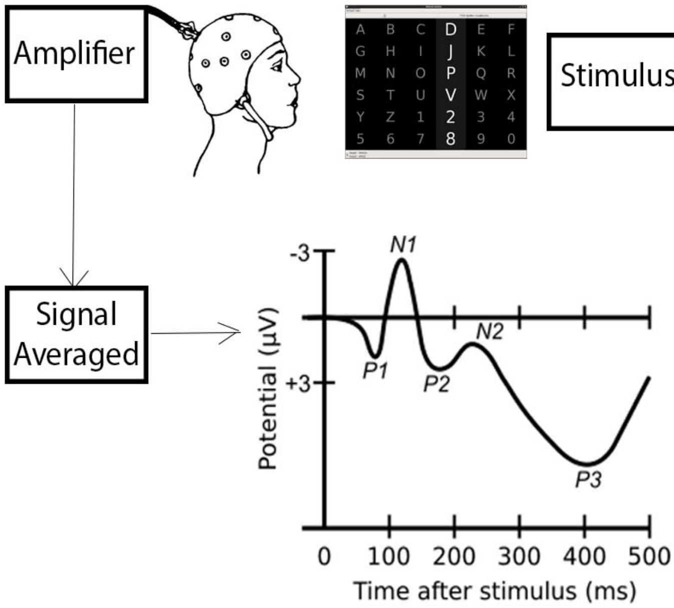

Figure 2.1: ERP generation process and ERP components

stimulus presentation to the patient. However, there are many different detection algorithms designed to detect and classify the P300 signal. In this section a selection of different methods of ERP classification are reviewed. The importance of ERP component detection is the direct relation between these patterns and the brain behavior. Discovering brain responds would eventually lead to finding the cause of some brain diseases and detection of brain disorders such as types of brain seizure and epilepsy. Although ERP component detection can enable the detection of dementia which is difficult to diagnose the symptoms via ordinary clinical diagnosis. Furthermore, those patterns provided a practical method to identify mental problems and the patients in a comatose condition. On the other hand, EEG and ERP are considered as an endeavor to provide a new way of communication between the human brain and the computer through the interpretations from the brain waves produced via the computer interface (Ebrahimi et al., 2003; Wolpaw et al., 2000; Peterson et al., 2005). The extracted information from brain impressively enabled researchers to find the patterns associated with the neuron illness, brain capability analysis and responses to external stimulus in different situations.

Base on literature, there are 4 distinctive steps in classification ERP components. The first step is to capture the brain signals. The signals are collected by electrodes around the scalp. The Neuroscan, WinEEG and NetStation softwares are designed to capture brain signals (*Net-Station Technical Manual. http://www.egi.com*, n.d.). These softwares allow recording, editing and analysis of continuously recorded EEG and Event-Related Potential data (ERP). The second step is feature extraction. Since EEG signals contain a mixture of brain target patterns and noises, the primary purpose of this step is to separate signals from the noises and disentangling overlapping patterns (Rong et al., 2007). Following is the feature extraction to find the main data feature to input into next step. The process of data cleaning and feature extraction can be done with advanced statistical methods such as Independent Component Analysis (ICA) and joint Time-Frequency Analysis (TFA). For instance, in (Jung et al., 2000), ICA was used to blindly separate the input ERP data into a sum of temporally independent and spatially fixed components arising from distinct or overlapping brain regions. The third step is data mining. Dou. et al. (2007) suggested the splitting of this step into two main steps as unsupervised and supervised learning. In the unsupervised learning, the clustering methods are used to group the signals base on their correlated features. However, in the supervised learning, the classification methods are used to assign the signals to predetermined classes. The classed are created in the training. The last step is interpretation and evaluation result. In this step, the signals are translated to be used or evaluated by experts in variety of applications.

In Rong et al. (2007), the process of classification of ERP components from EEG signals is proposed. They proposed a framework to extract ERP knowledge. Later, they enhanced the proposed method and introduced the Neuroelectromagnetic Ontologies framework (NEMO) (Dou. et al., 2007). The NEMO framework is used to extract and generate ERP component rules and then transforming them into ERP domain ontology. However, the results showed the difficulties in recognizing the ERP classes and patterns are split across the wrong classes. They suggested a further refinement of EEG and ERP patterns by employing in-depth pre-processing tools leading to a better classification. The reason is highly spatial, temporal and dimensional ERP signals. At each time point, many parts of the brain may be simultaneously active. Therefore, it cause the signals to overlap and results in uncertainty of signal classification. Figure 2.2 shows the classification of ERP components by using NEMO framework.

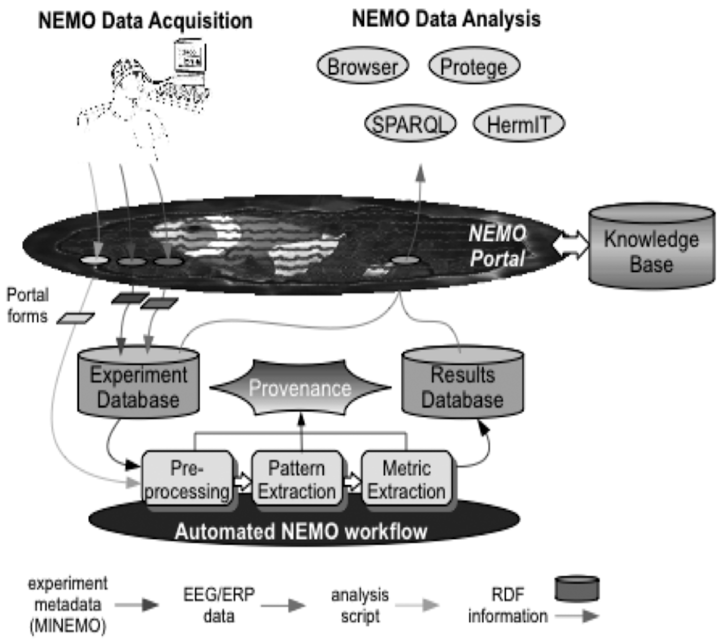

Figure 2.2: NeuroElectroMagnetic Ontologies (NEMO) framwork to classify ERP components and building ERP domain Ontology

Furthermore, as suggested in literature, the establishment of robust computational analysis methods such as the data preprocessing and feature extraction techniques are important in classifying of ERP components. For instance, a new approach in the classification of EEG signals in schizophrenic patients has been suggested by Sabeti et al. (2011). They used an auto-regressive model parameters, band passing filter and fractal dimension feature extraction as tools to classify the signals. They also employed both linear discriminant analysis (LDA) (Delac et al., 2005) and adaptive boosting (Adaboost) to categorize the reduced feature set (Sabeti et al., 2011). As a result, a highly accurate classification is attained through the LDA and Adaboost respectively. They have also tried to select more informative electrodes using EEG experiments of 20 schizophrenic patients.

2.3.1 Issues in ERP Classification

In the machine learning process, generally, there is a feature extraction. This is usually done before undergoing any classification process. The easiest way is the brute-force. In this process, all aspects of signal should be measured in order to find informative or relevant features. However, this process is not a direct option for any classification problems because the extracted information normally contained errors or noises and a step backward should be preprocessing (Zhang, Rodesch and Broadie, 2002). Figure 2.3 is an example of noise in EEG data. The brain data contained internal and external artifacts and environment noises. They can interrupt the whole classification process. A variety of preprocessing methods such as handling missing data (Batista and Monard, 2003) and dimensionality reduction of data are available (Liu and Motoda, 2001). Hodge and Austin (2004) have proposed a pre-processing method that reduced the sample size while the quality of the data is preserved. Another method is proposed by Liu and Motoda (2001). This method reduced the data and enabled the classifier to work more efficiently with large data sets. Meanwhile Markovitch and Rosentien (2002) proposed a possibility of the precision of classification models be affected having many features are dependent on each other. According to them, the solution of this issue is by creating new features from rudimentary feature set. Furthermore, the extraction of more eloquent features of the collected data can help in creating a more precise classifier. In other words, a better classification could be generated from extraction of more features from the data. In other word, extraction of more signal features and properties would resulted to a better classification of brain data patterns.

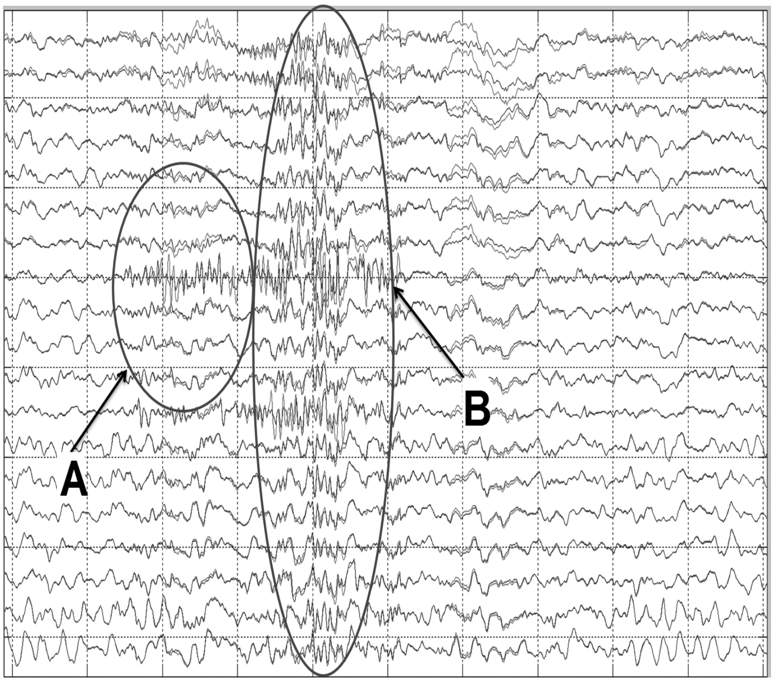

Figure 2.3: Encountered eye-muscle artifacts during experiment. The points of A and B are showing the effect of artifacts/noises on the EEG signals

2.4 Brain-Computer Interface (BCI) and P300 Detection in EEG Data

In this section, a review of BCI researches associated with P300 ERP component will be given and the current methods of P300 detection in EEG data in BCI will be discussed. Brain-Computer interface (BCI) is a direct communicative pathway between brain and an external device. Such structures let individuals to communicate through straight capacities of brain activity, deprived of needing any effort (Allison et al., 2007; Kostov and Polak, 2000; Birbaumer and Cohen, 2007). BCIs are often to support, expand, or fix human cognitive or sensory-motor functions. The BCI, research and development have focused primarily on neuro-prosthetics applications, aiming to restore damaged hearing, sight and movement. It may be the only connection probable for individuals unable to communicate via straight means due to the plain motor disabilities. Such disabilities are like spinal cord injuries such as the disease, Amyotrophic Lateral Sclerosi (ALS) and it is also known as the Lou Gehring's disease (Birbaumer and Cohen, 2007; Birbaumer et al., 1999). The EEG technique is stressed upon main BCI researches due to advantages mentioned in previous sections.

A BCI is typically consisted of four main components aided in interpreting the neural signal processing. First, the signal is attained via an amplifier. Then is the pre-processing and feature extraction. Finally the signals are classified and commands are sent to external device. The stimuli and the responses are used to detect event-related potentials (ERP), steady-state evoked potentials, motor imagery or slow cortical potentials which made up the EEG classification strategy.

The ERP and specifically the P300 applications are focused on BCI related researches. This is due to the P300 patterns are closely associated to the mental courses of perception and discriminating attention of the brain. The P300 arose in a time-locked record as positivity, naturally seeming around 300 to 400 milliseconds after the stimulus demonstration. The timing may different as well, however, from 250 milliseconds and ranging to 800 milliseconds, with an amplitude changing from 4.2 μV to a normal boundary of 18.9 μV for auditory and visual evoked potentials. Even amplitudes with 40 μV have been known (Coles et al., 1995). The P300 is possibly a well-known ERP component in examining the discriminating attention and info processing (Sutton et al., 1965). This is because of comparatively large amplitude unlike other ERP components and simplistic elicitation in experimental contexts. Furthermore, P300 supports the design of an inner environmental model in which a stimulus can be assessed (Donchina and Colesa, 1988). The straight association between P300 timing and subject response time strengthened this concept (McCarthy and Donchin, 1981). The P300 is tangled in stimulus assessment to the amount of activating the context-based apprising. Alternatively, the context closure model arose as a substitute to the context updating model; qualifying the notion reproduced by the P300 of the action of the memory trace and renovation post-detection of a marked stimulus (Desmedt, 1980; Verleger, 1988). The P300 has been practical to an extensive variety of medical research sceneries. Such researches are of schizophrenia which is a illness of cognitive trouble (Roth and Cannon, 1972).

The pattern recognition methods are used in the grouping and the discovery of precise brain patterns. Most of the operative solutions are used in the machine learning models, (Lotte et al., 2007; Müller et al., 2008; Muller et al., 2004). Although neuroscience delivered information and strategies to perceive the probable signals. However machine learning methods permitted the forming of the signal variability over time and over subjects. Support vector machines (SVMs) (Blankertz et al., 2002), Neural networks (Anderson and Devulapalli, 1995; Cecotti and Graser, 2008; Felzer and Freisieben, 2003; Haselsteiner and Pfurtscheller, 2000; Rakotomamonjy and Guigue, 2008) and hidden Markov models Obermaier et al. (2001); Zhong and Gosh (2002) have previously been used in BCI and EEG signal classifications. Neural networks with back propagation is used for signal recognition by Hiraiwa et al. (1990), shows the neural networks can categorize EEG signals and improve BCI's current applications.

2.5 The P300 Speller Paradigm

In this section, BCI P300 speller paradigm is reviewed and the linked boundaries and problems are elaborated. Many applications have been developed in BCI researches. Each application is focused on specific paradigm and ERP components in order to establish a communication between brain and external computer. One of well known BCI applications is P300 speller. This BCI system is designed for disabled bodies to communicate with others by making words through choosing alphabets (characters) on the monitor in front of them. The P300 speller is a benchmark paradigm. The 6×6 character matrix on the monitor is composed of 26 alphabetical (A-Z) and 10 numerical characters (0-9). This matrix is shown to the user on the computer screen by randomly flashing the rows and columns. Once the user focuses on the character during the flashing light, the signals corresponding to those row and column of depicted character have P300 signal. Detection of P300 wave make it possible to recognize the character by matching the responses to one of the rows and one of columns. Figure 2.4 is showing the Farwell and Donchin BCI P300 speller in row and column paradigm.

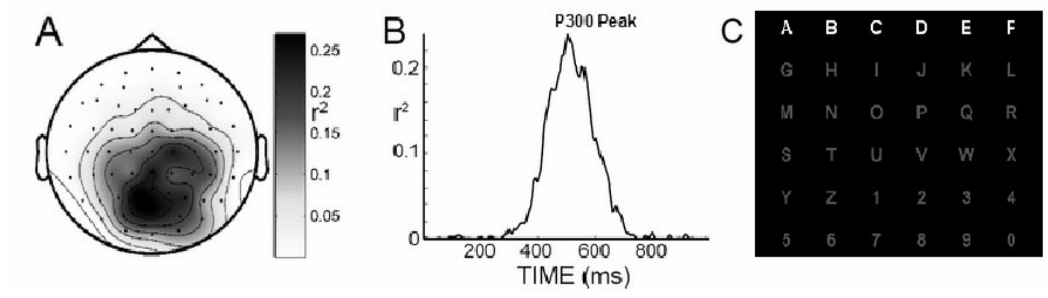

Figure 2.4: B is showing P300 signal peak and A is the brain region that P300 peak is occurring, C is showing BCI P300 Speller application: the row/column paradigm (Donchin et al., 2000)

2.5.1 P300 Detection

The P300 signal is an event-related potential in EEG recording. That means P300 wave is a time-locked and averaged EEG pattern. The signal is positive at the latency of about 300 milliseconds after the stimulus and location is mostly around parietal lobe and occipital sites (Krusienski et al., 2008). Figure 2.5 shows the P300 signal peak in recording. The detection of P300 signal is equivalent in identifying the location that has user attention on. Having accurate detection of P300 waves on the P300 Speller paradigm would result in better character recognition. There are two type of classification in P300 speller paradigm. Classification of EEG patterns into either P300 or non-P300 in EEG recordings. Due to artifacts and noises, however there is uncertainty in P300 classification attempt. The second classification type is the character identification problem. The output of EEG classification are evaluated to classify the application characters and symbols. The character identification process has strong certainty as the characters are given to user clearly.

2.5.2 Database

BCI P300 Speller dataset II from the third BCI competition was applied in different methods (Blankertz et al., 2006; Cecotti and Graser, 2011). The Wadsworth Center has provided the database which is briefly presented in Table 2.1. This data set has records of P300 evoked potentials from two subjects (A and B). In the experiment, a character matrix of 6×6 is pre-

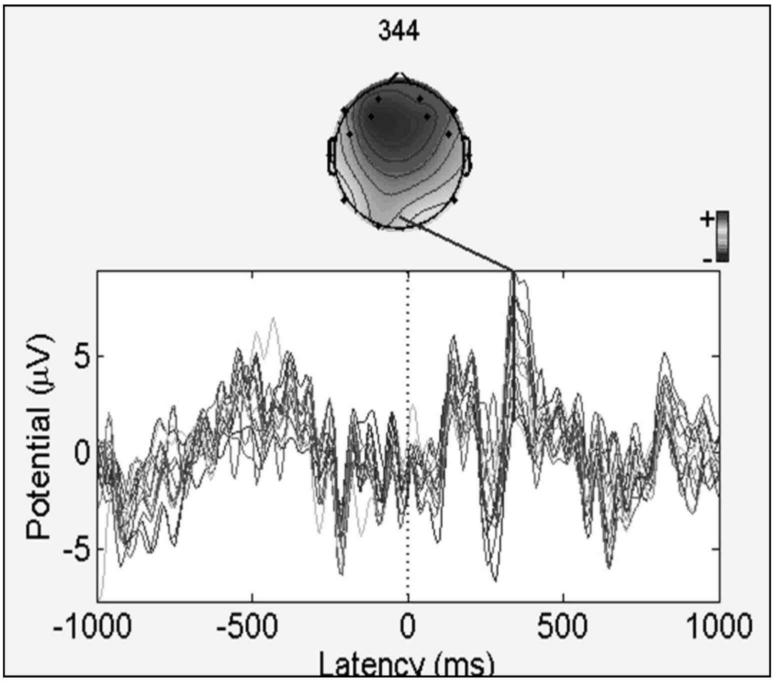

Figure 2.5: P3 or P300 occurs around 300 to 400 milliseconds time after presentation of stimulus and suggests the perception of stimulus by subject

sented to Subjects. The characters in matrix are $[A-Z]$ and $[0-9]$. The characters from the presented words are focused sequentially by the subjects. The six columns and six rows are sequentially and arbitrarily intensified at a rate of 5.7 Hz. Character selection is done by intensifying a column and a row and then consequently 2 of the 12 intensifications should contain a P300 signal in the respond sample. The matrix was shown to the Subjects for only 2.5 seconds in each trial, therefore each character will have the same intensity. Then each column and row in the matrix is arbitrarily intensified for 100 milliseconds. Character matrix is blanked for 75 milliseconds after the intensification of a column or row. Arbitrarily, The intensifications of columns and rows are intersected in blocks of 12. For each character trial which contains the rows/columns, the sets of 12 intensifications are repeated 15 times. Therefore, 30 possible P300 responses should exist for each character. The channels (electrodes) are ear-referenced channels and totally 64 channels are used in this experiment. The sampling rate is 240 Hz and is band-pass filtered from 0.160 Hz. The test dataset has 100 characters and training dataset has 85 characters. By flashing a row and a column, therefore there should be two P300 signal recorded for each character. The number of P300 signals in training dataset is $85 \times 2 \times 5$ and in test dataset is $100 \times 2 \times 15$. The number of samples for both databases and for each subject is presented in Table 2.1.

Table 2.1: The size of dataset for each subject in BCI database

Label \ Dataset	Training	Test
Negative P300	12750	15000
Positive P300	2550	3000

2.5.3 Current Methods in P300 Speller Application

A BCI is a system providing an interface for users to control external systems/devices by brain activities. However the transformation of user‘s intentions into the commands to read by external device, is still a challenge. The successful method should have an interaction of two effective and adaptive controllers. The brain activities that contains the user‘s intentions such as intending to look at or read a letter or word and a BCI system that captures and transforms brain activities into computer commands. To improve and develop BCI systems, various signal analysis techniques and methods have been proposed from many research labs around the globe. Many techniques and methods in machine learning and pattern recognition have shown enormous results.Besides, BCI competitions are held to provide a formal evaluations of proposed methods for BCI application. Along with other BCI applications, P300 speller was included in BCI competition III 2004 and was a benchmark for proposed methods in this paradigm (Blankertz et al., 2006). Some of the current works with best results are explained in following subsection. These methods are based on multi-classifiers strategy or used progressive signal handing techniques for preprocessing the data. On the other hand, it is not easy to compare the proposed classifiers and methods because the data entries are not same in size and other features of used data are different. The proposed methods are vary in amount of measured channels and the time latency considered for each pattern group for P300 signal.

- The first proposed method in competition has used a joint SVMs and reported by Rakotomamonjy and Guigue in (Rakotomamonjy and Guigue, 2008). In the proposed method, after each stimulus presentation to users (flashing light to user‘s eyes from character board), the EEG waves are extracted until 667 milliseconds time gap and marked as P300 pattern. Then the pattern is bandpass filtered with an 8 order screen with cutting of frequencies in-between of 0.1 and 20 Hz. The waves are coming through EEG electrodes also known as Channels from the net around user head. The wave is well defined by 14 topographies for each channel. Therefore the amount of the input to the SVMs is 896 patterns which are 14 topographies times to 64 channels (14×64). There are 85 characters to predict in the training dataset. The training record is divided into 900 clusters and each cluster is linked to the predicting of five characters. So the training database is partitioned into 17 groups. A channel assessment process is executed and a linear SVM is trained on each group. The channel assessment algorithm is a recursive channel exclusion based on measures in relation to the confusion matrix of the test validation. Adding all the marks of the SVMs has aided in reaching the character recognition. The row and column that get the maximum mark is considered as the coordinate of the character to guess.

- The next method is proposed by Li Yandong. He reported another technique consisting of three stages. First, a preprocessing method is applied to training dataset. The data cleaning was done by a band pass filtering at 0.5 to 8 Hz. Then, the independent component analysis (ICA) is used for the entire data to eliminate the eye movement artifacts and reduce signal dimension. The classification in this proposed method is also based on SVMs. The EEG waves are extracted from 100 to 850 milliseconds time gap after each stimulus presentation to users (flashing light to user‘s eyes from character board) and marked as P300 pattern (Breiman, 1994). In the preprocessing, a subdivision of channels is chosen prior to the classification to reduce the size of dataset. Then, by the voting