THESIS

P300 WAVE DETECTION USING EMOTIV EPOC+ HEADSET: EFFECTS OF MATRIX SIZE, FLASH DURATION, AND COLORS

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Abstract

P300 WAVE DETECTION USING EMOTIV EPOC+ HEADSET: EFFECTS OF MATRIX SIZE, FLASH DURATION, AND COLORS

Brain-computer interfaces (BCIs) allow interactions between human beings and computers without using voluntary muscle. Enormous research effort has been employed in the last few decades to design convenient and user-friendly interfaces. The aim of this study is to provide the people with severe neuromuscular disorders a new augmentative communication technology so that they can express their wishes and communicate with others. The research investigates the capability of Emotiv EPOC+ headset to capture and record one of the BCIs signals called P300 that is used in several applications such as the P300 speller. The P300 speller is a BCI system used to enable severely disabled people to spell words and convey their thoughts without any physical effort. In this thesis, the effects of matrix size, flash duration, and colors were studied. Data are collected from five healthy subjects in their home environments. Different programs are used in this experiment such as OpenViBE platform and MATLAB to pre-process and classify the EEG data. Moreover, the Linear Discriminate Analysis (LDA) classification algorithm is used to classify the data into target and non-target samples.

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CHAPTER 1

Introduction

Technology dominates much of modern humanity's existence, and the medical field is no different. Decades ago, the intersection of different interdisciplinary fields, such as engineering, mathematics, psychology, and computer science, would have been a confused notion; today, this intersection forms a partnership that saves countless lives every day. For more than two decades, scientists and researchers have been developing methods to increase the quality of life of paralyzed people and to provide them a more independent life. According to the Christopher & Dana Reeve Foundation [25], 1.9% of the United States population is suffering from motor disabilities as a result of neuromuscular disorders, such as amyotrophic lateral sclerosis, brainstem stroke, cerebral palsy, and spinal cord injury and other diseases of the peripheral nervous system. These types of diseases result in these individuals losing conventional communication methods due to the disruption of their neuromuscular channels. There are three ways to restore function of the muscular system [69]. The first option is to use the remaining pathways instead of the damaged muscular channels. For instance, the non vocally disabled can use hand movements to produce synthetic speech [18]. The second method is to establish a detour around the breaks in the neural pathways that control muscles. For people who are suffering from spinal cord injury, electromyographic (EMG) can be employed to restore useful movement[24]. The last method that is used for restoring the function of the muscles is opening a non-muscular channel between the human brain and computers to translate the brain activities into commands that can be used for control and communication purposes; this method is well known as a brain-computer interface (BCI).

Brain-computer interfaces (BCIs), also known as brain-machine interfaces (BMIs) or Mind-Machine Interfaces (MMIs), are communication and control systems that are used to provide a direct form of communication for disabled people who have lost their ability to communicate by using peripheral nerves and muscles. A variety of methods for monitoring and recording brain activity have been used. These include electroencephalography (EEG), magnetoencephalography (MEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and optical imaging [69]. Table 1.1 provides an overview of current functional brain imaging technologies [50]. Among these methods, EEG is considered as the most attractive way to record brain signals due to its simplicity and affordability. In 1929, Hans Berger, a German neurologist, discovered electroencephalography (EEG) as well as the alpha wave [31]. Two methods are used to record the signals from the brain: invasive technologies, in which electrodes are implanted directly into brain tissue, and non-invasive technologies, in which electrodes are placed on the scalp and detect neuron activity. Over the past two decades, many studies have shown that different types of signals can be recorded from the scalp including P300 potential, mu or beta rhythms, and cortical neuronal activity recorded by implanted electrodes. The BCIs have been employed in many applications that are necessary for a daily usage; for instance, locomotion applications such as controlling a wheelchair [63], and environmental control applications such as controlling an appliance [13]. One of the most popular types of BCIs that relies on event-related potentials and the P300 signal is well known as a P300-BCI.

In this study, an affordable and low-cost consumer-grade EEG device, namely Emotiv EPOC+, is used to investigate one of the brain-computer interfaces applications called the P300 speller. With the P300 speller, users can convey their thoughts without using any voluntary muscles. In other words, the P300 speller is a communication tool for those who cannot convey their emotions and thoughts by using the conventional methods due to the damage to nerve fibers that are involved in control of voluntary muscles used that might be used in communication tasks.

1.1. What is a Brain Computer Interface ?

In the 1970s, Jacques Vidal applied the term brain-computer interface to describe any computer-based system that obtained information about brain function [68]. Over the past two decades, many researchers have discussed different definitions for brain-computer interfaces. The following list provides some definitions for BCIs:

- The researchers in Wadsworth center have defined the BCI as the following [41]: "The brain-computer interface is a system which takes a biosignal measured from a person and predicts (in real time/on a single-trial basis) some abstract aspect of the person's cognitive state."
- J. J. Vidal [64]: "The BCI system is geared to use both the spontaneous EEG and the specific evoked responses triggered by time-dependent stimulation under various conditions for the purpose of controlling such external apparatus as for example prosthetic devices."
- A.B. Schwartz [60]: "Microelectrodes embedded chronically in the cerebral cortex hold promise for using neural activity to control devices with enough speed and agility to replace natural, animate movements in paralyzed individuals. Known as cortical neural prostheses (CNPs), devices based on this technology are a subset of neural prosthetics, a larger category that includes stimulating, as well as recording, electrodes."

Table 1.1. Overview of current functional brain imaging technologies [50]

Technique	**Physical Property**	**Measurement Mechanism**	**Advantages**	**Disadvantages**
Electro-encephalograph (EEG)	Electrical potential	Electrodes are placed on the scalp in order to measure the weak electrical potentials generated by neural activity in the brain	• Portable, wearable • High temporal resolution	• Low spatial resolution due to noise added when signals move through fluid,bone, and skin • Requires carful placement of electrodes on scalp
Magneto-electrograph (MEG)	Magnetic potential	Measures magnetic fields generated by the electrical activity of the brain	• MEG enables much deeper imaging and is much more sensitive that EEG, since skull is almost completely transparent to magnetic waves	• Bulky and expensive equipment due to necessity for superconductivity
Positron Emission Tomography (PET)	Blood flow	Detects chemical activity of injected radioactive tracers by measuring gamma ray emission		• Bulky and expensive equipment • Unsuitable for sustained use due to need to inject radioactive substances
Single Photo Emission Computed Tomography (SPECT)	Blood flow	Works like PET except that uses photomultiplier tubes to measure photons generated by gamma rays	• Slightly less expensive that PET	• Low temporal resolution and spatial resolution than PET • Bulky and expensive equipment • Unsuitable for sustained use due to need to inject radioactive substances
Functional Magnetic Resonance Imaging (fMRI)	Blood flow	Measures magnetic properties of blood to determine the decrease in deoxyhemoglobin to active brain region	• High spatial resolution ($\sim$ 1mm–1cm)	• Low temporal resolution (5–8 s) because inflow of blood is not an immediate phenomenon • Bulky and expensive equipment due to need for superconducting magnets
Functional Near Infrared (fNIR)	Blood flow, Changes in cortical tissue	Measures the absorption and scattering of near infrared light directed into the brain to determine changes in tissue oxygenation (slow response) as well as changes in neuronal membranes during neuron firing (fast event related response)	• High spatial resolution (<1cm) • Similarity to fMRI allows transfer of knowledge • Portable, wearable • Does not require large amount of expertise to set up • Non-ionizing light safe for extended use	• Low temporal resolution (5-8 s) when using slow response measurements

- J.P. Donoghue[19]: "A major goal of a BMI (brain-machine interface) is to provide a command signal from the cortex. This command serves as a new functional output to control disabled body parts or physical devices, such as computers or robotic limbs."
- J. Wolpaw et al. [70]: "A direct brain-computer interface is a device that provides the brain with a new, non-muscular communication and control channel."

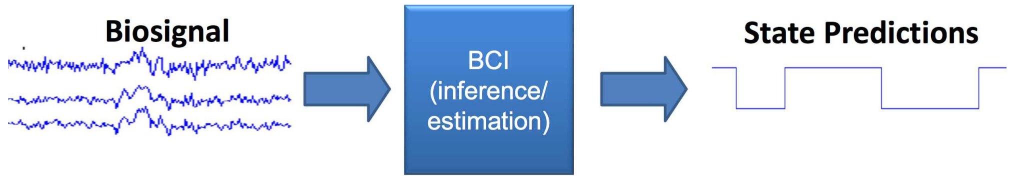


FIGURE 1.1. This figure illustrates the definition of BCI that has been given by the researchers in Wadsworth center [41].

The BCIs can be categorized into three types. The first type is active BCIs, in which the user can control a device by conscious voluntary thought. For example, the user can focus on a control thought such as imagining moving limbs and directly trying to manipulate an application. The other type is reactive BCIs, in which the user utilizes brain processes that happen in response to external events. One application of reactive BCIs is focusing on a flickering light and the BCI analyzes the brain responses to this input. The last type is passive BCIs, where the BCI essentially picks up any brain processes that the brain generates for the purpose of studying the interaction between the human brain and the environment.

1.2. Motivation

Today, incredibly powerful EEG headsets are available on the market. Therefore, the issue of choosing a suitable headset that can be used daily must be considered. Unfortunately, few of them are feasible for daily usage due to the size, price, or difficulty of use. There are many reasons behind choosing Emotiv EPOC+ to be utilized in this research. The first reason is the commercial factor, since the price of the Emotiv EPOC+ headset is $200-400 for a consumer edition and $500 for a research edition, which is reasonable for all users if we compare it with other EEG headsets' prices. Another reason is that it is a wireless headset, which makes it suitable for out-of-lab applications.

The majority of EEG headsets are not easy to be used since they require long setup times and a specific way to place the electrodes in a specific position. However, the Emotiv EPOC+ headset does not require extensive time for setting up and can be successfully utilized by any user after a few sessions of training. Another important aspect behind choosing Emotiv EPOC+ as a recording device in this study is that some EEG headsets require numerous training sessions to achieve high and sufficient accuracies; however, the Emotiv EPOC+ headset necessitates only 3 to 4 training sessions to achieve high accuracy, as it is explained in Chapter 4. All these reasons are motivating to test the performance of P300 speller when the Emotiv EPOC+ device used as an EEG detection headset.

Designing an optimal paradigm for P300 spelling is another objective that motivates us in this study. The researchers have been investigating the effect of different variables such as matrix size, inter-stimulus interval, position of the letters, etc. on the P300 speller performance [3][61][36][38]. In this research, the effect of the matrix size, flash duration, and changing of colors in the P300-BCI have been tested to study their impact on the P300 speller accuracy.

1.3. Research Questions

The primary purpose of this research is to design a successful online brain-computer interface system that can be used by paralyzed people as a communication tool instead of using a conventional communication method. As it is explained previously in Section 1.2, Emotiv EPOC+ headset is chosen to be utilized in this study. This study attempts to answer the following questions:

(1) How does the brain-computer interface (BCI) work?

(2) Does Emotiv EPOC+ have the capability to record P300 waves?

(3) What is the effect of matrix size, inter-stimulus interval, and colors on P300 speller performance?

(4) Can anyone use P300 speller correctly?

(5) How many training sessions are required to achieve the highest online accuracy?

1.4. Overview

The thesis is organized as follows. Chapter 2 presents a background on the brain structure and its function followed by the BCI structure and related works that use the Emotiv headset in different BCI applications. Next, Chapter 3 explains the methodology of this study and how the data are acquired from the participants. Moreover, the design and implementation of the research are discussed in Chapter 3. Chapter 4 discusses the results that have been obtained from five healthy subjects. Finally, the work is concluded in Chapter 5 and the future work is also outlined in this chapter.

CHAPTER 2

Background and Related Work

2.1. Brain Structure and Function

The main organ of the human nervous system is the brain. The brain is divided into three major parts, the forebrain, the midbrain and the hindbrain. The forebrain is the largest part of the brain, most of which is made up of the cerebrum also known as telencephalon and diencephalon. The cerebrum consists of two hemispheres: right and left hemispheres divided by the longitudinal fissure. The left hemisphere controls the limb movements of the right side of the body, while the right hemisphere controls the limb movements of the left side of the body.

As Figure 2.1 illustrates, each hemisphere is composed of frontal, temporal, parietal, and occipital lobes. The frontal lobes are located at the top part of the brain behind the eyes and are responsible for voluntary movements and memory. The parietal lobes come behind the frontal lobes and are responsible for many tasks such as processing the sensory information and language processing. The temporal lobes are located on each side of the brain. Moreover, the temporal lobes have many functions such as production of speech, understanding language, and memory acquisition. The occipital lobes, the smallest lobes in the brain, are located at the back of the head. In addition, the occipital lobes contain the primary visual cortex which is responsible for processing the visual information. The central sulcus separates the frontal lobe from the parietal lobe, and the lateral sulcus separates the temporal lobe from the frontal and parietal lobe. The information is transferred between the right and left hemispheres through a sheet of fibers called the corpus callosum.

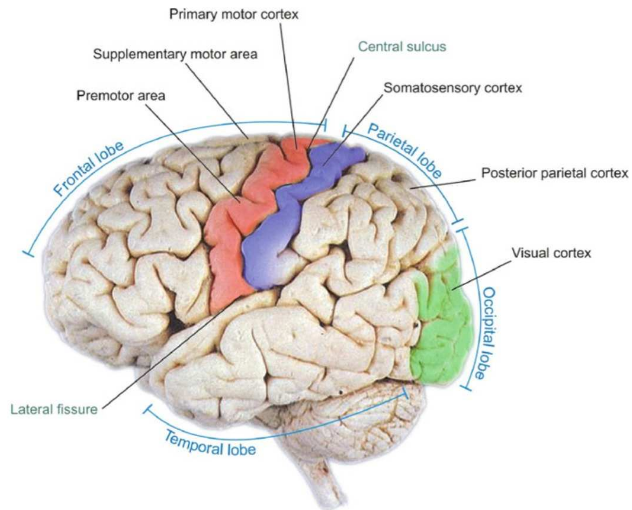


FIGURE 2.1. The cerebrum and its four lobes: frontal, parietal, occipital, and temporal [28].

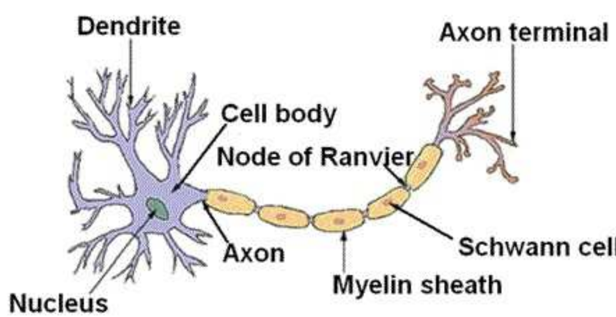


FIGURE 2.2. The main structure of a single neuron cell which involves the cell body, dendrites, and axon [65].

The human brain consists of billions of neurons. The neuron cells of the nervous system can transmit information in the form of electrical or chemical signals along its axon. The neuron cells are classified into three types based on the different functions. The first category is the sensory neuron cells, where they pick up information from the senses and send signals to the neural system. Motor neuron cells are the second type of the neuron cells, where they send out the signals and information from the brain and spinal cord to the rest of the body. The third type of the neurons is interneurons which are located in the central nervous system (CNS). The interneurons connect the central nervous system with the sensory and motor neurons. Figure 2.2 shows the anatomy of a single neuron.

The structure of the neuron cell involves the cell body, the axon, and the dendrites. The cell body controls all the functions of the cell and produces the proteins to the axon and dendrites. The dendrites are responsible for receiving information from other neurons at synapses. The last part of the neuron cell is the axon, which transmits electrical or chemical impulses from the cell body to other neurons.

The EEG waves are the continuous recording of the electrical signals the brain produced by the firing of neurons [71]. When the dendrites of a neuron receive the neurotransmitters from the axon of other neurons, it causes an electrical polarity change inside the neuron. This polarity change is what the EEG is recording. It is the post-synaptic dendritic currents from cortical pyramidal cells. The activity from one single neuron is not big enough to be detected with the EEG device. However, there are so many pyramidal cells parallel to each other. These cells are stimulated at the same time and produce large voltage changes which can be detected outside the head.

2.2. BCI Structure

The brain-computer interface is a communication and control system. Therefore, it has the main structure for any communication and control systems which are: input, output, and processor. The general structure of BCIs is presented in Figure 2.3

A typical BCI system consists of several components. The first component is the signal acquisition, which records neural activity from the brain. The signal acquisition component consists of electrodes, which are placed on the scalp or inside the brain to record the brain signals. The second component of the BCI system is the signal processing, which has three stages. The first stage is the preprocessing, which involves amplification, filtering, and analog to digital (A/D) conversion. The human brain generates very low signals, less than 100 μV, so they need to be amplified to increase the power of the signals. In addition, in this stage, a specific filter can be used to remove the artifacts from the signals without losing any relevant information. The preprocessing step plays a significant role in the BCI systems because it improves the quality of the signals by increasing the signal-to-noise ratio (SNR) and removes the redundancy from the EEG channels.

The second stage in the signal processing is the feature extraction. The brain patterns can be categorized into different features such as amplitudes, frequency bands, and firing rates. Feature extraction methods extract the information from the brain signal either in time domain, frequency domain, or time-frequency domain. Several feature extraction techniques such as self-organizing fuzzy neural networks (SOFNNs) [17], Fourier Transform (FT) [1], continuous/discrete wavelet transform [1], and autoregression models [35] have been employed to construct a reliable BCI system with high speed and accuracy.

Once the signal features have been extracted, they are classified to find out which kind of mental task the subject is performing. Several algorithms have been employed in the BCIs field to classify the EEG signals. These might use linear methods, such as linear discriminant function, or nonlinear methods, such as neural network. The last component of the BCIs is the output device. The output device receives the commands from the previous stages to perform a specific task, for example, controlling a wheelchair or moving a cursor.

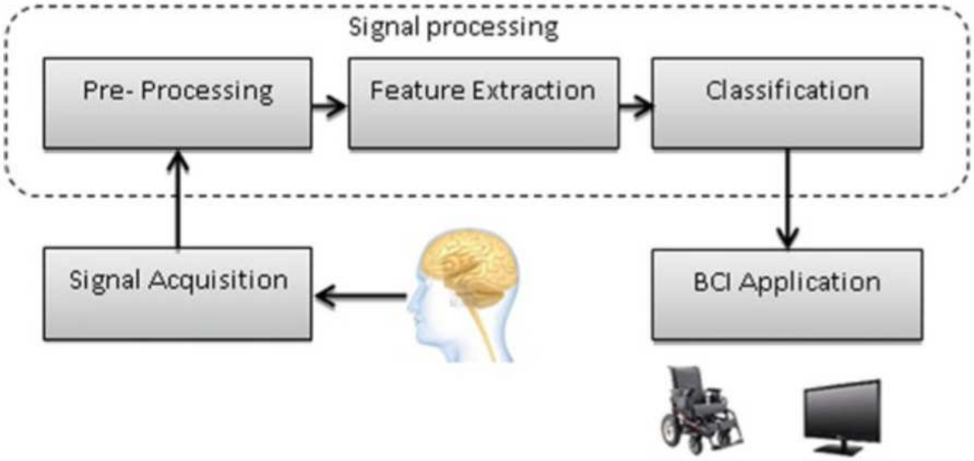


FIGURE 2.3. General structure of the brain-computer interface [32].

2.3. EEG Waves

As it is stated in Section 2.2, the information can be extracted from EEG signals in the frequency domain. The brain waves are categorized according to their frequency bands into five waves as Figure 2.4 shows. These waves are as follows [33]:

- Delta (δ): It lies within the frequency range of 0.5 – 4 Hz. The amplitude of delta wave is the highest comparing with the other brain waves. However, it tends to be the slowest wave. It is usually seen in adults (in frontal lobe) and babies (in posterior lobe). Moreover, it is associated with fatigue, deep sleeping, deep physical relaxation, unconsciousness.
- Theta (θ): Theta wave lies within the frequency range of 4 – 7 Hz. The amplitude of the theta waves are usually greater than 20 μV. Theta waves are associated with attention lapses, memory consolidation, meditation.
- Alpha (α): Alpha waves were discovered by Hans Berger, a German neurologist. It is lies within the frequency range of 8 – 13 Hz and voltage range of 30 – 50 μV. Alpha waves can be generated by all parts of the cortex. It is associated with closing

the eyes and relaxation. In addition, it is recorded from sensorimotor areas in the brain.

- Beta (β): It can be seen on both sides of the brain in a symmetrical distribution. In addition, the frequency of the beta wave is ranged from 13 – 30 Hz and the voltage lies between 5 – 30 μV. The beta wave is associated with active thinking, active attention, and focus on the outside world or solving concrete problems. Moreover, the beta waves usually are divided into $\beta 1$, which is linked to increase in mental abilities, and $\beta 2$, which is linked to alertness.
- Gamma (γ): Gamma wave which lies within the frequency range of > 35 Hz and reflects the mechanism of consciousness. Also, it is shown during short term memory activities. Moreover, it can be obtained by placing the electrodes on the somatosensory cortex.

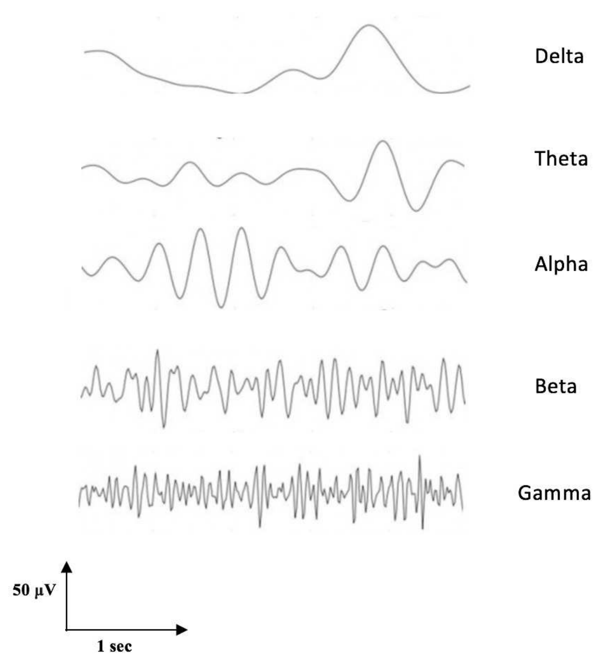


FIGURE 2.4. Five typical dominant brain normal rhythms.

2.4. P300 and P300 Speller

The P300 wave is the most important and studied component of event-related potentials (ERPs). The ERP is the response of the brain for an external stimulus. The P300 waves can be acquired invasively by implanting ECoG electrodes or non-invasively by placing EEG electrodes around the parietal, central, or occipital lobe [9][26]. Most often, P300 waves are recorded from central or parietal lobe. However, for Emotiv headset users, the P300 waves are recorded from the occipital lobe since Emotiv system does not provide central or parietal electrodes [42][12]. And there are by far more P300 studies that use systems other than Emotiv. In this research, O1 and O2 electrodes were found most useful in this study because central and parietal electrodes are not provided by Emotiv system.

The P300 is observed in an EEG as a significant positive peak 300 ms to 500 ms after an infrequent, but expected, stimulus has seen presented to a subject (see Figure 2.6). Figure 2.6 shows the averaged P300 response at electrode Pz , displaying a large positive peak from about 300–500 ms. In 1988, Farwell and Donchin introduced the P300 wave and proposed the P300 matrix speller [23]. Figure 2.5 shows the conventional P300 speller paradigm which is represented by 6x6 matrices of alphanumeric characters (letters of the alphabet and numbers 0–9). These characters are intensified in rows and columns in a random sequence. The user is instructed to focus his/her attention to the desired character he/she wishes to spell. To help the user to be concentrating on the target character, the user has to count mentally each time the row or column containing the target letter flashes. The intersection of the target row and column that have the desired character elicits the P300 signal. The researchers have developed P300-BCIs system other than the visual P300-BCI such as auditory and tactile P300-BCIs [8][14].

One drawback of the P300 waves is the low signal-to-noise ratio (SNR). The P300 wave is influenced by many sources of noise. For instance, the electrical signals produced by the eye movement (EOG signals) or muscle activity (EMG signals) can contribute to the EEG recorded from the scalp [69]. Many methods have been developed to detect the noise and enhance the SNR such as using matched filter or temporal filter. One of the methods used in this study to maximize the SNR is by averaging the signals for many consecutive trials. For that reason, the classification process required many trials to be able to distinguish the target and non-target characters.

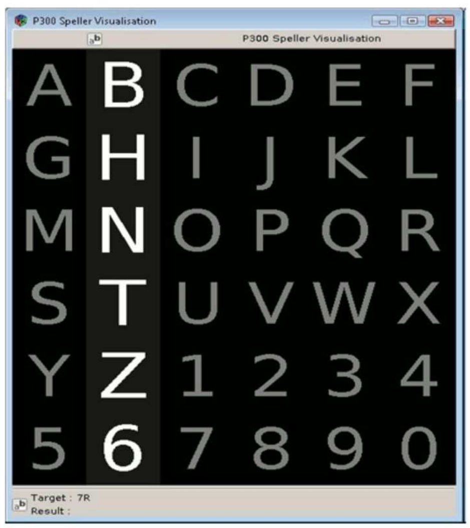


FIGURE 2.5. The conventional P300 speller paradigm that was first established by Farwell and Donchin in 1988 [21].

Various signal processing techniques and machine learning algorithms were developed to increase the reliability of the P300-BCI speller system [44][48]. To classify the target and non-target character, different classification algorithms have been implemented successfully such as Step Wise Linear Discriminant Analysis (SWLDA), Independent Component Analysis (ICA), Support Vector Machine (SVM), etc. In our study, we use OpenViBE platform which provides two different classification algorithms: Linear Discriminant Analysis (LDA) and Support Vector Machines (SVMs).

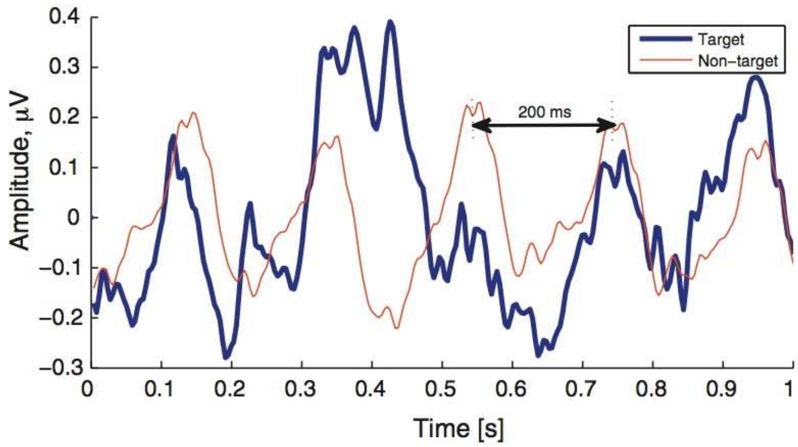


Figure 2.6. Average of 180 target epochs (in blue) and 900 non-target epochs (in red) recorded at channel Pz [53].

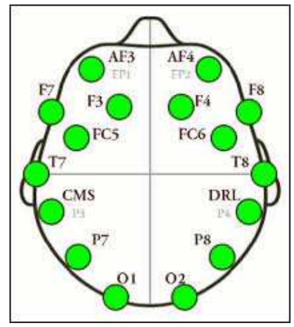
The LDA algorithm is used in this study to distinguish between target and non-target samples due to its simplicity of use and it requires a very low computational time.

2.5. Emotiv EPOC+ Headset

Emotive EPOC+ is a wearable headset used to capture the electroencephalograph (EEG) from the brain and send it wirelessly to a computer via a USB dongle. The Emotiv EPOC+ headset has become popular as a result of its low-cost price and features [5]. Figure 2.7 illustrates the Emotiv EPOC+ headset and its electrode positions. The Emotiv EPOC+ has 14 electrodes (AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1, O2) plus two standard reference electrodes (CMS, DRL) and gyroscope provides information about head movements. The Emotiv EPOC+ connects to the computer wirelessly and has considerable lithium-based battery autonomy of 12 hours. It has two different sampling rates,128 or 256 samples per sec per channel. Also, the Emotiv EPOC+ headset can detect different facial expressions such as blink, wink, furrow, and laugh. Moreover, the Emotiv EPOC+ headset has gyroscope which provides information about head movements.

The EMOTIV Inc. company has released three types of headsets: Emotiv EPOC+, Emotiv EPOC, and Insight. The Emotiv Insight is a five channels portable device allows the user to capture and understand the the brain activity in real-time. With the Emotiv Insight, the user can optimize his/her cognitive performance and monitor mental health and fitness. The Emotiv EPOC+ is the updated model of EPOC headset. Both headsets have 14 channels around the head, plus 2 reference channels in CMS/DRL configuration. The EPOC+ headset has more features than the EPOC headset. The EPOC+ headset has seven more axis inertial motion sensors than EPOC headset and allows additional motion/positional tracking and monitoring. In addition, the EPOC+ headset provides Bluetooth that allows the users to connect the headset to their PC or mobile device in additional to the EPOC dongle. More details can be found in Table 2.1. Comparing to other commercial EEG recording devices available on the market such as Insight, NeuroSky, the Emotiv EPOC headset is the best commercial EEG device in terms of usability according to a comparative study that has been done by Stamps and Hamam [62].

(A) Emotiv EPOC+ Headset.



(B) Electrodes position

FIGURE 2.7. Emotiv EPOC+ headsets and its electrodes location

TABLE 2.1. EPOC+, EPOC, and Insight headsets with their features [16].

Feature	**EPOC+**	**EPOC**	**Insight**
Sensor Count	14+2 references	14+2 references	5+2 references
Frequence Response	0.16 – 43 Hz	0.16 – 43 Hz	0.5 – 43 Hz
Connectivity	Proprietary 2.4GHz wireless, Bluetooth	Proprietary 2.4GHz wireless	Proprietary 2.4GHz wireless, Bluetooth
Resolution	14 bit or 16 bit per channel	14 bit per channel	14 bit or 16 bit per channel
Sensor Technology	Saline soaked felt pads	Saline soaked felt pads	Long life semi-dry polymer
Pricing	$799	$200 - $500	$299

2.6. OpenViBE Software

OpenViBE is an open-source software platform written in C++ for designing and testing BCIs in real-world and in virtual environment. The first version of the OpenViBE was released in 2009. The main purpose of the OpenViBE platform is to design different scenarios for brain-computer interfaces applications such as P300 speller. There are many free open-source software packages that have been utilized in BCI applications, such as BioSig [59], BCI2000 [57], CEBL [29], etc. The OpenViBE software has several features that make it unique among the existing softwares [55]. These features are summarized in the following points:

- The OpenViBE software has different modules, and each module has a particular function. For example, "Acquisition client box" which is used to import the recorded EEG data from the headset and then distribute it into the scenario. Other modules can be used for signal processing and visualization. Connecting these modules in a particular way allows the users to design and implement different scenarios to test a specific BCI application based on their needs.
- Most of the BCI platforms are required to be run by specialists since it requires more knowledge of the brain process or programming skills. On the contrary, the OpenViBE platform is appropriate to be used by different types of users.
- The OpenViBE platform can be run independently from other software and hardware.
- Connection with virtual reality (VR) environment.
- Several predefined scenarios for common BCI applications have been designed in the OpenViBE software such as BCI based on P300, BCI based on SSVEP, and BCI based on motor activity which are ready to be used.

- The OpenViBE software is a free and open-source software and can be operated on Windows and Linux.

2.7. Related Work

The Emotiv headset is designed mainly to allow the user to play video games by merely thinking. Today, much reaserch has utilized the Emotiv headset in different BCI applications [10][49][43]. In addition, much research has been focused on providing the disabled people alternative ways of communication and control just by their thoughts. However, there is limited amount of studies that used Emotiv EPOC headset to record the P300 waves from the brain. In this section, a critical review of the research is presented that has used Emotiv EPOC headset or recorded P300 waves by using other headsets.

Campbell et al., [10] discovered a new way to control a mobile phone without using voluntary muscles. They used Emotiv EPOC headset to acquire P300 waves from the brain. Nine photos of contacts from the address book are displayed on an iPhone and flashed randomly, and the user has to focus his/her attention on the photo of the person to be contacted. After 300 ms, a P300 wave is generated and transmitted wirelessly to the iPhone then the phone number is automatically dialed. To evaluate the system, they tested the wink and think modes in a variety of scenarios (e.g., sitting, walking). In the winking mode, the user generates EEG signals different than P300 signals. The classifier performed well on data collected for sitting-relaxed scenarios (95.58%). While the users achieved accuracy of 92.58% when they were walking. The subjects used the same application when they are in different situations: sitting, sitting with loud background music, and standing up. The data were averaged over a set time interval (20 s, 50 s, 100 s). The results showd that the accuracy increased as the time interval increased.

Similarly, English et al., [22] proposed a new framework named "EyePhone" which can help paralyzed people to control a cell-phone by their eyes. They used the Emotiv headset to detect EOG signals so that the user can control the mobile phone. The researchers conducted experiments in various settings to evaluate the efficacy and efficiency of the developed prototype. The users were able to control mobile phone through eye or facial movements with accuracy between 100% and 93%.

The P300 waves have been used to control an internet browser [47]. Three individuals with ALS and 10 healthy volunteers participated in the study. The user executed different browser functions: navigation (forward, back, reload, and home), data form entry, address bar entry, and scroll up and scroll down. These functional options are presented in a 8x8 matrix in BCI2000. The P300 waves were averaged across 270 trials. In this study, stepwise linear discriminant analysis (SWLDA) was performed to classify the target and non-target samples. The ALS patients achieved an average accuracy of 73% and a subsequent information transfer rate (ITR) of 8.6 bits/minute. The healthy participants achieved over 90% accuracy and an ITR of 14.4 bits/minute.

Münßinger et al. [49], created a new BCI application, P300-Brain Painting, that allows paralyzed people to create expressions which is another way of communication. The signals were acquired from Cz channel and band-pass filtered between 0.1 to 30 Hz. A 6 x 8 matrix contains letters of the German alphabet, numerals 0–9 and some additional punctuation marks was used. In this study, 380 trials were averaged across all subjects for targets and 4560 trials for non-targets. The patients with amyotrophic lateral sclerosis (ALS) achieved accuracy above 89%.

Some comparative studies have been done between Emotiv headset and other EEG headset devices. Duvinage et al., [20] compared the performance of Emotiv headset in a P300 BCI with the performance of a medical device, the ANT system. A 2 x 2 matrix was presented to the user. Each row/column is flashed 12 times per trial. The results showed that the performance of ANT system is better than the performance of Emotiv headset. Nevertheless, the study suggested that the Emotiv headset can be used just for non-critical applications such as communication systems and games due to its lacking of reliability.

Another study [45] compared the performance of extraction event related potentials (ERPs) between Emotiv headset and six traditional EEG disc electrodes. The performance of Emotiv headset is worse than the performance of the six traditional EEG disc electrodes as the study showed. Badcock A. et al., [4] used the Emotiv headset to record auditory ERPs from 21 adults and compared it with Neuroscan EEG system. The P300 response averaged over around 600 stimuli. The results suggested that the Emotiv headset can be utliized as an alternative system to record auditory ERPs.

Zach Cashero [11] did a comparison of three blind source separation (BSS) algorithms: independent component analysis (ICA), maximum noise fraction (MNF), and principal component analysis (PCA). These techniques are useful in extracting the P300 source information from the background noise. The main goal of Zach's work was to compare ICA with MNF and PCA and study the effect of adding temporal information to the original data. Two different datasets were used in the study. Dataset A was recorded using a 64-electrode cap and contains 2550 target trials. Dataset B was recorded using the Biosemi active electrode system and contains 540 target trials. The results showed that using BSS techniques improved the classification accuracy. However, the results showed no difference between the three BSS methods. The results also suggested that adding temporal information to the original data reduces the classification accuracy.

CHAPTER 3

Methodology

3.1. Data Acquisition

The EEG signals were acquired using Emotiv EPOC+ headset from all 14 channels (AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1, O2). The EEG signals were recorded and sent to the OpenViBE software wirelessly via a USB dongle. The EEG signals were sampled at 128 Hz, therefore a sample is taken approximately every 8 ms. Sampling the data at 128 Hz provides enough samples for the frequency ranges of the four frequency bands, which contain the valuable ERPs information, (Nyquist rate = 128/2 = 64 Hz) [40][51][39]. The user was seated in front of a computer screen. A 6x6 or 3x3 matrix size was presented to the user during the experiment. The user was instructed to focus his/her attention to the letter they wished to spell. In addition, the user was asked to relax and avoid unnecessary movements.

The Emotiv EPOC+ headset was prepared before placing the electrodes on the user's head. One of the advantages of the Emotiv EPOC+ headset is that the preparation time is much less than other EEG headsets. It takes about 2 – 3 minutes comparing with other EEG headsets which required more than 10 minutes for preparation step. A few drops of saline liquid were applied to wet the sensors and reduce the electrodes impedance. It is important to check the contact quality before starting the acquisition step. To check the quality of the sensors connection, we run a software called the Emotiv Xavier SDK. The Emotiv Xavier SDK panel has many functions one of which is to provide feedback to the user about the contact quality for each sensor on the Emotiv headset. The Emotiv Inc. company suggests some steps to improve the contact quality when problems are detected.

To improve the contact quality, the headset should be fully charged. The Lithium battery can be fully recharged in approximately 4 hours. In addition, more drops of saline solution should be added on each felt. Moreover, we have to make sure that the sensors are fitted properly and they are in contact with the head.

3.2. Participants

Five healthy subjects, four males and one female, aged 25–32, participated in the study. All subjects' native language was Arabic, and they were familiar with the alphanumerical displayed during the experiment. None of the subjects had previous BCI experience before or had a history of neurological diseases such as ALS or spinal cord injury. All participants gave informed consent prior the experiment (see Appendix).

3.3. Linear Discriminant Analysis (LDA) Algorithm

Classification is a kind of supervised learning, using training data with known input vectors as well as corresponding target vectors. The goal in classification is to take an input vector x and assign it to one of K discrete classes, C_k, where $k = 1, 2, ..., K$ [6]. In our case, we have two classes (k=2): target and non-target. In 1936, R. A. Fisher developed the linear discriminant analysis (LDA). The LDA is a classification method used in machine learning to find a linear combination of features that separate two or more classes of objects [66]. In addition, the LDA has been widely applied in different BCI applications and achieved high classification performance [7][58][27].

Assume we have the following linear discriminant function:

$$y(x) = w^T x + w_0 \tag{1}$$

where w is called a weight vector, x is an input vector, and w_0 is a bias. If $y(x) \geq 0$, the input vector x is assigned to class C_1 and to C_2 otherwise. Figure 3.1 illustrates the geometry of a linear discriminant function in two dimensions.

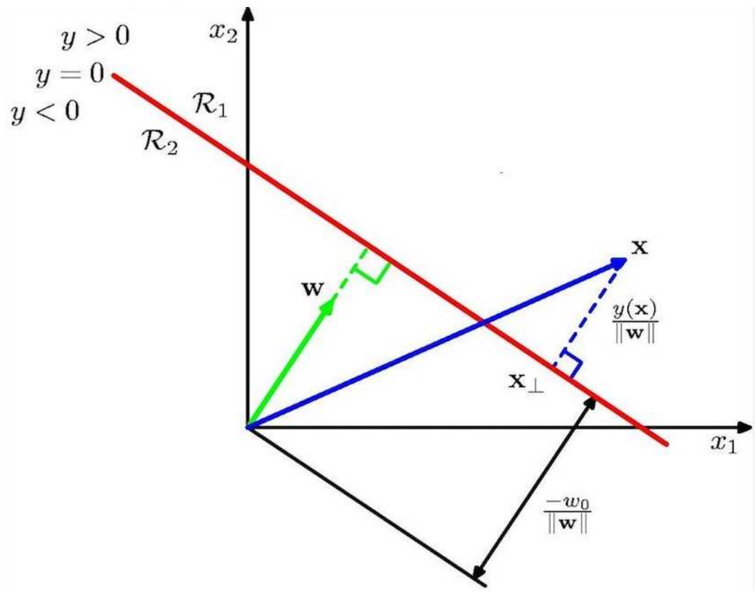


FIGURE 3.1. Illustration of the geometry of a linear discriminant function in 2-D [6].

The decision boundary is defined by the relation $y(x) = 0$. If x is a point on the decision surface, the normal distance from the origin to the decision surface is given by:

$$\frac{w^T x}{\|w\|} = -\frac{w_0}{\|w\|} \tag{2}$$

We can see from the previous equation that w_0 determines the location of the decision surface.

3.4. OpenViBE Scenarios

Three different OpenVibe scenarios are used in this study. Each scenario contains different modules with unique functionality for each module. These scenarios are as follow:

- P300 speller acquisition scenario.
- Training LDA classifier scenario.
- Online scenario.

Before running the scenarios, we first connect the Emotiv EPOC+ with OpenViBE platform through the acquisition server which forwards the recorded EEG signals to OpenViBE scenarios. Once the Emotiv EPOC+ connected with OpenViBE platform, the first scenario can be implemented. The first scenario "P300 speller acquisition" is used as a first step to collect some training data. These data will later be used to train a spatial filter and LDA classifier for the online scenario. Figure 3.2 shows the "P300 speller acquisition" scenario and its modules. At the beginning of this scenario, the "a" key on the keyboard has to be pressed to start the data collection and to generate and send a specific stimulation to the P300 speller stimulator module telling it to start the flash sequence. The recorded EEG signals are received by the acquisition client module from the Emotiv EPOC+ headset. Then, the acquisition client module forwards the EEG signals to the other modules in the scenario.

A 6x6 matrix or 3x3 matrix (depending on the condition) is presented to the user and the target character is highlighted by a blue color so the user knows which character he/she should focus on. Once the "a" key has been pressed, a specific stream of stimulation is sent to the P300 speller stimulator module to start the generation process. Through this module, we can adjust the intensification configurations used for the P300 speller. For example, the number of rows, columns, repetitions, and trials can be set up using P300 speller module. In our study, the number of trials and repetitions are fixed at 12 and 10, respectively. However, the number of rows and columns are changed to create different matrix size in order to investigate the impact of different matrix sizes on the P300 speller performance.

The flash duration is another factor that has been studied in many research. In our study, the flash duration is selected to be 100 ms and 175 ms. The 'Target Letter Generation' module receives stimulations from the P300 speller stimulator module and generates random target letters according to a Lua script file. The 'Identity' module is used for connection purposes. The P300 speller visualization module receives sequence stimulations from the

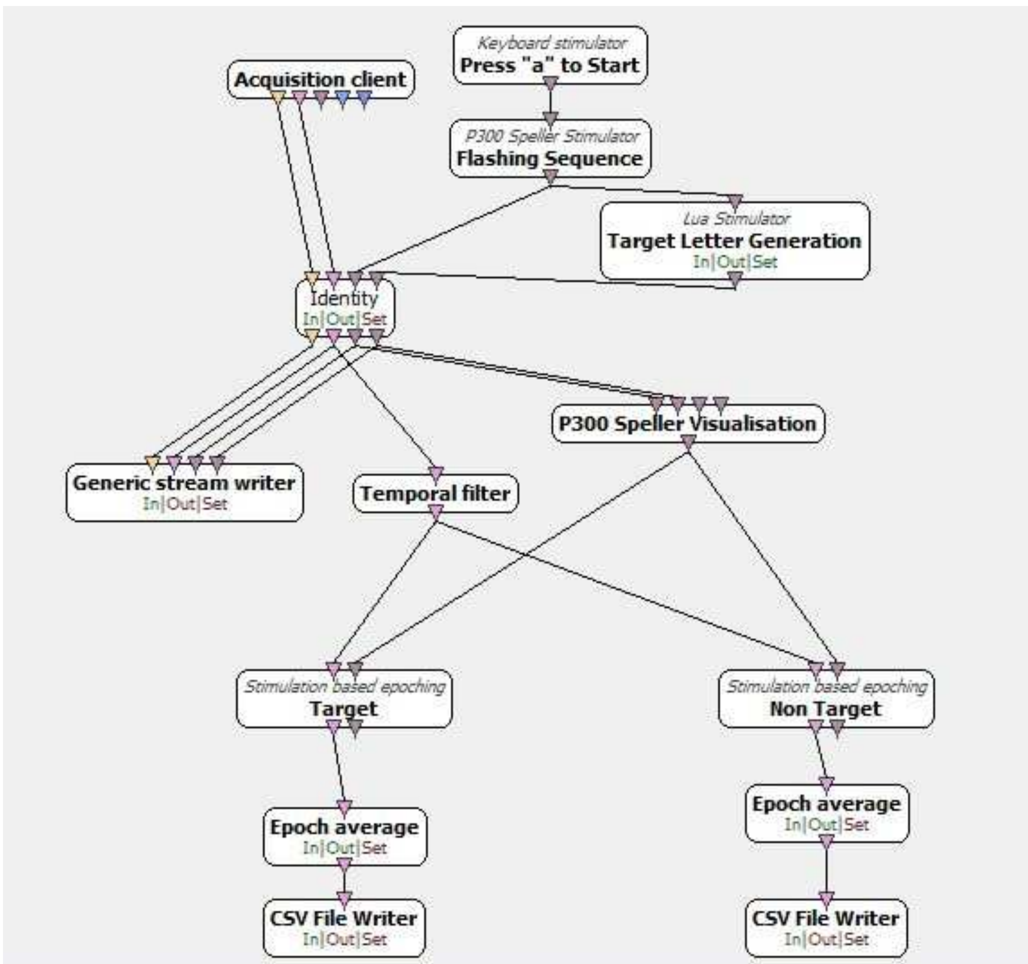


FIGURE 3.2. P300 speller acquisition scenario.

P300 speller stimulator module and target stimulations from Lua stimulator module. Also, it visualizes the P300 matrix which has letters (A-Z) and numbers (0-9). The rows and columns are intensified sequentially based on the sequence and target stimulations received by the module. All the EEG data then are saved in .ov file by "Generic stream writer" so they can be used in the next scenarios.

Once the EEG signals have been received by the 'Acquisition client' module, they are passed to 'Temporal filter' box for filtering. The EEG signals passed to a Butterworth bandpass filter of fourth order and the low cut frequency equal to 0.1 Hz and the high cut frequency equal to 30 Hz because it content EEG data as Section 2.3 describes . After that, the filtered signals are sent to two different 'Stimulation based epoching' modules, one is for the target characters and the other one is for the non-target characters. This module selects part of the EEG signal at a certain event. Here, there are two events: target and non-target. When the row or column that contains target character is intensified, this box starts to save the signal for 600 ms since the P300 wave occurs about 300 ms after the flashing of the desired character, and the same procedure is done for the non-target characters. To increase the SNR, the EEG signals are averaged over time. The 'Epoch average' module is used to average the target and non-target signals and then send it to the 'CSV file writer' module to save the averaged signals. Then, we use MATLAB to read the signals from the 'CSV file writer' module and visualize the target and non-targets waves, as in Section 4.1.

In this research, the linear discriminant analysis (LDA) classifier is employed to classify the target samples from the non-target samples. Figure 3.3 shows the LDA classifier training scenario. The same steps are followed at the beginning of this scenario. The EEG data are read by the 'Generic stream reader' module the sent to the 'Temporal filter' module. Next, the 'P300 Speller Visualization' box sends target/non-target flagging to the 'Stimulation based epoching' modules for target and non-target selection. Each time the row or column that contains the target character is intensified, the target selection box stores 600 ms of

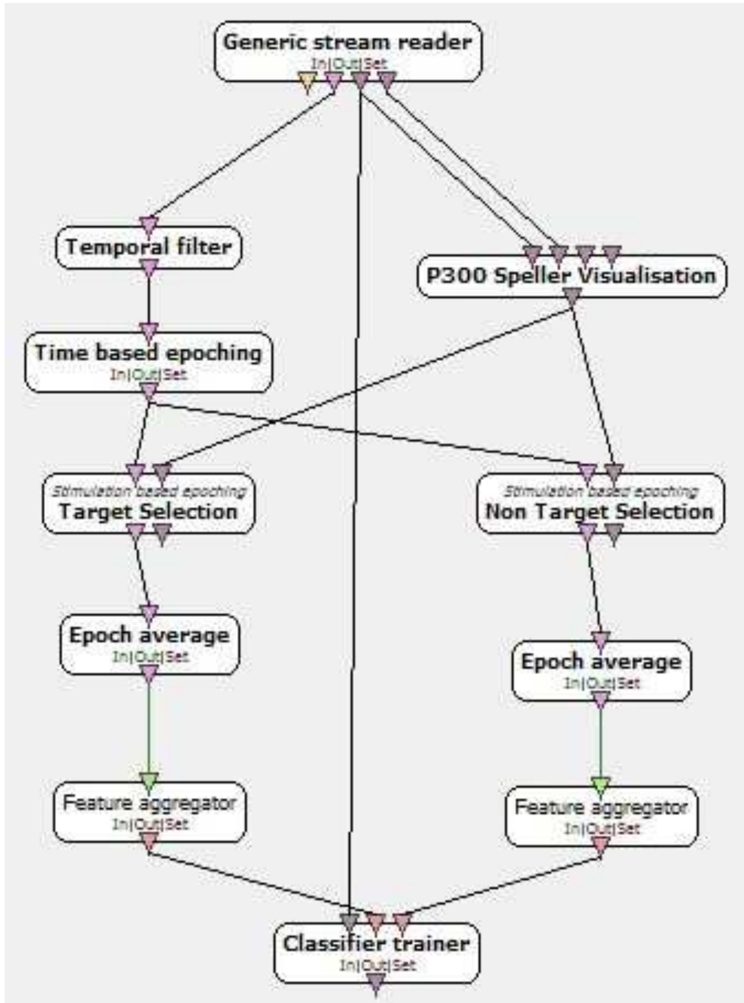


FIGURE 3.3. Training the LDA classifier scenario.

the EEG signals at this event. On the other hand, the non-target selection box stores the signals all the time except when the row or column that has the desired letter is flashed.

The averaging step comes next to increase the signal-to-noise ratio. The averaging type used here is epoch block average which receives streamed matrix and averages across time. In this study, we used 10 trials for both 6 x 6 and 3 x 3 matrix. In the 6 x 6 matrix, each row and column is flashed 12 times per trial. Therefore, this box receives 240 target epochs and 1200 non-target epochs. In the 3 x 3 matrix, epoch block average box receives 240 target epochs and 480 non-target epochs. The averaged signals then are sent to the 'Feature aggregator' module. This module recieves a stream of matrices containing features and aggregates them to feature vectors to be used for classification. In other words, it takes a signal in the form of a matrix, then produces corresponding vectors that can be utilized by the Classifier/Trainer boxes.

After that, the feature vectors are sent to the 'Classifier trainer' module which is used to train the LDA classifier. In this step, the module performs classifier training with k-fold cross validation which gives an estimation of the classifier accuracy. The idea of the k-fold test is to split the data into training and testing sets then the classification algorithm is trained on the training sets and then we evaluate the algorithm on the testing sets. The testing is repeated k times (we selected k=20 in this study), and then the accuracies are averaged over the different partitions. The accuracy here gives a good prediction of how the classification algorithm will work on the online performance.

Figure 3.4 shows the last scenario implemented is the online scenario. There are 12 paths for the 6x6 matrix (9 paths for the 3x3 matrix) in this scenario. Each path is responsible for a row or a column processing. Each column/row has its specific P300 detection pipeline. The pipeline consists of several boxes. First, the 'Simulation based epoching' box receives the filtered EEG signals and selects a segment of a signal start when for a specific row or column contains desired character is flashed. Then each 'Stimulation based epoching' box sends epoched signals to the 'Epoch average' box to average them to enhance the P300 signals. After that, the averaged signals are converted to feature vectors and sent to the 'Classifier processor' box. The 'Classifier processor' box chooses whether the selected signal is a target or non-target signal. Finally, the 'Voting Classifier' box chooses which of the candidate column or row has the P300 signal and sends the result to the 'P300 speller visualization' module to display the result for the user. If the results are not good enough, the EEG data recorded in this scenario are sent to the second scenario to train the LDA classifier again.

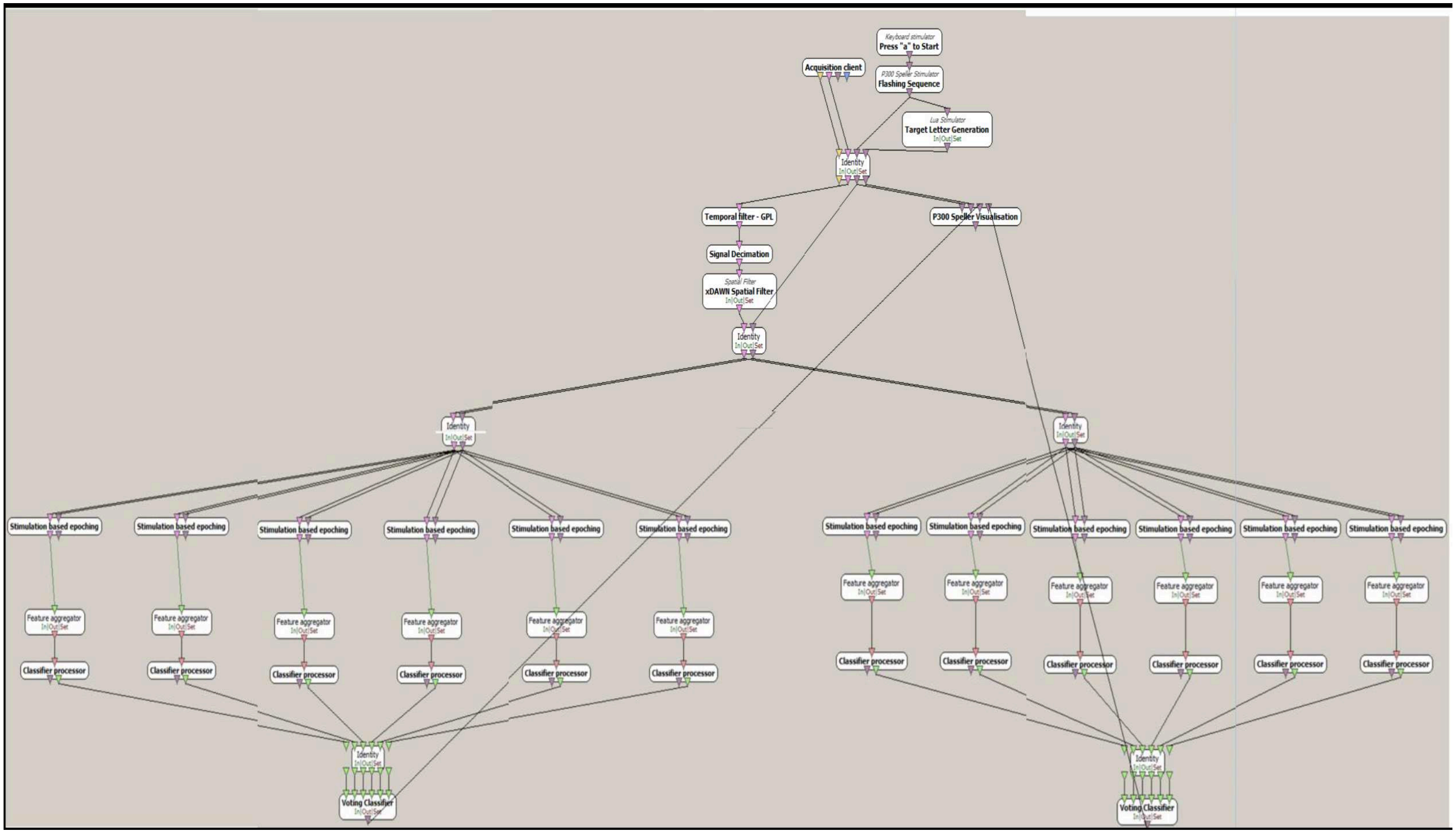


FIGURE 3.4. Online scenario .

CHAPTER 4

Results and Discussion

4.1. The Capability of Emotiv EPOC+ headset for Detecting P300 Wave

The first goal of this research is to evaluate the capability of Emotiv EPOC+ headset to detect P300 waves. Figures 4.1 and 4.2 show the recorded responses of the subjects (S1, S2, S3, S4, S5) to the visual stimulation during the experiment. Four different experimental conditions are tested in this study as follow:

- 6x6 matrix size with flash duration 100ms
- 6x6 matrix size with flash duration 175ms
- 3x3 matrix size with flash duration 100ms
- 3x3 matrix size with flash duration 175ms

Figures 4.1 and 4.2 illustrate the participants' responses from all 14 channels when a 6x6 matrix size is presented with flash duration 100 ms. The other conditions above were applied, and participants' responses were recorded and showed approximately the same results.

Before explaining Figures 4.1 and 4.2, it is important to understand the difference between the two subcomponents of P300 which are P3a and P3b. These ERPs can be distinguished according to the task that elicits them, the amplitude size (P3b is greater that P3a), and the lobe location that generates the signal [54]. The P3a is generated from the frontal-central areas of the brain with latency between 150 ms to 300 ms. While the P3b wave is generated from the parietal-occipital areas with latency between 250 ms to 600 ms. Accordingly, four channels out of 14 channels of the Emotiv EPOC+ headset are believed to be the best channels to use of those that are available on the Emotiv system : P7, P8, O1, and O2. Further analysis has been done in this research to investigate the most active channels during acquiring P300 signal to reduce the number of channels used to capture P300 signal. The results in Section 4.2 show that O1 and O2 are the most active channels. Hence, our focus in this research is on these two channels.

Figures 4.1 and 4.2 below are clear evidence that prove the capability of Emotiv EPOC+ headset to detect the P300 signal. Figures 4.1 and 4.2 show two different waves: target (in blue) and non-target (in red). The target waves are the averaged signals elicited by visual target stimulus, while the non-target waves represent the averaged signals that elicited by the other visual stimulus during the experiment. It can be seen from Figures 4.1 and 4.2 that the target waves (in blue) are remarkably distinguishable from the non-target wave (in red) for most subjects. Moreover, because each human has a unique brain structure, the response of the subject to the visual stimuli is different from one to another.

It can be noticed from Figures 4.1 and 4.2 that the response of each participant is different from channel to another. Clearly, participant #2 respond weakly to the visual stimulus, where the amplitude signal generated from O1 channel is 1.76 μV and the latency is 390 ms. However, the amplitude signal generated from O2 channel is 1 μV and the latency is 429.7 ms. In contrast, the response of participant #5 to the visual stimulus was the strongest respond compared to other participants from both channels (O1 and O2), where the amplitude signals are 4.01 μV and 4.91 μV,for O1 and O2 channels respectively. The amplitude of the P300 signal (especially the amplitude of the target wave) reflects how the participant responds to the target and non-target visual stimulation and determines whether the participant can use a P300-based BCI or not. In other words, if the user produces a higher amplitude of the target signals, then the classifier can detect the target character which the user is intended to spell. According to [2], 10% of the users do not produce a distinguishable amplitude peak between target and non-target waves; therefore, they are not able to use the P300-based BCI even if they increase the number of training sessions or use more advanced signal processing methods.

Several studies have investigated the effect of the subject factors (age, gender, etc.) as well as different stimulus characteristics on the P300 amplitude. For instance, it has been reported that longer inter-stimulus interval (ISIs) decreases the P300 amplitude and classification accuracy for disabled users [34]. The same study showed that healthy subjects produced higher amplitude at the P300 peak than disabled subjects (around 2 μV for the healthy subjects and 1.5 μV for the disabled subjects). The current study examines the effect of matrix size, flash duration, and colors on the P300 speller performance.

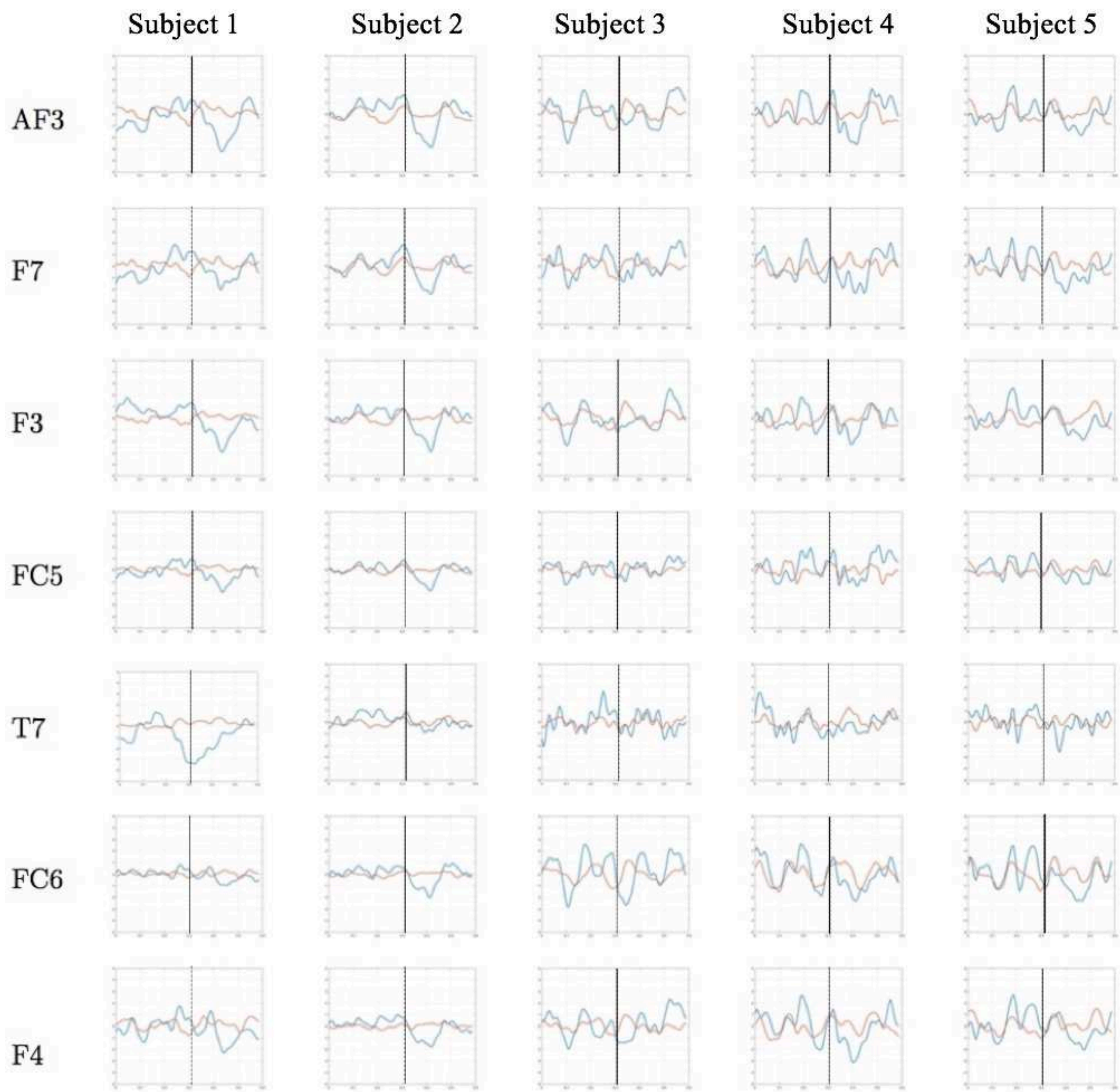


FIGURE 4.1. EEG amplitude versus time at AF3, F7, F3, FC5, T7, FC6, and F4 average over 240 trials for target letters and 1200 trials for nontarget letters. Each plot is for 6 x 6 matrix and 100 ms flash duration. For each plot, x-axis represents time (ms) and y-axis represents amplitude (μV). The time length in each plot is 600 ms. The vertical line represents the time at 300 ms

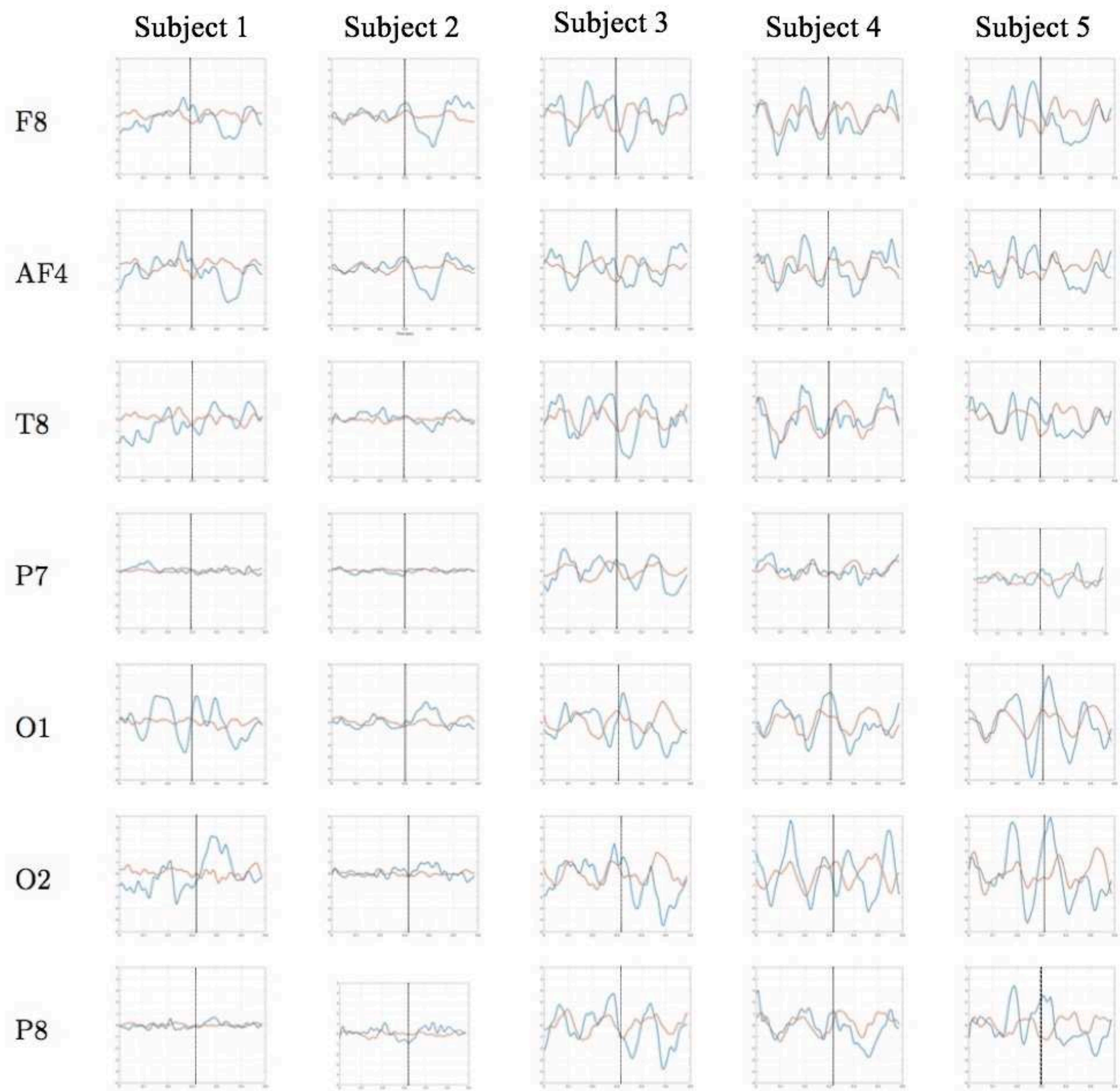


FIGURE 4.2. EEG amplitude versus time at F8, AF4, T8, P7, O1, O2, and P8 average over 240 trials for target letters and 1200 trials for nontarget letters. Each plot is for 6 x 6 matrix and 100 ms flash duration. For each plot, x-axis represents time (ms) and y-axis represents amplitude (μV). The time length in each plot is 600 ms. The vertical line represents the time at 300 ms

4.2. The Most Active Channels for P300 Wave Detection

As illustrated in Figure 2.11, the Emotiv headset has 14 channels distributed over the scalp. One of the aims of this research is to reduce the number of channels employed in the study and use only the most effective channels. Some studies have been shown that using a large number of channels to acquire the brain signals is a way to increase the P300 speller accuracy [15]. However, utilizing a large number of channels increases the system cost and setup time. Further analysis has been done by using EEGLab toolbox, which is an open source Matlab toolbox for processing EEG signals and other biosignals such as MEG and ECG, and the result is shown in Figure 4.3.

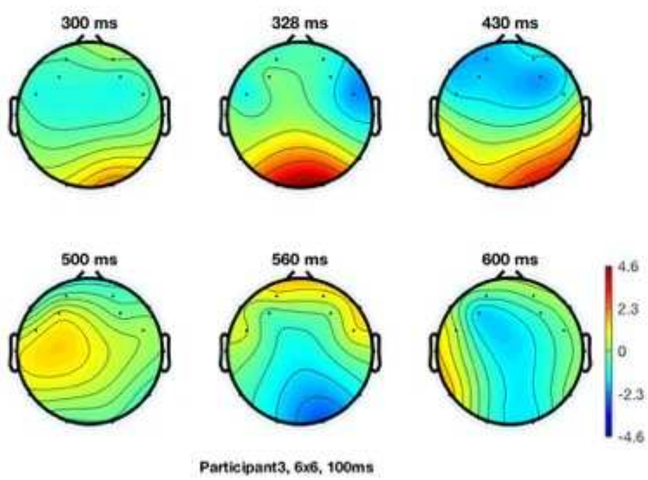


Figure 4.3. The distribution of the event-related potentials (ERPs) over the scalp of participant #1 at different time after a target visual stimulation.

Figure 4.3 shows the topographic distribution of average potential at the specified latencies (300 ms, 328 ms, 430 ms, 500 ms, 560 ms, 600 ms). As it can be seen in Figure 4.3, the most active channels (in red) are located on the back of the brain, which are O1 and O2 channels. In other words, O1 and O2 channels contain the strongest amplitude EEG of those provided by Emotiv, even though central and parietal are usually found to have the strongest P300s. This result was expected before analyzing the distribution of ERPs over the scalp since these two channels are located on the visual cortex, which its function is to receive visual information from retina and process them.

Tong J. et al. [37], designed a portable dialing system and they used Emotiv headset to record P300 signals. In their study, they computed the averaged r-squared (coefficient of determination) values for all participants, which gives the proportion of the variance in the dependent variable that is predictable from the independent variable. The results then were plotted as in Figure 4.4. The red area in Figure 4.4 represents the activated area of the brain after a P300 visual stimulation, which are O1 and O2 channels.

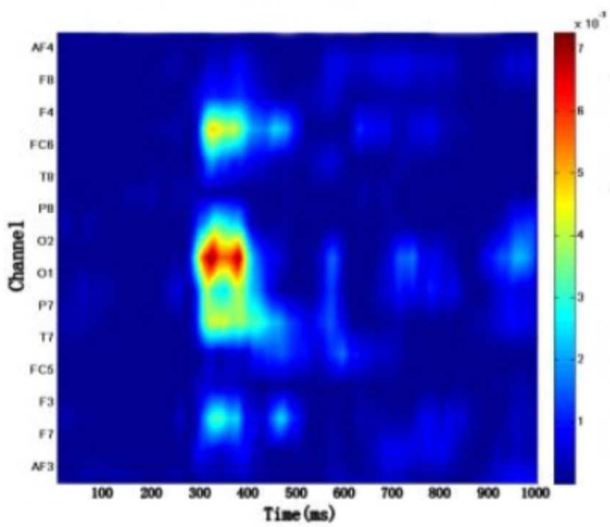


FIGURE 4.4. The averaged r-squared values plot for all participates [37]

4.3. THE EFFECTS OF MATRIX SIZE ON THE P300 SPELLER PERFORMANCE

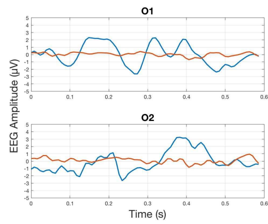
There are many variables and parameters that have to be considered when designing an effective and accurate P300-BCI system, one of them is the matrix size. As it is stated in Section 2.4, the P300-BCI system presents the user a matrix containing characters (letters and symbols) and the user has to pay attention to the character he/she wants to spell. Each row and column is flashed in a random sequence. The intersection of the row and column containing the desired character (the target) is elicited P300 wave. Many studies have investigated the effect of the matrix size on the P300 performance and improved the matrix size to get an optimal size that makes the user communicate more effectively. Our goal in this research is to study the impact of using different matrix size (6x6 and 3x3) on the P300 amplitude and the online and offline accuracies.

Previous studies have shown that there is a proportionality relationship between the matrix size and the P300 amplitude. In other words, when the probability of the occurrence of the desired character (the target) decreases, the P300 amplitude increases, and vice versa. In a 6x6 matrix, the probability of the occurrence of the target character is 5.56% in each trial (we have 36 characters and each character is flashed 2 times/trial, one for row and one for column. The target character is flashed 2 times/trial, so the probability of the occurrence of the target character is $2/36 = 5.56\%$). In 3x3 matrix, the probability of the occurrence of the target character is greater. There are 9 characters, and each character is flashed 2 times/trial, so the probability of the occurrence of the target character is $2/9 = 22.22\%$.

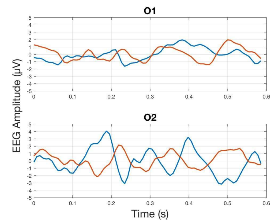
Table 4.1 and Figure 4.5 present the P300 amplitude obtained from O1 and O2 channels for all the participants where the flash duration is 100 ms. The EEG amplitudes at O1 and O2 averaged over 240 target letter trials and 1200 non-target trials for 6x6 matrix size, and averaged over 240 target letter trials and 480 non-target trials for 3x3 matrix size. It can be seen that the P300 amplitudes are larger for 6x6 matrix for all the participants. These findings are similar to other results from different studies. Brendan Z. et al. [3], did an experiment to assess the effect of three different matrix size (4x4, 8x8, and 12x12) on the P300 speller performance. The results showed that larger matrix size produced larger P300 amplitude. In another study [61], the researchers tested two different matrix size (3x3 and

6x6). They found that the P300 amplitude was greater for the 6x6 matrix and the accuracy increased when the matrix size increased.

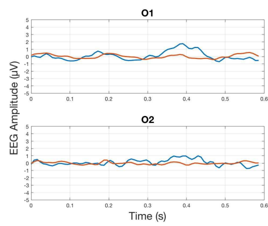
Figure 4.6 and Figure 4.7 show the averaged offline and online accuracies for all participants across six sessions when 6x6 and 3x3 matrix size presented and the flash duration is 100 ms. The offline accuracy is an offline testing to predict the performance of the LDA classifier (k-fold). The online accuracy is the number of correctly spelled characters divided by the total number of characters spelled (10 letters in our study). We can see that the matrix size has no significant effect on the offline accuracy. In contrast, the effect of the matrix size on the online accuracy is very clear. The performance of all participants is increased when a 6x6 matrix is presented to them except for participant #2. Participant #2 reached an averaged online accuracy of 45% when using a 6x6 matrix and 50% when using 3x3 matrix and this result was not surprising since participant #2 was suffering from extreme fatigue during using 3x3 matrix size, as he reported. For the 6x6 matrix version, participants #1,#2, and #5 were able to control the speller with 90% accuracy after four training sessions. Participant #4 was able to spell 6 letters correctly out of 10 after three training sessions. The lowest performance was obtained by participant #3 where he could spell 5 letters after five training sessions.



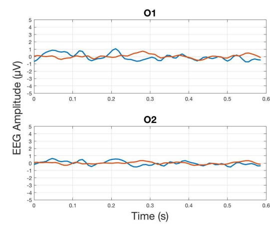
(A) Participant 1, 6x6



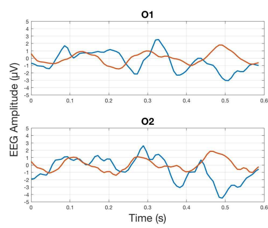
(B) Participant 1, 3x3



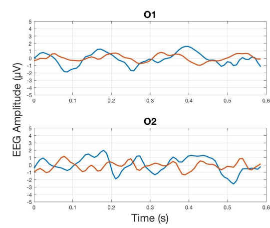
(C) Participant 2, 6x6



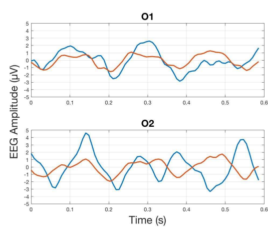
(D) Participant 2, 3x3



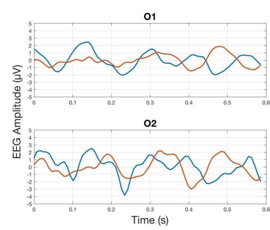
(E) Participant 3, 6x6



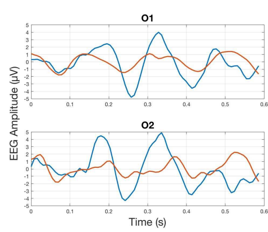
(F) Participant 3, 3x3



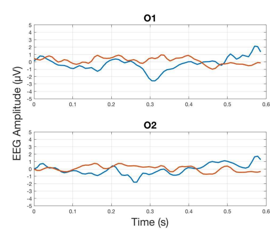
(G) Participant 4, 6x6



(H) Participant 4, 3x3



(I) Participant 5, 6x6



(J) Participant 5, 3x3

FIGURE 4.5. EEG amplitudes at O1 and O2 averaged over 240 target letter trials (in blue) and 1200 non-target trials (in red) for 6x6 and averaged over 240 target letter trials and 480 non-target trials for 3x3 matrix sizes. The flash duration is 100 ms.

Table 4.1. EEG amplitudes at O1 and O2 averaged over 240 target letter trials and 1200 non-target trials for 6x6 and averaged over 240 target letter trials and 480 non-target trials for 3x3 matrix sizes. The flash duration is 100 ms.

Participants	O1 channel amplitude(μV)		O2 channel amplitude (μV)	
	6 x 6	**3 x3**	**6 x 6**	**3 x 3**
1	2.28	1.96	3.25	3.23
2	1.76	0.35	1.0	0.35
3	2.54	1.60	1.85	1.31
4	2.60	1.54	3.74	1.63
5	4.01	2.13	4.91	1.72

The performance of the participants was lower for 3x3 matrix size. Participants #1 and #2 reached an accuracy of 70% and 80%, respectively, after 4 training sessions. Participant #4 could not spell any letter in session #5 and the highest accuracy was 20% after 3 training sessions. Participant #1 reached 50% after just one training session.

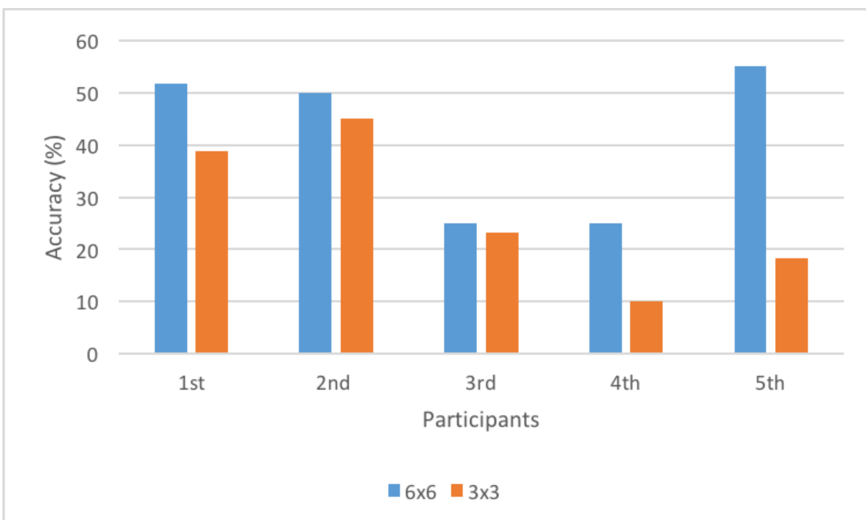


Figure 4.6. The average online accuracy for all participants for matrix sizes 6x6 and 3x3 with flash duration of 100 ms.

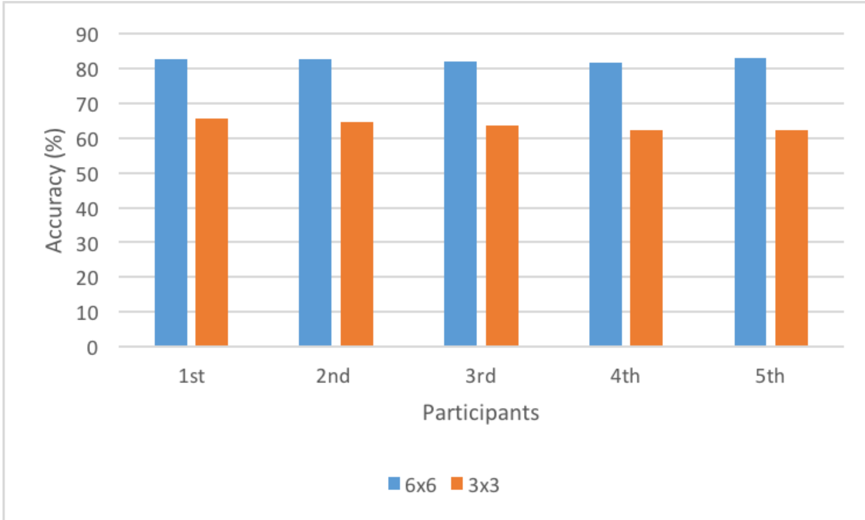


FIGURE 4.7. The average offline accuracy for all participants for matrix sizes 6x6 and 3x3 with flash duration of 100 ms.

4.4. The effect of flash duration on the P300 speller performance

The effect of the flash duration was studied in this research. One of the factors that have been investigated and tested its affect on P300 speller performance is the inter-stimulus interval (ISI). The inter-stimulus interval (ISI) starts from the onset of the flash of one row or column to the onset of the flash of the next row or column [23].

The ISI has two parts: flash duration and no flash duration of the row and column. The flash duration was manipulated in this study (either 100 ms or 175 ms) while the no flash duration was fixed at 175 ms. This manipulation was done through P300 speller stimulator box in OpenViBE. Participants #3 and #4 were invited to undertake more training sessions (six sessions where the matrix size is 6x6 and flash duration is 175 ms and six sessions where the matrix size is 3x3 and flash duration is 175). Tables 4.2 and 4.3 and Figures 4.8 and 4.9 show the results.

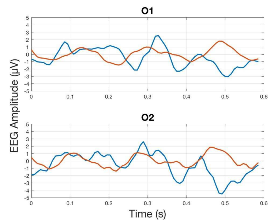
Tables 4.2 and 4.3 present the amplitudes of the averaged EEG amplitudes at O1 and O2 for participants #3 and #4 at different flash duration (100 ms and 175 ms). As it can be seen, the P300 amplitudes are increased with longer ISI for both versions of the matrix size (except the amplitude obtained from O1 channel for participant #4 in 6x6 matrix). Lawrence et al. [23] reported that longer ISI produces larger P300 amplitude. Moreover, six adults participated in a study examining the effect of the stimulus rate (target to target interval) [46]. Four different ISI were tested (31.25 ms, 62.5 ms, 125 ms, and 250 ms). The results showed that the P300 amplitude is increased with larger ISI.

TABLE 4.2. A comparison of using different flash duration (100 ms, 175 ms) on the EEG amplitudes for participants #3 and #4. The EEG amplitudes at O1 and O2 averaged over 240 target letter trials and 1200 non-target trials. The matrix size is **6x6**.

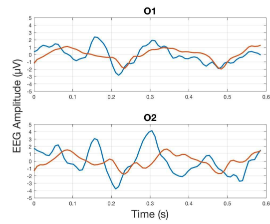
Participants	O1 channel amplitude(μV)		O2 channel amplitude (μV)	
	100 ms	**175 ms**	**100 ms**	**175 ms**
3	2.54	2.93	1.85	3.41
4	2.60	1.94	3.74	4.16

TABLE 4.3. A comparison of using different flash duration (100 ms, 175 ms) on the EEG amplitudes for participants #3 and #4. The EEG amplitudes at O1 and O2 averaged over 240 target letter trials and 480 non-target trials. The matrix size is **3x3**.

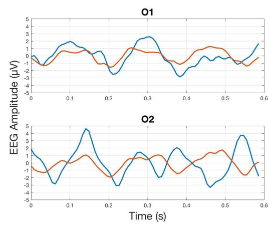
Participants	O1 channel amplitude(μV)		O2 channel amplitude (μV)	
	100 ms	**175 ms**	**100 ms**	**175 ms**
3	1.60	2.48	1.31	3.33
4	1.54	1.56	1.63	3.62



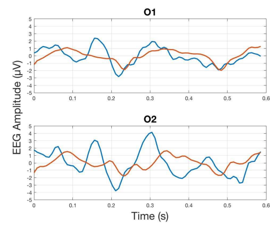
(A) Participant #3, 100 ms duration



(B) Participant #3, 175 ms duration

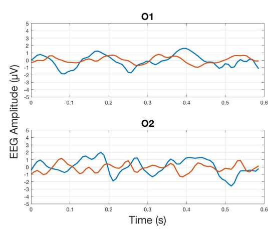


(C) Participant #4, 100 ms duration

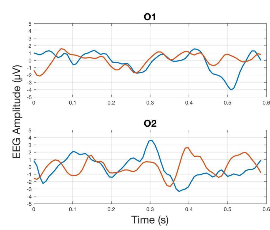


(D) Participant #4, 175 ms duration

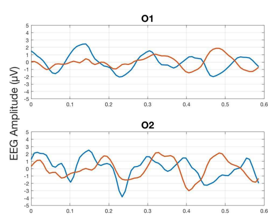
FIGURE 4.8. EEG amplitudes at O1 and O2 averaged over 240 target letter trials and 1200 non-target letter trials for 6x6 matrix size and different flash durations (100 ms and 175 ms).



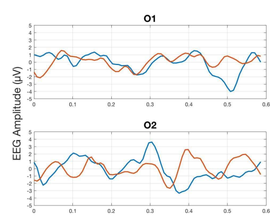
(A) Participant #3, 100 ms duration



(B) Participant #3, 175 ms duration



(C) Participant #4, 100 ms duration



(D) Participant #4, 175 ms duration

FIGURE 4.9. EEG amplitudes at O1 and O2 averaged over 240 target letter trials and 1200 non-target letter trials for 3x3 matrix size and different flash durations (100 ms and 175 ms).

Figure 4.10 shows the average offline and online accuracies for both participants #3 and #4. The results show that the ISI does impact the performance of the participants. In both participants, the online performance was better for shorter ISI (A,C). In other words, the online accuracy increased as ISI decreased. For 100 ms flash duration, participant#3 reached an average accuracy of 23.33 %, but this accuracy dropped to 16.67 % with 175 ms flash duration. Participant #4 as well has better performance with 100 ms flash duration (accuracy of 25%) than 175 ms flash duration (accuracy of 23.33 %). These results are similar to the results in [46][61]. Figure 4.10 shows that the ISI has no significant impact on the

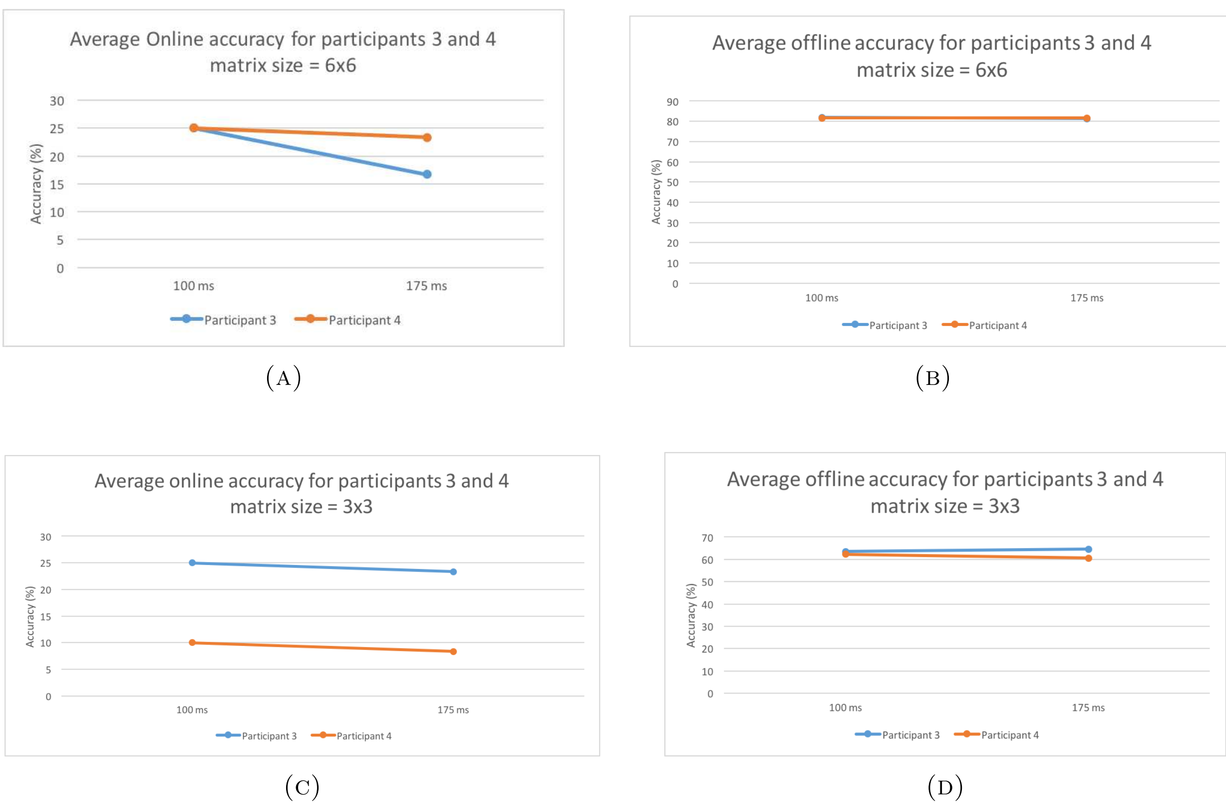


FIGURE 4.10. This figure illustrates the average online and offline accuracies for participants #3 and #4.

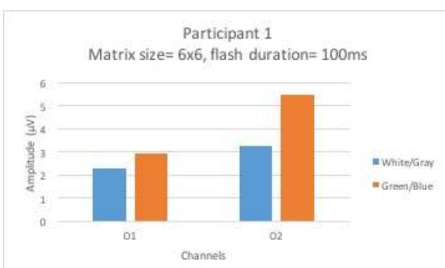
offline accuracy (B,D). In contrast, there are other studies have found that higher accuracy rate can be achieve with longer ISI as in [23]. As reported in [46], the reasons behind this difference in findings between studies are unclear.

4.5. The effect of using colored matrix on the P300 amplitude

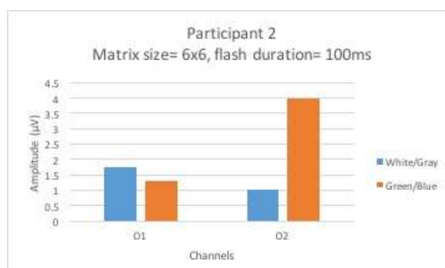
When the user uses the P300 speller system, it is instructed to relax and avoid unnecessary movements to reduce the noise and so increase the SNR. However, this is considered as a difficult task since the user can not stay in a comfortable situation for a long time. Hence, providing a suitable and quiet environment helps the user using the P300 speller more effectively. One of the factors that makes the user feel relaxed during using P300 speller system is the color of the matrix. The colors have different wavelengths which affect our brain, especially the visual cortex. Researchers have found that the colors that have cool shades such as green and blue can make us feel relaxed and aid our concentration [67].

The current study investigated the impact of using colored matrix on the amplitude of the P300 wave. We did not investigate the effect of using colored matrix on the accuracy because it requires using the previous OpenViBE scenarios again. No one of the participants was able to participate in more training sessions. However, participants #1,#2 and #3 were invited to use P300 speller system with colored matrix instead of a conventional P300 speller system which presents white/black matrix to the user. This experiment takes about 5 minutes. Figure 4.11 shows the P300 amplitudes for participants #1,#2, and #3 when using a conventional (white/gray) and colored (green/blue) P300-BCI speller paradigm. According to the results in Section 4.2, the most effective channels in the P300-BCI system are located on the occipital lobe of the brain which are O1 and O2 channels, so we tested the effect of the colored (green/blue) matrix on the P300 signals obtained from these two channels.

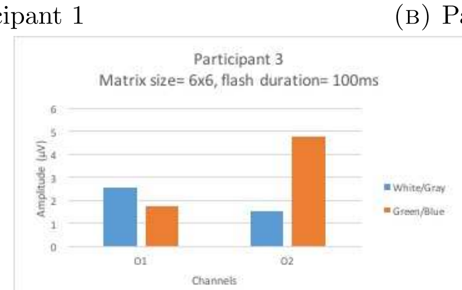
In Figure 4.11, participants #2 and #3 produced higher P300 amplitudes from O1 channel when a white/gray matrix was presented to them during the experiment. In contrast, the P300 amplitude for participant #1 from O1 channel was higher under the green/blue condition (colored matrix). This fluctuation in the results suggests that the effect of using a colored matrix is unclear and can be different from one person to another. The results are surprising since the O1 channel is located on the left hemisphere of the brain as Figure 2.11 (B) shows. In addition, various studies have investigated which part of the brain has the function of colors recognition. The results show that the colors processing is associated with the right hemisphere [56][5]. Our results in Figure 4.11 suggest that O2 channel, which is located on the right hemisphere, involved in color processing. For all the participants, the P300 amplitudes obtained from O2 channel are higher under the green/blue condition than under the white/gray condition. At the end of the experiments, all the participants reported that using a colored matrix (green/blue) was more comfortable for their eyes and made them focus and concentrate on the desired characters more than using a conventional matrix (white/gray).



(A) Participant 1



(B) Participant 2



(C) Participant 3

FIGURE 4.11. P300 amplitudes for participants #1,#2, and #3 when using a conventional (White/Gray) and colored (Green/Blue) P300-BCI speller paradigm.

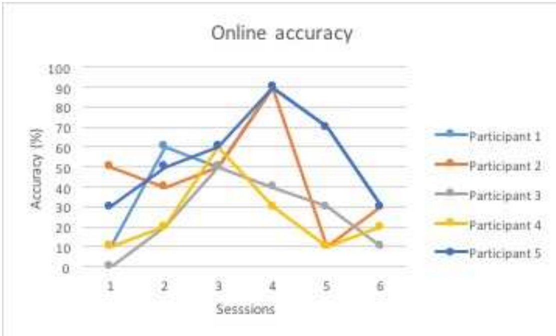
4.6. Exploring the significance of the Number of Training Sessions

The number of training sessions required to allow the user to use the P300-BCI system daily with an effective and accurate performance is explored in this study. It is a difficult task for a user to use the P300-BCI system as a communication tool with just one training session especially if the user has not had BCI experience before. However, 100 subjects participated in a study to test a P300-based BCI system to spell a 5-character word with only 5 min of training. The results showed that 72% of the subjects achieved 100% accuracy after only 5 minutes of training [30].

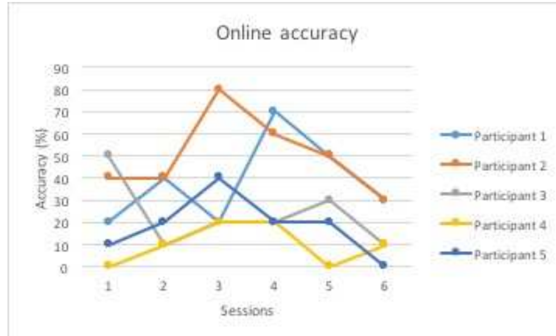
Figure 4.12 depicts the online accuracy for the participants during six training sessions under four different conditions. In the 6x6 matrix and 100 ms flash duration (A), participants #1,#2, and #5 reached 90% accuracy after four training sessions. The best performance for participant #4 was after three training sessions (60%). The same amount of training sessions was done by participant #3 who reached 50% accuracy. In the second condition, 3x3 matrix and 100 ms flash duration, all the participants did six consecutive training sessions. The results of the online accuracy are shown in (B). We can see that participants #2,#4, and #5 achieved the best performance after three training sessions (80%, 20%, 40%). For participant #3, he reached 50% accuracy after 5 sessions of training but then the accuracy dropped sharply to 10% in the next session. Lastly, for this condition, four training sessions were enough for participant #1 to acheive accuracy of 70%.

To investigate the effects of the variation of the flash duration on the online accuracy, participants #3 and #4 were invited to participate in two different conditions (6x6 matrix and 175 ms, 3x3 matrix and 175 ms). It can be seen from (C) and (D) that each participant reached the best performance after doing different number of training sessions. In (C), participants #3 and #4 achieved the highest online accuracy (30% and 50%, respectively) after 3–4 training sessions. Similarly in (D), participant #3 reached 20% accuracy after 4 training sessions while participant #4 needed just three training sessions to achieved 50% accuracy.

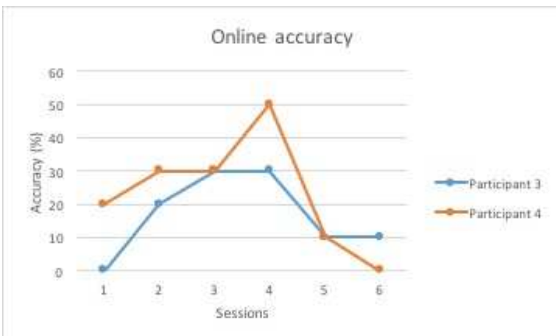
To conclude, we can see from the results in Figure 4.10 that three to four training sessions are sufficient to get high online accuracy depends on the user's performance. It is the fact that in this study none of the participants reached 100% accuracy and this might be due to many factors such as the limitation of the number of the training sessions (six training sessions), signal quality, or electrodes placement. Some users may need more training sessions to adapt with P300-BCI speller system and consequently they can not use it accurately and effectively when they do few training sessions. One of our goals in the future is to minimize the required number of training sessions by using more advanced signal processing techniques and more advanced classification algorithms.



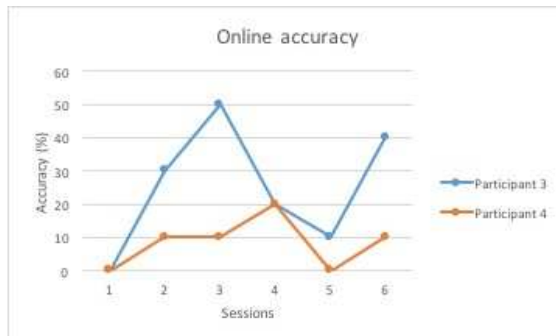
(A) 6x6 100 ms



(B) 3x3 100 ms



(C) 6x6 175 ms



(D) 3x3 175 ms

FIGURE 4.12. This figure illustrates the online accuracy for all participants in each training session

CHAPTER 5

Conclusion and Future Work

The aim of the BCI field is to provide the people with severe neuromuscular disorders a new augmentative communication technology so that they can express their wishes and communicate with others. That can be done by recording the EEG activities from the scalp and then translate them into commands that operate a certain device allows a person to communicate with the external world. Different EEG signals can be recorded from the scalp include P300 signal, mu rhythm, etc. In this study, we are interested in capturing the P300 signal and use it in one of the P300-BCI application called P300 speller. In this thesis, the P300 signals were recorded from five subjects using non-invasive commercial and affordable EEG headset namely Emotiv EPOC+. The capability of the Emotiv EPOC+ of detecting the P300 signals was studied in this research.

Five research questions were addressed in this research mentioned in Section 1.3. The first point is about the structure of the brain and how it works. Section 2.1 covered information about the brain structure and the electrical signals in nervous system. The second question was about the feasibility of the Emotiv EPOC+ to capture the P300 waves. The results in Section 4.1 provide evidence of capability of the Emotiv EPOC+ to detect the P300 signals from two channels, O1 and O2. Investigating the effect of different factors (matrix size, flash duration, colors) on the P300 amplitude and accuracy is another important point that was addressed in question #3. The results show that when the matrix size or flash duration increases, the P300 amplitude increases. The effect of using the colored matrix was very clear on the O2 channel since it is located on the right hemisphere which is responsible for color processing. The next question was about the capability of the user to use the P300 speller correctly. The results show that some users reached accuracy above 70% after a certain number of training sessions. The last question in this research was about the number of training sessions required to use the P300 speller with a high accuracy. To answer this question, each participant did six consecutive training sessions for each condition. The results suggest that three to four of training sessions are enough to reach highest online accuracy. The results in this research show that when the ISI increases, the P300 classification accuracy decreases. However, when the ISI increases, the P300 amplitude increases.

The future works are summarized in the following points:

- The performance of the P300 speller can be evaluated by measuring the accuracy or the information transfer rate (ITR). In our thesis, we measured the accuracy of the participants for different conditions. However, the ITR have not been calculated in this study. One of our goal in the future is to calculate the ITR and to find a way to increase it so we can get better performance. In 1980, Pierce defined a formula to calculate the ITR as follows [52]:

$$B = log_2 N + P log_2 P + (1-P) log_2 (\frac{1-P}{N-1}) \tag{3}$$

  where B id the ITR in bit rate, N is the number of possible targets, and P is the probability that the target character will be selected.

- The BCIs applications mainly targeted paralyzed people to help them in their daily life. One of the limitations of this study was to find disabled people to participate in the experiment. In our research, all the participants are healthy and no one has any neuromuscular disorders. In the future, we are looking to involve participants with neuromuscular disorders in the study to get more reliable results.

- Another limitation of this study was to find a large number of subjects to participate in the research. In this study, the EEG data were collected from five participants. Increasing the number of participants is one of our goals in the future to get more accurate and reliable results.
- In this thesis, the linear discriminant analysis (LDA) classifier was used to classify the target and non-target samples. There are many other powerful machine learning algorithms available and they can be used for the classification purpose. However, the OpenViBE software provides just two classification algorithms which are LDA and support vector machines (SVMs). Therefore, we can use the SVMs classifier and compare the results with the LDA classifier. Furthermore, we can use software other than OpenViBE such as Biosig or CEBL.

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APPENDIX A

Informed consent form to participate in a research project

Colorado State University

COLORADO STATE UNIVERSITY
INFORMED CONSENT TO PARTICIPATE IN A RESEARCH PROJECT

TITLE OF PROJECT: Removing Barriers to the Practical Use of Non-Invasive Brain-Computer Interfaces

NAME OF PRINCIPAL INVESTIGATOR:
- Charles Anderson, PhD - Dept. of Computer Sciences, (970) 491- 7491; chuck.anderson@colostate.edu

NAME OF CO-PRINCIPAL INVESTIGATORS AND OTHER INVESTIGATORS:
- Patricia Davies, PhD - Dept. of Occupational Therapy, (970) 491-7294; patricia.davies@colostate.edu
- William Gavin, PhD - Dept. of Human Development and Family Studies, (970) 227-9999; William.gavin@colostate.edu
- Marla Roll, MS - Dept. of Occupational Therapy, (970) 491-2016; marla.roll@colostate.edu

Why am I being invited to take part in this research?
You have indicated interest in being in our study that is exploring the brain activity used to run a computer. We call this kind of research a *brain-computer interface* (BCI) study. This study is exploring one type of technology that may help people who have motor impairments use equipment, such as computers, with less difficulty.

Who is doing the study?
Faculty members (listed above) from the Computer Science, Occupational Therapy, and Human Development and Family Studies Departments and the Assistive Technology Resource Center are doing this study. Graduate and undergraduate students that work with these faculty members will also be involved in this study. Graduate students may run the session without the faculty members present. This project is funded by the National Science Foundation.

What is the Purpose of this study?
The purpose is to study how we can use brain signals to operate equipment, like a computer, for people with motor impairments who have difficulty using equipment. Brain signals, which are also called electroencephalogram (EEG), are brainwaves that naturally occur in the brain. Once this technology is developed it can be used to run equipment like a wheelchair, television, or computers.

Where is the study going to take place and how long will it last?
This study will take place in your home or in one of our laboratories on the CSU campus. We ask that you participate in one to up to four sessions on separate days. Each session will last 2 to 4 hours, with the total time commitment being from 2 to 12 hours. Before you sign this form we will tell you exactly the number of sessions and time commitment for you. The sessions will be scheduled to fit easily into your schedule.

What will I be asked to do?
You will be seated in a comfortable chair in your home or in one of our laboratories on the CSU campus. A cap, similar to a bathing cap, with metal EEG sensors will be placed on your head. The sensors rest on the scalp and record your brain activity. In order for the sensors to record brain activity or EEG, gel may be placed between the sensors and your scalp. The gel is water based and washes out easily. While you

Page **1** of **3** Participant's initials _______ Date _______

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wear the cap, we may ask you to think about doing several tasks. We will be able to see if your brain activity is different for each of the tasks. You may also be asked to watch a computer screen and think about a particular item that you would select from the screen. A light will flash from item to item. You may also be asked to use the computer while wearing the cap. You will also be asked to fill out a questionnaire about personal information. The questionnaire includes things like gender, age and race. This will let us see if any of these factors influence brain activity. There are also questions about any medical conditions and precautions that we need to consider if you choose to participate. You may be asked to fill out a questionnaire regarding your experience as a user of these BCI systems. We may ask your permission to videotape or photograph your session to assist in the development of training materials that will be used with caregivers and clients on how to use this type of technology.

Are there any reasons why I should not take part in this study?
If you currently have or have a past history of neurological conditions (e.g., traumatic brain injury or stroke) or psychiatric conditions (e.g., epilepsy, schizophrenia or bipolar) you will not be able to participate in this study.

What are the possible risks and discomforts?
The EEG recordings are performed according to standard practices within the field. There are no physical risks in recording your brain activity. In placing scalp or other skin-surface sensors it is possible that you may experience slight tenderness in the spot where the skin surface was cleaned, especially if you have very sensitive skin. This tenderness should disappear quickly. Please inform us if you have a history of fainting in the doctor's office or other location when excited. It is not possible to identify all potential risks in research procedures, but the researchers have taken reasonable safeguards to minimize any known and potential, but unknown, risks.

Are there any benefits from taking part in this study?
There are no direct benefits for you from taking part in this study. However, the results of this research may help the research team and other scientists refine this technology. This technology can be used by persons with motor impairments to use certain equipment that they may not otherwise be able to use.

Do I have to take part in the study?
Your participation in this research is voluntary. If you decide to participate in the study, you may withhold your consent and you may stop participating at any time without penalty or loss of benefits to which you are otherwise entitled.

Who will see the information that I give?
We will keep private all research records that identify you, to the extent allowed by law. We are required by our grant to publically share the raw EEG data collected in this study but we will not share any identifying information. You may choose to share additional personal information below by checking the box.

☐ Yes, you may share my basic demographic information, including gender, age, handedness (left, right or both) and location that recording took place (i.e., home or lab). But I understand that my name will not be included in this information.

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We may publish the results of this study; however, we will keep your name and other identifying information private. All data collected for this study will only be identified by a participant code and not by your name or any other personal information in the computer or written forms. An example of the code that will be used is B002 (B=brain-computer interface project and 002=the number of the participants). We will make every effort to prevent anyone who is not on the research team from knowing that you gave us information. For example, your consent form that has your name will be kept separate from your research records and these two things will be stored in different places under lock and key. Any written training materials developed from this project will not contain any personal information. We may be asked to share the research files for audit purposes with the CSU Institutional Review Board ethics committee, if necessary.

Can my taking part in the study end early?
If you are unable to participate in multiple sessions when applicable you will be removed from the study.

Will I receive any compensation for taking part in this study?
This study is voluntary and does not come with a monetary compensation.

What happens if I am injured because of the research?
The Colorado Governmental Immunity Act determines and may limit Colorado State University's legal responsibility if an injury happens because of this study. Claims against the University must be filed within 180 days of the injury.

What if I have questions?
Before you decide whether to accept this invitation to take part in the study, please ask any questions that might come to mind now. Later, if you have questions about the study, you can contact the investigators, Charles Anderson at 970-491-7491 and Patricia Davies at 970-491-7294. If you have any questions about your rights as a volunteer in this research, contact the CSU IRB at: RICRO_IRB@mail.colostate.edu; 970-491-1553. We will give you a copy of this consent form to take with you.

Your signature acknowledges that you have read the information stated and willingly sign this consent form. Your signature also acknowledges that you have received, on the date signed, a copy of this document containing 4 pages.

____ ________________

Signature of person agreeing to take part in the study Date

____

Printed name of person agreeing to take part in the study

____ ________________

Name of person providing information to participant Date

____

Signature of Research Staff

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