

**Real-time Detection of P300 Brain Events:  
Brain-computer Interfaces for EEG-based  
Communication Aids**

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**A thesis submitted to  
Auckland University of Technology  
in partial fulfillment of the requirements for the degree  
of  
Master of Creative Technologies (MCT)**

**2012**

**Faculty of Design and Creative Technologies  
Interdisciplinary Unit of Creative Technologies and  
School of Computing and Mathematical Science**

# Table of Contents

<b>Attention of Authorship .....</b>	<b>xi</b>
<b>Acknowledgment .....</b>	<b>xii</b>
<b>Abstract .....</b>	<b>xiv</b>
<b>Chapter 1: Introduction .....</b>	<b>1</b>
1.1. Motivation .....	2
1.2. Research Scope and Focus .....	3
1.3. Research Questions .....	4
1.4. Contributions of the Study .....	4
1.5. Study structure .....	5
<b>Chapter 2: Literature Review of BCIs .....</b>	<b>7</b>
2.1. Introduction .....	7
2.2. Introduction to the Human Brain .....	8
2.3. Framework of a BCI system .....	10
2.3.1. Data Acquisition .....	11
2.3.2. Signal Pre-processing .....	11
2.3.3. Data Classification .....	12
2.3.4. Biofeedback .....	13
2.4. BCI Developments and Key Principles .....	14
2.4.1. Control Signals in BCIs .....	14
2.4.2. Types of BCIs .....	15
2.4.3. BCI Applications .....	16
2.4.3.1. BCI Applications for Locomotion .....	17
2.4.3.2. BCI Applications for Environmental Control .....	17

2.4.3.3. BCI Applications for Communication .....	18
2.4.3.4. BCI Application for Entertainments .....	19
2.4.3.5. BCI Applications for Nerve Restoration: Functional Electrical Stimulation (FES) BCIs .....	20
2.4.4. BCIs Problems .....	20
2.5.Conclusion .....	22
<b>Chapter 3: Methods Used for BCI: A Review .....</b>	<b>25</b>
3.1. Brain Imaging Techniques .....	25
3.1.1. Electrocorticography (ECoG) and Microarray Electrodes .....	26
3.1.2. Magnetoencephalography (MEG) .....	27
3.1.3. Hemodynamic Activity of the Brain: Near Infrared Spectroscopy (NIRS) and Functional Magnetic Resonance Imaging (fMRI) .....	28
3.1.4. Electroencephalograph (EEG) .....	28
3.2. EEG Data Acquisition Hardware .....	32
3.3. Platforms to Design a BCI Application .....	34
3.4. Feature Extraction Algorithms .....	36
3.5. Pattern Recognition Algorithms .....	37
<b>Chapter 4: Methodology .....</b>	<b>38</b>
4.1. Implementation of the P300 Speller .....	38
4.1.1. The P300 Speller and Communication Aids .....	38
4.1.2. OpenViBE Implementation .....	41
4.2. xDAWN Algorithm .....	45
4.3. Linear Discriminant Analysis (LDA) Algorithm .....	47
4.4. Support Vector Machine (SVM) Algorithm .....	48

4.5. The Research Framework for this Study .....	49
4.5.1. Subjects .....	49
4.5.2. Experimental Tasks and Procedure .....	50
4.5.3. The Framework .....	51
<b>Chapter 5: Design of Experiments, Analysis of Results and Discussion .....</b>	<b>53</b>
5.1. xDAWN Spatial Filtering Outcomes .....	53
5.2. Exploring the Emotiv Capability to Detect P300 Brain Waves: Brain Activity Data are Recorded from the Participants within 600 ms of the Visual Stimulation .....	56
5.3. Exploring the Importance of the Number of Training Sessions .....	59
5.4. The Design of Alphanumeric, Verbal and Graphical Spellers .....	64
5.5. A comparison between the Online and Offline Performance, and between the accuracy of the Target Class and the Overall Accuracy .....	68
5.6. Performance of the Classifiers .....	69
5.7. The Impact of Motivation and other Factors on Users' Performance and their Ability to Control the Interface .....	69
5.8. Conclusion and Analysis of Results .....	71
<b>Chapter 6: Conclusion and Future Directions .....</b>	<b>73</b>
6.1. Conclusion .....	73
6.2. Contributions of the Study .....	74
6.3. Limitations of this Study .....	76
6.1. Future Directions .....	76
References .....	79
Appendix A .....	93
Appendix B .....	95

## List of Figures

Figure 2.1: The structure of the cerebral cortex .....	9
Figure 2.2: the structure of single neurons .....	9
Figure 2.3: Brain functions localisation on the cortical cortex .....	10
Figure 2.4: The general frame work of a BCI system .....	10
Figure 2.5: General framework for acquiring brain signals presents the steps to input the data into a BCI in the appropriate format .....	11
Figure 2.6: A conceptual demonstration of a BCI classification task .....	13
Figure 2.7: The relationship between the fields of BCI applications, ITR and the given control capabilities to the users .....	16
Figure 2.8: Some examples of locomotion BCI applications .....	17
Figure 2.9: Brain Gate BCI for environmental control .....	18
Figure 2.10: A communication BCI .....	19
Figure 2.11: Some examples of entertaining BCI applications .....	19
Figure 2.12: The Bionic Eye .....	20
Figure 3.1: ECoG grid implementation on a human brain .....	26
Figure 3.2: Microarray electrodes implementation in the human brain .....	26
Figure 3.3: SQUI device used to collect MEG data .....	27
Figure 3.4: the devices used to collect fMRJ data and NIRS data .....	28
Figure 3.5: Examples of EEG medical acquisition systems .....	29
Figure 3.6: Electrical brain signal that is called action potentials transferring between cells through synapse .....	30
Figure 3.7: The electrodes' positions and the channels' names in the 10-20 international placement system .....	32
Figure 3.8: g.tec recording system .....	32
Figure 3.9: NeuroSky system and Enobio system .....	33
Figure 3.10: Emotiv EPOC neuroheadset .....	33

Figure 4.1: The matrix of the P300 Speller visualized in OpenViBE .....	38
Figure 4.2: Examples of verbal and graphical communication boards .....	40
Figure 4.3: Multiple screens interface .....	41
Figure 4.4: Screen shots of the flipping graphical speller .....	41
Figure 4.5: Data acquisition scenario used to collect the training data .....	42
Figure 4.6: The scenario employed to train the classifier .....	43
Figure 4.7: The scenario employed to train the xDAWn filter .....	45
Figure 4.8: Implementation of the online P300 Speller using OpenViBE .....	46
Figure 4.9: A hyperplane created by the LDA algorithm to spate the data into two classes .....	48
Figure 4.10: Graphic representation of the linear SVM algorithm .....	49
Figure 4.11: The proposed framework in this study .....	51
Figure 5.1: The selected channels for all participants .....	54
Figure 5.2: Scalp topographies recorded 300 ms after a target visual stimulation on the top compared to the ones recorded 300 ms after a non-target stimulus .....	54
Figure 5.3: Evolution of the contribution of VEP in the human brain .....	55
Figure 5.4: The average of participant #3 performance using xDAWN filter and without filtering .....	55
Figure 5.5: The average performance of participant #4 using xDAWN filter and without filtering .....	55
Figure 5.6: Typical course of the P300 control signal .....	56
Figure 5.7: The course of P300 signals recorded from each participant .....	57
Figure 5.8: The responses from two subjects within 500 ms of target stimuli .....	58
Figure 5.9: Training and online accuracies in dependence or 10 sessions using either the LDA or the SVM classification methods. Results were recorded from participant #5 and #6 on the <i>alphanumeric</i> speller .....	60

Figure 5.10: Training and online accuracies in dependence or 10 sessions using either the LDA or the SVM classification methods. Results were recorded from participant #5 and #6 on the <i>verbal</i> speller .....	61
Figure 5.11: Training and online accuracies in dependence or 10 sessions using either the LDA or the SVM classification methods. Results were recorded from participant #5 and #6 on the <i>graphical</i> speller .....	61
Figure 5.12: The performance of six participants using motor imagination BCI over three sessions. The figure represents the <i>left</i> class .....	62
Figure 5.13: The performance of six participants using motor imagination BCI over three sessions. The figures represent the <i>rest state</i> class and the <i>right</i> class .....	63
Figure 5.14: The means of the accuracies obtained from eight participants over 10 sessions, using the typical P300 BCI .....	63
Figure 5.15: The means of the accuracies obtained from ten contributors over 12 sessions, using auditory and visual P300 BCI .....	64
Figure 5.16: Individual accuracies obtained from six participants after three successive training and online validation sessions. The figures present the results collected from the <i>alphanumeric</i> speller .....	65
Figure 5.17: The inverse relationship between the ITR (spelling speed) and the interface accuracy .....	66
Figure 5.18: Individual accuracies obtained from six participants after three successive training and online validation sessions. The figures present the results collected from the <i>verbal</i> speller .....	67
Figure 5.19: Individual accuracies obtained from six participants after three successive training and online validation sessions. The figures present the results collected from the <i>graphical</i> speller .....	67
Figure 5.17: A comparison between the mean accuracy of the online and offline results obtained from six users in this study using the alphanumeric P300 Speller, xDAWN filter and LDA classifier, over three sessions .....	68
Figure 5.18: A comparison between the mean of the online and the offline results obtained from 11 users using the P300 Speller over four sessions .....	68
Figure 5.19: A comparison between the accuracy of the target class and the overall accuracy obtained from six users using the three versions of the P300 Speller .....	69
Figure 5.20: A comparison between the P300 brain waves recorded from highly motivated users and low motivated users .....	70

Figure 6.1: Classification task using eSNN and reservoir computing .....	77
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## List of Tables

Table 2.1: Control signals used in BCI applications, and their main characteristics .....	15
Table 3.1: EEG bands and their properties .....	31
Table 5.1: The performance of the classifiers with different numbers of channels that are selected using xDAWN filter on participant# 1 data .....	53

## **List of Abbreviations**

Amyotrophic lateral sclerosis (ALS)

Artificial Neural Network (ANN)

Brain activity pattern (BAP)

Brain computer interface (BCI)

Electrocardiography (ECG)

Electrocorticography (ECoG)

Electroencephalography (EEG)

Electromyography (EMG)

Evolving Spiking Neural Network (eSNN)

Functional electrical stimulation (FES)

Functional magnetic resonance imaging (fMRI)

Human-computer interaction (HCI)

Information transfer rate (ITR)

K-nearest neighbor (KNN)

Linear Discriminate Analysis (LDA)

Magnetoencephalography (MEG)

Near infrared spectroscopy (NIRS)

Optimum spatio-spectral filtering network (OSSFN)

Spinal Cord Injury (SCI)

Slow Cortical Potential (SCP)

Spectral spatio-temporal (SST)

Spectral spatio-temporal data (SSTD)

Spiking Neural Network (SNN)

Superconducting quantum interface device (SQUID)

Support Vector Machine (SVM)

Visual Evoked Potentials (VEPs)

## **Attestation of Authorship**

I hereby declare that this submission is my own work and that, to the best of my knowledge and believe, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgments), nor material which to a substantial has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Rehab Alkhater

April, 2012

## **Acknowledgments**

I am writing these acknowledgments at the end of my master study journey. I have the pleasure to thank numerous people who contributed to the success of this research in many ways after thanking my God for making this happen, and for all the gifts I have had in my life.

First of all, I am deeply grateful to my primary supervisor Professor Nikola Kasabov for suggesting the topic, for his valuable comments on my progress, and for the constructive criticism at different stages of my study. Many thanks for giving me the chance to be a member of the Knowledge Engineering and Discovery Research Institute (KEDRI); an international research institution developed through professor Kasabov's successful effort and where I enjoyed my time during the research for this thesis.

I feel highly indebted to my second supervisor Dr. Stefan Schliebs and I wish to express my sincere appreciation to him for being the source of encouragement and stimulation throughout my learning journey. I would like to express my deep sense of gratitude for his invaluable contribution, attention, inspiration, and patience. This thesis is the result of my extensive discussions with Dr. Schliebs about my work and his constant moral support.

I wish to thank my additional supervisor professor Charles Walker for his encouragement at the early stages of my research and for the inspiring discussions about creativity.

I convey my acknowledgment to Joyce D'Mello, the manager of KEDRI for her encouraging and kind words. Many thanks to Angela Anderson, the assistant registrar, for her personal attention which insured smooth running of my project. Many thanks to Diana Kasabova for her help with proofreading my thesis. I pay my appreciation to Elberta Chan for her endless support. Huge thanks to Karen Rutherford, Ngaire Rix, Jackie Granados-Johnson and Jim Buchan for their efforts to prepare me for a successful master study. I would like to expand my thanks to AUT Ethics Committee (AUTEC), especially Charles Grinter and Rosemary Godbold who helped me to obtain the ethical approval, and also to the staff of Auckland University of Technology for various forms of support during my study.

I am thankful to all KEDRI members for sharing their knowledge and for the cultural exchange. Many thanks to Linda Liang for many academic and non-academic discussions. The road to my thesis started with the inspiration by Nuttapod Nuntaild when he introduced the field of brain-computer interfacing to me and my colleagues. I take this opportunity to thank the people who took part in my experiment for their patience during long recording sessions. I wish to thank the OpenViBE team for allowing me to use the software and for providing a supportive environment.

I gratefully acknowledge King Abdullah of Saudi Arabia for giving me the chance to study in New Zealand and for providing generous financial support to me and my family. I am thankful to the members of The Ministry of Higher Education in Saudi Arabia and the members of The New Zealand Cultural Mission of Saudi Arabia, especially Dr. Sattam Alotaiby, Nabeel Abdrabalnabi, and Dr. Salim Alotaiby.

It is a pleasure to thank my great friends Zahrat, Fatimah, Eman, Sammer and Shahad who helped me feel at home in New Zealand through community gatherings, festivals, lovely trips around the country and delicious BBQs.

Words fail me to express my appreciation to the best parents, my father and mother. I would not have had this achievement without your great efforts to encourage and develop my passion for learning. Despite the geographical distance, my parents and siblings have been always behind me when I really needed support. I acknowledge your generous care and endless support. My father, I deeply appreciate your belief in me. You are the source of my inspiration. My mother, please accept my heart-felt gratitude.

Huge warm thanks to my lovely children, Nebras and Yara, for their patience and emotional support through the ups and downs in this journey. Words are not enough to express my eternal gratitude to my husband, Jihad Alkhater. You have been a constant source of support and strength. My shadow and my light, thank you for encouraging me, motivating me and keeping me going. I warmly appreciate your tireless help during the happy and hard moments. I am intellectually indebted to your ideas, invaluable contribution, and extended love toward me. This thesis is dedicated to you.

## **Abstract**

This thesis aims to design a real-time EEG-based communication aid using brain-computer interface (BCI) technologies. The study evaluates the feasibility of using the Emotive headset as an affordable EEG input system that is suitable for daily usage under realistic conditions. A further objective of this research is to increase the spelling speed of the P300 Speller. Multiple-screen verbal and graphical versions of the spelling paradigm are introduced to increase the number of letters that can be spelled in a particular time period. The experiments were conducted using the OpenViBE platform on six participants. The xDAWN spatial filter was used to detect the activated area of the brain while the LDA and the SVM were employed to classify the data into target and non-target samples.

In terms of Emotiv feasibility, this system has evidenced its capability to detect the P300 brain waves used as the control signals for the P300 BCI. The obtained accuracies are comparable to those presented in other studies in which expensive medical EEG recording systems were utilized. The users' performance with the verbal and graphical versions of the speller is similar to the performance obtained when using the typical alphanumerical speller, although with higher spelling speed. Accordingly, the use of these new versions is highly recommended

The results show significant differences between individual users' performance. The shape of their brain activity pattern recorded within 500 ms of the visual stimulation, which is used as a control signal, as well as other factors were considered. For most participants involved in this study, the target signals are remarkably distinguishable from the non-target ones; however, a case of BCI illiteracy is identified. To summarise, the interface performance is affected positively by higher amplitude of P300 brain waves and users' motivation; however, it is affected negatively by loss of attention, motor movements and mental fatigue.

## **Chapter 1: Introduction**

Human-computer interaction (HCI) is a rich research field. Researchers have been developing methods of communication with computers since the birth of the first computer, and throughout years, focusing on control and data entry schemes, and moving from punched cards to mouse and keyboard. Enormous research effort has been employed in the last few decades to design ergonomic and user-friendly interfaces; see for example Chen et al., (2007), and Burget et al. (2010). As a consequence, some successful products, such as gestures and voice recognition software, have been launched on the market.

The recent years have witnessed the emergence of a completely different scientific interest that concerns alternative interaction methods for people suffering from the loss of all voluntary muscle control (Kaur, Ahmed, & Noida, 2012). As modern computers develop along with neuroscience and an increased awareness of the human brain, it is possible nowadays to control computers and devices directly by using the brain's activity patterns. A Brain-Computer Interface (BCI) is defined by Tan and Nijholt (2010) as a real time interaction system that opens a direct communication channel between the human brain and computers. Accordingly, BCIs could restore some of the lost communication channels for severely disabled people (Pfurtscheller, Muller-Putz, Scherer, & Neuper, 2008). Besides, in the future BCIs may provide an entertaining way to supplement or even replace other interfaces for the general population (Jiang, & Yin, 2009).

The main idea behind BCIs is to record the brain's activity patterns (BAPs) when performing specific tasks that are associated with particular computer commands and then employ some powerful machine learning schemes to classify these patterns. When the user performs one of the tasks in real time, the classifier attempts to detect the associated command, which is then sent to the interface for execution, as indicated by Davlea and Teodorescu (2011). This thesis will focus on the P300 BCI, a communication tool used for spelling purposes. This interface is controlled by the signals that are generated in the human brain as a result of visual stimulation.



The rest of this chapter presents the motivation for this investigation, as well as the scope and the focus. It also discusses the research objectives and questions. Finally, the contribution of this study to the area of BCI and the structure of this thesis are outlined.

## **1.1. Motivations**

One of the most significant characteristics of human beings is their capability to communicate. The richness and complexity of communication between people play an important role in relationships (Campbel, 2011). However, direct conveyance of emotions, concepts and thoughts from one brain to another brain is still impossible. They have to be converted into verbal/written messages, drawings, gestures or other distinguishable expressions. Typically, written and verbal communications are sent using the throat, mouth and hands, although the expressions are generated earlier in the human brain. However, severely disabled people are unable to use the typical output channels for communication.

In December 1995, the well-known French writer Jean Dominique Bauby had a severe stroke which left him locked-in. Fortunately, his brain was not completely impaired and he was able to blink his left eyelid. Despite his situation, he decided to write a biography and did so using eye blinking through an exhausting spelling technique. In his book, Jean reflects how he was suffering from losing communication with his family and close friends, how stressed he was with the inability to control his environment, and with the need for 24-hour care. He described how upset he was of “being ignored while madly blinking at the nurse to turn the TV off” (Bayliss, 2001, p.7). Bauby’s book was published on the 6<sup>th</sup> of March, 1997, and he died three days after that. For detailed information about Jean’s story, the methodology he used to write his book and triumph of the human spirit, see Bauby (1997).

It is not only Bauby who needed effective tools to give him the ability to convey his wishes to care givers, or to have some control of the external environment. The number of potential users for BCIs is high, since there are around 103 million people worldwide suffering from long-term or life-long disability as stated by Erdogan (2009). For example, there are over 2 million patients (5000 cases annually) suffering from Amyotrophic Lateral Sclerosis (ALS) in the USA alone (Felbecker, 2010). This disease attacks motor neurons in the brain resulting in complete and permanent paralysis. Still,

these patients are fully conscious, and have needs, feelings and a deep desire to communicate with others. These factors motivated this researcher to focus on brain-computer interfaces in this study, and particularly on the P300 spelling paradigm, which has been investigated in several recent studies due to its importance. See for example, McFarland, Sarnacki, Townsend, Vaughan and Wolpaw (2011), and Li, Raju, Sankar, Arbel and Donchin (2011).

## **1.2. Research Scope and Focus**

In order to be recognized, a research study has to be useful and meaningful to the community. Similarly, it needs to be educational and informative in its field. To this end, this research focuses on BCIs which represent a contemporary technology that is rapidly growing. This new technology is believed to have a great effect on the society as declared by Mak and Wolpaw (2009), and Thakor (2009). This research investigates the P300 spelling paradigm, a well known BCI used to enable severely disabled people to spell words and convey their thoughts without any physical effort (Li, et al., 2011). More details about this interface are provided in Chapter 4 of this thesis.

Most of the previous studies on this interface were conducted offline under silent laboratory experimental conditions where the participants were required to remain completely focused on the interface, in order to avoid the negative effects of artifacts, as discussed by Rebsamen et al. (2010), and Gouy-Pailler, Congedo, Brunner, Jutten, and Pfurtscheller (2010). Additionally, EEG data was recorded offline by EEG experts, using expensive medical recording devices, which requires long preparation time (Panicker, Puthusserypady, & Sun, 2010). The proposed study aims to design a real-time interface that is affordable for disabled people, and useful for daily usage in realistic conditions. As the recent technological advances have made commercially available EEG headsets inexpensive and accurate, this thesis evaluates the suitability of such devices. The Emotiv EPOC headset, which was originally created for computer games, is tested through an experimental study on six participants, using two BCI scenarios developed by a powerful platform called OpenViBE.

According to Brunner, Ritaccio, Emrich, Bischof, and Schalk (2011), a major problem of modern BCIs is the unsatisfying information transfer rate (ITR) measured in number of bits per minute. The P300 Speller allows beginner users to spell 2-3 letters per

minute, while advanced users are able to spell 6 letters per minute. Although this is considered a great start, it is far removed from the need of daily use. Boosting the ITR of the speller is unachievable for recently developed technologies. The modifications to improve the functions of keyboards and mice include better design of the software interfaces as discussed by Lidwell, Holden and Butler (2010), and Ward and Grinstein (2010). This study takes a similar approach to increase the number of letters spelled per minute using the P300 Speller, in order to further the usability of this BCI.

### **1.3. Research Questions**

As mentioned previously, the main objective of this research is to design a new BCI and more specifically, to further the efficiency of the P300 BCI through increasing the number of letters that can be spelled per minute and through employing an affordable EEG system that can be used by the general public. Consequently, the following questions are addressed in this study:

1. How do brain-computer interfaces work? What difficulties do they present when used?
2. How variable is the BCI performance from person to person; more specifically, can everybody learn how to operate the P300 BCI within a reasonable number of testing sessions?
3. Recent technological advances have made commercially available EEG headsets inexpensive. How well do devices such as the Emotiv EPOC perform with the P300 Speller, under realistic conditions rather than in pre-designed artificial conditions?
4. Based on the available BCIs technologies, how can we increase the number of letters spelled per minute using the P300 Speller?

### **1.4. Contributions of the Study**

The contributions of this study are outlined in the following points:

- A critical literature review of BCI applications and some practical technologies used for their implementation.

- The employed EEG datasets in BCI studies are often provided by a third party but not collected during the study. However, the data for this study is collected by the researcher.
- This study is conducted on real-time closed-loop BCI in contrast to most of the previous studies on BCIs that are carried out in offline mode.
- The data is collected under realistic conditions rather than pre-designed artificial laboratory conditions where the participants are required to remain completely focused on the interface and motionless.
- A new BCI framework is proposed in this study that employs an affordable EEG recording system which is easy to use and hence suitable for the general public. This is in contrast to the available EEG datasets provided by medical institutions that are recorded using highly expensive medical recording devices which require expertise, long preparation time and are not suitable for daily usage.
- Additionally, a simple approach is presented to significantly increase the number of letters that can be spelled per minute using the P300 BCI.
- A paper is in preparation to be submitted to the NCEI workshop (8<sup>th</sup> June 2012) and later to be published by Springer.

## 1.5. Study structure

To answer the research questions, this thesis is structured as the follows:

Chapter 2 is a comprehensive literature review of brain-computer interfaces, taking into consideration the fundamental concepts of BCIs, the history of this technology and the latest developments. In addition, several examples of the currently available BCIs are highlighted. To further the critical analysis, some challenges of the topic are also discussed.

In Chapter 3, the researcher pays attention to the recently available technologies that can be used to design and implement a usable online BCI for out-of-laboratory usage. This covers: brain imaging methods, powerful software to generate online framework for

personalised BCIs and artifact removals, feature extraction methods and efficient pattern recognition algorithms.

Chapter 4 describes the methodology used in this study in details, provides participants' specifications, and discusses data acquisition and processing techniques.

In Chapter 5, a comparison between the outcomes of this study and other previous works in the field is conducted in terms of feature selection and classification methods. The results of the experiment regarding the verbal and graphical versions of the P300 Speller, as a communication aid for locked-in patients are also presented. Furthermore, the performance of Emotiv EPOC system is tested and evaluated by comparing it to other medical devices employed in former studies. Additionally, users' performances are investigated in relation to their P300 brain waves, motor movements and other factors.

Chapter 6 concludes this research. Strengths and limitations of the study are outlined. Additionally, some recommendations for future work are provided.

## Chapter 2: Literature Review of BCIs

A brief introduction to the technology of BCIs was given in Chapter 1. In this chapter, a critical literature review is presented, starting with a brief introduction explaining the purposes and concepts of BCIs. Section 2.2 briefly introduces the structure and functionality of the human brain.

Having explained the basics of a BCI framework in section 2.3, including data recording, pre-processing, classification and biofeedback, the chapter proceeds to explore the recent developments in BCIs in section 2.4. Some of the current applications are outlined and different types of BCIs are highlighted. Furthermore, attention is paid to the main control signals and some major problems in BCI systems.

### 2.1. Introduction

A direct correlation between the mental tasks, cognitive functionality, and the brain activities was identified many years ago by the scientific community. That sparked the curiosity about the multidisciplinary field of neuroscience, culminating with a new non-muscular channel to communicate with the external world (Cecotti et al., 2011). BCI research groups have increased over the last couple of decades, stimulated and inspired by the new advances of neurophysiology, by the advance of computer mechanism, and by the increasing awareness of the needs of disabled people.

A real-time detection of brain signals was firstly achieved by Vidal (1977). With the continuing scientific interest, there are presently over 100 active research groups worldwide focusing on BCIs developments and their potential applications, compared with only six groups ten years ago (Fernando, Alonso, & Gomez 2012). The first 40 groups are listed in Smith (2004). In the same way, the number of articles published on BCI has increased exponentially over the last few years as reported by Konrad and Shanks (2010). A formal definition of a BCI was specified in the first international BCI workshop which was held in the USA, 1999:

*“A brain-computer interface is a communication system that does not depend on the brain’s normal output path way of peripheral nerves and muscles” (as cited in Wolpaw et al, 2000, p.165).*

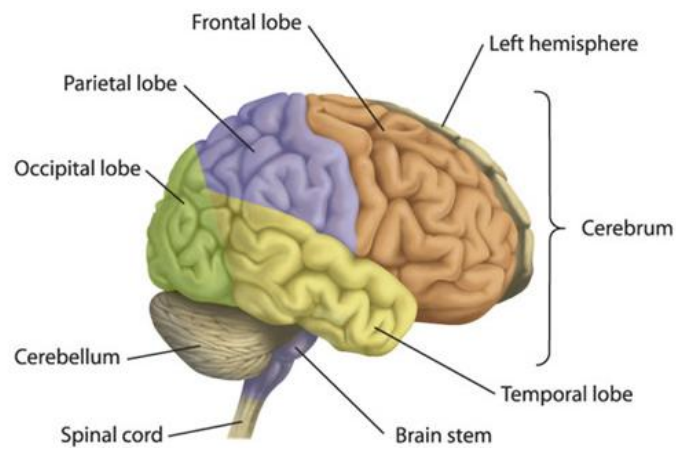
In basic terms, a BCI depends on monitoring the brain signals, which can be done via different imaging techniques discussed in the next chapter. This is done in order to detect specific distinguishable brain wave alterations which can be controlled by the user. Different waves are associated with different commands representing a new communication mechanism. The framework of a BCI is described in detail after the brief introduction to the human brain neurophysiology provided in the next sections.

## **2.2. Introduction to the Human Brain**

In order to understand the background of BCI technology and to find out about the source of the P300 control signals, the fundamental principles of the human brain structure and functions are briefly introduced in this section. For detailed review, refer to Marín-Padilla (2010). Humanity's insatiable curiosity has explored every part of the human body. Particularly great attention has been paid to discovering the anatomical structure of the brain and its functionality. The first experiments were performed on animals and humans with serious illnesses as indicated by Canolty et al. (2012). Over time, a substantial knowledge of brain physiology has been acquired, leading to an even greater desire for understanding the psychological and physiological operations of the human brain.

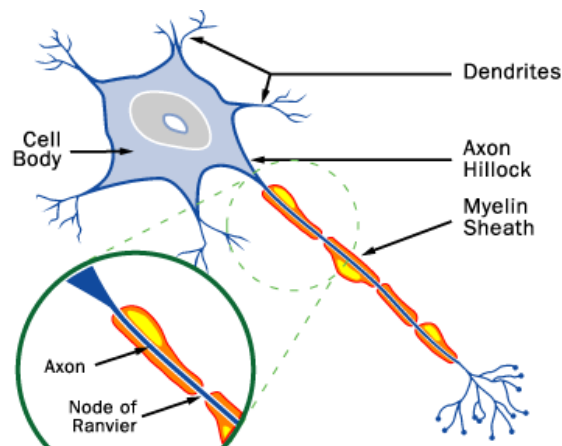
The human brain is “*a dynamic, evolving information-processing system and the most complex one*” (Kasabov, 2007, p.275). One of the most interesting and lasting fields of research is the study of the human brain. The brain evolves initially from stem cells, and then grows and develops by evolving its structure and functionality to reach the adult brain state. This contrasts with the cognitive process which evolves and develops throughout life time in a continuous way to enable the brain to learn and progress as revealed by Yingxu (2010).

The human brain made up of two hemispheres: right and left. The right hemisphere is in charge of the left side of the body and the left hemisphere has the responsibility for the right side of the body. Each hemisphere consists of four lobes: the frontal, temporal, parietal, and occipital as illustrated in Figure 2.1.



*Figure 2.1.* The structure of the cerebral cortex: frontal, temporal, parietal and occipital lobes (Frackowiak, 2004).

It is constructed of 100 billion neurons (Azevedo et al., 2009). As shown in Figure 2.2, the structure of single neurons involves the cell body, the axon, and the dendrites.



*Figure 2.2.* the structure of single neurons involves the cell body, the axon, and the dendrites (Frackowiak, 2004).

There are different types of neurons resulting in the emergence of functional compartments. As reported by Benuskova and Kasabov (2007), each functional system of the human brain has a different spatial region and is in charge of processing special sorts of information. The cognitive functions occur mainly in the cerebral cortex which is a thin outer layer of the human brain with thickness of 2-4 mm. With the assistance of brain imaging technologies, specifically the functional magnetic resonance imaging (fMRI), the brain functions has been precisely localized as shown in Figure 2.3. For example, the primary motor cortex is in charge of the initiation of voluntary movements. Since the P300 Speller depends on visual stimuli, this study focuses on the visual cortex which is responsible for processing visual information.



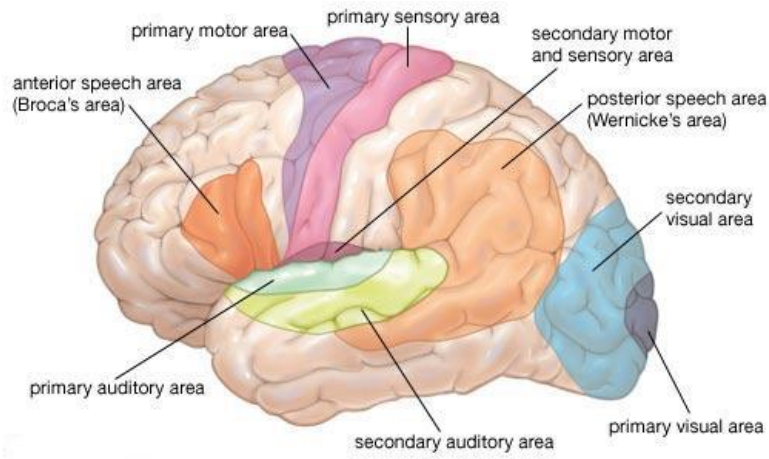


Figure 2.3. Brain functions localisation on the cortical cortex (Frackowiak, 2004).

The brain activity patterns can be acquired by recording the electrical, metabolic or magnetic measurements of the neurons, forming what is called brain data. A review of brain imaging techniques is conducted in Chapter 3 in order to select a proper methodology for the proposed study.

### 2.3. Framework of a BCI System

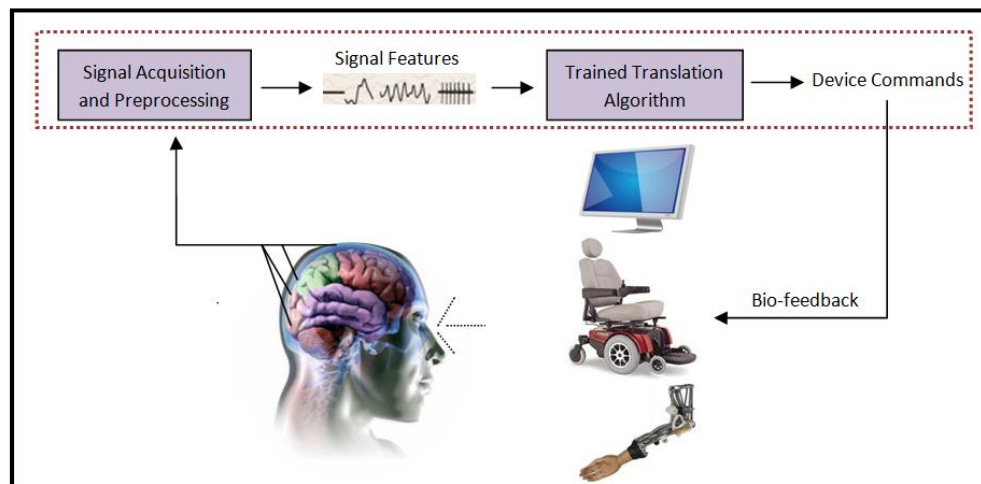


Figure 2.4. The general framework of a BCI system.

The fundamentals of BCIs need to be clearly understood in order to achieve the study objectives. The general framework of a BCI is presented in Figure 2.4. According to Sugiarto and Putro (2009) and Mason and Birch (2003), it comprises data acquisition, pre-processing, classification and biofeedback. These four steps are described in detail in the next section.

### 2.3.1. Data Acquisition

There are different types of data collection methods resulting in different kinds of data. More details are discussed in Chapter 3. The brain signals are acquired and relayed to the computer while the user is performing the appropriate mental task for the used BCI, or while paying attention to a specific stimulus. For example, suitable mental tasks used for moving a wheelchair might be imagining moving the right/left hand and the right/left foot. Other scenarios are possible as well. The user may focus his/her attention on a visual stimulus to spell a letter, which is then translated by the interface into a command.

The data is modified before being transferred to the computer as shown in Figure 2.5. The signals are amplified and then passed through an analog-to-digital converter before they are transferred to the data acquisition unit and then to the acquisition software in the computer for processing. There are different methods to collect these signals from the brain (Lehtonen, Jylanki, Kauhanen, & Sams, 2008; Thomsen, et al., 1997). Detailed description of the meaning of brain signals and the characteristics of acquisition systems is provided in Chapter 3.

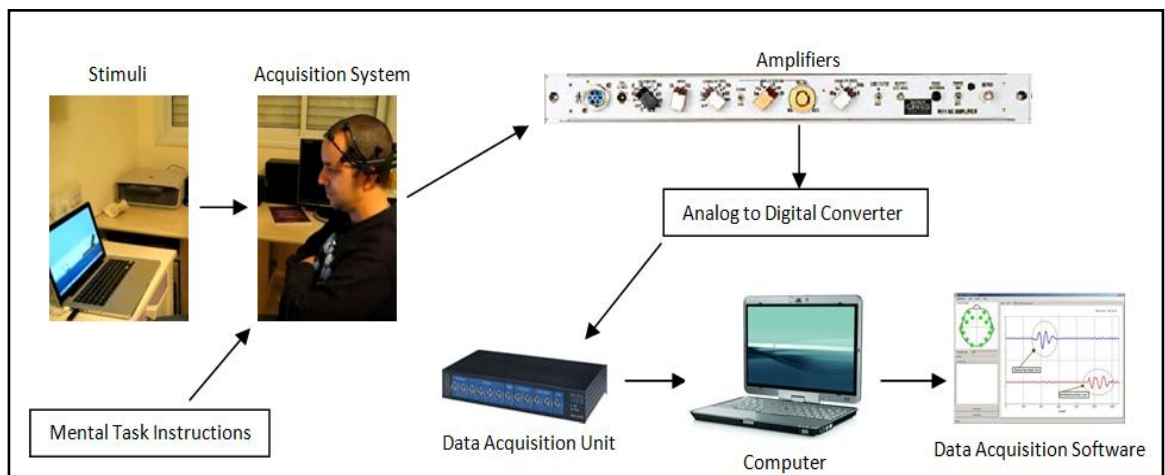


Figure 2.5. General framework for acquiring brain signals presents the steps to input the data into a BCI in the appropriate format.

### 2.3.2. Signal Pre-processing

As indicated by Cerutti (2010), Mammone, Foresta, and Morabito (2012) and Mahadevan, Acharya, Sheffer, and Mugler (2008), pre-processing is required for the brain data due to the fact that the acquired data could be affected by artifacts which are generated by non-cerebral origins. There are two types of artifacts: biological and

environmental. Examples of the biological artifacts include: eye-induced artifacts such as eye movements, muscle-activation-induced artifacts (also referred to as electromyography (EMG) which are electrical signals recorded to detect the skeletal muscles activities), and cardiac artifacts identified as electrocardiography (ECG) which are heart's electrical signals. In contrast, environmental artifacts are generated outside the human body, and can be produced by electrode movement, or electronic devices causing rhythmic bursts. The mentioned artifacts may produce lower and higher frequencies out of the normal signals of the human brain, resulting in poor signal-to-noise-ratio and lower classification accuracy. Thus, the brain data should be filtered to remove the undesired noise. Effective artifact removals result in significant improvements on the interface performance. Evidences are shown in (Anderson, Knight, O'Connor, Kirby, & Sokolov, 2006; Murguialday, Soares & Birbaumer, 2010). Additionally, the data is generally normalized.

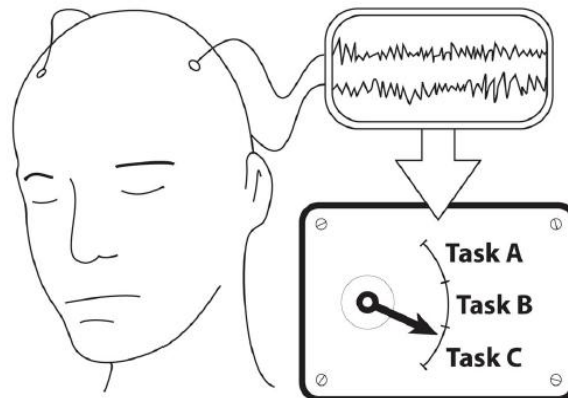
Noting that the brain signals are demonstrated in a high-density spatio-temporal format that contains a considerable amount of redundant data, temporal and spatial filters are required. According to (Xiang, Dezhong, Wu & Chaoyi, 2007), attention should be focused on the channels that are located in the top of the responsible cortex loop for the performed mental task. Moreover, temporal filters are required to locate the time frame of the intended samples of the data, noting that the brain data is measured in milliseconds. Reducing the density of the brain data in both the temporal and the spatial axes is reported to produce some remarkable effects on BCIs performance as reflected in the experimental studies. For example, the classification accuracy of a motor imaginary BCI was increased using optimum spatio-spectral filtering network (OSSFN) by 10-36% in (Haihong et al., 2011). In the same way, the temporal windowing technique is the key for event-related BCI (Chaunchu, Cuntai & Haihong, 2006) and is discussed in the next section of this chapter. A review of the pre-processing methods is presented in Chapter 3 in order to select suitable schemes for this investigation.

### **2.3.3. Data Classification**

As clarified in (Townsend, Graimann, & Pfurtscheller, 2004), BCIs success depends very much on classification. A classification algorithm is trained firstly using a categorized dataset or a number of datasets. These categories (class labels) are associated with mental tasks and commands for communication. For example, if the

class label is ‘right’, the mental task performed by the user is imagine moving the right hand, and the associated command is to move a wheelchair to the right side by the interface. Principally, classification algorithms are based on analogical reasoning and similarity measurements between the characteristic/patterns of the training samples and the new samples in order to predict the intended command; Figure 2.6 represents a conceptual demonstration of a BCI classification task. Generally, the datasets involve the acquisition time of each sample and its class in addition to the brain activity measurements. Mason et al. (2003) stress the importance of data reliability. The data needs to be adequate and accurate, with a good number of samples, but not excessive as this will lead to confusion rather than clarification, resulting in a low speed of processing and synthesis. After training, the classifier might be tested in order to obtain a predicted accuracy of the real-time BCI. Finally, users may start using the interface in a real-time mode.

The main classifiers used in the BCI related research involve: K-nearest neighbor (Dong, Moses, & Li, 2011), Support Vector Machine, Linear Discriminate Analysis and Neural Networks (Lotte et al., 2007). A review of the BCIs’ classifiers is conducted in Chapter 3 to identify an appropriate classification algorithm to be used in this investigation.



*Figure 2.6.* A conceptual demonstration of a BCI classification task.

#### **2.3.4. Biofeedback**

Biofeedback is the procedure in which a human obtains knowledge about his/her physiological state. This could happen repeatedly in a loop allowing the subject to monitor one physiological state or more in order to assist in a task performance.

Neurofeedback was firstly used by Hair in the early 1970s to aid in meditation and relaxation (Smith, 2004). Although some researchers are skeptical about it, others such as Trejo, Rosipal, and Matthews (2006) and Congedo, Lubar, and Joffe (2004) consider it a powerful therapeutic tool that can be used to learn self-regulation of the body systems, to stabilize mood, to normalize behaviour and to improve the mental performance. The effect of biofeedback on BCIs was tested on children (Ali-Nazari & Berquin, 2010). In agreement with their hypothesis, the children's performance was improved when feedback was provided.

## **2.4. BCI Developments and Key Principles**

This section explores the key principles and the state-of-the-art of BCIs. First, different control signals in BCI are explained, and then different types of BCIs are highlighted. The advances of principal worldwide BCI research-groups and their ongoing work are reviewed, and some of the current applications are outlined. Furthermore, attention is paid to some major problems in BCI systems.

### **2.4.1. Control Signals in BCIs**

A control signal is defined as a particular brain wave that has unique characteristics and is generated consciously by performing a cognitive task or unconsciously by stimulations. Accordingly, the classifier predicts the class of a new sample by evaluating the similarity and difference of measurements between the control signal and the new sample. As stated in (Fernando et al., 2012; Wolpaw, 2007; Jerbi et al, 2011), there are four different types of control signals in current BCI applications. The types and properties of these signals are presented in Table 2.1 which provides the names of the control signals, a brief description of each of them, the required amount of training, the number of choices (e.g. the numbers of samples in the P300 matrix used for spelling), the information transfer rate using these control signals that has direct correlation with the application speed, and also some examples of BCI applications that employs these control signals.

Table 2.1

*Control signals used in BCI applications, and their main characteristics*

Signal	Phenomena	Number of Choices	User training	ITR	Example
<b>Sensor-motor Rhythms</b> (Bai et al., 2011)	Modulations in sensorimotor rhythms synchronized to motor activities.	2-5	Extensive training is required	3-35 bits/min	BCI wheelchair (Tanaka et al., 2005)
<b>Visual Evoked Potentials (VEPs)</b> (Dan et al., 2010)	Modulations in the visual cortex rhythms synchronized to a visual stimulus.	High	No	60-100 bits/min	VEP BCI to control a hand orthotic for paralyzed people (Ortner et al., 2011)
<b>P300</b> (Mugler, Ruf, Halder, Bensch, and Kubler, 2010)	Positive peaks in the brain waves due to infrequent visual, auditory or somatosensory stimuli. These peaks elicited about 300 ms after attending to an oddball stimulus among several frequent stimuli.	High	No	20-25 bits/min	P300 Speller (Furdea et al., 2009)
<b>Slow Cortical Potentials (SCPs)</b> (Hinterberger et al., 2004)	Slow voltage shifts in the brain waves correlated with increased/decreased neuronal activity.	2-4	Extensive training is required	5-12 bits/min	On-screen cursor control (Hinterberger et al., 2004)

#### 2.4.2. Types of BCIs

Mainly, there are two types of BCIs as reported by Jackson and Mappus (2010): synchronous and asynchronous. A synchronous BCI is based on system initiation. Interaction is only allowed in a fixed time window. Most synchronous interfaces count on event-related potentials that are generated by a stimulus, e.g. visual or auditory stimulus, produced in a known time frame. A good example is the P300 Speller. This system depends on the synchronisation between visual evocation and the brain activity patterns. This type is easier to design. Additionally, the classification is less affected by artifacts as a result of the windowing techniques. In contrast, asynchronous interfaces depend on user initiation. They do not impose specific time frames for interaction and offer a more natural way for communication. However, designing and evaluating asynchronous systems is more complicated. To prevent accidental detection, the mental task must be unique. Appropriate control signals could be the sensor-motor rhythms as explained in (Fernando et al., 2012).

BCI applications can be also divided into exogenous and endogenous interfaces (Fernando et al., 2012). Exogenous interfaces depend on external cues. Users training is

not required since the control signal can be easily and quickly set up. Reasonable ITR can be achieved after a sufficient training, and good results can be achieved using a minimum number of channels, down to one. Nevertheless, this type may cause tiredness for some users while focusing their attention on the stimuli for long periods leading to significant decrease of the user performance. Contrary, endogenous interfaces are independent of any stimulation, thus, they are useful for users who are suffering from sensory organs damage. Despite that, user training is required and it is time consuming. Several months could be spent to reach a good performance, and still the speed is very low with an ITR of 3-35 bits/minute. The study by Hochberg et al. (2006) presents a good example of an endogenous interface.

### 2.4.3. BCI Applications

It is worth clarifying the distinction between a BCI and its applications while the term ‘BCI’ defines the system that collects, processes and interprets the input brain data into commands that an interface executes as a particular control function, BCI applications define the way that a BCI is used. Consequently, BCI applications are divided onto five major areas: locomotion, nerve restoration (neuroprosthesis), environmental control, entertainment and communication. Figure 2.7 illustrates the relationships between these types of applications relating to the ITR and the users capacities for control. As demonstrated in the figure, most BCI applications are created for entertaining purposes. The capabilities offered to healthy users and non-severely disabled people are higher than these offered to locked-in syndrome patients. However, there are no applications reported for completely locked-in patients. Among the five types, communication BCIs have the lowest ITR capabilities of control offered to the users. Interestingly, nerve-restoration (neuroprosthesis) BCIs have the highest ITR capabilities offered to the users.

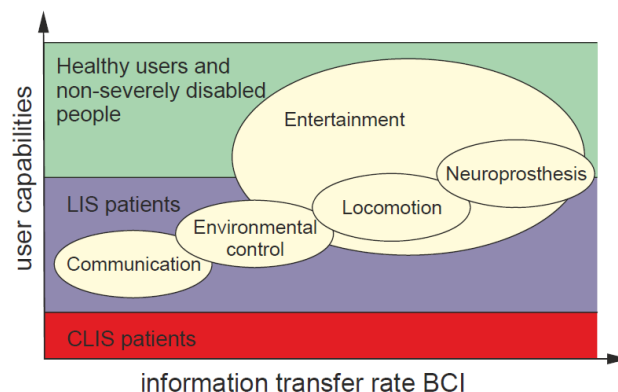


Figure 2.7. The relationship between the fields of BCI applications, ITR and the given control capabilities to the users (Fernando et al., 2009, p. 1248).



#### 2.4.3.1. BCI Applications for Locomotion

Locomotion interfaces represent an important type of BCI application. They are employed to control the spatial location of an object, such as a robot or a robotic arm as shown in Figure 2.8. It appears that the first system of this kind was a wheelchair developed by Tanaka et al (2005). Their study was undertaken on six healthy users where the floor was divided into a number of squares. The users were able to drive the chair by imagining left or right limbs movements, which produced distinguishable beta rhythm used as a control signal. The wheelchair is shown in Figure 2.8. Another study by Grychtol, Lakany, Valsan, and Conway (2010) investigates a similar approach to drive a virtual reality wheelchair by visually evoked potentials. The results of these experiments are promising, with correctly classified commands ranging between 46%-100% depending on the training period and the users' ability to learn. However, the long training and the low speed of the interface are drawbacks.

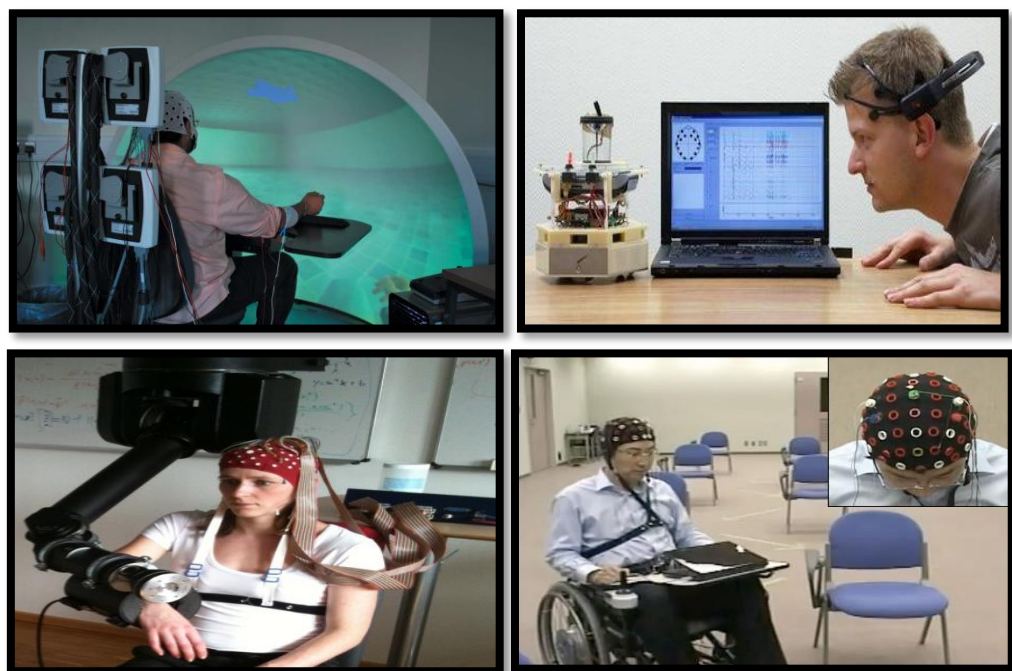


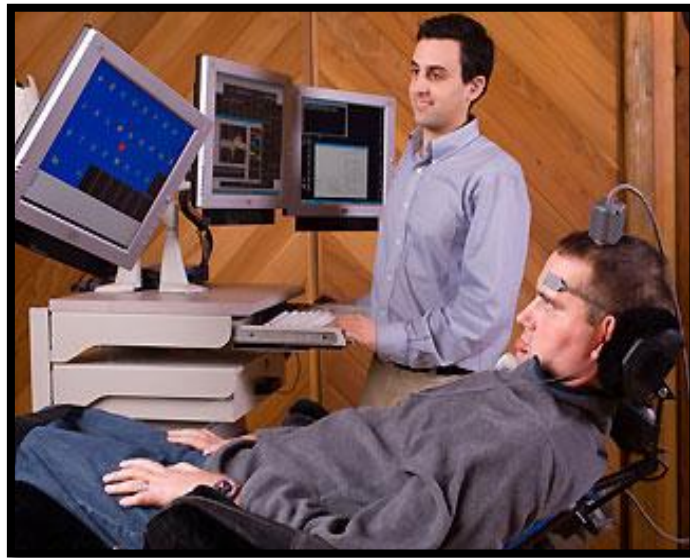
Figure 2.8. Some examples of locomotion BCI applications. From top right: (Kasabov, 2012, p.11), (Kawate, 2012), (TU Darmstadt, 2011), and (Bogue, 2010).

#### 2.4.3.2. BCI Applications for Environmental Control

Some studies such as the one by Cincotti et al. (2008) focused on developing BCI applications that allow users to control the surrounding environment, for example, to control a television, light or a mobile phone. Hochberg et al. (2006) successfully implemented a novel interface called Brain Gate using attached sensors to the primary motor cortex of a paralyzed patient allowing him to take control over an on-screen



cursor by imaging limb motions. The results are remarkable as the user was able to draw a circle, operate a television and handle e-mail applications, see Figure 2.9.



*Figure 2.9. Brain Gate BCI for environmental control (Hochberg et al., 2006).*

#### **2.4.3.3. BCI Applications for Communication**

Lots of attention has been given to communication BCI applications generally and to the P300 Speller specifically (shown in figure 2.10). This paradigm was firstly proposed by Farwell and Douching (1988). It is based on the P300 control signals. These are presented as positive peaks in the brain waves generated by the infrequent visual stimuli (row/column flashing). The peaks elicited about 300 ms after attending to the oddball stimulus (the target letter) among several frequent stimuli, non-target letters (Chaunchu, 2006).

Unfortunately, it is difficult to detect the target letter within one trial, which is the time needed to intensify all the rows and columns for one time. This is due to the fact that brain data is influenced by the artifact and noise which makes it impossible to distinguish the target reactions from the not-target responses within a single trial. OpenViBE's (2011) recommends using 12-trial interface for beginners with an average of 28 sec of time to spell one character, leading to a very low speed. This fact is the main reason behind a major problem of the P300 Speller for untrained users, namely the low ITR. Once the classifier has been well trained, the number of trials can be reduced to 5 or even less. Despite this drawback, the P300 Speller is one of the most effective and accurate BCIs used for communication purposes up to date (Brunner et al., 2011).

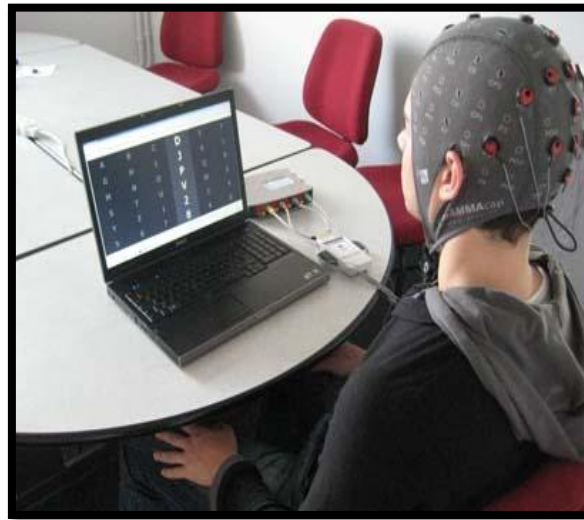


Figure 2.10. Communication BCI (Westly, 2011).

#### 2.4.3.4. BCI Application for Entertaining

As BCI research focuses on disabled people, entertainment-oriented BCIs have had a lower priority. Nevertheless, a significant interest in BCI for games has arisen in recent years owing to the latest developments in this technology. Some interfaces have been developed to control virtual characters while others attempt to move realistic objects such as a ball. Figure 2.11 shows some examples of BCI applications for entertainment that can be played through motor imagery for one or multiple users.

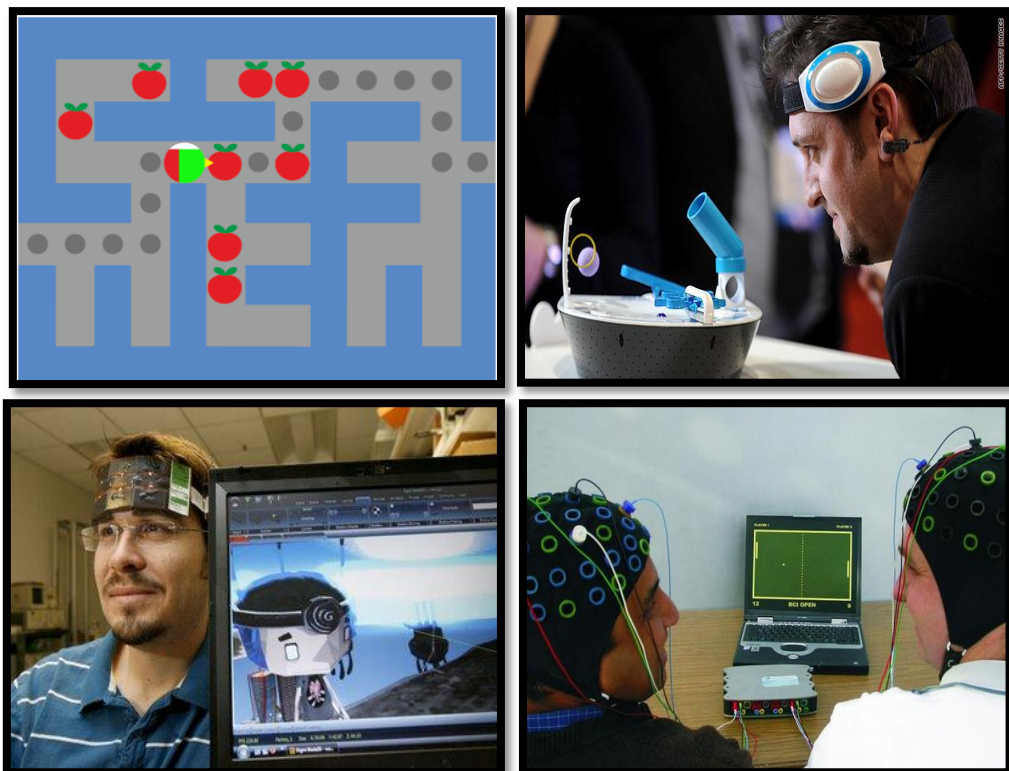


Figure 2.11. Some examples of entertainments BCI Application (g.tec, 2012; Marentette, 2008; Squidoo, 2012).

#### **2.4.3.5. BCI Applications for Nerve Restoration: Functional Electrical Stimulation (FES) BCIs**

This is a new type that does not fit into the general framework. Researchers are turning their heads to FES BCI applications which aim to restore some of the lost nerve functions for spinal cord injury (SCI) patients, and other disabled people in order to achieve independence from homecare services. This can be achieved by generating artificial control signals by depolarizing intact peripheral nerves for the operation of functional electrical stimulation that innervate the targeted muscles and cause a muscle contraction. A review of FES BCI applications can be found in Braz, Russold, and Davis (2009). Pfurtscheller G., Müller, Pfurtscheller J., Gerner, and Rupp (2003) have developed an interface that allowed a tetraplegic patient suffering from SCI, to grab a cylinder by his paralyzed hand through imagining moving his foot. A long training period was needed; however, the user succeeded to open and close his hand. Another approach is presented in Muller-Putz, and Pfurtscheller (2008). The Bionic Eye, shown in Figure 2.12, demonstrates an ongoing research at the NICTA research institution, Australia National University (Barnes, 2012). It is based on the FES to stimulate the retina, in order to assist individuals with vision impairment.



*Figure 2.12. The Bionic Eye (Barnes, 2012).*

#### **2.4.4. BCIs Problems**

Although the BCI research field has been developing rapidly over the last two decades, numerous problems and obstacles still need to be considered. The major drawbacks are highlighted in this section with regard to users' training, the curse of dimensionality, the cost of data acquisition devices, offline and online processing, the limited laboratory applications and BCI performance metrics.

BCI systems are not yet used autonomously by paralyzed people due to the help needed to wear the acquisition tool. In the same way, the user could be enabled to turn the BCI off but how can they turn it on again? This forms the '*Midas Touch*' problem. Additionally, a high cognitive load is required to run a BCI system which seems to be tiring for the users. Despite these problems, the first step in developing a home-based, long-term and independent BCI has been taken; see Sellers, Vaughan, and Wolpaw (2010) for more details.

The required time to train the users reflects a major problem in endogenous applications as training might take several months, depending on the user's learning ability and motivation (Artusi, Niazi, Lucas & Farina, 2011). While users' training is not required for stimulation-based interfaces, classifiers performance might dramatically decrease due to the '*small sample size problem*'; this problem is due to the small number of training examples in relation to the large number of features/channels as stated by Hoffmann, Vesin, Ebrahimi and Diserens (2008). The *curse of dimensionality* can be solved by enlarging the training data, nevertheless, this is difficult as it is time-consuming and tiring for the users. Hence, it is highly recommended to decrease the number of channels by feature extraction methods.

Another problem of BCIs is the low ITR which results in the low speed of BCI systems, particularly the ones designed for communication purposes. Accordingly, beginner users can spell 2-3 letters per minute (about one word in 2-3 minutes) while advanced users may spell 6-7 letters per minute, which is time consuming and not efficient for regular users.

An additional problem that the researchers face is the comparison method. Well-defined performance metrics are required for evaluation purposes. Although some research groups have identified this problem, (Mason et al., 2003), further investigations are still needed, as the accuracy alone cannot form a proper performance metric for complicated BCI applications.

On the other hand, most brain-imaging systems are extremely expensive, thus, they are not reachable by the general public, or by the researchers in some cases. Added to that, the data can only be collected by experts and under certain conditions. These reasons lead the researchers to omitting the data-acquisition step and using some of the available datasets for training and testing. Accordingly, the testing is conducted offline by means of cross-validation. This is used to estimate the validation accuracy after training the

classifier. The testing data is split resulting in an average accuracy from different partitions of the sample data. This approach could be suitable for various applications, but when it comes to BCI as a temporal system, some inherent issues appear by spreading independent elements that may not be identically distributed (Lemm, Blankertz, Dickhaus & Müller, 2011). Similarly, Townsend et al. (2010), and McFarland, Krusienski, and Wolpaw (2006), claim that offline analysis cannot address realistic issues when the data is processed in a casual manner with non-stationary datasets, due to the changes related to users' motivations, fatigue and other factors. This is not aligned with the offline processing setups conducted by the analyst who observes the statistics of the data across an entire session, with the aim of fine-tuning the algorithms and long-term computations. Fernando et al. (2012, p.1240) agree with this and confirm that:

*“Classification algorithms have traditionally been calibrated by users through supervised learning using a labeled data set. It is assumed that the classifier is able to detect the patterns of the brain signal recorded in online sessions with feedback. However, this assumption results in a reduction in the performance of BCI systems, because the brain signals are inherently non-stationary. Although some researchers test new algorithms with only offline data, both offline simulation and online experiments are necessary for effective algorithm design in closed-loop systems. In other words, offline simulation and cross-validation can be valuable methods to develop and test new algorithms, but only online analysis can yield solid evidence of BCI system performance”.*

Despite current advances in BCI systems, proper applicability requires greater ease of use which means minimizing the time for training, calibration, and preparation. This cannot be achieved using the expensive medical neuro-imaging systems that are limited to the laboratory environment. The new developments are demonstrated by the latest affordable data-acquisition devices oriented towards the general public. Although these new systems, e.g. Emotiv EPOC and NeuroSky, were designed for BCI games and entertainment, some researchers (Ekanayake, 2010; Stytsenko et al., 2011) prompt that these devices can be evaluated for use in general BCI applications, and under realistic conditions.

## **2.5. Conclusion and Open Problems**

In this chapter, a critical literature review was presented, with attention to the purposes and concepts of BCIs, the human brain nervous system and its construction, structure

and functionality. Moreover, the basics of the BCI framework was clarified in terms of data recording, pre-processing, classification and biofeedback. The recent developments of BCIs were also reported and some of the current applications were outlined. Furthermore, attention was paid to the main control signals in BCIs and some of the major problems in this field.

The literature review has highlighted a number of open problems including:

**Problem 1:** The cost of the medical brain-signal acquisition systems and the difficulty of their use leading to the following obstacles:

- The BCI applications are designed using medical acquisition systems and are not reachable for the potential users in the general public.
- The BCI applications designed using the medical acquisition systems are tested only offline using brain datasets available on the web and which are collected by experts. Cross-validation approach may result in spreading independent elements that are not identically distributed. Moreover, offline analysis cannot address realistic issues when the data is processed in a casual manner with non-stationary datasets, due to the changes in users' motivations and other environmental factors. This is not aligned with the offline processing setups conducted by the analyst who observes the statistics of the data across entire sessions, with the aim of fine-tuning the algorithms and long-term computations, resulting in a reduction in the interfaces' performances in real-time mode.

**Problem 2:** The low ITR and speed of the applications designed for communication purposes.

This research will focus on these two problems. The recent technological advances have made the commercially available acquisition systems that are oriented towards the general public inexpensive. Consequently, this thesis aims to identify and evaluate an appropriate tool for the P300 communication application, under realistic conditions following Stytsenko's et al. (2011) recommendations. To avoid the weaknesses of the offline experiments, this study will be conducted online in a closed-loop system as suggested by Fernando et al. (2012). To address the low speed of spelling using the P300 CBI (an average of 2-3 letters per minute for beginners) this study investigates an

enhanced design of the interface using verbal and graphical versions of the speller instead of the typical alphanumerical interface. More details about this are discussed in Chapter 4 of this thesis.

## **Chapter 3: Methods Used for BCI: A Review**

In this chapter, attention will be paid to the recently available technologies that can be used to design and implement an online BCI for out-of-laboratory usage in order to identify appropriate methods for this investigation. This will cover:

1. Brain imaging methods for BCI application.
2. Brain data acquisition hardware.
3. Platforms used to design a BCI application.
4. Feature extraction schemes.
5. Efficient pattern recognition algorithms.

These issues are addressed in the following five sections. The investigation will be limited to the technologies that are: affordable and open for the general public, portable, suitable for every day usage (i.e. easy to use with minimum preparation time), and also appropriate for the domestic environment. It is worth noting that the only imaging technique that covers all these requirements is Electroencephalography (EEG). However, there are some other techniques used in BCIs applications such as electrocorticography (ECoG), microarray electrodes, magnetoencephalography (MEG), near infrared spectroscopy (NIRS), and functional magnetic resonance imaging (fMRI). Although these methods were not available options for this study, they are briefly outlined in the next section to provide background information for the BCI technology and to justify the exclusion of these techniques from this research.

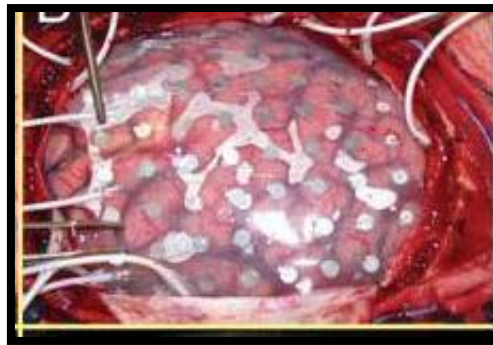
### **3.1. Brain Imaging Techniques**

Older studies of the human brain and cognition were qualitative in nature and with a limited applicability (Posner, 1990). Despite that, cognitive science has made remarkable progress driven by the studies that investigated both qualitative and quantitative measurements of the brain (Smith et al., 2002). It is well-known that BCIs are controlled by the quantitative measurements of the brain activity patterns (BAPs), but what do these measurements mean? Depending on the methodology used to measure these patterns, BAPs have different interpretations. There are several imaging techniques employed to detect a particular brain activity pattern. Relevant imaging technique for BCI applications and their characteristics are explained in this section.



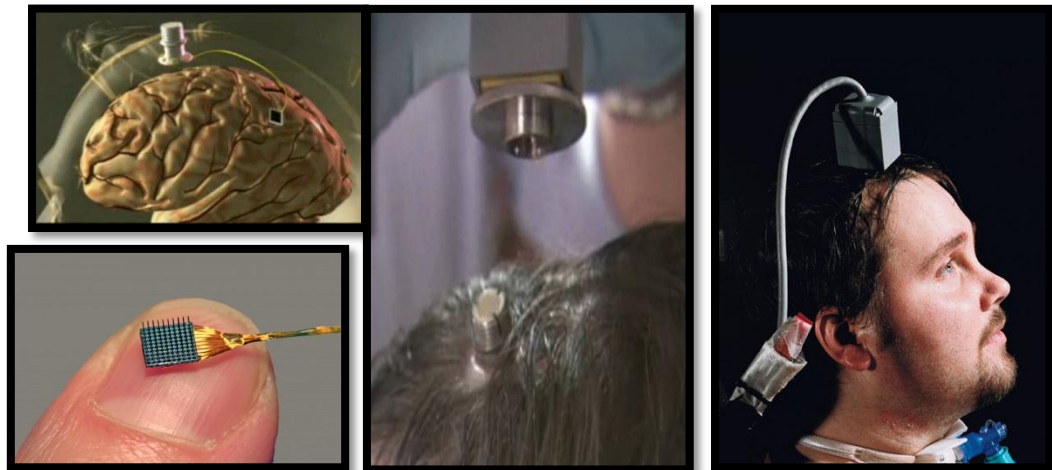
### 3.1.1. Electrocorticography (ECoG) and Microarray Electrodes

ECoG is an invasive procedure to measure the brain electrical activities. Billions of neurons are embodied in the human brain. When the nerve cells are activated, small electrical signals called action potentials are generated. ECoG practice involves a surgical operation to implement a grid of biocompatible electrodes on the cortex surface as described by Wolpaw J. and Wolpaw E. (2012). Figure 3.1 shows the electrodes grid implemented on a human brain.



*Figure 3.1.* ECoG grid implementation on a human brain (Erdodan, 2009, p.12).

A similar approach uses microarray electrodes to improve the data quality by integrating analogue circuits, allowing the recording of the activity of a single neuron and reflecting a higher spatial resolution and leading to outstanding signal-to-noise ratio (Figure 3.2).



*Figure 3.2.* Microarray electrodes implementation in the human brain (Neurogadget, 2011).

Waves are less influenced by the conductivity of the skull and the muscular artifacts comparing to other external brain imaging techniques, which makes ECoG an appropriate strategy to be used in BCI application (Wolpaw et al., 2012).

In spite of the quality of the data acquired by microarray electrodes and ECoG, there are critical handicaps as reported in Smith (2004). This includes the invasive nature of these systems, and the potential inconsistency between the neurons and the electrodes, as well as the possible infections which may result in blocking the data transmission.

### **3.1.2. Magnetoencephalography (MEG)**

According to Smith (2004), MEG is a noninvasive scheme for measuring the brain activity. This method works by measuring the magnetic field generated by the electrical flow in the cortex. The superconducting quantum interface device (SQUID) is used in this model, as shown in Figure 3.3.



*Figure 3.3. SQUI device used to collect MEG data (Erdodan, 2009, p.14).*

Although MEG systems collect data with a remarkably high spatial resolution data (up to 3 mm), and can significantly improve the speed of BCIs, its usage in BCIs is limited to few studies, e.g. Lal et al. (2005), and Kauhanen et al. (2006). The reason behind that is the size of the SQUID instrumentation, the extremely high costs, and the non-portable style of the device. Thus, MEG is not applicable for real-world BCIs' applications as it is not practical for real-time analysis.

### 3.1.3. Hemodynamic Activity of the Brain: Near Infrared Spectroscopy (NIRS) and Functional Magnetic Resonance Imaging (fMRI)

Both NIRS and fMRI are used to monitor the oxygen levels of the blood passing through the brain, since the consumption of oxygen increases in active neurons. Devices used to collect the data are shown in Figure 3.4. The advantage of these technologies is the impressive spatial resolution. Actually, neurons' functionality can be distinguished from other parts of the brain and not only from the cortex as other imaging techniques. However, the acquisition equipments are large and extremely expensive. Added to that, the temporal resolution is poor (responds within a few seconds), therefore, studies such as (Weiskopf et al., 2004; Hong, Coyle, Ward, Markham & McDarby, 2004), reject the usability of NIRS and FMRI after they tested them in BCIs' applications.



*Figure 3.4.* Devices used to collect fMRI data on the left, and NIRS data on the right (Waisman Lab, 2007).

### 3.1.4. Electroencephalograph (EEG)

This technique is very similar to ECoG technique, as it depends on measuring the electrical activity of the cortex using a number of electrodes. However, EEG is generally a noninvasive procedure. Instead of implementing the electrodes on the cortex surface by a surgical operation, EEG electrodes are simply placed on the patient's scalp. Despite the poor spatial resolution, EEG is the main technique used in current studies, and it has

been investigated by numerous researchers (Darvas et al., 2010; Shiliang, 2010). Smith (2004, p.9) claims that:

*“It has excellent temporal resolution of less than a millisecond. It is also relatively inexpensive and simple to acquire making it the only practical non-invasive brain imaging modality for repeated real-time brain behavioural analysis”*

There are various systems available for recording EEG data. Comparing to the discussed imaging techniques, EEG acquisition systems are cheaper. They are also smaller and more portable. Some examples are shown in Figure 3.5.

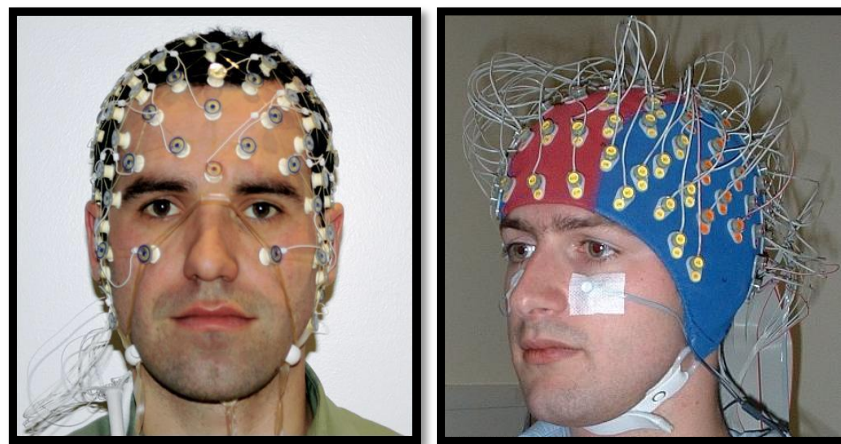
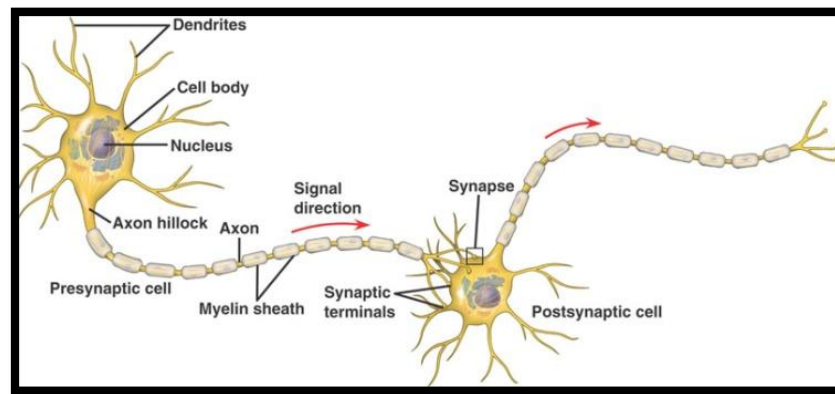


Figure 3.5. Examples of EEG medical acquisition systems (Waisman Lab, 2007).

It is clear that EEG imaging technique for the human brain is the best candidate to be employed in this investigation as it covers all the requirements specified earlier. A short review of the main concepts of EEG is presented below.

As stated by Erdodan (2009), the existence of electrical signals in the human brain was discovered by Richard Caton, a British surgeon, in 1875. However, it was 1924 when the first EEG data was recorded by Hans Berger, a German neuropsychiatrist. He evidenced that weak electrical brain signals can be recorded and presented on a piece of paper without involving invasive surgical procedure, using his standard radio to amplify the electrical signals. When humans perform any activity such as move, smile or even think, some nerve cells are activated and generate short electrical signal called action potentials (Wolpaw et al., 2012). These potentials are transferable between cells through synapses (Figure 3.6).



*Figure 3.6.* Electrical brain signals called action potentials are transferred between cells through synapse (Tortora & Derrickson, 2010).

Abhang, Rao, Gawali and Rokade (2011) define the EEG as a methodology to illustrate the electrical activity patterns of the brain's surface, the cortex, or more precisely as a way to signify the reflection of the summed synaptic potentials of the nerve cells. The frequency of these potentials measure between 1 Hz to over 30 Hz, and they are divided into six bands depending on the frequency. BCI applications utilize the band frequencies of 1-30 Hz, while potentials measures of less than 1 Hz or higher than 30 Hz are only used for limited clinical purposes (Abhang et al., 2011). Table 3.1 presents the characteristics of these six bands including their names, frequency range, shapes and properties.

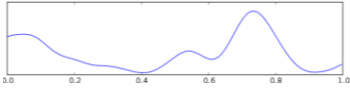
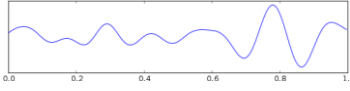
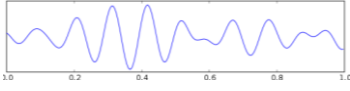
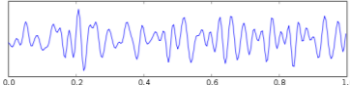
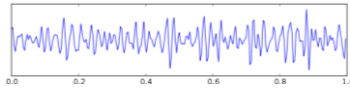
EEG data is typically recorded by small electrodes. There are different types of electrodes available: disposable electrodes, metal cup electrodes, needle electrodes (invasive), and gelled electrodes cups. The metal and gelled electrodes are currently used for BCI applications (Stieglitz et al., 2009). Despite that, some researchers are attempting to develop user-friendly dry electrodes to minimize the preparation time required (Liao et al., 2012).

Although studies use different numbers of electrodes according to the mental tasks analysed, EEG electrodes are generally placed at particular locations on the scalp. The International Federation of Societies for EEG and clinical physiology made the first step to standardise the placement methodology allowing researchers to compare their outcomes in a better and practical way as reported by Koessler et al. (2009). The 10-20 international standard EEG placement system consists of 21 electrodes. However, it was extended over the time reaching the number of 512 electrodes for some medical application. Normally, BCI applications use a small numbers of electrodes to reduce the

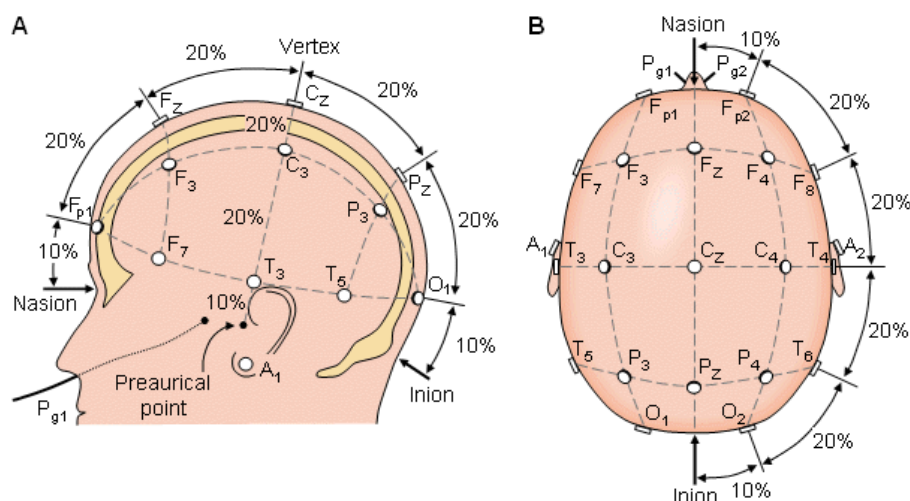


Table 3.1

*EEG bands and their properties* (Abhang et al., 2011)

Signal	Frequency	Shape	Properties
Delta	1-3 Hz		This wave has high amplitude but low frequency. It is seen in young children normally, and also in adults when they are sleeping.
Theta	4-7 Hz		This signal is normally seen in young children, it could be as well generated in older children and adults in arousal or drowsiness. It is also associated with medications, relaxation and creative status.
Alpha	8-13 Hz		This is the first type of wave discovered in the human brain. It has high amplitude. It emerges with eyes closing and relaxation, and attenuates with opening the eyes and mental exertion.
Beta	14-30 Hz		Beta wave can be also called sensorimotor rhythm, as it accrues when arms or hands idle. It could be associated with drugs and anxious thinking. It is generated from the frontal lobe, and is widely used for motor BCI applications. In the case of cortical damage this wave could be absent.
Gamma	>30 Hz		This pattern is associated with alertness, working and motor movements.

long preparation time and because the real-time processing of large amount of EEG data by current technologies is inadequate. Figure 3.7 shows the electrodes' positions and the channels' names in the 10-20 placement system.



Noting that hand-operated placement of EEG electrode is a challenging and time-consuming task, Electro Caps and EEG headsets were introduced to save time and efforts. A brief review of EEG headsets is presented in the next section.

### 3.2. EEG Data Acquisition Hardware

A good example of Electro Caps that is used in most BCI studies is the g.tec system which can be used with 8 to 256 electrodes over the skull (Figure 3.8.). It is capable of collecting a high quality data with low interface and fast montage as reported in numerous studies such as (Pires, Nunes, and Castelo-Branco, 2011; Guger et al., 2009; Cecotti, 2011). On the other hand, it is costly. Furthermore, the preparation time to use the system is very long especially because of the large number of channels. These disadvantages make g.tec as well as other EEG medical systems more useful for laboratory experiments where the data is collected by experts, but not for daily use or for the general public.



Figure 3.8. g.tec recording systems (g.tec, 2012).

The recent technological advances have made some commercially available EEG headsets inexpensive. Examples of EEG headset that are suitable for daily usage are NeuroSky headset, a recent release by NeuroSky Inc. (2011) in the USA, and Enobio that is created by Starlab (2011) in Spain (Figure 3.9). Public users could obtain such headsets at a minimum cost starting at US \$99. These headsets are evidenced to produce good quality data when evaluated by Mostow, Chang and Nelso (2011) and Mihai and Gheorghe (2010). Despite that, they have the limitation of collecting data from only one channel (NeuroSky) or four channels (Enobio). These channels might be useful for some applications such as testing the cognitive load, but not for general BCI applications. A review of commercial EEG headsets is provided by Zhang, Wang and Fuhlbrigge (2010).



Figure 3.9. NeuroSky system on the right (NeuroSky Inc., 2011), and Enobio system on the left (Starlab, 2011).

'Emotiv EPOC neuroheadset' which is developed by Emotiv systems (2012), Australia, is one of the first EEG headset developed specifically for BCIs applications (Figure 3.10). It was released on the market in the USA in 2010 to open a direct communication channels between a user brain and a computer and cost US \$299. It has 14 channels to cover most of the cortex area. The tool is wireless and the preparation time is short.



Figure 3.10. Emotiv EPOC neuroheadset (Emotiv systems, 2012).

Emotiv headset is designed mainly for playing computer games in contrast to the expensive medical devices. This study tests the feasibility of the use of the Emotiv system for communication BCI. This might not only lead to a great reduction of the cost



and the preparation time to use the P300 Speller but also might help to diminish the stigma and stereotypical notion of disability. EPOC headset was chosen to be used in this study for a number of reasons:

1. Emotiv is affordable in contrast to other medical EEG headsets which are expensive and consequently not accessible by numerous potential users.
2. It is wireless in comparison to medical sets that require a wire connection between each electrode, the amplifier and the computer. That is inconvenient for daily use, and also it presents the problem of artifacts created by the head movements.
3. Unlike the medical applications, experts are not required for the collection of the data using Emotiv. In fact, a person can collect his/her EEG data by following some simple instructions.
4. The required preparation time to make Emotiv headset ready to use is about 2 minutes. In contrast, most of the medical equipments require over 20 minutes for preparation.
5. The quality of the data collected using Emotiv headset was tested in a few recent studies. In comparison with the well-known medical system g.tec, Ekanayake (2010, p.16) claims that “Emotiv EPOC does capture actual EEG”. Similarly, a recent study by Stytsenko et al. conducted in June, 2011 evidences that the “comparison between the two EEG devices suggests that data is alike in general, but the signal is cleaner and stronger in the g.tec device”. Despite that, it describes recording EEG data using g.tec as a ‘challenge’, but praised the ‘free moving capability’ of Emotiv. Accordingly, it recommends employing Emotive system in BCI research and suggests future work to focus on investigating the P300 Speller and other applications such as mismatch negativity event-related potentials.

### **3.3. Platforms Used to Design a BCI Application**

There are few platforms for the design and implement BCIs. A critical review of the available platforms was conducted, in order to choose an appropriate one. Since the focus of this research is on affordable BCIs, the review was restricted to the free and open source software. Several systems are available for offline and online processing of EEG signals. Schlogl et al. (2007) briefly reviewed them. Some of the essential functionalities for designing a BCI were overlooked in some of them, and only four platforms met the criteria of this study:

- Bio Sig which was developed by Schlogl and Brunner (2008). It is a fully open-source package offering a variety of data management modules, importing and exporting data, and preprocessing including feature extraction, artifact removals and quality control. It is powerful for real-time processing of biomedical signals generally and EEG data specifically. Despite that this package depends on Matlab which is costly proprietary software. In addition, the Emotive headset cannot be integrated with this system as it requires expensive medical EEG electrodes.
- BCI2000: This software was created by Mellinger and Schalk (2007) for general BCIs' research and is freely available. It is based on C++ and is used to develop real-time BCIs through assembling a number of modules. This software was rejected to use in this study due to its complexity, its coarser modularity, and the extensive programming required throughout the implementation of a BCI.
- BCI++ is another recent platform. It is presented in Perego, Maggi and Parini (2009). It is based on C/C++. However, the package used for online validation is not freely available.
- OpenViBE is a powerful free software platform that gives the opportunity to design, test and use BCIs in real-world and in virtual environment. It is well-known that designing a BCI-based communication instruments require expertise and skill in diverse domains including: neurophysiology, signal processing, interface design, programming, and human-computer interaction. Consequently, designing a BCI presents a challenging multidisciplinary task. OpenViBE was created to simplify this task. OpenViBE is a well-funded French project. It was developed recently by Yann and Lotte (2010). It contains a set of modules which could be integrated smoothly and effectively to create offline and online BCIs. OpenViBE was selected to be employed in this study due to the following utilities that lack in other available platforms:
  1. High modularity and reusability: OpenViBE consists of two modules; 1. The Acquisition client that is used to import EEG data for online or offline processing, and 2. The Designer which enables data pre-processing, processing and visualization.
  2. Portability: OpenViBE is independent from other software and hardware, and has an abstract level of representations allowing integrating different acquisition methodologies including the Emotive EPOC that was chosen to be evaluated in this

study. Furthermore, it accommodates different data types such as EEG and MEG, and it can be operated on Linux and Windows operating systems.

3. Open-source software: It is also based on other open-source software such as VRPN, IT++, GCC, GTK+, and GSL that can be used for related tasks such as designing the user-interface of a BCI.
4. Connection with real-world interfaces and virtual reality.
5. Supportive for all the necessary functionalities for BCI experimental studies and usage including data acquisition, pre-processing, filtering, offline data processing, classifier training and real-time usage.
6. Provides real-time biofeedback.
7. Availability of different tools for data visualization including 2D/3D real-time visualization of brain activities.
8. Appropriateness for different types of users. In contrast to other platforms, users may choose to write codes to run their experiment or could design the study with the available graphical language.

A number of scenarios created by OpenViBE will be investigated in this thesis. They are described in details in Chapters 4.

### **3.4. Feature Extraction Algorithms**

A number of different channel selection methods were evaluated on BCIs in which they reflect valuable outcomes in terms of decreasing the computation time, the headset preparation time and the noise, and consequently increasing the classification accuracy in some cases. For example, the accuracy was increased using optimum spatio-spectral filtering network (OSSFN) by 10-36% in (Haihong et al., 2011) despite the minimized costs. Feature extraction algorithms used in BCIs is extensively reviewed in Cecotti et al. (2011).

xDAWN is a filter available in OpenViBE. It is a recently developed spatial filter designed by Rivet, Cecotti, Souloumiac, Maby and Mattout (2011) specifically for the P300 spelling paradigm. This model is used to identify the relevant channels for a particular classification problem. It was tested by Rivet et al. (2011) and it succeeded in reducing the number of channels from 32 to 10 with nearly the same classification success rate of 94% and to 5 only channels with a similar performance of 92%.

However, the experiment was conducted using a medical EEG recording system that has extra and different locations of channels, hence, it is not comparable to this study. For the reasons mentioned xDAWN will be utilized in this thesis.

### **3.5. Pattern Recognition Algorithms**

There is a wide range of classification algorithms and many of them have been tested for BCIs. A comprehensive literature review of BCI classification algorithms is presented in Lotte et al. (2007) in which the authors suggest to use different schemes for different interfaces. Focusing on the P300 Speller, they suggest using linear and stable classifiers such as Linear Discriminate Analysis (LDA), Artificial Neural Networks (ANN), and k-nearest neighbour (KNN). This is supported by a number of studies on the P300 Speller, for example, Kaper, Meinicke, Grossekathoefer, Lingner and Ritter, (2004) and Bostanov, (2004). Since ANNs and KNN are not part of OpenViBE, this study will focus on SVM and LDA classifiers only.

Based on the literature, these algorithms reported a significant performance. SVM has been successfully employed in numerous BCI applications. For example, it was used by Kaper et al. (2004) in which it achieved a remarkable accuracy of 100% after 5 recording sessions and outperformed other classifiers. Furthermore, SVM was the winner in the BCI competition III when it was tested on the P300 spelling paradigm by Rakotomamonjy and Guigue (2008). In the same way, LDA achieved a success rate of 95% and 90% in (Scherer, Muller, Neuper, Graimann & Pfurtscheller, 2004) and (Muller, Krauledat, Dornhege, Curio, and Blankertz, 2004) respectively. It was also elected as one of the winning methods in the BCI competition II in the P300 Speller (Bostanov, 2004). Therefore, these schemes will be employed in this study. They are described in detail in Chapter 4.

## Chapter 4: Methodology

After identifying the appropriate technologies to be used in this investigation in Chapter 3, this chapter presents the methodology undertaken to conduct the experimental study. First, the implementation of the P300 Speller is described, taking into consideration the improvements made to increase the number of letters spelt per minute, and the employed scenarios to design the interfaces using OpenViBE. After that, xDAWN, LDA and SVM algorithms are explained in sections 4.2, 4.3, and 4.4 respectively. Moreover, the framework proposed in this study is described. The participants' specifications, and the experimental tasks and procedure are outlined.

### 4.1. Implementation of the P300 Speller

#### 4.1.1. The P300 Speller and communication aids

As stated in Chapter 2, synchronous BCIs are based on event-related potentials, which occur during or after the presentation of a stimulus. One example of these applications is the P300 spelling paradigm that depends on the visual evoked potentials (VEP). This paradigm was first proposed by Farwell and Douching (1988). It is represented by 6×6 matrices of alphanumeric characters as demonstrated in Figure 4.1. The visual stimulations are represented by sequential flashes of the matrix rows and columns in a random order, with a defined duration time between the consecutive flashes (the inter-stimulus interval). To use this communication system, a user is instructed to focus his/her attention on a particular target and count the intensifications when the columns or the row that contains the target character (called the *target intensification*) is flashed.

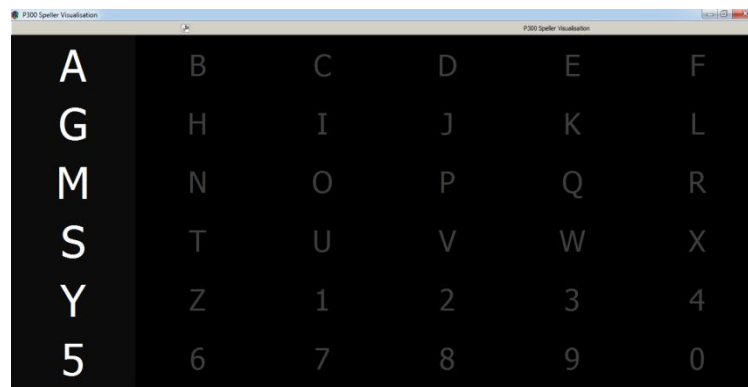


Figure 4.1. The matrix of the P300 Speller visualized in OpenViBE.

The P300 Speller, also referred to as the oddball paradigm, is based on detecting the samples containing a P300 potential, evoked by a target intensifications, which are distinguishable from the samples synchronized with frequent ignored non-target stimuli. The P300 potentials reflect peaking signal patterns observed to occur around 300ms after the visual stimulus. Detecting the target letter  $T$  with a coordinate  $(x, y)$  is done through detecting the target row  $x$  and the target column  $y$  which intersect at the target letter. The data collected of the P300 BCI is normally imbalanced since there is only one target column and one target row comparing to five non-target columns and five non-target rows. Hence, only  $2/12 = 16.67\%$  of the data is categorised as the *target* label comparing to  $10/12=83.33\%$  of the samples categorised as a *non-target* class.

Unfortunately, it is difficult to detect the target letter within one *trial* which is the duration taking to intensify all the rows and columns for only one time. This is due to the fact that EEG data is much influenced by the artifact and noise which makes it not possible to distinguish the target reactions from the not-target responses within a single trial. Yann and Lotte (2010) recommend using a 12-trial interface. Therefore, beginner users need an average of 28 sec to spell one character. Kleih, Nijboer, Halder, and Kübler (2010) also suggest spending 26 sec per selection while Guger et al. (2009) recommend allocating 28.8 to 54 sec for one target. This fact is the main reason behind a major problem with the P300 Speller for untrained users, namely the low ITR that can be defined as the number of bits transferred per minute according to Brunner et al. (2011). Once the user and the classifier have been well trained, the number of trials can be minimized to five or even fewer for some users. Despite this drawback, the P300 Speller is one of the most effective and accurate BCIs used for communication purposes up to date.

In this study, the spelling speed of the speller is investigated. Rather than attempting to increase the ITR like other studies (Schreuder, Tangermann, and Blankertz, 2009), this study introduce verbal and graphical versions of the P300 Speller with the aim to increase the number of letters spelt per minute. Similar types of communication aids are already available in assistive technologies stores (Figure 4.2). However, they were developed to be used by hands. Thus, their usage is limited to patients who are able to move their hands.



Figure 4.2. Examples of verbal and graphical communication boards (Lausd, 2007).

Generally, graphical communication boards are designed for children or beginner users. Each sample on the board represents a word or a sentence. On the other hand, verbal communication boards are normally used by adults. This thesis will consider the use of these communication aids as BCIs by the means of the P300 Speller. In this case, the user will be allowed to spell a word or a sentence instead of a letter, e.g. the user could spell 'food' (four letters) or 'I need to see the doctor, please' (32 letters) in a minute. Seeing that these versions of the speller limit the number of words/phrases that can be spelled by users, we suggest using multiple screens as illustrated in Figure 4.3. This technique does not affect the information transfer rate; however, it increases the number of letters users can spell within a fixed time frame.

Due to the practical limitations faced for the implementation of a graphical version of the speller, a similar scenario was employed with some changes. The number of rows is three and the columns is four instead of six in the original version. The intensification is done to each sample individually by flipping the hidden card rather than flashing the whole row/column (Figure 4.4). However, these changes do not affect the human responses to the visual stimulation

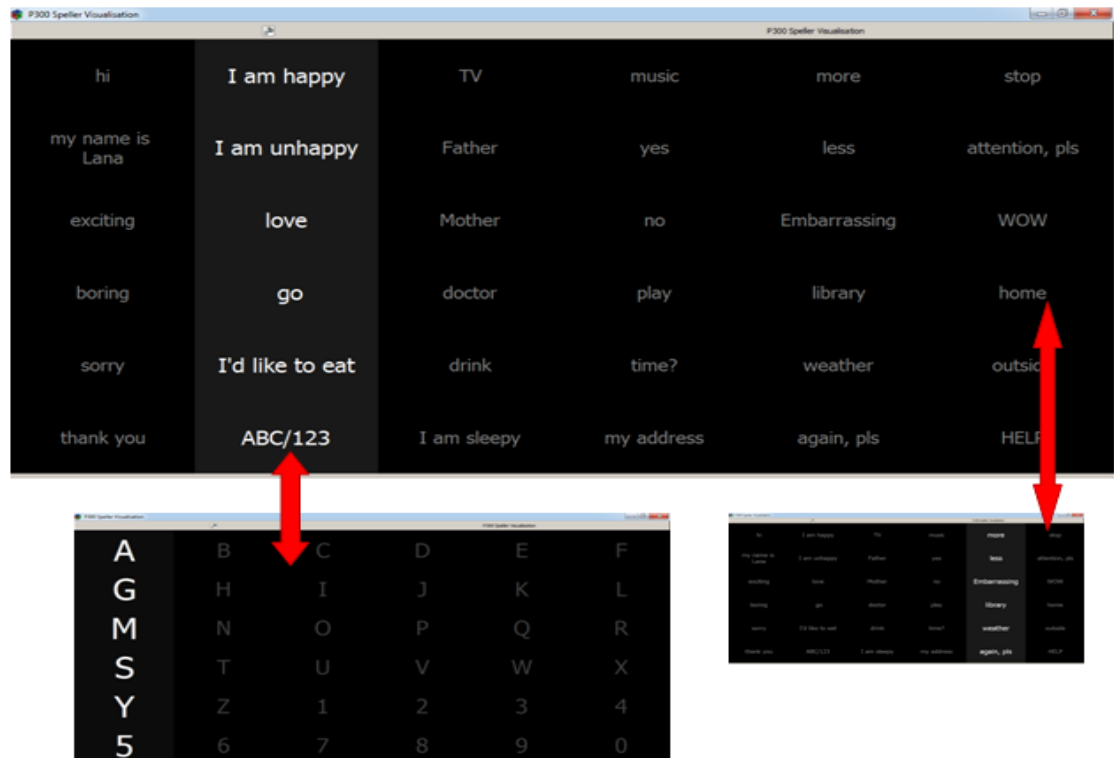


Figure 4.3. Multiple screens interface devised to avoid the limitations of the verbal and graphical versions of the P300 Speller. Users could be shown different screens by selecting specific targets. For example, users may like to be shown the alphanumerical speller or to another screen related to the words normally used by the user at home or with his/her doctor.

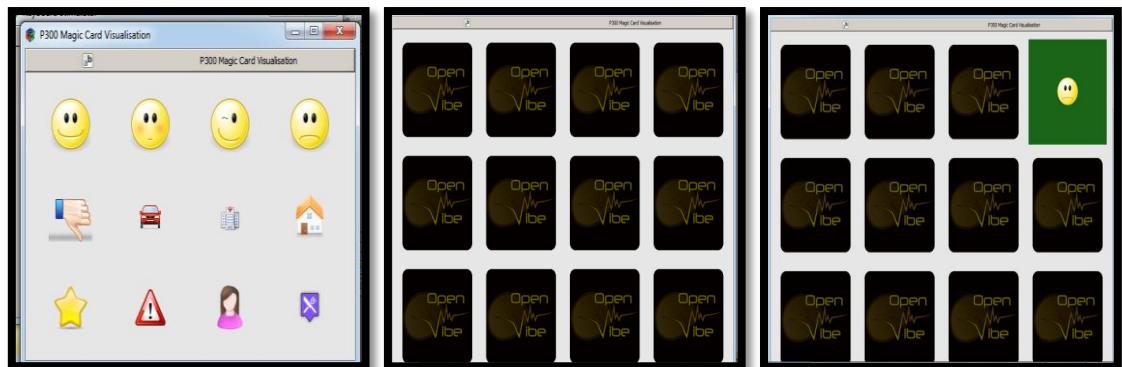


Figure 4.4. Screen shots of the flipping graphical speller. The target is highlighted in green.

#### 4.4.2. OpenViBE Implementation

As noted in Chapter 2, OpenViBE is based on distributed computing techniques. Correspondingly, four separate scenarios are employed in this case study: 1. Acquiring the training data; 2. Training xDAWN filter if used; 3. Training the classifiers and then 4. Using the interface in real time. Each scenario is created using a number of modules with particular functionalities for each module. The scenario shown in Figure 4.5 is used



to import the data collected by the acquisition client that is connected to Emotiv EPOC, and to create a new EEG data set using the generic stream writer. The intensification configurations, e.g. the number of trials and targets, the flash duration, and the inter-trial delay time, can be set up using the ‘Flashing Sequence’ module. The user is allowed to choose the target letters in advance using the ‘Target Letter Generation’ module. The data is collected during visualizing and running the P300 Speller matrix via the ‘P300 Speller Visualization’ module for the alphanumerical and verbal interfaces or the ‘P300 Magic Card Visualization’ module for the graphical version. The three interfaces were designed using Glade 3 and then uploaded to OpenViBE. Data collection starts after pressing ‘a’ on the computer keyboard. The ‘Identity’ module is used only for connection purposes.

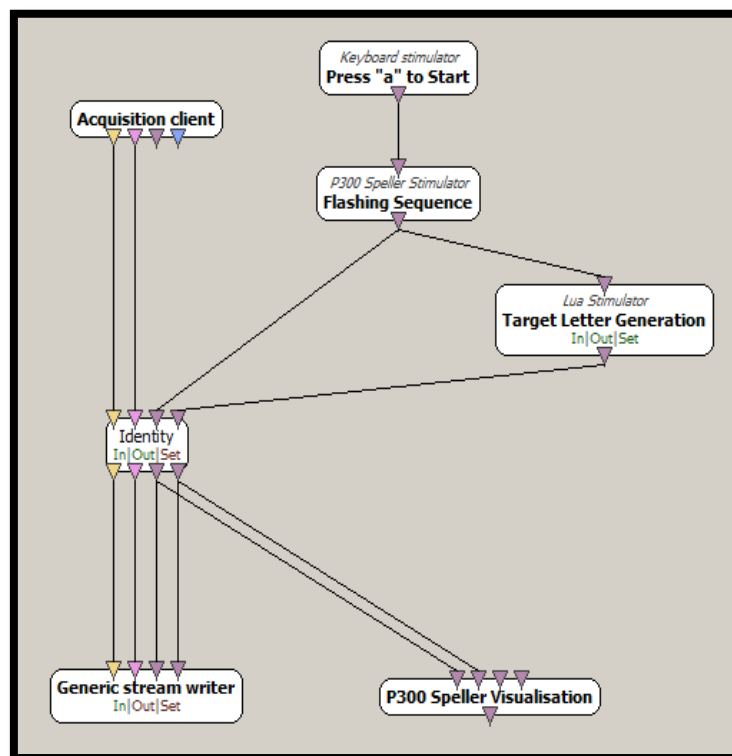


Figure 4.5. Data acquisition scenario used to collect the training data.

Once the training data has been collected, the spatial filter xDAWN is trained, utilizing the scenario displayed in Figure 4.6. The collected data is passed to the ‘Generic Stream Reader’ module. After that, signals are passed through a simple filter to remove the signals bellow 1 Hz or higher than 30 Hz because the normal EEG data recorded from adults should be in the range of 1-30 Hz (Yann et al., 2010). The ‘Signal Decimation’ module determines the sampling rate used by the spatial filter and the classifier while the ‘Target Selection’ module is operated to select a time frame window. Generally, the time frame window utilized for the P300 Speller starts just after the stimulation and ends

600 msec later, noting that the typical P300 response of the human brain is generated 300 msec after the visual stimulation. The ‘Time Based Epoching’ module sets the time intervals between epochs. On the final stage of this scenario ‘xDawn Spatial Filter Trainer’ is called to train the filter. The number of channels to be selected can be optimized. When the filter has been trained, the ‘Player Controller’ module hands the control over to the analyst to end the running scenario and move to the next step.

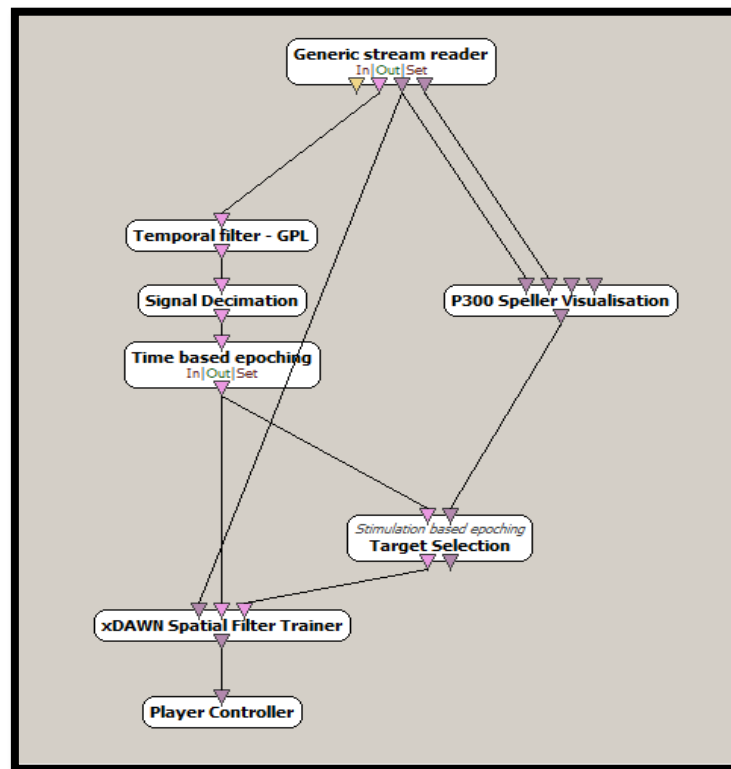


Figure 4.6. The scenario employed to train the xDAWN filter.

A further training step is required for the classifier to reach the final stage. Figure 4.7 presents the classifier training scenario. The first steps are similar to the steps described earlier in the xDAWN scenario. Again, after loading the training data to the reader, it is pre-processed using the temporal filter. The sampling rate and epoching duration are confirmed and then the channels are selected using the ‘xDAWN Spatial Filter’ which is connected to the ‘xDAWN Spatial Filter Trainer’ from the previous scenario through a configuration file. The collected data is then processed via the ‘Feature Aggregator’ module which is in charge of aggregating the data collected from the selected channels/features into one feature vector that can be used by the classifier. After that, the feature vector collected from the target rows/columns and the feature vector collected from the other non-target rows/columns are sent to the classifier using different input directions to train the classifier to distinguish between the target and non-target responses produced by the user’s brain. At the final stage an offline testing is

conducted. This is done by the means of k-fold cross-validation in which the data set is divided into k identical sized subsets. The testing is then repeated k times through employing a different subset for testing at a time (Liang, 2009). Next, the overall classification accuracy is calculated. The resulting accuracy presents a predicted outcome of the online performance. This technique is beneficial noting that all samples are utilized for both training and testing. Furthermore, each sample is tested only one time. Nevertheless, disadvantages do exist. That is demonstrated by the repetitive training process that requires k times of computation costs to make an evaluation.

Once the classifier has been trained the interface is now ready to be used in real time in order to obtain validated results. The scenario designed for the online usage is more complicated than other scenarios as it collects the data, pre-processes it, classifies it, and provides online bio-feedback. As shown in Figure 4.8, this scenario imports the data collected by the Acquisition Client. The intensification configurations can be set up using the 'Flashing Sequence' module and the user is allowed to choose the targets in advance using the 'Target Letter Generation' module. The first steps are similar to the steps described earlier. The acquired data is pre-processed using the temporal filter. The sampling rate and epoching duration are confirmed and then the channels are selected using the 'xDAWN Spatial Filter' which is connected to the 'xDAWN Spatial Filter Trainer' from the xDAWN training scenario through a configuration file.

As explained earlier in this chapter, detecting the target letter  $T$  at matrix position  $(x, y)$  is done through detecting the target row  $x$  and the target column  $y$ . Therefore, the path of this scenario is divided into two directions: one for rows and one for columns. Then each direction is also divided into six sub-paths; each sub-path receives the data collected according to the times when a specific individual row/column flash. The 'Simulation Based Epoching' module sets the epoching duration after the stimulations. The collected data by these time frames is then processed via the 'Feature Aggregator' module that aggregates the data collected from the selected channels into one feature vector to be used in the 'Classifier Processor' module. This module classifies the samples into two classes; target and non-target, and it is connected to the 'Classifier Trainer' module on the training scenario through a configuration file. The predicted class labels from all the classifiers (for each column/row) are then passed to the 'Voting Classifier' module. This simple classifier is in charge of choosing between the classifiers. For example, if the samples collected from two different rows were labeled with the target class, the 'Voting Classifier' module decides which one of these two

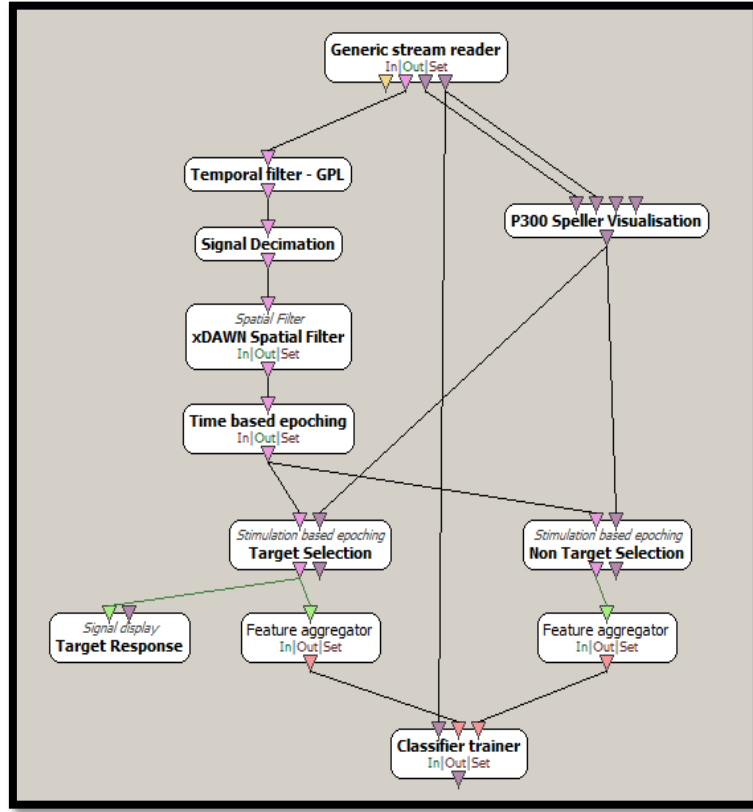


Figure 4.7. The scenario employed to train the classifier.

samples was more active. The final results are then sent to the ‘P300 Speller Visualisation’ module to show the feedback to the user.

#### 4.1. xDAWN Algorithm

Despite other spatial filters, xDAWN focuses on the signal-to-noise ratio (SNR) rather than on the overall classification accuracy which is believed to be a useful procedure for EEG sensor selection. SNR is a measurement used to compare the meaningful information (desired signals) to the background noise (unwanted signals). The xDAWN algorithm is based on the following assumption:

The data consists of two characteristic reactions, one is generated by the flashing targets and one is generated by all stimuli (target and non-target). Suppose:  $X = D_1 A_1 + D_2 A_2 + N$ , where  $X \in R^{N_t \times N_s}$  is the recorded data,  $N_t$  is the number of samples,  $N_s$  is the number of channels/sensors.  $A_1 \in R^{N_1 \times N_s}$  are the signals synchronized with the target stimuli and  $A_2 \in R^{N_2 \times N_s}$  are the responses associated with the non-target stimuli.  $D_1 \in R^{N_t \times N_1}$  and  $D_2 \in R^{N_t \times N_2}$  are Toeplitz matrices in which the first column entries are zero with the exception of the ones corresponding to the target stimuli time

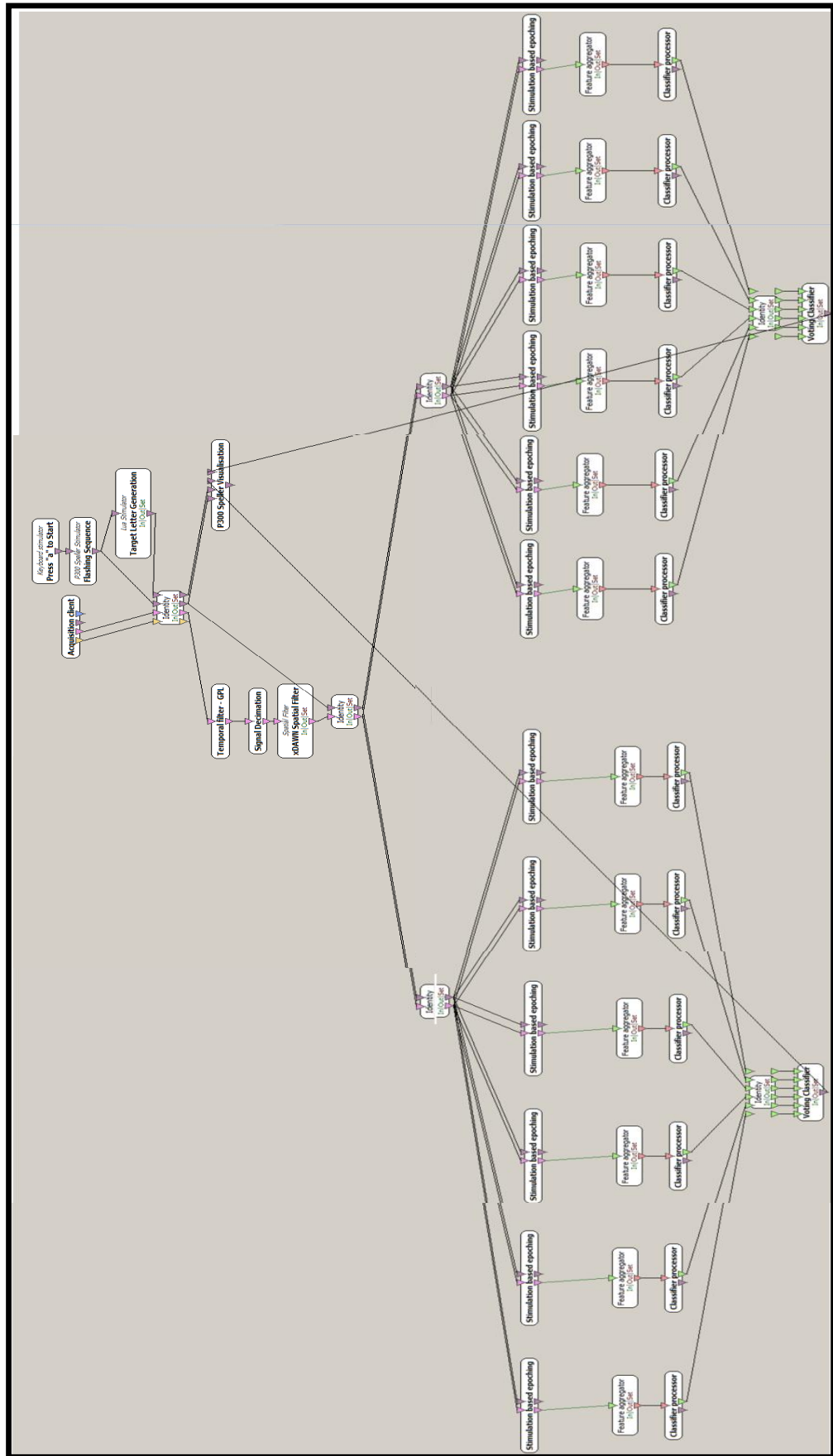


Figure 4.8. Implementation of the online P300 Speller using OpenViBE.

indexes, respectively.  $N_1$  and  $N_2$  represent the samples quantity for  $A_1$  and  $A_2$ , and  $N_f$  is the residual noise. xDAWN assumes that the reactions generated by the target stimuli can be enhanced by spatial filtering, and accordingly aims to estimate  $N_f$  spatial filters  $U_1 \in R^{N_s \times N_f}$  to maximize the SNR that can be defined by:

$$g(U) = \frac{Tr(U^T \hat{\Sigma}_1 U)}{Tr(U^T \hat{\Sigma}_x U)}, \quad \hat{U}_1 = \arg \max, g(U_1)$$

where  $Tr(.)$  is the detection driver and  $\hat{\Sigma}_1 = \hat{A}_1^T D_1^T D_1 \hat{A}_1$ ,  $\hat{\Sigma}_x = X^T X$ .  $\hat{A}_1$  is the lowest mean square estimated of the not known target evoked reactions  $A_1$ . As  $D_1 A_1$  and  $D_2 A_2$  may overlap,  $\hat{A}_1$  is calculated from:

$$\begin{pmatrix} \hat{A}_1 \\ \hat{A}_2 \end{pmatrix} = (D^T D)^{-1} D^T X$$

in which  $D = [D_1, D_2]$  the spatial filters  $\hat{U}_1$  are estimated from  $\hat{U}_1 = R_X^{-1} \Psi_{1:N_f}$  after computing the  $QR$  decompositions  $X = Q_X R_X$  and  $D_1 = Q_1 R_1$ .  $\Psi_{1:N_f}$  is the sequence of the  $N_f$  individual vectors  $\Psi_z$  that are correlated with the  $N_f$  highest individual values  $\lambda_z$  given by the individual value factors of  $R_1 B_1^T Q_X = \Phi \Lambda \Psi^T$ , where  $\Lambda$  is a diagonal matrix,  $\Phi$  and  $\Psi$  represent the unitary matrices and  $\hat{A}_1 = B_1^T X$ . In this case, the enhanced signals are specified by the following formula in the final stage:

$$\hat{S}_1^{\Delta} = X \hat{U}_1 = D_1 A_1 \hat{U}_1 + D_2 A_2 \hat{U}_1 = N \hat{U}_1$$

## 4.2. Linear Discriminant Analysis (LDA) Algorithm

LDA is a well-known data mining algorithm. It has been widely applied in numerous different classification problems. It is simple to use and requires a very low computational time. It has achieved high classification performance in different BCI applications: the P300 Speller (Bostanov, 2004), asynchronous (Scherer, Muller, Neuper, Graimann & Pfurtscheller, 2004), and multiclass (Garrett, Peterson, Anderson & Thaut, 2003).

According to Yoon, Roberts, Dyson and Gan (2011), the LDA classifier aims to separate the dataset into two classes using hyperplanes. The class of a sample is determined by the side of the hyperplane in which a sample, or as it is also called, a feature vector is placed on, as shown in Figure 4.9.

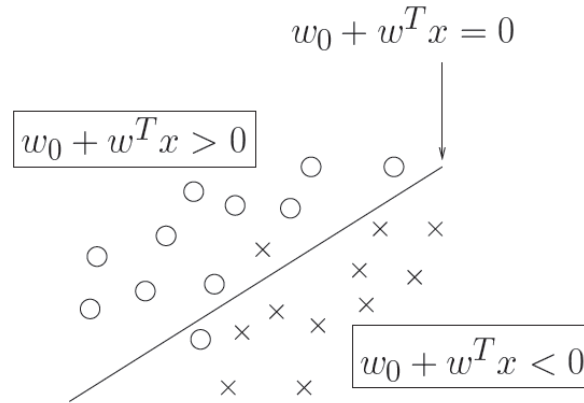


Figure 4.9. A hyperplane created by the LDA algorithm to split the data into 2 classes (Yoon et al., 2011).

This algorithm assumes normal distribution of the conditional probability density functions  $P(\vec{X}|y=0)$ , and mean of  $P(\vec{X}|y=1)$ . Based on that, samples are associated with the second class if the log-likelihoods ratio is smaller than scalar  $T$ :

$$\vec{X} - \vec{M}_o^T \sum_{y=0}^{-1} (\vec{X} - \vec{M}_o) + \ln \left| \sum_{y=0} 1 - (\vec{X} - \vec{M}_1)^T \sum_{y=1}^{-1} (\vec{X} - \vec{M}_1) - \ln \left| \sum_{y=1} \right| \right| < T$$

### 4.3. Support Vector Machine (SVM) Algorithm

Linear SVM is a powerful classification scheme. It was originally introduced by Vapnik (1998). This algorithm has been successfully applied in different BCI applications and general classification problems. Focusing on the P300 Speller, SVM has outperformed other algorithms and was the winner in the third BCI competition (Rakotomamonjy & Guigue, 2008).

To classify a set of binary labeled data, this algorithm also uses a hyperplane to separate the data into two classes. After training the algorithm on a given dataset, the discriminate hyperplane is optimized and selected based on the maximum margins between the hyperplane and the data. This is done through transforming the data from the input space into feature space in which linear classification is achievable. This can

be achieved through accommodating outliers and allowing errors during the training stage (Bashashati, Fatourehchi, Ward & Birch, 2007) and is shown in Figure 4.10.

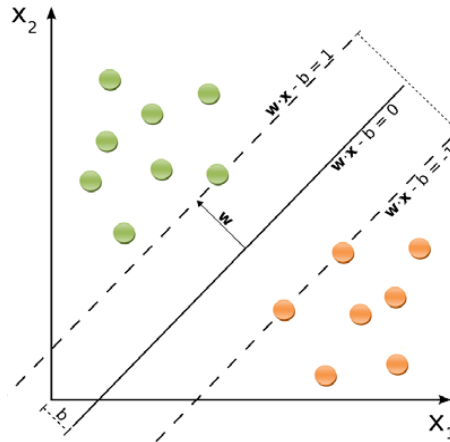


Figure 4.10. Graphic representation of the linear SVM algorithm (Liang, 2009).

SVM is mathematically formulated by the following formula to classify the data set  $D$ :

$$D = \{((x_1, y_1), \dots, (x_i, y_i)) \mid x \in R^n, y \in \{-1, 1\}\}_{i=1}^m$$

where  $x$  is the  $n$ -dimensional vector. The class name that  $x$  belongs to is represented by  $y$ , and the hyperplane is defined by the following equation:

$$w^T(w_1, \dots, w_n) \times x + b = 0$$

in which  $w$  is the weight vector:  $w(\Lambda) = \min C(w, b, \Lambda)$  and  $b$  is the scalar. For detailed description, refer to Vapnik (1998).

## 4.5. The Research Framework for this Study

### 4.5.1. Subjects

Due to the fact that BCI applications are personalized systems (user-dependent), studies are conducted with a small number of people. For example Blankertz et al. (2010) conducted their study of the P300 Speller on eight users, while five people took part in the study conducted by Meinicke, Kaper, Hoppe, Heumann and Ritter (2002) and four people in the study by Sirvent-Blasco, Iáñez, Úbeda, and Azorín (2012). Similar to other studies, six healthy subjects, aged between 22-38 years, participated in the experiment for this study including two males and four females. Participants were not suffering



from any neurological disorders or mental health problems, and were not using any type of medications as these may result in abnormal patterns of the brain activity. Furthermore, their vision was normal and no corrections were required since the P300 interface depends on eye gazing.

#### **4.5.2. Experimental tasks and procedure**

Former to the experiment, a number of people were invited to take part in this investigation after obtaining the ethical approval number 11/227 (Appendix A). Participants were given generous meals for their participation. To prepare the headset, few drops of saline solution were applied to properly wet a number of felt pads before placing the sensors in their positions of the Emotiv system that has 14 channels. After confirming the good contact of all the sensors, the data collection was started at a sampling rate of 64 Hz.

Guger et al. (2009) explained that five minutes of recording is sufficient to train a classifier to detect the P300 potentials. Accordingly, one session was recorded in this study for each participant (approximately five minutes) for training the filter and the classifiers and then three sessions, similar to the ones described by Iáñez, Azorín, Úbeda and Ferrández (2010) were performed online for each of the three versions of the speller. However, two participants out of the six were invited to complete 10 online sessions for each version of the speller to investigate the effects of additional training on their performance as suggested by (Finke, 2009; Nijboer et al., 2008; Klobassa et al., 2009). The experiment was conducted in a home in a quiet but not completely silent environment. During the recording sessions, each participant sat in a comfortable chair in front of a 14-inch monitor screen at a distance of 60 cm approximately following Brunner et al. (2010) suggestion. During this time, the users were instructed to attempt to spell ten randomly selected targets in each session through focusing their attention on the computer screen and count the intensifications when the columns or the row that contains the target character is flashed. As we used a 12-trial interface, each letter was intensified 24 times (12 times for the row and 12 times for the column that contain the letter). Hence, 28 sec was spent for each target. The employed flash duration was 0.10 sec with an inter-trial delay of four sec, and the sampling rate was 64 Hz. Participants were told that loss of attention as well as any kind of movement may result in a significant degrading of the spelling performance. However, they were allowed to move.

The recorded data was passed to two machine learning algorithms, LDA and SVM. Both algorithms were used to classify the normalized data into either target or non-target samples. 20-fold cross validation technique was employed during the training phase. A linear kernel was used for the SVM classifier. We were also interested in the suitability of the xDAWN filtering method. In a second learning run, we applied this pre-processing technique before passing the filtered data to the two learning algorithms. For this setup, the parameters of LDA and SVM remained unchanged.

#### 4.5.3. The Study Framework

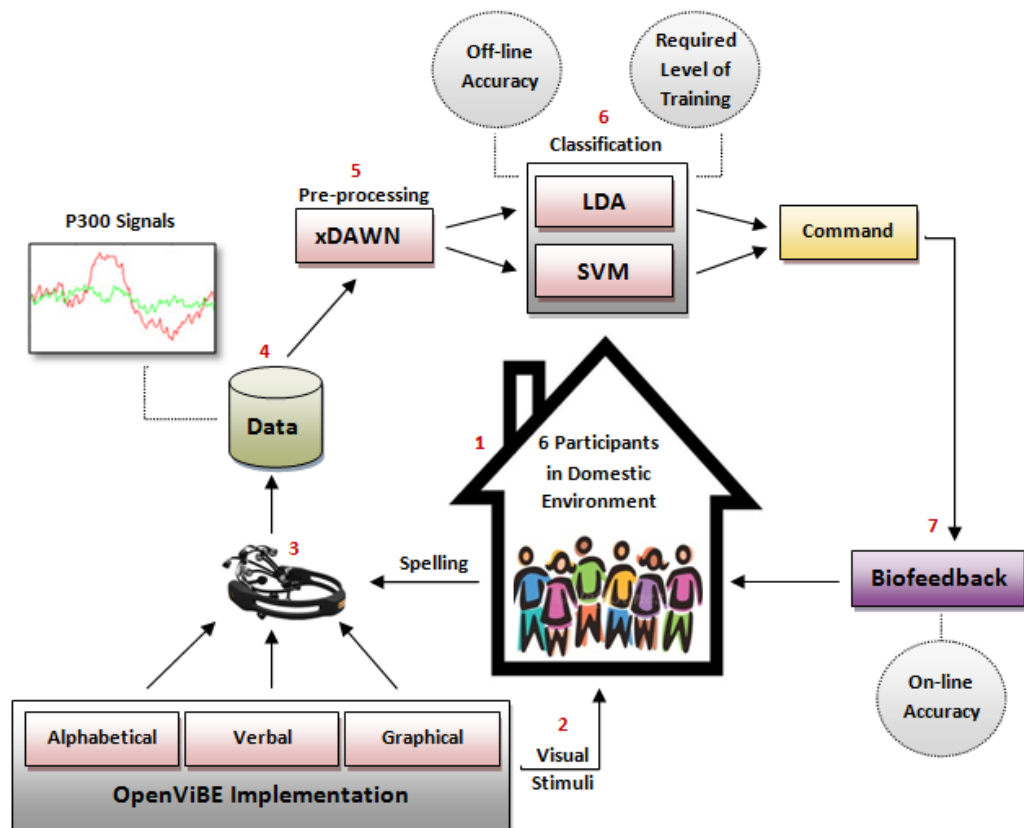


Figure 4.11. The proposed framework for this study.

The proposed framework for this study is presented in Figure 4.11. The experiment starts with using OpenViBE implementation of the P300 Speller where the visual stimuli (1) are generated and presented in turns to the six participants (2) who are located in a domestic environment and attempting to spell ten random samples in each session. Then, the electrical responses to the visual stimuli produced by their brains are measured using EEG headset, namely Emotiv EPOC (3). The collected data (4) contains

both target samples that are represented by peak curves (generated when the target letter is intensified) and non-target samples (generated when non-target letters are intensified). The data is pre-processed and filtered using the spatial filter xDAWN (5) which is used to identify the useful sensors and clean the redundant data. When the data is ready it is then sent to the classifiers, LDA and SVM (6). The data recorded in the first session is used only for training the filter and classifiers. The online validation starts from the second session and the data is then fed to the classifier for training. The offline accuracy and the required level of training are the output of the offline testing. Accordingly, the online testing shows the obtained validation accuracy and sends a biofeedback to the users (7) to let them know whether the target sample was correctly detected or not. This procedure is repeated a number of times for each participant using the alphanumerical, verbal and graphical versions of the speller.

## Chapter 5: Design of Experiments, Analysis of Results and Discussion

In this chapter, the results obtained from the experiment are presented, analysed and discussed. First, the outcomes of the spatial filtering are shown in section 5.1. That is followed by evaluation of Emotiv's performance when detecting the P300 brain signals. Furthermore, the effects of training are discussed in section 5.3. The results of the Alphanumeric, verbal and graphical spellers are presented in section 5.4. Detailed Experimental results are presented in Appendix B. Comparisons between the classifiers, the offline and online accuracies, and between the overall results and the result of the target class are performed in sections 5.5 and 5.6. Section 5.7 investigates the differences in users' performance related to their P300 brain waves, motor movements and attention/fatigue.

### 5.1. xDAWN Spatial Filtering Outcomes

As reported in Chapter 3, the xDAWN filter was tested only by its developers, Rivet et al. (2011). Their experiment was undertaken on the P300 Speller in which xDAWN succeeded to reduce the number of channels from 32 to 10, with nearly the same classification success rate of 94% and to five channels only with a similar performance of 92% success rate. However, the experiment was conducted using a medical EEG recording system that had 64 electrodes with additional locations, hence, their results are not comparable to this study.

In order to choose the number of channels to be employed in this experiment, the classifiers were tested offline using different numbers of channels selected by xDAWN filter. The results are presented in Table 5.1 which shows the LDA and SVM performance using ten, six, three, two and one sensor.

Table 5.1

*The performance of the classifiers, LDA and SVM, with different numbers of channels selected using xDAWN filter on participant# 1 data (first session). Results are collected using the alphanumeric speller*

Channel #	LDA	SVM
10 channels	91.11%	91.93%
6 channels	93.43%	93.12%
<b>3 channels</b>	<b>95.54%</b>	<b>92.89%</b>
<b>2 channels</b>	<b>95.43%</b>	<b>93.28%</b>
1 channel	59.93%	62.16%

The best performance of the classifiers is obtained when two or three channels are selected. The accuracy drops sharply when using only one channel. Therefore, the xDAWN filter was trained in order to detect two channels for each participant. The selected two channels for all participants are identical, channels  $O_1$  and  $O_2$  as shown in Figure 5.1. These results are not surprising, since the location of  $O_1$  and  $O_2$  is close to the visual cortex, the brain area where the P300 signals are generated, as indicated previously in Chapter 2.

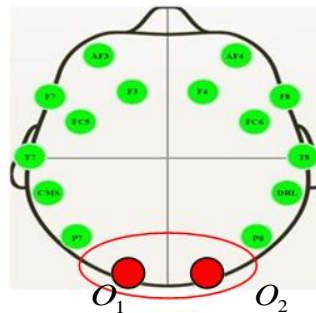


Figure 5.1. The two selected channels for all participants are highlighted in red.

The selected channels were compared to the channels employed in other studies. Zhang, Zhao, Jin, Wang and Cichocki (2012) confirm the validity of the affected area of the brain by the scalp topographies recorded from the participants 300 ms after a P300 visual stimulation and non-target stimulation. Figure 5.2 shows the activated area in colour red. Similarly, the interface presented in (Middendorf, McMillan, Calhoun, & Jones, 2000) employs the  $O_1$  and the  $O_2$  channels. The system performance was tested on eight users and it reached an average of 92% correct selections.

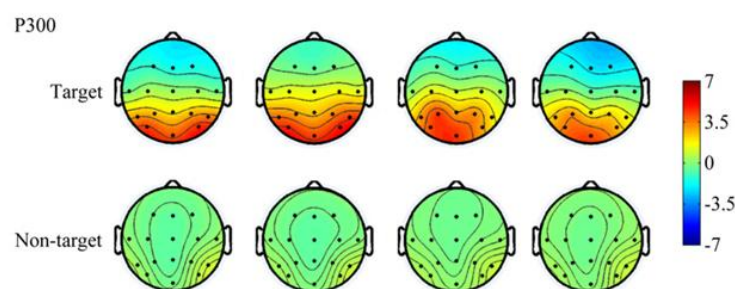


Figure 5.2. Scalp topographies recorded 300 ms after a target visual stimulation (top row) compared to the ones recorded 300 ms after a non-target stimulus (Zhang et al., 2012).

However, additional channels are employed over the central area of the cortex (e.g. C3, C4, Cz and Fz) by Sirven-Blasco, Iáñez, Úbeda, and Azorín (2012) as a result of the topographic map recorded in their study which shows the evolution of the contribution

of VEPs in the human brain in the 400 ms after a visual stimulation. Figure 5.3 represents the activated area of the brain in colour red.

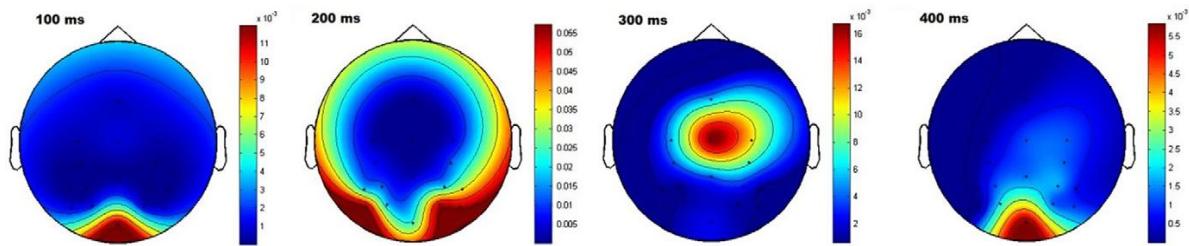


Figure 5.3. Evolution of the contribution of VEP in the human brain as presented by Sirven-Blasco et al. (2012).

The impact of the additional xDAWN filtering appears less significant in this study. Generally, the filter reports only slightly increased training accuracies compared to the unfiltered data as presented later in this chapter (up to +7%). However, the application of xDAWN shows noticeable effects on the performance of participants #3 and #4 as presented in Figures 5.4 and 5.5. The performance of participant#3 is even lower when the filter is used. This might be resulted of losing some meaningful information by minimizing the number of channels. However, participant #3 is reported as a potential outlier as discussed in section 5.2. In contrast, the performance of participant #4 increases remarkably with using the filter, up to +18%.

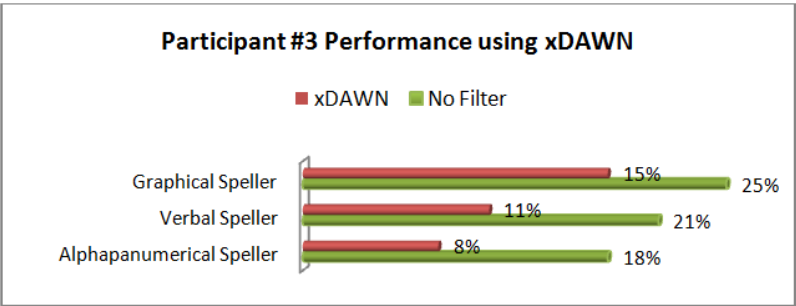


Figure 5.4. The average of participant #3 performance when using xDAWN filter and without filtering.

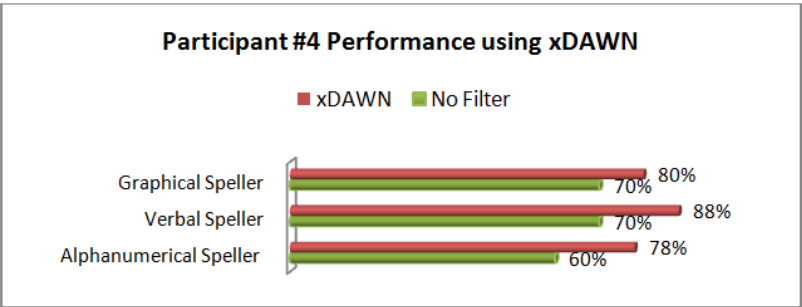


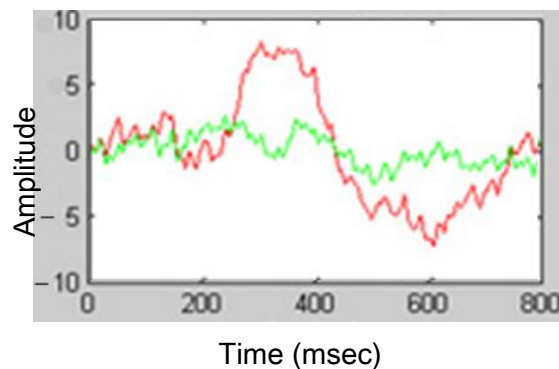
Figure 5.5. The average performance of participant #4 when using xDAWN filter and without filtering.

Regardless, the filtering has a clear effect on the computational costs of the training process. Since the filter selects a subset of the channels for classification, the computational time is significantly decreased from 43 minutes to 4 minutes and 56 sec when the filter is used with the SVM classifier. In the same way, the computational time taken by the LDA classifier for training is about 25 sec when using 14 channels while it takes less than 4 sec when using the xDAWN filter. Additionally, the preparation time taken to install 14 channels is 2-3 minutes comparing to approximately 30 sec to prepare the headset with only two channels which is helpful for everyday usage.

## **5.2. Exploring the Emotiv Capability to Detect P300 Brain Waves: Brain Activity Data are Recorded from the Participants within 600 ms of the Visual Stimulation**

In this section, the recorded responses of the participants to the visual stimulation are presented and compared to the typical shape of the P300 control signal, shown in Figure 5.6. The higher the amplitude of the peak generated by the target letter stimuli, the higher the chance to detect the target letter and achieve the desirable success rate. In contrast, the accuracy falls when the gap between the target signal and non-target signal is smaller due to the lower amplitude of the target signal as explained by Escolano, Antelis and Minguez (2009).

The participants' responses to the target visual stimulus are presented and compared to the one generated by a non-target stimulus in Figure 5.7. The P300 signal is recorded from each of the six participants. Each diagram shows a target and a non-target EEG signal recorded immediately after the onset of the visual stimulus, e.g. a flashing target letter, word or image. Since the P300 signal is assumed to be most prominently observable at around 300ms, we show here the signals over a time window of 600ms.



*Figure 5.6.* Typical course of the P300 control signal generated by a target letter (in red) and a non-target letter (in green) (Escolano et al., 2009).

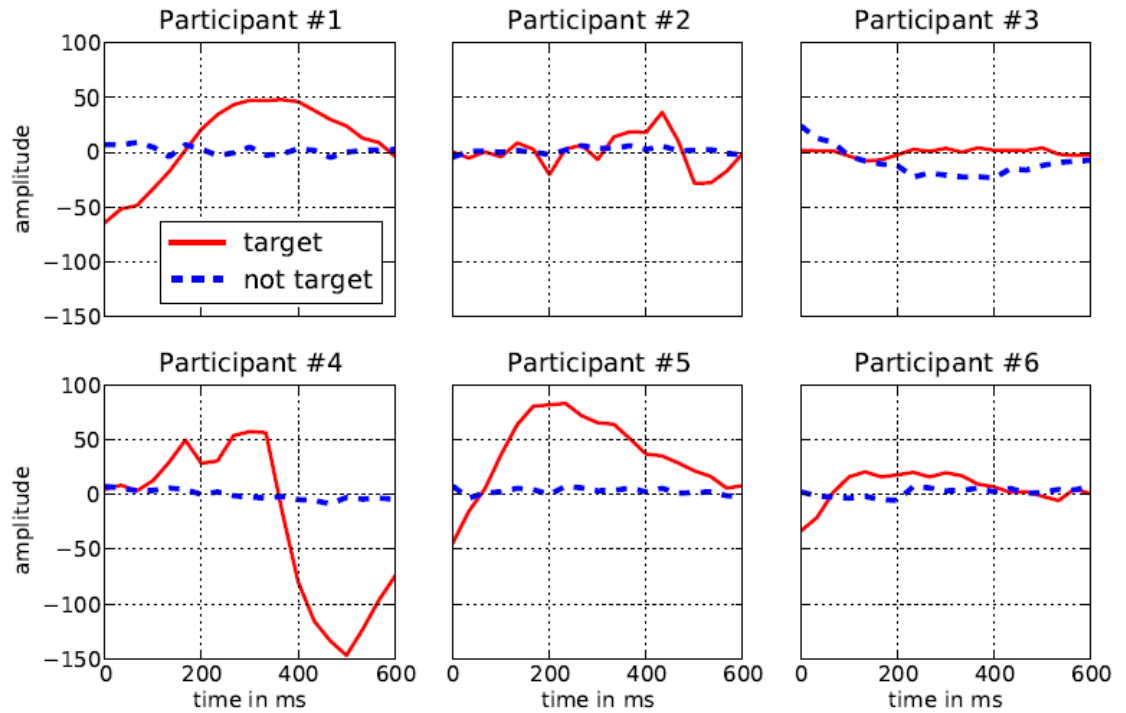


Figure 5.7. The course of P300 signals recorded from each participant. The target signals (red solid lines) are visibly distinguishable from the non-target ones (blue dashed lines). Sampling rate in this case is 32Hz, therefore  $0.6\text{sec} \times 32\text{Hz} = 19$  discrete time points are obtained within the 600ms of recording.

Regarding Emotiv EPOC, these figures evidence the capability of this system to detect the P300 signals, suggesting its suitability for a P300-based BCI. As it can be seen from the figure, the responses of the participants to the visual stimuli varies from one to another. Each human brain is unique and hence the different responses to stimulations. Accordingly, some researchers such as Yang et al. (2011) have employed the P300 brain waves for person identification applications.

For most participants involved in this study, the target signals are remarkably distinguishable from the non-target ones. Clearly participants #1 and #4 respond strongly to the visual stimulus. Accordingly, they achieved the highest classification accuracies among the tested scenarios, reaching a peak accuracy of over 90% in some cases as reported later in this chapter. In contrast, the amplitude of the signals generated by participants #3 and #6 is low and not as distinguishable from the non-target signals as other users, resulting in a very low performance of one of them as shown previously in this chapter. The participant was able to spell one letter out of ten in some sessions and achieved a better performance when using the complete set of 14 electrodes.



This reflects a potential problem in BCI applications introduced by Brendan and Neuper (2010) in their study “could anyone use a BCI?” in which they investigate a new phenomena called ‘*BCI illiteracy*’. According to their review, 10-20% of people will not be able to use a P300-based BCI as they are not capable to produce a distinguishable response to target stimuli no matter how long the training is. This estimation might be as high as 15%-30%, as suggested by Vidaurre and Blankertz (2010). Various responses of different users reported in a previous work are displayed in Figure 5.8. More examples of different shapes of the P300 brain wave are given by Sellers et al. (2006).

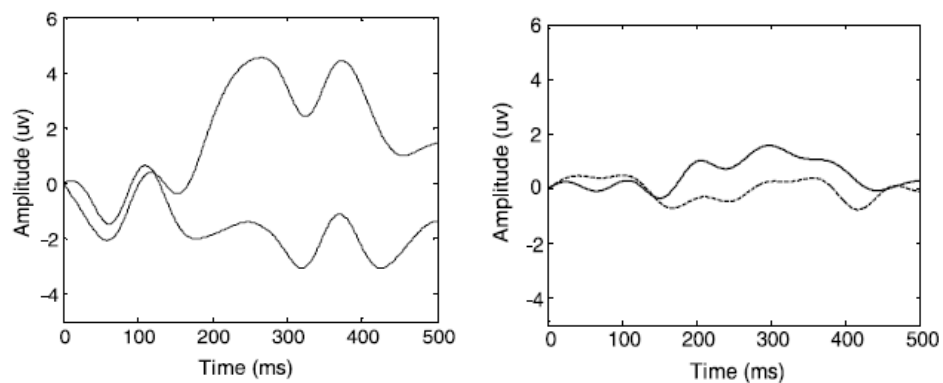


Figure 5.8. The responses from two subjects within 500 ms of target stimuli: the right panel displays a weak response from a person who was illiterate with the P300 BCI whereas the left panel illustrates a strong response to the stimulation (Brendan et al., 2010, p.41).

This problem needs to be investigated. One way to solve it is by improving the classification algorithms. This has been heavily pursued over major data analysis competitions; see for example Wang et al. (2004). However, this probably reduces but does not eliminate BCI illiteracy as it cannot help the user who is not able to generate any detectable brain activity to distinguish different states.

Further steps can be made towards customising the classification algorithm for each user due to the fact that humans’ brains produce slightly different activity patterns. Regarding the collected data in this study, these differences are reflected by the different times when the participants produced responses to the stimuli. A simple way to improve the accuracy in this case could be user-specific evaluation to specify when the P300 responses are typically apparent, e.g. 300-500 ms after the stimulus, in order to exhibit a strong differences between the samples that belong to different classes.

Exploring different neuroimaging methods is another way to address the problem. Over 80% of BCI applications are EEG-based as stated by Mason, Bashashati, Fatourechi,

Navarro and Birch (2007). Despite that, no articles were found that investigate whether a specific person who is illiterate with an EEG-based BCI is able to perform better using different approaches.

Employing spelling-error correction methods might represent a valuable addition to the P300 BCI and help reduce the error rate and prevent spelling meaningless commands (Tan & Nijholt, 2010). Nevertheless, these systems are not useful for a user who is unable to convey anything in the first place.

The best approach to solve this problem could be to employ brain signals that are detected more easily. A considerable success is presented by Nikulin, Hohlefeld, Jacobs and Curio (2008). This can be achieved through three ways:

1. By improving the interface, e.g. by changing the colour of the intensified letters to red instead of white.
2. By switching to another approach. Further research on BCI demographics would help to identify the appropriate approaches. For illustration, a person who is illiterate in German or Arabic might be fluent in English. In the same way, a person who has strong abilities in dance, sports or other movement-oriented hobbies is expected to perform better using motor-imagination BCI applications. On the other hand, people who perform well on computer games or visual attention tests might achieve higher accuracy when using the P300 BCI (Brendan et al., 2010). For instance, Allison et al. (2010) found that older participants performed worse using visual evoked potential BCI.
3. By developing novel BCI approaches or through investigating new control signals. This could be achieved by joint projects between neuroscientists and computer researchers.

### **5.3. Exploring the Importance of the Number of Training Sessions**

Guger et al. (2009) claim that one training session for around five minutes is sufficient to achieve a satisfying spelling accuracy. However, other researchers, e.g. Iáñez, Azorín, Úbeda and Fernández (2010), do not agree. The goal of our first experiment is to identify how many training sessions are needed for a satisfying classification performance. Each training session requires approximately five minutes. During this

time, the user has to focus on the computer screen and follow the BCI scenario. Losing attention may result in a significant degrading of the spelling performance. Therefore, it is desirable to keep the training time as short as possible, such that the user remains motivated and focused on the given task.

Participants #5 and #6 were invited to undertake ten consecutive training sessions in which we monitored the users training and validation accuracies. Studies investigating similar BCI scenarios reported that ten training sessions are generally sufficient to observe the effects of training using the P300 spelling paradigm (Klobassa et al., 2009). The data recorded from the two participants during the ten training sessions was passed to two machine learning algorithms, the LDA and the SVM. Both algorithms were used to classify the normalized data into either target or non-target samples.

The results of the three versions of the speller, alphanumerical, verbal and graphical, are shown in Figures 5.9, 5.10, and 5.11. It is worth noting that the online accuracy presented here is the accuracy of the target class only unlike the training accuracy that reflects the overall accuracy, hence it is more stable. Further discussion on this subject is provided in section 5.4.

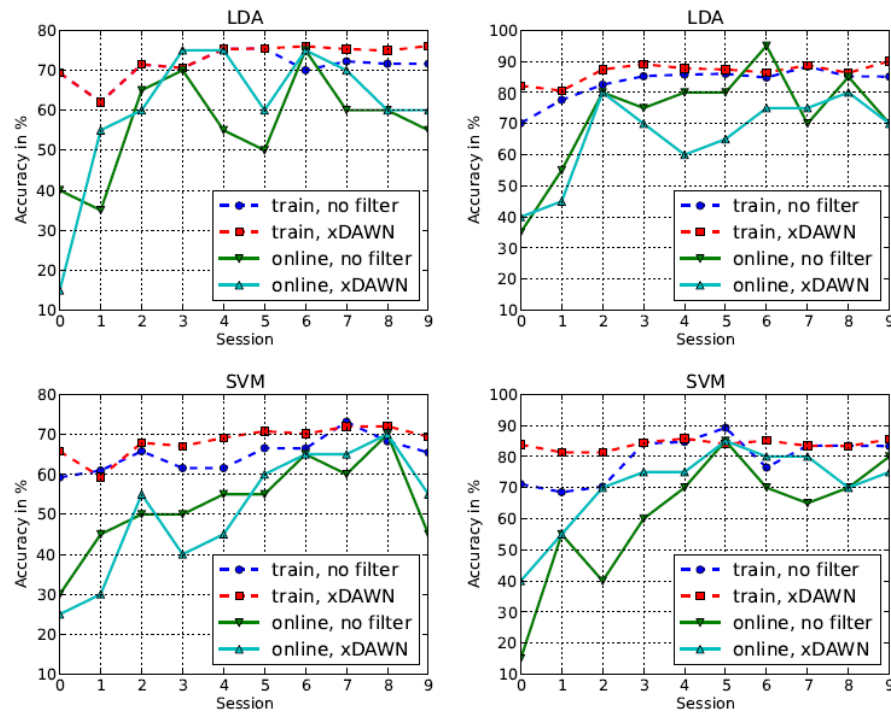


Figure 5.9. Training and online accuracies over 10 sessions using either the LDA (top diagrams) or the SVM (bottom diagrams) classification methods. Results were recorded from participant #5 (left diagrams) and participant #6 (right diagrams) on the *alphanumerical* speller.

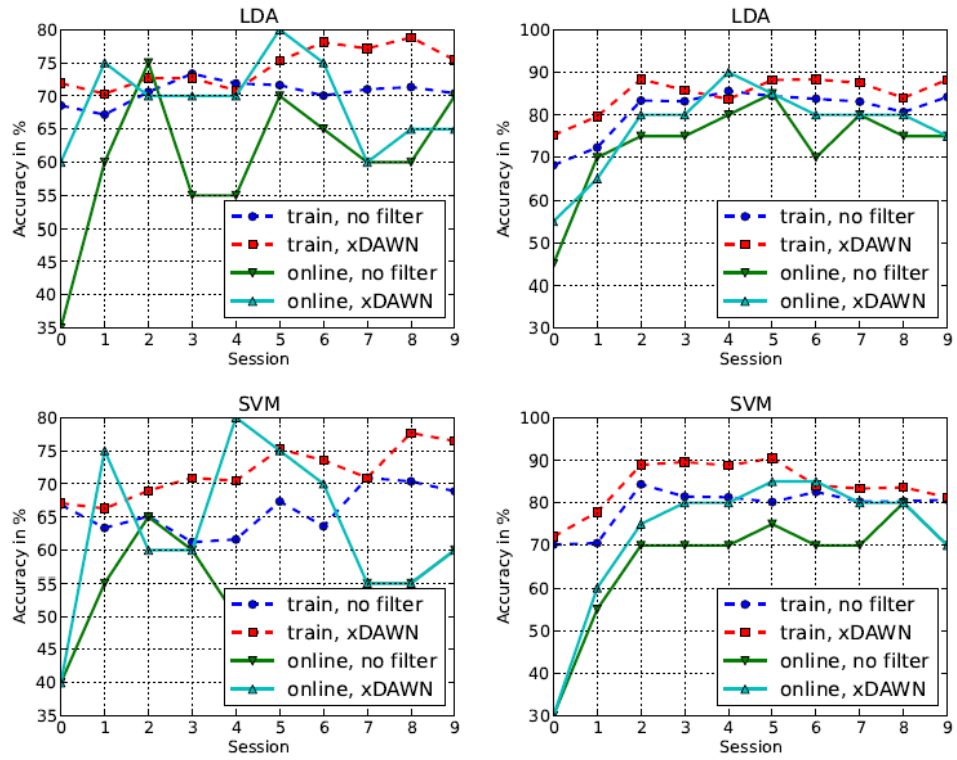


Figure 5.10. Training and online accuracies over 10 sessions using either the LDA (top diagrams) or the SVM (bottom diagrams) classification methods. Results were recorded from participant #5 (left diagrams) and participant #6 (right diagrams) on the *verbal* speller.

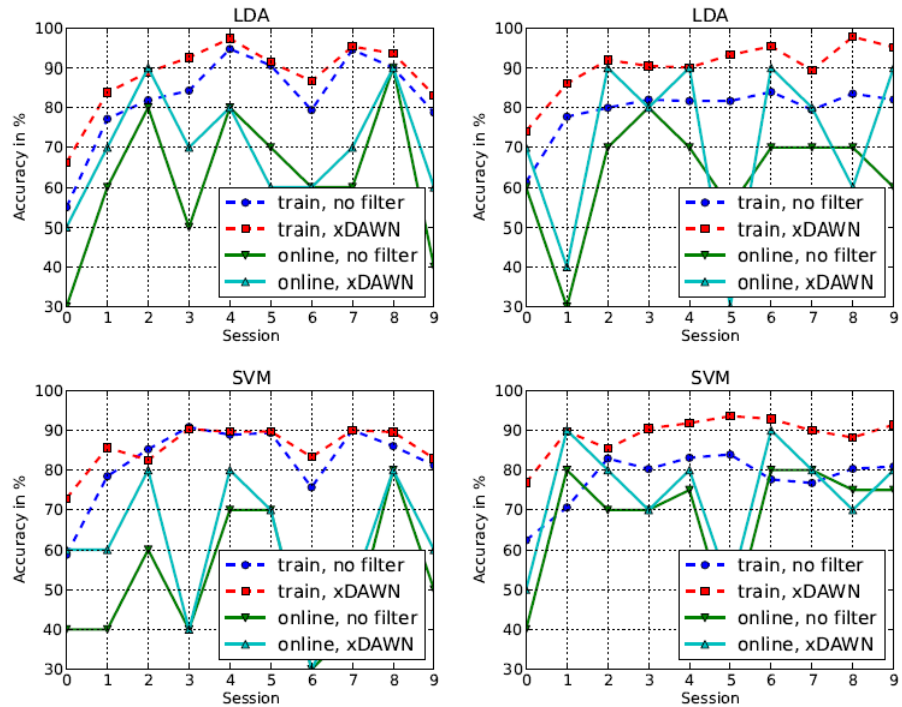


Figure 5.11. Training and online accuracies over 10 sessions using either the LDA (top diagrams) or the SVM (bottom diagrams) classification methods. Results were recorded from participant #5 (left diagrams) and participant #6 (right diagrams) on the *graphical* speller.

The diagrams show the evolution of the training and validation accuracies in over the ten consecutive training sessions. The left and right plots show the results for participant

#5 and #6, respectively. For each participant, the results using the LDA and the SVM classifiers are presented (top and bottom plots). Independent of the employed learning method, it can be clearly observed that the training accuracies do not increase any further after approximately three training sessions when using the alphanumerical version of the speller (Figure 5.9). In the case of the LDA training, a similar observation can be made for the validation accuracies. From session #0 to session #2, we notice a sharp improvement of the user's performance, however, in the remaining sessions the results vary significantly. Longer training does not reflect a well defined modality. The training process with the SVM appears slightly slower and the validation performance of the users seems to benefit from more training sessions. Similar observations can be made for the verbal and graphical spelling paradigms investigated here. A potential loss of attention or motivation and fatigue could explain the high variability of the validation accuracies in later sessions as well as other reasons mentioned in sections. From the obtained results, we conclude that a larger number of training sessions is not always beneficial. In fact, after only three sessions, the two users reported a satisfying ability to operate the P300 Speller. For the other participants in this study, we will use only three training session for each of the three BCI scenarios, similarly to Iáñez et al. (2010).

Iáñez et al. (2010) evaluate a BCI application on six people. The interface developed in their study demonstrates an attempt to control a robotic arm for writing/drawing purposes, and it is based on motor imagination. Similarly to this study, their findings reflect a remarkable improvement between the first and the second sessions in two classes (the *rest state* class and the *right* class); however, the performance shows a considerable drop in the third session. Nevertheless, this does not apply to the third class, *left* class, which presents an opposite trend as shown in Figures 5.12 and 5.13.

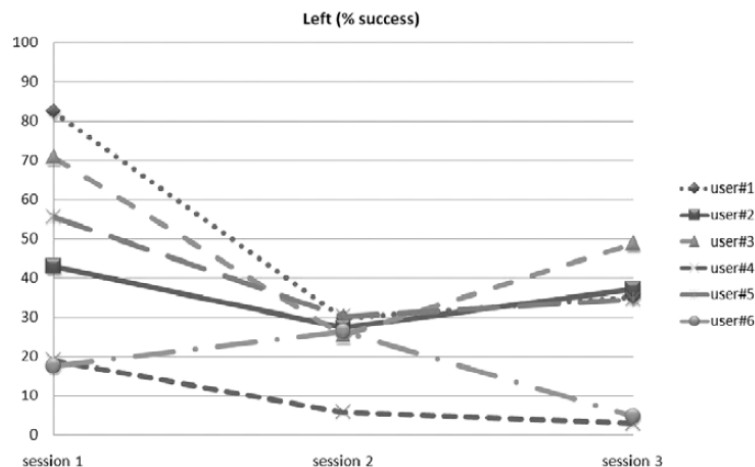


Figure 5.12. The performance of six participants using motor imagination BCI over three sessions. The figure represents the *left* class (Iáñez et al., 2010, p.1242-1243).

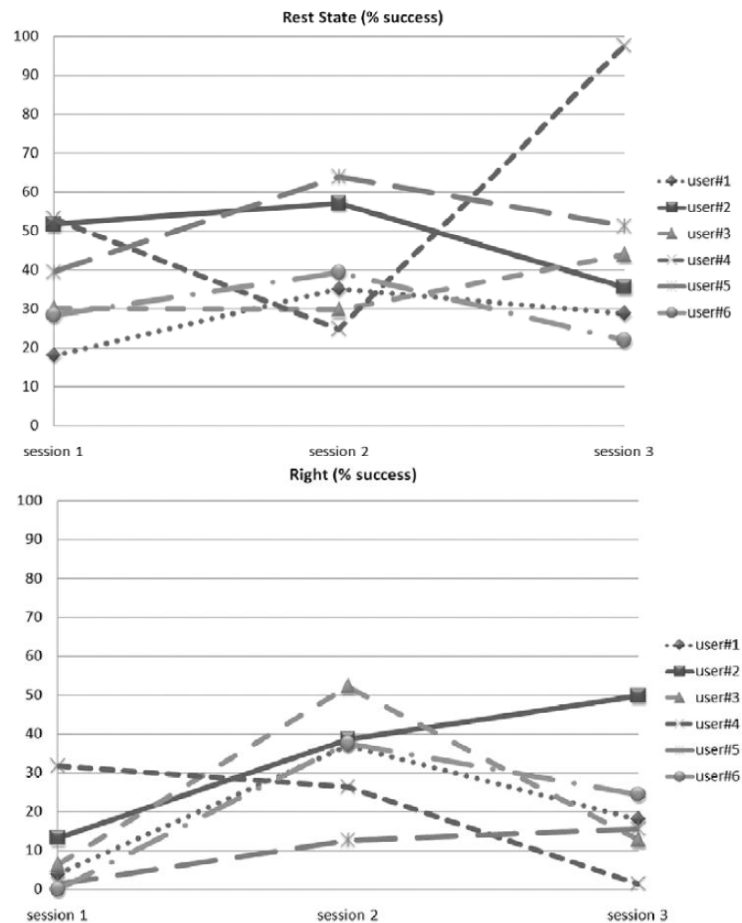


Figure 5.13. The performance of six participants using motor imagination BCI over three sessions. The figures represent the *rest state* class on the top and the *right* class on the bottom (Iáñez et al., 2010, p.1242-1243).

Nijboer et al. (2008) observed the performance of 10 users using auditory and visual P300 BCIs; the findings of their study are shown in Figure 5.15. The diagram illustrates the fluctuation in users' performance over 12 sessions of training. The outcomes from the study by Klobassa et al. (2009) are similar as displayed in Figure 5.14. Again, the figure does not reflect a well defined modality regarding the density of training after two sessions. The results are obtained from eight users over ten sessions using the typical P300 interface. Regardless, both figures indicate a variation in the users' performances.

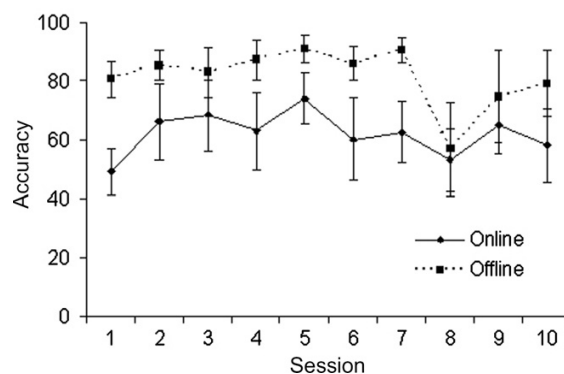


Figure 5.14. The means of accuracies obtained from eight participants over 10 sessions, using the typical P300 BCI (Klobassa et al. 2009 p.1256).

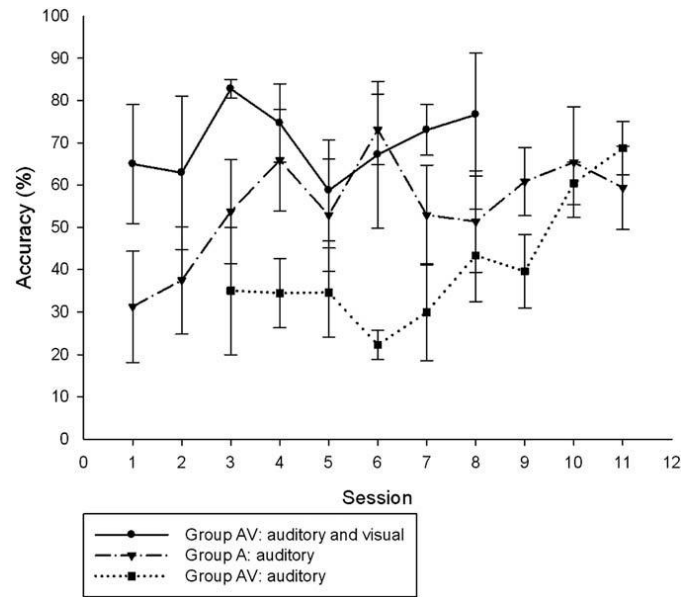


Figure 5.15. The means of the accuracies obtained from 10 contributors over 12 sessions, using auditory and visual P300 BCI (Nijboer et al., 2008, p.1913).

## 5.4. The Design of Alphanumerical, Verbal and Graphical Spellers

In this section, the results obtained from the P300 Alphanumerical Speller are presented. The goal of our first experiment is to further evaluate the feasibility of the Emotiv system as an input scheme for a communication BCI application through comparing the study results with the outcomes of other research conducted on the P300 interface using advanced EEG devices. Additional objective is to compare the results of the alphanumerical, verbal and graphical versions of the speller.

The results of this experiment report significant differences between different participants. Excluding participant #3 who appears as potential BCI illiterate as discussed in section 5.2, the performance of all the users is reasonable, with a mean of 84% success rate for the offline training and an average of 60.5% overall accuracy for the online validation using the LDA classifier with the xDAWN filter (Figure 5.16). It is worth mentioning that the performance of the participants is correlated, in most cases, with the strength of their responses to the visual stimuli as shown previously in Figure 5.7. As it can be seen, participants #1 and #4 have the best performance among the participants while participant #3 reflects a clear outlier.

Concerning the Emotiv headset, the accuracies obtained using this system are comparable to those presented in other studies where expensive medical EEG recording systems were used by experts. For example, the performance of six users was evaluated

on the P300 Speller designed by the BCI2000 platform in Nijboer et al. (2008), using 16 Ag/AgCl electrodes and the Weighted Complete Linear Discriminant Analysis (WCLDA) algorithm. The stated offline results are in the range of 69% to 91%, with a mean of 78%, while the online results shown are in the range of 50% to 87%, with a mean of 65%. Another study done by Sirvent-Blasco et al. (2012) was undertaken with four participants using the well known g.tec system with 16 sensors. Their results are similar to the results from this study. The users were able to use the P300 Speller to conduct online search operating the Google search engine, with a success rate of 60% to 93% and mean of 76% using five channels. In that experiment the Stepwise Linear Discriminant Analysis (SWLDA) was used to classify the data. Nevertheless, studies that allowed longer time for a selection (with more trials of flashing stimulation leading to lower spelling speed, e.g. 1.5 letter per minute) or used modification techniques, such as combining P300 potentials with motion onset visual evoked, achieved higher rates; see for example Kleih, et al. (2010), and Jin, Allison, Wang, and Neuper (2012), noting that the relation between the ITR (spelling speed) and the interface accuracy is inverse as shown in Figure 5.17.

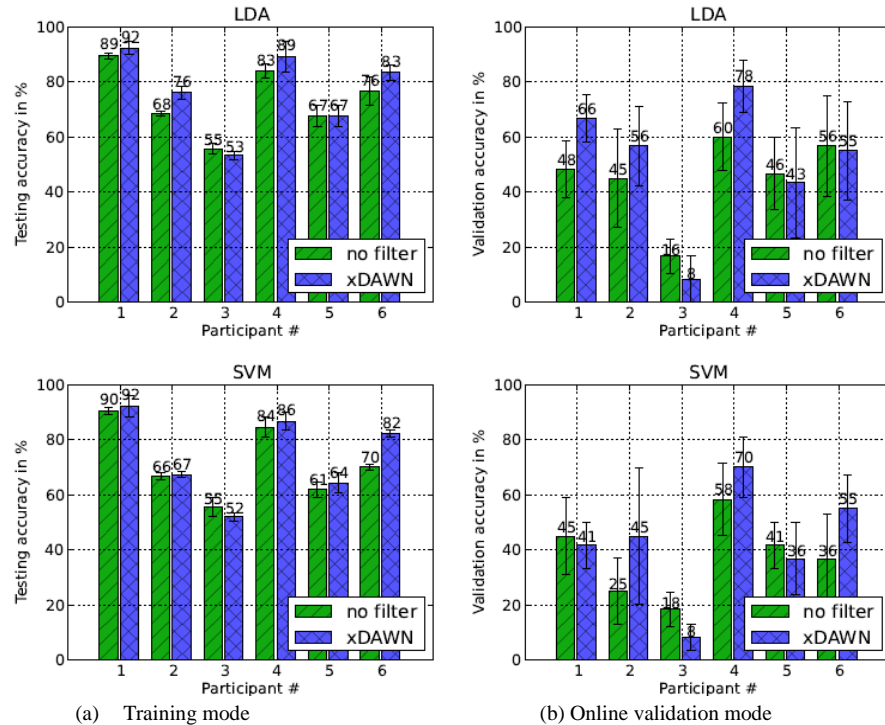


Figure 5.16. Individual accuracies obtained from six participants after three successive training and online validation sessions. The colours of the bars indicate whether the xDAWN filter was used to pre-process the recorded EEG signals. The figures present the results collected from the *alphanumeric* speller, and the online accuracy is a reflection of the target class accuracy unlike the training accuracy that represent the overall performance.



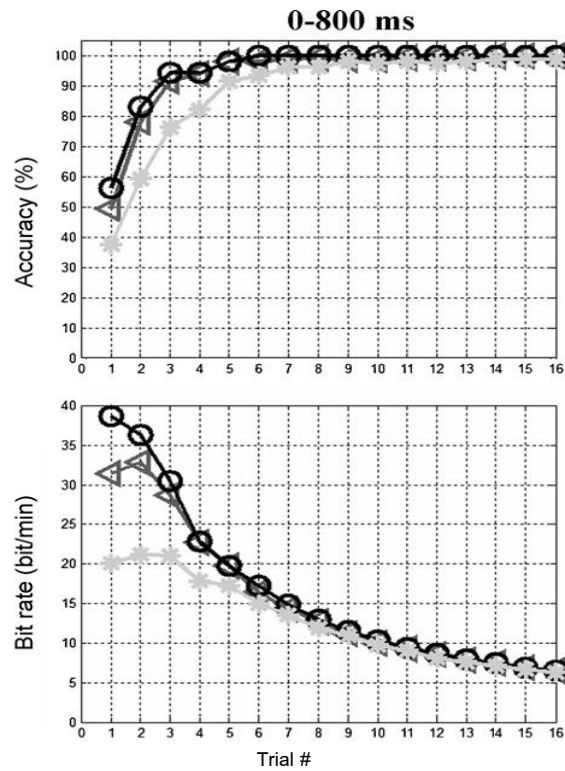


Figure 5.17. The inverse relationship between the ITR (spelling speed) and the interface accuracy (Jin et al., 2012)

As presented in Figures 5.18 and 5.19, the users' performance when using the verbal and graphical versions of the speller is very similar to the obtained results when using the typical alphanumeric speller, with a mean of 82% and 74.5% success rate for the online and offline accuracies respectively, using the verbal version with the LSA and xDAWN processing methods (excluding the results of participant #3). Similarly, the spelling accuracy reached by the participants has a mean 82% success rate for the offline training and a mean of 68% overall accuracy for the online validation using the LDA classifier and xDAWN spatial filter (excluding the results of participant #3). Accordingly, the use of these new versions of the speller is highly recommended for increasing the number of letters spelt per minute.

As stated previously, different from the training accuracies that demonstrate the overall performance, the online accuracies shown in the figures represent the accuracy of the target class only, which is more important than the overall accuracy. However, a considerable drop is noticed between the overall accuracy and the accuracy of the target class, and also between the training and validation results. These observations are compared to previous work in section 5.5.

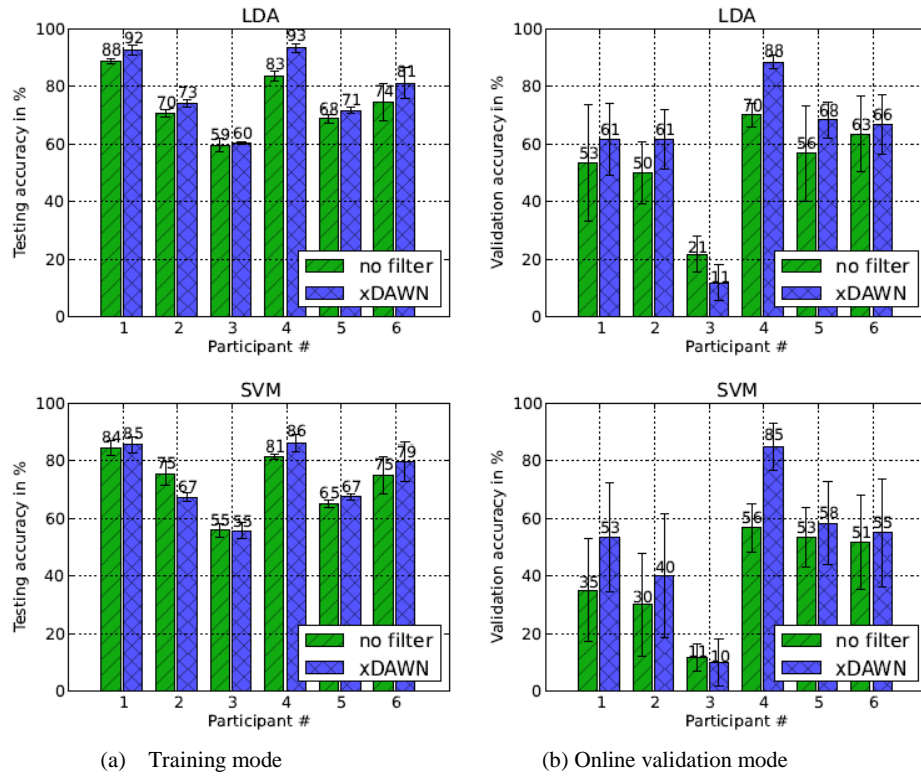


Figure 5.18. Individual accuracies obtained from six participants after three successive training and online validation sessions. The colours of the bars indicate whether the xDAWN filter was used to pre-process the recorded EEG signals. The figures present the results collected from the *verbal* speller, and the online accuracy is a reflection of the target class accuracy unlike the training accuracy that represents the overall performance.

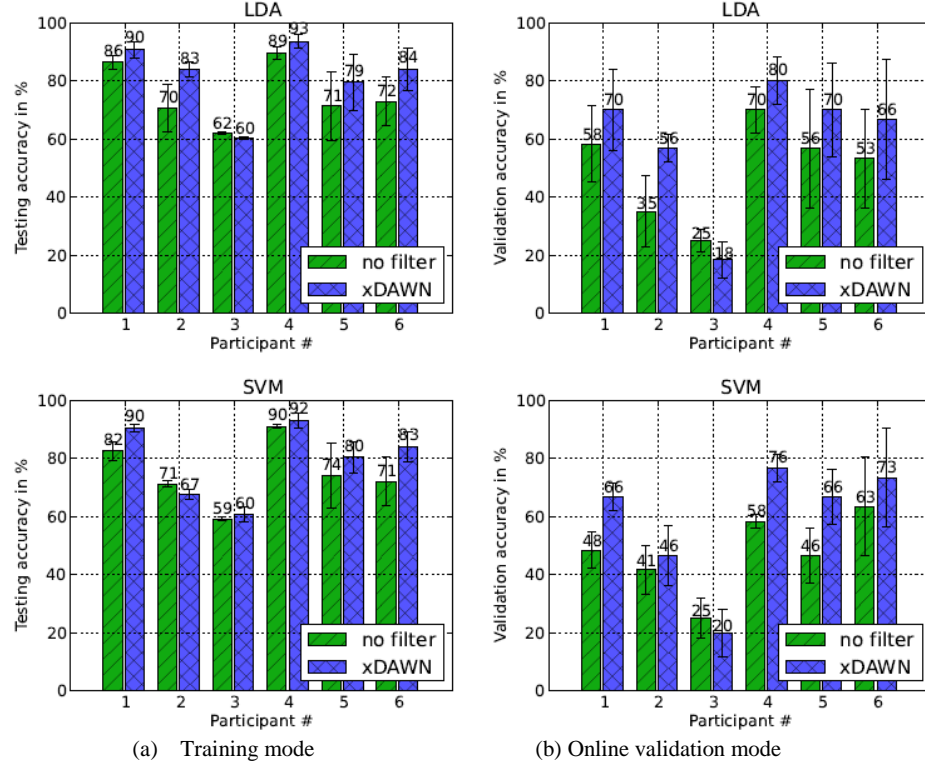


Figure 5.19. Individual accuracies obtained from six participants after three successive training and online validation sessions. The figures present the results collected from the *graphical* speller, and the online accuracy is a reflection of the target class accuracy unlike the training accuracy that represents the overall performance.

## 5.5. A comparison between the Online and Offline Performance, and between the Accuracy of the Target Class and the Overall Accuracy

The obtained results in this study indicate a noticeable decline and fluctuation in the online performance when compared to the offline outcomes which appear finer and stable (Figure 5.17). Previous experimental studies such as (Klobassa et al., 2009) and (Finke, Lenhardt, and Ritter, 2009) have similar conclusions as illustrated in figures 5.15 and 5.18. Further investigation is required in the future work to provide a clear explanation behind these outcomes.

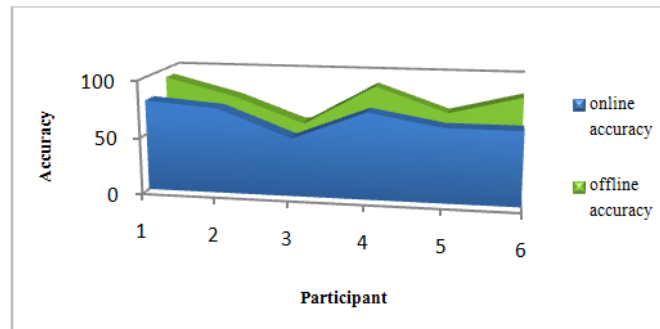


Figure 5.17. A comparison between the mean accuracy of the online and offline results obtained from six users in this study using the alphanumerical P300 Speller, xDAWN filter and LDA classifier, over three sessions.

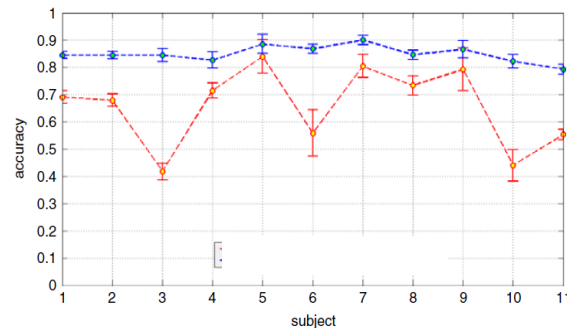
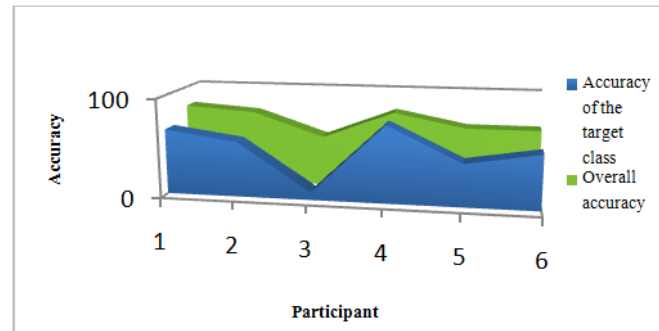


Figure 5.18. A comparison between the mean of the online (in red) and the offline results (in blue) obtained from 11 users using the P300 Speller over four sessions (Finke, 2009, p.1332).

It is also noticeable that the recorded accuracy of the target class is lower comparing to the overall accuracy in this study (Figure 5.19). The explanation of this fact is related to the significant imbalance between the two classes' sizes. The target samples represent a small part, 16.67%, of the dataset while the non-target samples are 83.33%. Furthermore, the chance percentage to correctly classify the target samples and detect a target letter is  $[1/(6 \text{ rows} \times 6 \text{ columns})] \times 100 = [1/36] \times 100 = 2.78\%$  while the chance percentage to correctly classify a non-target letter is  $(35/36) \times 100 = 97.22\%$ , using the alphanumerical and verbal spellers. Generally, BCI studies reveal only the overall accuracy. However, BCIs' users would not be satisfied if the interface overall accuracy

is over 90% when the real spelling accuracy they can achieve is as low as 35%, for example. Therefore, we recommend future BCI studies to focus on the accuracy of the target class to demonstrate the realistic accuracy offered to the potential users, and to form a better performance metric for comparing the different applications presented in different studies.



*Figure 5.19.* A comparison between the accuracy of the target class and the overall accuracy obtained from six users using the three versions of the P300 Speller achieved in this study.

## 5.6. Performance of the Classifiers

The LDA and SVM classifiers were employed in this investigation. According to the results, the performances of the two classifiers were similar. However, the learning process of the SVM appears slightly slower and the validation performance of the users seems to benefit from more training sessions. In the same way, the SVM algorithm takes longer to train, namely 5 minutes comparing to less than 4 sec for the LDA algorithm. Due to the faster learning ability of the LDA classifier and the reduced computation costs, the LDA classifier is preferred.

It is worth indicating that the LDA classifier has achieved high performance in different BCI applications (Scherer, Muller, Neuper, Graimann & Pfurtscheller, 2004; Garrett, Peterson, Anderson & Thaut, 2003). It was also elected as one of the winner algorithms in the BCI competition II in the P300 Speller (Bostanov, 2004).

## 5.7. The Impact of Motivation and other Factors on Users' Performance and their Ability to Control the Interface

In this section, the participants' ability to operate the P300 BCI is discussed. It was expected that the users would achieve similar accuracies in the same experimental

setups. However, the differences between the users' performances turned out to be significant. Therefore, the reasons for these differences are considered in this section. As concluded previously, the performance of the participants is correlated, in most cases, with the strength of their responses to the visual stimuli (their P300 brain signals) as shown previously in Figure 5.7. However, some other factors are observed to affect the performance of the users as well. These factors include motivation, movements and fatigue.

It was noticed that users' performance is associated with their motivation, attention and motor movements. As described in the methodology, participants were allowed to move but were informed that movements impact the spelling accuracy negatively. Remarkably, motivated contributors such as users #1 and #4 tend to be still/motionless and more attentive to the interface. Accordingly, they achieved better performance as shown previously in this chapter, in contrast to participants #2 and #6. In addition, it was obvious that participant #5 was also motivated; however, the high expectation of the interface performance that did not match the spelling accuracy the participant could reach over long recording sessions result in losing the interest. In the same way, Kleih, et al. (2010) signify the effects of users' motivation on their spelling success rate by showing stronger responses of the highly motivated users were reflected by their recorded P300 brain waves (Figure 5.20).

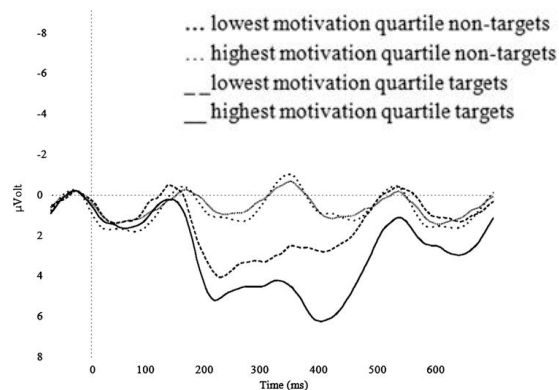


Figure 5.20. A comparison between the amplitudes of the P300 brain waves recorded from highly motivated users and low motivated users, noting that the amplitude is inversed here (Kleih, et al., 2010).

Regarding participant #3, although the participant was completely still during the recording sessions, this volunteer is considered to be BCI illiterate. It was observed that this participant's performance was associated with tiredness and fatigue. As stated by the participant, the P300 BCI "*can be useful for hypnotism*". Murata, Uetake and Takasawa (2005) suggest that the P300 interface might cause *mental fatigue*, loss of

productivity/capability and of willingness to effort. They recommend future studies to investigate this problem through a well defined methodology seeing that it is difficult to assess the level of the mental fatigue.

Other factors were also investigated in related works. For example, Kaufmann, Vögele, Sütterlin, Lukito and Kübler (2012) identified a significant predictor for a user performance in the P300 BCI, namely the heart rate variability (HRV). Yueqing (2009) found that the interface performance is associated with the screen size, reporting lower performance using a smaller screen size. Another study by Guger et al. (2009) observed a direct correlation between the sleep hours and the users' performance. Poor sleepers who sleep for less than eight hours a day reflect lower performance as indicated in their results.

Despite that, the noticed impacts of motivation, attention and fatigue in this study are based on subjective observations. Hence, further investigation is required to test the validity and extent of these factors through a well defined quantitative methodology.

## **5.8. Conclusion and Analysis of Results**

In this chapter, a case study was conducted on six participants to evaluate the feasibility of Emotiv EEG recoding system as an affordable input method for the design of communication BCIs. Additionally, we aimed to evaluate the usability of verbal and graphical versions of the P300 spelling paradigm to increase the number of letters spelt per minute.

The LDA and SVM classifier were employed in this experiment. The best performance of the classifiers was obtained when two/three channels were selected using xDAWN filter. Despite that, the impact of the additional filtering appears less significant. Generally, the filter reports only slightly increased training accuracies compared to the unfiltered data. Regardless, the filter has a clear effect on the computational costs. Due to the faster learning ability of the LDA classifier and the reduced training time, it is preferred in this study.

In terms of Emotiv feasibility, this system has evidenced its capability to detect the P300 brain waves used to control the P300 Speller. Furthermore, the accuracies obtained using the headset are comparable to those presented in other studies in which expensive

medical EEG recording systems were used by experts. The results suggest that Emotiv is suitable for a P300-based BCI.

The users' performance using the verbal and graphical versions of the speller is similar to the obtained performance using the typical alphanumerical speller. Accordingly, the use of these new versions is highly recommended to increase the number of letters spelt per minute in basic communication aids.

The results show significant differences between users performance. Thus, the shape of their brain activity pattern recorded within 500 ms of the visual stimulation, as well as other factors were considered. For most participants involved in this study, the target signals are remarkably distinguishable from the non-target ones. However, a sample of BCI illiterates is reported. To summarise, the interface performance is affected positively by a higher amplitude of the P300 brain waves and users' motivation; however, it is affected negatively by the loss of attention, motor movements and mental fatigue.

## **Chapter 6: Conclusion and Future Directions**

In this chapter, the whole study is outlined and its major outcomes are summarised. Furthermore, the strengths and limitations of the presented thesis are highlighted. Finally, potential future directions are indicated.

### **6.1. Conclusion**

BCI represents a remarkable research field that is rapidly growing. However, most recent BCI applications are a long way from reaching the main goals of this field, e.g. controlling devices at the speed of thoughts. Still, some available applications perform well enough to be used by the public. Despite that, their usage is restricted to laboratory's conditions, mainly as a result of the expensive equipments used to acquire brain data that require expertise to be used. In this thesis, a case study has been undertaken to evaluate the feasibility of Emotiv EEG recording system as an affordable input method for a real-time communication BCI that is simple to be used by people who have no knowledge of neuroimaging technologies. An additional aim is to evaluate the usability of verbal and graphical versions of the P300 spelling paradigm, in order to increase the number of letters spelt per minute.

A literature review on brain-computer interfaces has been accomplished, taking into consideration the fundamental concepts of BCIs, the history of this technology and the latest developments. Attention has been paid to the recently available technologies that can be used to design and implement a usable online interface. Finally, a comparison between the outcomes of this study and previous work in the field was performed.

The experimental study was conducted on six participants who attempted to operate three different versions of the speller using Emotiv system. Ten sessions were performed by two users for each version of the speller to investigate the amount of training required to reach good performance, while three sessions were recorded with the rest of the participants.

The LDA and SVM classifier were employed in this experiment. The best performance was obtained when two to three channels were selected using xDAWN filter. The LDA classifier was superior in view of the learning ability and the computational costs. However, the longer training does not reflect a well defined modality.



In terms of Emotiv feasibility, the results evidence the capability of this system to detect the P300 brain signals and its suitability for a P300-based BCI. The accuracy obtained using the headset is comparable to those presented in other studies in which expensive medical EEG recording systems were used by experts. Regarding the verbal and graphical spelling paradigms, the use of these new versions is recommended to increase the number of letters spelt per minute in basic communication aids.

The results show significant differences between the brain activity patterns recorded from individual users within 500 ms of the visual stimulation, and accordingly on their performance. For most participants involved in this study, the target signals are considerably distinguishable from the non-target ones; however, a potential sample of BCI illiterates was identified. To summaries, the interface performance is affected positively by the higher amplitude of the P300 brain wave and users' motivation; however, it is affected negatively by the loss of attention, motor movements and mental fatigue although that the effects of the motivation, attention, movements and fatigue are based on subjective observation, hence, further investigation is suggested.

This thesis aimed to answer four research questions formulated in section 1.3. The first question was about how BCIs work and what difficulties they present in practice use. The first question was answered in the review presented in chapter 2 and 3, and also through the implementation of the P300 spelling paradigm using OpenViBE. The second question was whether everybody could learn to control a P300-based BCI. The results obtained from the experiment showed that not everybody can learn that as 16% of the participant were considered BCI illiterate in this study. The third question concerned the feasibility of using the Emotiv EPOC system under realistic conditions. Findings demonstrate its capability to detect the P300 control signals, suggesting its suitability for a P300-based BCI. The last objective was to find a way to increase the number of letters that can be spelled per minute using the P300 BCI. Accordingly, this thesis introduced the multiple-screen verbal and graphical spelling paradigms and evidenced normal performance (i.e. similar to the performance achieved using the typical alphanumerical speller) among the participants.

## **6.2. Contributions of the Study**

The contributions and the strengths of this study are summarised in the following points:

Most of the previous studies on BCIs are carried out on offline mode that contrasts the definition of a BCI system: a real time interaction system that opens a direct communication channel between the human brain and computers (Tan et al., 2010). Additionally, the offline processing setups are conducted by analysts who observe the statistics of the data across entire sessions, with the aim of fine-tuning the algorithms. However, this does not align with the inherently non-stationary nature of the brain data, leading to a reduction in the interface performance in real-time. In contrast, this study is conducted on a real-time closed-loop BCI, since only online analysis can yield solid evidence of the performance.

The EEG datasets employed in BCI studies are often provided by a third party, usually medical institution or EEG experts, and are not collected during the study. In contrast, the data used in this study was collected by the researcher.

Generally, the brain data is collected under silent laboratory experimental conditions where the participants are required to remain completely focused on the interface in order to avoid the negative effects of artifacts. However, the interface designed in this study was tested under realistic conditions (domestic environment) where the contributors' behaviour was not controlled.

Additionally, the available EEG datasets provided by medical institutions are recorded using highly expensive medical recording devices that require long preparation time. In contrast, this study has introduced a real-time interface that is affordable for disabled people, and useful for daily usage. According to the findings of this study regarding the P300 Speller, Emotiv EPOC (originally created for computer games) can replace the expensive EEG systems that are unsuitable for public usage for several reasons.

In order to boost the number of letters that can be spelt per minute using the P300 Speller, previous studies attempted to increase the number of bits transferred per minute which is complicated. In this study, a simpler approach was presented. The number of letters spelt per minute can be remarkably improved through a verbal or a graphical version of the interface and by using multiple matrixes. In this case, the user is enabled to spell three words or sentences in a minute instead of three letters with the typical alphanumerical P300 Speller. In addition, a paper is in preparation to be submitted to the NCEI workshop (8<sup>th</sup> June 2012) and to be published by Springer.

### **6.3. Limitations of this Study**

The limitations of this study are summarised in the following points:

Although the comparison between the Emotiv system and medical EEG electrodes is comprehensive, it could be stronger if it had been conducted with the same scenario using OpenViBE and the same experimental setups, as part of this thesis. The results of other studies, which were compared to our results, were performed under different platforms and different setups. However, this study had limited recourses that led to this limitation.

In addition, the focus was limited on the P300 Speller in this thesis. However, Emotiv capability to detect P300 brain waves does not necessarily mean it could capture more complex patterns of the brain activities for general BCI applications.

### **6.4. Future Directions**

Based on the limitations of this study and some other studies on BCIs, we conclude with a number of issues that need to be considered in future work:

It is recommended to evaluate the feasibility of Emotiv EPOC to detect different patterns of brain activities, e.g. motor imagination. We would suggest that results from future work be compared in a comparative style with results obtained from medical EEG systems under the same experimental setups.

As it was clarified in this thesis and other studies on the P300 Speller, the P300 brain waves that are generated by the target stimuli may not be produced 300 ms after the stimulation. Some users show faster response while others present lower speed responses. Therefore, it is advised to employ a temporal filter in order to apply a personalized time frame that can be modified according to related factors such as training and the user's alertness.

Although the simple classification algorithms, SVM and LDA used in this study, had a reasonable performance in this experiment, results could be improved using recent more advanced approaches to suit the high level of complexity in EEG data. As suggested by Kasabov (2012), spectral spatio-temporal data (SSTD) analyzing methods is well

aligned with EEG's features, as they enable the analyst to describe each sample of the data by a triple matrix. SST processing algorithms have shown their capabilities to integrate different dimensions including frequency, time and spatial space, e.g. for processing fMRI brain data (Sona, Veeramachaneni, Olivetti & Avesani, 2011).

Traditional Artificial Neural Networks (ANNs) are a widely used method for processing SST data, although these techniques often over simplify the temporal dimension. However, the new generations of ANNs, e.g. evolving Spiking Neural Networks (eSNN), have the potential to encode both spatial and temporal events through trains of spikes transmitted at particular times to express the temporal dimension among spatially located synapses and neurons to demonstrate the spatial dimension of the input data (Figure 6.1). Spiking neurons are connected through weights that have a complex dynamic behaviour to form an SSTD memory. Despite the complexity of the liquid state machine, reservoir computing techniques have also demonstrated better performance than simple classifiers; see for example (Schliebs, Hamed & Kasabov, 2011; Maass, Natschlaeger & Markram, 2002; Schliebs, Nuntalid & Kasabov, 2010; Kasabov, Dhoble, Nuntalid & Mohemmed, 2011).

In relation to the large amount of noise present in EEG data, probabilistic neural models based on SNN have shown better learning ability than traditional SNN, especially in noisy environment (Rokem, Watzl, Gollisch, Stemmler & Herz, 2006; Nuzly, Kasabov & Shamsuddin, 2010). Hence, these algorithms are highly recommended to be used in future work for a better performance of P300 BCIs, and to analyse EEG data in a continuous manner rather than single-time-point frames due to the importance for the learning algorithm to learn the whole spatio spectral-temporal patterns in the data.

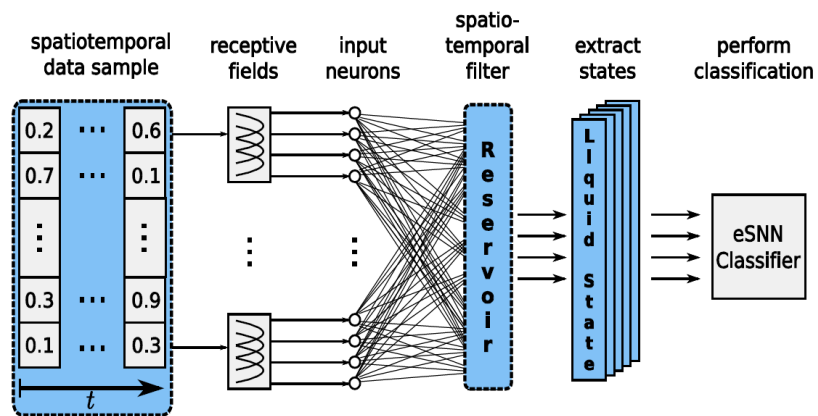


Figure 6.1. Classification task using eSNN and reservoir computing (Kasabov, 2012, p.8)

Studies on the P300 Speller attempt to analyse static objects (intensified letters/ non-intensified letter). In (Wysoski, Benuskova & Kasabov, 2010) the captured features were aggregated into visual and audio perceptions and used for person authentication. eSNN was employed in their study that is based on four layers of connected SNN, similar to the way the cortex works in order to recognise an image or different types of complex stimuli. Nevertheless, this model is also limited to static objects, e.g. image, but not applicable to moving objects. Although eSNN can process moving objects using sequence frames of static objects, they do not learn the complex association between the spatial/spectral and temporal patterns in the data (Kasabov, 2012). Thus, these models are deterministic and not suitable for complex stochastic SSTD. Analysing the human brain perception of moving objects, e.g. video, could be a valuable step toward new BCI applications.

*'BCI illiteracy'* is a new concept. Although 15-30% of users are affected as reported in related work (Blankertz, 2010) this concept is mentioned in very few studies. We would recommend future work to investigate this problem. Solutions could be related to customising the classification algorithms through automatic personalized optimizing of the classifier parameters, employing different neuroimaging technologies, improving the feedback procedure, and most importantly, generating control signals that are easier to categorise.

As a result of this study, a strong awareness of BCI fundamentals and drawbacks was built. Moreover, the researcher has developed a clear understanding of how BCIs work and about the principle components involved in designing a BCI system, leading to further curiosity to investigate some of the existing problems and to develop new concepts in the remarkable field of BCI.

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## Appendix A: Ethical Approval Document



# MEMORANDUM

## Auckland University of Technology Ethics Committee (AUTEC)

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To: Nikola Kasabov  
From: Dr Rosemary Godbold Executive Secretary, AUTEC  
Date: 11 November 2011  
Subject: Ethics Application Number 11/227 EEG-Based Spatio - temporal pattern recognition model for a personalised brain computer interface.

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Dear Nikola

Thank you for providing written evidence as requested. I am pleased to advise that it satisfies the points raised by the Auckland University of Technology Ethics Committee (AUTEC) at their meeting on 22 August 2011 and I have approved your ethics application. This delegated approval is made in accordance with section 5.3.2.3 of AUTEC's *Applying for Ethics Approval: Guidelines and Procedures* and is subject to endorsement at AUTEC's meeting on 28 November 2011.

Your ethics application is approved for a period of three years until 10 November 2014.

I advise that as part of the ethics approval process, you are required to submit the following to AUTEC:

- A brief annual progress report using form EA2, which is available online through <http://www.aut.ac.nz/research/research-ethics/ethics>. When necessary this form may also be used to request an extension of the approval at least one month prior to its expiry on 10 November 2014;
- A brief report on the status of the project using form EA3, which is available online through <http://www.aut.ac.nz/research/research-ethics/ethics>. This report is to be submitted either when the approval expires on 10 November 2014 or on completion of the project, whichever comes sooner;

It is a condition of approval that AUTEC is notified of any adverse events or if the research does not commence. AUTEC approval needs to be sought for any alteration to the research, including any alteration of or addition to any documents that are provided to participants. You are reminded that, as applicant, you are responsible for ensuring that research undertaken under this approval occurs within the parameters outlined in the approved application.

Please note that AUTECH grants ethical approval only. If you require management approval from an institution or organisation for your research, then you will need to make the arrangements necessary to obtain this.

When communicating with us about this application, we ask that you use the application number and study title to enable us to provide you with prompt service. Should you have any further enquiries regarding this matter, you are welcome to contact me by email at [ethics@aut.ac.nz](mailto:ethics@aut.ac.nz) or by telephone on 921 9999 at extension 6902.

On behalf of AUTECH and myself, I wish you success with your research and look forward to reading about it in your reports.

Yours sincerely

Dr Rosemary Godbold  
Executive Secretary  
Auckland University of Technology Ethics Committee

## Appendix B: Experimental Results

Table 1

*Classification accuracies obtained from six participants after three successive training and online validation sessions. The results were collected from the alphanumerical speller scenario using the LDA classification method.*

LDA						
Person	Train 1	Train 2	Train 3	Online 1	Online 2	Online 3
1	0.907	0.8799	0.8987	0.5	0.35	0.6
2	0.6711	0.69	0.6883	0.2	0.6	0.55
3	0.5708	0.569	0.5322	0.15	0.1	0.25
4	0.8373	0.809	0.8722	0.45	0.6	0.75
5	0.6933	0.6204	0.7146	0.4	0.35	0.65
6	0.7014	0.776	0.8251	0.35	0.55	0.8
LDA (xDAWN)						
1	0.9528	0.894	0.9235	0.55	0.7	0.75
2	0.7348	0.756	0.7927	0.4	0.55	0.75
3	0.5283	0.516	0.5527	0	0.05	0.2
4	0.8113	0.935	0.9277	0.65	0.85	0.85
5	0.6933	0.6204	0.7146	0.15	0.55	0.6
6	0.8221	0.8055	0.8738	0.4	0.45	0.8

Table 2

*Classification accuracies obtained from six participants after three successive training and online validation sessions. The results were collected from the alphanumerical speller scenario using the SVM classification method.*

SVM						
Person	Train 1	Train 2	Train 3	Online 1	Online 2	Online 3
1	0.919	0.8866	0.907	0.25	0.55	0.55
2	0.6577	0.6577	0.6861	0.1	0.25	0.4
3	0.5046	0.5804	0.5766	0.1	0.2	0.25
4	0.8016	0.841	0.8945	0.4	0.7	0.65
5	0.5922	0.6094	0.6577	0.3	0.45	0.5
6	0.7115	0.6855	0.7031	0.15	0.55	0.4
SVM (xDAWN)						
1	0.9312	0.9623	0.8701	0.5	0.3	0.45
2	0.6861	0.6604	0.6693	0.1	0.65	0.6
3	0.5022	0.54	0.5178	0.05	0.05	0.15
4	0.8261	0.87	0.9054	0.55	0.75	0.8
5	0.6574	0.5933	0.6788	0.25	0.3	0.55
6	0.8383	0.81335	0.8133	0.4	0.55	0.7

Table 3

*Classification accuracies obtained from six participants after three successive training and online validation sessions. The results were collected from the verbal speller scenario using the LDA classification method.*

LDA						
Person	Train 1	Train 2	Train 3	Online 1	Online 2	Online 3
1	0.8951	0.8951	0.8768	0.25	0.65	0.7
2	0.7063	0.69	0.7244	0.35	0.55	0.6
3	0.5784	0.5806	0.63	0.2	0.15	0.3
4	0.86	0.8333	0.8184	0.65	0.7	0.75
5	0.6855	0.6718	0.706	0.35	0.6	0.75
6	0.682	0.7233	0.8336	0.45	0.7	0.75
LDA (xDAWN)						
1	0.9207	0.9073	0.9478	0.45	0.65	0.75
2	0.735	0.7578	0.7264	0.5	0.6	0.75
3	0.6011	0.5959	0.6077	0.05	0.1	0.2
4	0.9178	0.9544	0.9289	0.85	0.9	0.9
5	0.719	0.7033	0.7267	0.6	0.75	0.7
6	0.7522	0.7962	0.8835	0.55	0.65	0.8

Table 4

*Classification accuracies obtained from six participants after three successive training and online validation sessions. The results were collected from the verbal speller scenario using the SVM classification method.*

SVM						
Person	Train 1	Train 2	Train 3	Online 1	Online 2	Online 3
1	0.8791	0.8333	0.8177	0.25	0.2	0.6
2	0.7766	0.7	0.7896	0.15	0.2	0.55
3	0.5538	0.5333	0.589	0.05	0.15	0.15
4	0.8205	0.8023	0.8166	0.65	0.45	0.6
5	0.6685	0.6335	0.6509	0.4	0.55	0.65
6	0.7019	0.7052	0.8433	0.3	0.55	0.7
SVM (xDAWN)						
1	0.8808	0.8177	0.8686	0.4	0.4	0.8
2	0.6933	0.675	0.6527	0.3	0.2	0.7
3	0.5918	0.5551	0.5223	0	0.2	0.1
4	0.8835	0.8807	0.8211	0.75	0.85	0.95
5	0.6708	0.6627	0.6896	0.4	0.75	0.6
6	0.7204	0.778	0.889	0.3	0.6	0.75

Table 5

*Classification accuracies obtained from six participants after three successive training and online validation sessions. The results were collected from the graphical speller scenario using the LDA classification method.*

LDA						
Person	Train 1	Train 2	Train 3	Online 1	Online 2	Online 3
1	0.8639	0.8899	0.8368	0.4	0.65	0.7
2	0.5961	0.7835	0.7388	0.2	0.35	0.5
3	0.6211	0.6131	0.627	0.25	0.2	0.3
4	0.9273	0.8822	0.8822	0.7	0.8	0.6
5	0.5499	0.7717	0.8187	0.3	0.6	0.8
6	0.6128	0.7771	0.7996	0.6	0.3	0.7
LDA (xDAWN)						
1	0.912	0.8718	0.938	0.5	0.8	0.8
2	0.81	0.874	0.8333	0.5	0.6	0.6
3	0.6077	0.6077	0.5963	0.2	0.1	0.25
4	0.9701	0.923	0.9166	0.7	0.9	0.8
5	0.6622	0.8381	0.889	0.5	0.7	0.9
6	0.7411	0.8601	0.9198	0.7	0.4	0.9

Table 6

*Classification accuracies obtained from six participants after three successive training and online validation sessions. The results were collected from the graphical speller scenario using the SVM classification method.*

SVM						
Person	Train 1	Train 2	Train 3	Online 1	Online 2	Online 3
1	0.7951	0.8133	0.8705	0.4	0.55	0.5
2	0.7045	0.7028	0.7279	0.3	0.5	0.45
3	0.5929	0.6	0.583	0.15	0.3	0.3
4	0.9123	0.9166	0.9008	0.55	0.6	0.6
5	0.5874	0.7845	0.8523	0.4	0.4	0.6
6	0.6239	0.7062	0.8291	0.4	0.8	0.7
SVM (xDAWN)						
1	0.8962	0.9218	0.8921	0.7	0.6	0.7
2	0.6811	0.6933	0.6519	0.35	0.6	0.45
3	0.57175	0.6336	0.6201	0.1	0.2	0.3
4	0.955	0.9395	0.8933	0.8	0.7	0.8
5	0.7288	0.8565	0.825	0.6	0.6	0.8
6	0.7683	0.8971	0.854	0.5	0.9	0.8



Table 7

*Training and online accuracies of participant #5 obtained over ten training and online sessions using either the LDA or the SVM classification methods. Results were recorded on the alphabetical speller scenario.*

Session	LDA (no filter)		LDA (xDAWN)		SVM (no filter)		SVM (xDAWN)	
	Train	Online	Train	Online	Train	Online	Train	Online
1	0.6933	0.4	0.6933	0.15	0.5922	0.3	0.6574	0.25
2	0.6204	0.35	0.6204	0.55	0.6094	0.45	0.5933	0.3
3	0.7146	0.65	0.7146	0.6	0.6577	0.5	0.6788	0.55
4	0.7055	0.7	0.7055	0.75	0.6155	0.5	0.6705	0.4
5	0.753	0.55	0.753	0.75	0.6155	0.55	0.6912	0.45
6	0.7546	0.5	0.7546	0.6	0.6653	0.55	0.7076	0.6
7	0.7001	0.75	0.76	0.75	0.6644	0.65	0.7011	0.65
8	0.7222	0.6	0.753	0.7	0.7311	0.6	0.719	0.65
9	0.7162	0.6	0.7492	0.6	0.6825	0.7	0.72	0.7
10	0.7162	0.55	0.7607	0.6	0.6544	0.45	0.694	0.55

Table 8

*Training and online accuracies of participant #5 obtained over ten training and online sessions using either the LDA or the SVM classification methods. Results were recorded on the verbal speller scenario.*

Session	LDA (no filter)		LDA (xDAWN)		SVM (no filter)		SVM (xDAWN)	
	Train	Online	Train	Online	Train	Online	Train	Online
1	0.6855	0.35	0.719	0.6	0.6685	0.4	0.6708	0.4
2	0.6718	0.6	0.7033	0.75	0.6335	0.55	0.6627	0.75
3	0.706	0.75	0.7267	0.7	0.6509	0.65	0.6896	0.6
4	0.7335	0.55	0.7267	0.7	0.612	0.6	0.7091	0.6
5	0.7188	0.55	0.7085	0.7	0.6161	0.5	0.7045	0.8
6	0.7163	0.7	0.7529	0.8	0.6734	0.5	0.7523	0.75
7	0.7005	0.65	0.7809	0.75	0.6361	0.45	0.7355	0.7
8	0.71	0.6	0.7715	0.6	0.709	0.55	0.7091	0.55
9	0.7133	0.6	0.7883	0.65	0.7036	0.55	0.7767	0.55
10	0.704	0.7	0.7541	0.65	0.6888	0.6	0.7644	0.6

Table 9

*Training and online accuracies of participant #5 obtained over ten training and online sessions using either the LDA or the SVM classification methods. Results were recorded on the graphical speller scenario.*

Session	LDA (no filter)		LDA (xDAWN)		SVM (no filter)		SVM (xDAWN)	
	Train	Online	Train	Online	Train	Online	Train	Online
1	0.5499	0.3	0.6622	0.5	0.5874	0.4	0.7288	0.6
2	0.7717	0.6	0.8381	0.7	0.7845	0.4	0.8565	0.6
3	0.8187	0.8	0.889	0.9	0.8523	0.6	0.825	0.8
4	0.8427	0.5	0.9259	0.7	0.9081	0.4	0.9028	0.4
5	0.9471	0.8	0.9734	0.8	0.8886	0.7	0.8962	0.8
6	0.9062	0.7	0.9144	0.6	0.8933	0.7	0.8971	0.7
7	0.7938	0.6	0.8665	0.6	0.7567	0.3	0.8327	0.3
8	0.9455	0.6	0.9533	0.7	0.9	0.4	0.9	0.5
9	0.9001	0.9	0.936	0.9	0.8603	0.8	0.8955	0.8
10	0.7875	0.4	0.8311	0.6	0.8118	0.5	0.829	0.6

Table 10

*Training and online accuracies of participant #6 obtained over ten training and online sessions using either the LDA or the SVM classification methods. Results were recorded on the alphabetical speller scenario.*

Session	LDA (no filter)		LDA (xDAWN)		SVM (no filter)		SVM (xDAWN)	
	Train	Online	Train	Online	Train	Online	Train	Online
1	0.7014	0.35	0.8221	0.4	0.7115	0.15	0.8383	0.4
2	0.776	0.55	0.8055	0.45	0.6855	0.55	0.81335	0.55
3	0.8251	0.8	0.8738	0.8	0.7031	0.4	0.8133	0.7
4	0.8523	0.75	0.8911	0.7	0.8416	0.6	0.845	0.75
5	0.8577	0.8	0.8776	0.6	0.8467	0.7	0.8577	0.75
6	0.8601	0.8	0.8738	0.65	0.8922	0.85	0.84	0.85
7	0.848	0.95	0.8644	0.75	0.7645		0.8511	0.8
8	0.8833	0.7	0.887	0.75	0.835	0.65	0.8343	0.8
9	0.8521	0.85	0.863	0.8	0.835	0.7	0.8333	0.7
10	0.851	0.7	0.9007	0.7	0.8333	0.8	0.8552	0.75

Table 11

*Training and online accuracies of participant #6 obtained over ten training and online sessions using either the LDA or the SVM classification methods. Results were recorded on the verbal speller scenario.*

Session	LDA (no filter)		LDA (xDAWN)		SVM (no filter)		SVM (xDAWN)	
	Train	Online	Train	Online	Train	Online	Train	Online
1	0.682	0.45	0.7522	0.55	0.7019	0.3	0.7204	0.3
2	0.7233	0.7	0.7962	0.65	0.7052	0.55	0.778	0.6
3	0.8336	0.75	0.8835	0.8	0.8433	0.7	0.889	0.75
4	0.8318	0.75	0.8581	0.8	0.8145	0.7	0.8955	0.8
5	0.8559	0.8	0.8367	0.9	0.8128	0.7	0.8876	0.8
6	0.8441	0.85	0.8818	0.85	0.8016	0.75	0.9043	0.85
7	0.8377	0.7	0.8833	0.8	0.8255	0.7	0.8406	0.85
8	0.8311	0.8	0.875	0.8	0.8025	0.7	0.8333	0.8
9	0.8065	0.75	0.84	0.8	0.8032	0.8	0.8361	0.8
10	0.8422	0.75	0.8825	0.75	0.8071	0.7	0.8128	0.7

Table 12

*Training and online accuracies of participant #6 obtained over ten training and online sessions using either the LDA or the SVM classification methods. Results were recorded on the graphical speller scenario.*

Session	LDA (no filter)		LDA (xDAWN)		SVM (no filter)		SVM (xDAWN)	
	Train	Online	Train	Online	Train	Online	Train	Online
1	0.6128	0.6	0.7411	0.7	0.6239	0.4	0.7683	0.5
2	0.7771	0.3	0.8601	0.4	0.7062	0.8	0.8971	0.9
3	0.7996	0.7	0.9198	0.9	0.8291	0.7	0.854	0.8
4	0.82	0.8	0.9044	0.8	0.8028	0.7	0.9044	0.7
5	0.8166	0.7	0.9005	0.9	0.831	0.75	0.9179	0.8
6	0.8166	0.55	0.9322	0.3	0.839	0.4	0.9355	0.5
7	0.8395	0.7	0.9538	0.9	0.7766	0.8	0.9284	0.9
8	0.7947	0.7	0.894	0.8	0.7676	0.8	0.8992	0.8
9	0.835	0.7	0.9777	0.6	0.8033	0.75	0.8818	0.7
10	0.8201	0.6	0.9517	0.9	0.8089	0.75	0.9139	0.8