January 2014

P300, Steady State Visual Evoked Potentials, And Hybrid Paradigms For A Brain Computer Interface Speller

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P300, STEADY STATE VISUAL EVOKED POTENTIALS, AND HYBRID PARADIGMS FOR A BRAIN COMPUTER INTERFACE SPELLER

by

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Bachelor of Science, Shiraz University, 2007

A Thesis

Submitted to the Graduate Faculty

of the

University of North Dakota

In partial fulfillment of the requirements

for the degree of

Master of Science

Grand Forks, North Dakota
August
2014

This thesis, submitted by Setare Amiri, in partial fulfillment of the requirements for the Degree of Master of Science from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

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August 4, 2014

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Title P300, STEADY STATE VISUAL EVOKED POTENTIALS, AND HYBRID PARADIGMS FOR A BRAIN COMPUTER INTERFACE SPELLER

Department Electrical Engineering

Degree Master of Science

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Setare Amiri
06/24/2014

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS

BCI: Brain Computer Interface

SSVEP: Steady State Visual Evoked Potentials

EEG: Electroencephalogram

MEG: Magnetoencephalogram

fMRI: functional Magnetic Resonance Imaging

ECoG: Electrocorticogram

NIRS: Near Infrared Spectroscopy

ERD/ERS: Event-Related Desynchronization/Synchronization

ERPs: Event Related Potentials

SCPs: Slow Cortical Potentials

ACKNOWLEDGMENTS

The author expresses the great gratitude to all the individuals who support and assist during the process of this thesis. The support of Electrical Engineering Department is appreciated.

Special thanks to Dr. Reza Fazel-Rezai, my supervisor for all his support during this research. The author also appreciates the contributions of her committee members; Dr. Sima Noghanian and Dr. Kouhyar Tavakolian.

The author would also like to thank fellow students that have helped with this project, M. Riadh Arefin, and Ahmed Rabbi.

The author would like to thanks her family for being supportive, specially my dearest brother, Ali Amiri.

To my mother and father

ABSTRACT

The goal of this research was to evaluate and compare two types of brain computer interface (BCI) systems, P300 and steady state visually evoked potentials (SSVEP), as spelling paradigms and combine them as a hybrid approach. There were pilot experiments performed for designing the parameters of the SSVEP spelling paradigm including peak detection for different range of frequencies, placement of LEDs, design of the SSVEP stimulus board, and window time for the SSVEP peak detection processing. The next experiment was to evaluate the SSVEP spelling paradigm. Six subjects participated in the task. The accuracy of each frequency and average accuracy for each subject were considered. The second experiment was designed to compare the performance and accuracy of SSVEP, P300, and the combination of both paradigms as a simultaneous task. Ten subjects were considered for performing this experiment. Overall the average accuracy of the SSVEP spelling paradigm was 80.00 % and higher than the P300 spelling paradigm average accuracy which was 72.50 %, and both of the spelling paradigms have better accuracy than the hybrid paradigm with the average accuracy of 64.39 %.

Chapter 1. BACKGROUND AND LITERATURE REVIEW

1.1 Brain Computer Interface

A Brain-Computer Interface (BCI) system can provide a communication method to convey brain messages independent from the brain's normal output pathway [1]. Brain activity can be monitored using different approaches such as standard scalp-recording electroencephalogram (EEG), magnetoencephalogram (MEG), functional magnetic resonance imaging (fMRI), electrocorticogram (ECoG), and near infrared spectroscopy (NIRS) [1-4]. However, EEG signals are considered as the input in most BCI systems. In this case, BCI systems are categorized based on the brain activity patterns such as event-related desynchronization/synchronization (ERD/ERS), steady-state visual evoked potentials (SSVEPs), P300 component of event related potentials (ERPs), and slow cortical potentials (SCPs) [5-16]. In this thesis, the focus is on the SSVEP and P300 types of BCI which will be explained in details in the following sections.

1.2 Electroencephalogram

Electroencephalography is a technique for acquiring brain signals based on electrical activity of brain neurons. The signal is called electroencephalogram (EEG) [1]. As a noninvasive technique, for recording EEG, surface electrodes are used. There are many features which can be extracted from EEG, for example, six brain rhythms can be distinguished in EEG based on the differences in frequency ranges; delta (1- 4 Hz), theta

(4-7 Hz), alpha (8-12 Hz), mu (8-13 Hz), beta (12-30 Hz), and gamma (25-100 Hz). The delta and theta rhythms occur in high emotional conditions or in a sleep stage. The alpha rhythm happens in awake and eyes closed relax condition. The oscillation in alpha rhythm has smooth pattern. The beta rhythm pattern is desynchronized and the condition is the normal awake open eyes. The gamma rhythm can be acquired from somatosensory cortex and mu rhythm from sensorimotor cortex. In Figure 1, EEG signal is shown.

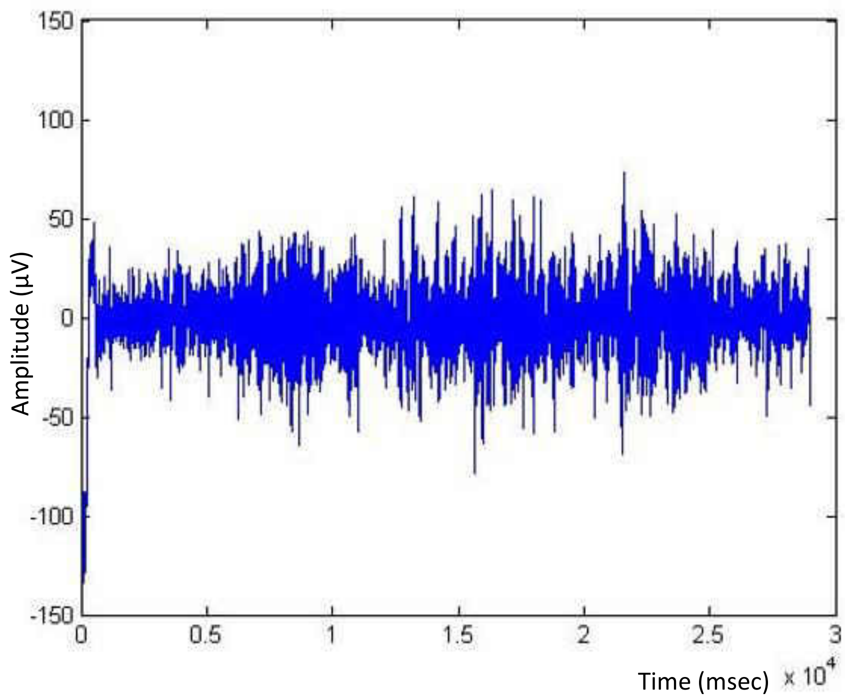


Figure 1. EEG Signal.

1.3 P300-based Brain Computer Interface

1.3.1 The P300 Component

Event related potentials (ERPs) are the measurement of brain responses to specific cognitive, sensory or motor events. One of the main approaches towards BCI is based on ERPs. P300 is a major peak and one of the most used components of an ERP. In P300-based BCIs, intention of the subjects is measured using the P300 component of the brain evoked response [17]. After stimulus onset, positive and negative deflections occur in the EEG. These deflections are called event-related potential (ERP) components. Depending on the latency of these deflections, they are grouped as “exogenous components” and “endogenous components” [10]. The exogenous components occur until about 150 msec after the eliciting stimulus. The endogenous components have longer latency. The largest positive deflection that occurs between 250 and 750 msec after the stimulus onset is called “P300”. The P300 component is the most used ERP component in BCI systems. The paradigm that elicits P300 is called the “oddball paradigm” [18]. In an oddball paradigm, events that elicit the P300 fall into two classes in which one of the classes is less frequent. Inter-stimulus interval time and the frequency of the oddball stimulus are among the parameters that determine the amplitude of the P300 component. The first BCI P300-based system was introduced by Farwell and Donchin for spelling characters in 1988 [13].

1.3.2 Properties of P300

The spatial amplitude distribution is strongest in the occipital region of brain and is symmetric around central location Cz recorded based on the 10-20 international system [19]. The spatial amplitude distribution of 10-20 international system and the electrodes that P300 is typically recorded from are shown in Figure 2. In terms of temporal pattern, P300 wave amplitude is typically in the range of 2 to 5 μV with duration of 150 to 200 msec as shown in Figure 3 which is the ensemble of 10 P300 wave. Considering the P300 low amplitude relative to background activities of the brain (in the rage of 50 μV), it is clear that P300 detection requires special signal processing. One of the simplest approaches is ensemble averaging EEG over multiple responses to enhance P300 amplitude to identify it while suppressing background EEG activities.

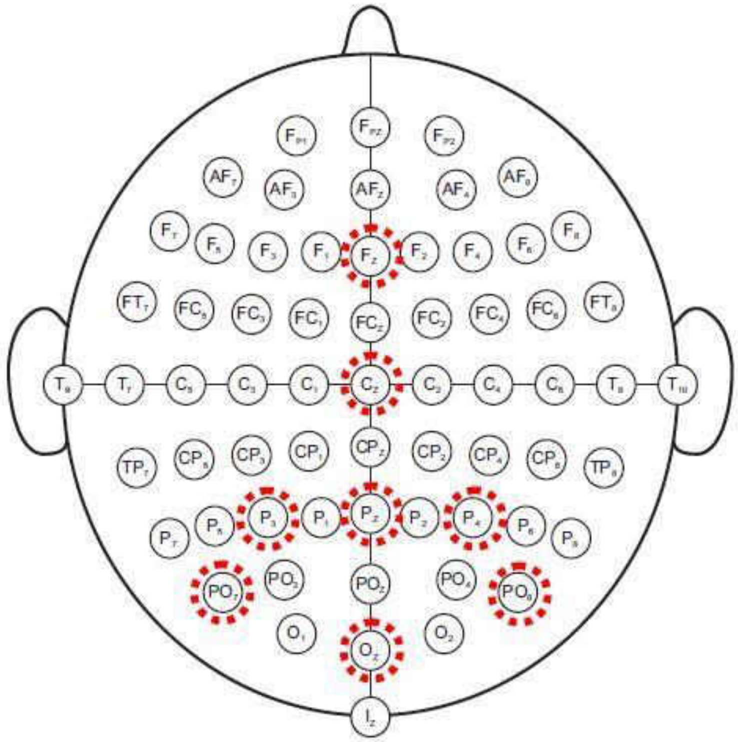


Figure 2. Recoding of EEG based on 10-20 system and location of the electrodes typically used for P300 detection [19].

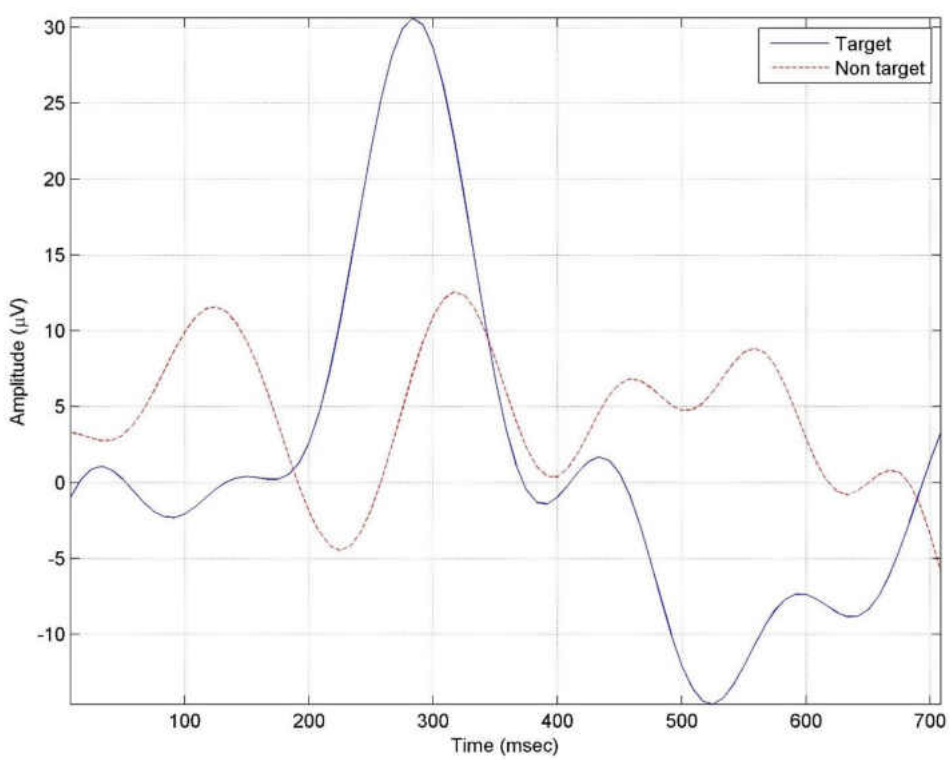


Figure 3. Temporal pattern of P300 component.

P300-based BCI has been used as one of the most widely used BCI systems since 1988 [1]. New advancements in inexpensive and portable hardware made it possible to have real-life application outside of laboratory environment [17] [1] [20]. P300-based BCI has been used from controlling a wheelchair for helping disable people to a virtual keyboard for spelling word and interacting with computers. This type of BCI systems possesses the potential to improve the quality of life. P300-based visual speller paradigms are attracting much attention as they could provide means to communicate letters, words, and simple commands to computer directly from the brain. In the following sections, we will review the classical speller paradigm and discuss current and future trends in this area. Processing and successful use of P300 wave in a BCI application requires several processing steps. First of all, the recorded EEG data have to be processed to reduce the effect of noise. A feedback mechanism is required where a visible signal is presented in the monitor correlated with the recorded signal. A pattern recognition or classification algorithm has to be developed to identify the P300 wave in the recorded ERP epochs. The algorithm parameters should be adjustable to adapt according to the change of user characteristics [21] [17]. The classical paradigm for P300-based BCI speller was originally introduced by Farwell and Donchin in 1988 [13]. This Row-Column (RC) paradigm is the most popular speller format. It consists of 6×6 matrix of characters as shown in Figure 4. This matrix is presented on computer screen and the row and columns are flashed in a random order. The user is instructed to select a character by focusing on it. The flashing row or column evokes P300 response in EEG. The non-flashing rows and columns do not contribute in generating P300 [1]. Therefore, the computer can determine the desired row and column after averaging several responses. Finally, the desired character is selected.

Figure 4. A typical row/column paradigm.

It is interesting to note that P300-based BCI did not receive much attention when it was first proposed. However, recent trend is quite different where P300 BCI has emerged as one of the main BCI approaches. The researchers have focused on identifying the scopes of improvement of the traditional paradigm by introducing new ways of flashing, introducing colors, or investigating other ways to enhance the ERPs. Much focus has put on applying advanced digital signal processing techniques and classification methods in order to improve the classification results. Also, there have been several attempts to introduce new paradigms to evoke P300 potentials. Figure 5 shows such a different approach which is called single character (SC) paradigm that only single character is flashed instead of a row or column. The SC paradigm randomly flashes one character at a time with a delay between flashes. The delay in SC speller is longer than the delay in RC speller. Though SC speller is slower than RC speller, SC speller can produce larger P300 amplitude.

Figure 5. Single character paradigm where each character is flashed [1].

Checkerboard (CB) speller is another paradigm proposed to overcome a problem associated with RC speller [17]. This drawback is arising from the distraction or inherent noise due to row/column association [17]. CB speller effectively reduces these two limitations as the characters are arranged in a checkerboard style as shown in Figure 6 CB speller also increases Information Transfer Rate (ITR) [20].

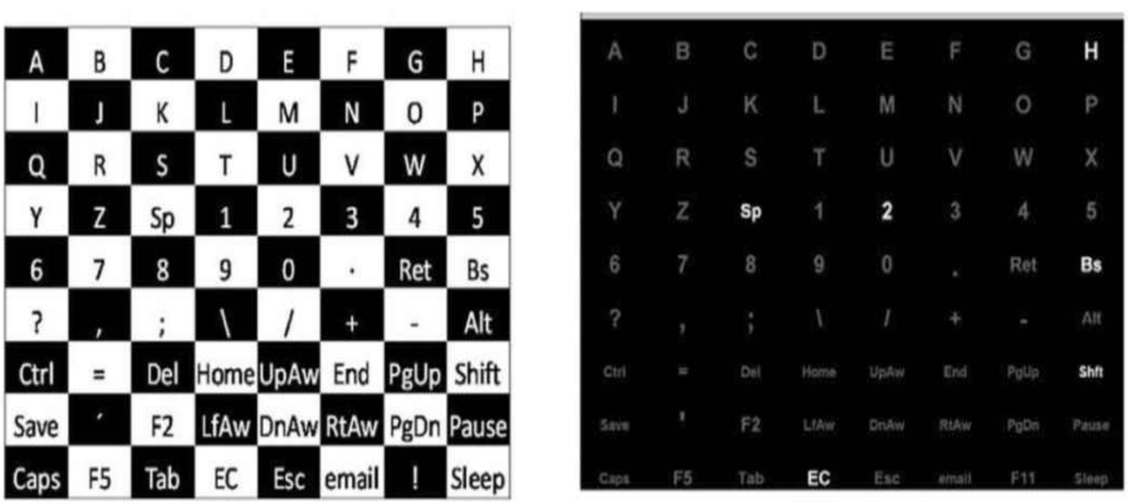


Figure 6. Checkerboard paradigm [20].

The region-based (RB) paradigm was proposed by Fazel-Rezai et. al. in 2009 [22]. It is a two-level speller where the regions have to flash instead of rows and columns. In the first level, characters are placed in several regions (seven groups) as shown in Figure 7. The users are instructed to focus attention on a specific character in one of the seven regions. After several flashes the desired region is selected. In the second level, characters are distributed following the same rule used in the first level and each character flashes in similar order. After several flashes, the desired character is identified [22].

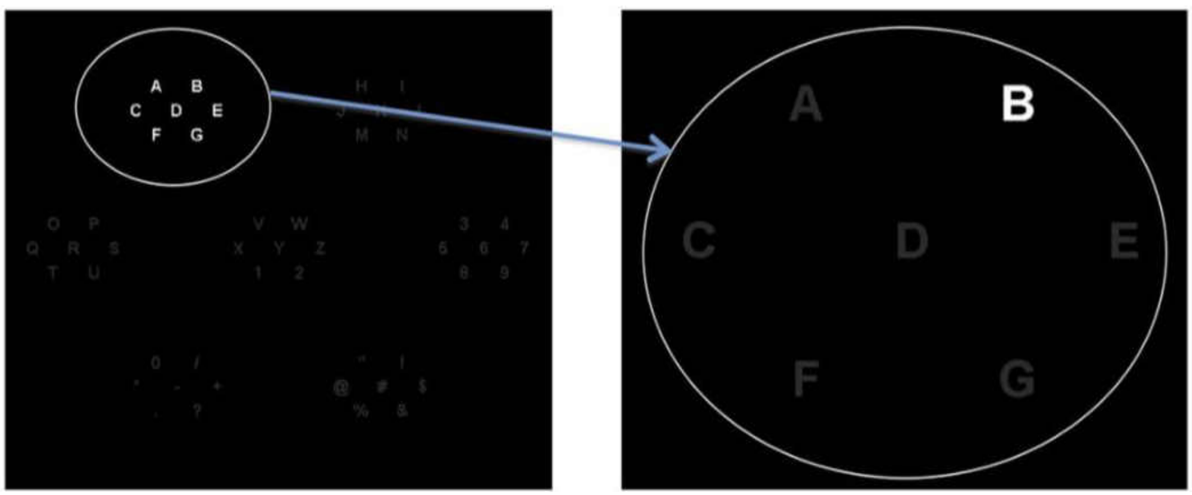


Figure 7. Region based paradigm where a set of characters in level 1 (E) are expanded in level 2 for spelling character “B” (F).

It is reported that RB speller has decreased the adjacency problem significantly [20] [22] [17] [23]. The RB and CB paradigms show new directions in BCI speller paradigms apart from RC speller. There has been much progress in bringing BCI technology out of lab environment to real-life applications. BCI has widely been studied in helping disable people, for example, enabling controlling a wheel chair using brain signals [24]. The other promising applications are in managing smart home environment, controlling a virtual reality environment, and next generation gaming [25].

1.3.3 P300 Feature Extraction and Classification

For P300 detection, time domain or time-frequency domain features such as wavelets are appropriate. Classifiers such as Fischer's linear discriminant analysis (FLDA), Bayesian linear discriminant analysis (BLDA), stepwise linear discriminant analysis (SWLDA), and support vector machine (SVM) are utilized [25] [26].

1.4 SSVEP-based Brain Computer Interface

1.4.1 SSVEP Stimulus

Evoked response in EEG signals to repetitive visual stimulations is called SSVEP. In a SSVEP BCI paradigm, specific frequencies are allocated to the repetitive stimuli. For SSVEP detection, the frequency spectrum of the EEG is computed. Around the frequency of the repetition of stimulus in which the subject focuses, there will be peak on the frequency spectrum. By detecting this frequency, an intention of the subject can be detected. This can be translated to a control signal for a BCI system. One of the most important issues about SSVEP BCIs is the gaze dependence [9, 27]. It is shown that SSVEP BCIs are not entirely dependent on muscle-based gaze control. Another issue is that in some users, the flickering stimulus is annoying and produces fatigue. Using higher frequencies for the flickering stimuli reduces the annoyance, but on the other hand, it is harder to detect the SSVEP [6, 28, 29].

1.4.2 Properties of SSVEP

Compared to other modalities for BCI approaches, such as the P300-based and the SCP BCIs, SSVEP-based BCI system has the advantage of higher accuracy, higher ITR and short/no training time and fewer EEG channels are required. However, similar to other

BCI modalities, most current SSVEP-based BCI techniques also face some challenges. Two important features of each BCI system are information transfer rate and required training time. A general comparison of different BCI approaches is shown in Figure 8 [30].

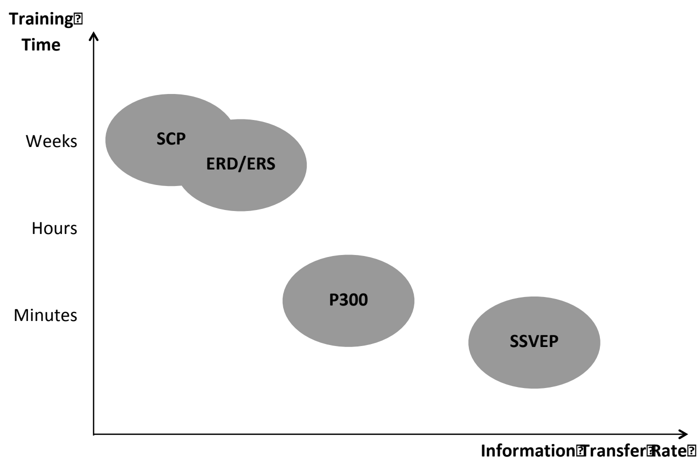


Figure 8. A general comparison of SCP, ERD/ERS, P300, and SSVEP with respect to their training time and information transfer rate.

1.4.3 SSVEP Detection

The process of detecting patterns from EEG is divided to three steps [21]; signal pre-processing, feature extraction, and classification. The first step is to remove noise such as artifacts or power line noise which is added to EEG. So filtering is the first step in EEG signal pre-processing. Band pass and notch filters are the most common filters utilized in EEG signal filtering. In the next step, features that are selected in feature extraction step and the type of classifier should be chosen based on the type of BCI. For SSVEP feature extraction and classification, different methods such as the Fast Fourier transform (FFT), the canonical correlation analysis (CCA), stimulus-locked inter-trace correlation (SLIC), and the common special patterns (CSPs) have been used [9] [31]. Considering the frequency spectrum of the signal, and utilizing the frequency domain features and power spectral density (PSD), is one of the basic methods for SSVEP detection as the signal has higher peak at the stimulation frequency and its harmonics. The frequency spectrum of EEG signal in a SSVEP experiment is shown in Figure 9. In Figure 10 , and Figure 11 peaks at the stimulation frequency and its first harmonic are shown for the signal with stimulus frequency of 17 Hz respectively.

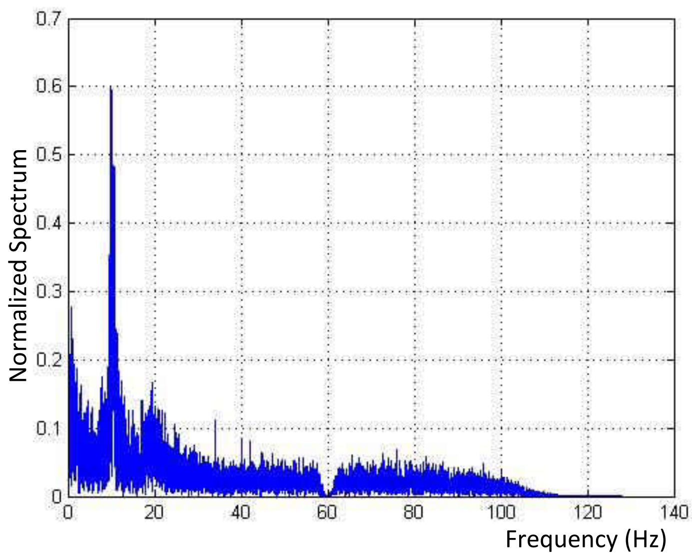


Figure 9. Frequency spectrum for a typical EEG signal.

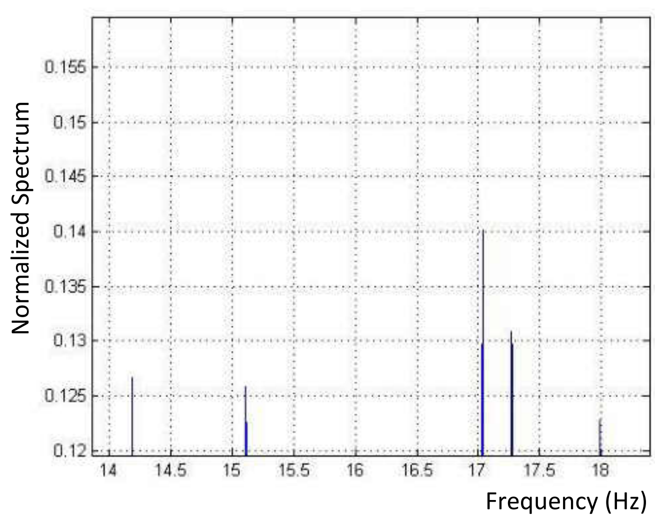


Figure 10. Frequency spectrum of EEG shows higher amplitude at the stimulation frequency of 17 Hz.

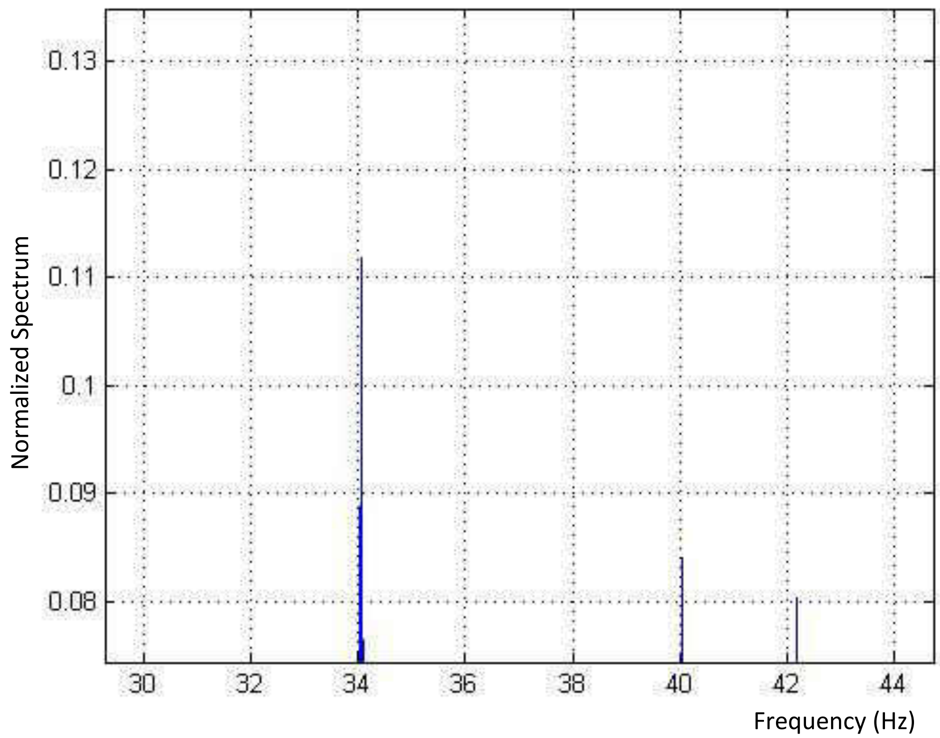


Figure 11. Frequency spectrum of EEG shows higher amplitude at the first harmonic of the stimulation frequecy, 34 Hz.

1.4.4 Other types of Brain Computer Interface

Slow negative voltage shifts that occur in the EEG recorded over sensorimotor cortex, while actual or imagined movement happens [9] are called SCP. SCP-based BCI consists of series of trials [32]. Early SCP BCIs were especially slow, since in each trial only one selection was possible and the time needed for each selection was at least 10 sec. The temporal efficiency was improved by Kubler *et al.* to 4 sec [33]. Shortening the time process further was not possible because users were uncomfortable with the shortened trial time. Over the past decade studies about the SCP approach have been limited because of several SCP BCI problems, which reduce the applicability of this type of BCI. Among others, SCP BCIs have three main problems: poor multidimensional control, high probability of error, and long-term training.

Rhythmic activity of EEG in terms of event-related desynchronization /synchronization (ERD/ERS) has been used as one of the sources in BCI [1]. Motor imagery is one way to induce changes in ERD/ERS and has been used in many BCI systems [34]. During motor imagery of movements, ERD occurs predominantly over the contralateral brain motor area and, therefore can be used as a signal for a BCI system. ERD/ERS BCIs have been used in different applications such as achieving two-dimensional cursor control.

1.5 Hybrid Brain Computer Interface

1.5.1 Introduction

Each BCI type has its own shortcoming and disadvantages. To utilize the advantages of different types of BCIs, different approaches are combined, called hybrid BCIs [15, 16]. In a hybrid BCI, two types of BCI systems can be combined. It is also possible to combine one BCI system with another system which is not BCI-based, e.g., combining a BCI system with an electromyogram (EMG)-based system. However, one can debate if this type of system should be defined as hybrid BCI. In the rest of this section, we assume that if an EEG BCI system is combined with another physiological signal (e.g., EMG) based system, a hybrid BCI system will be constructed.

Although different BCI methods can be combined, it should be noted that not all combinations of different brain imaging methods are feasible and possible. One of the limiting factors is the technology. For example, although MEG is a very high resolution brain imaging technique, it is not practical to use it when subjects need to move around. In addition, different techniques and their combinations should be utilized based on the application that the hybrid BCI is going to be used for. The main purpose of combining different systems to form a "hybrid" BCI is to improve accuracy, reduce errors, and overcome disadvantages of each conventional BCI system. Different types of hybrid BCI systems can be defined according to the types of systems which are combined, how systems are joined, and what types of inputs are considered. In non-hybrid BCIs, based on the property of EEG signals used as the input of BCI system, four major EEG-based BCIs are considered: SSVEP, P300, SCP, and ERD/ERS.

In general, in a hybrid BCI, two systems can be combined sequentially or simultaneously [35]. In a simultaneous hybrid BCI, both systems are processed in parallel. Input signals used in simultaneous hybrid BCIs can be two different brain signals, one brain signal, or one brain signal and another input. In sequential hybrid BCIs, the output of one system is used as the input of the other system. This approach is mostly used when the first system task is to indicate that the user does not intend to communicate or as a "brain switch" [35].

The combinations of the BCI types and a summary of important features of different hybrid BCIs which are discussed in this chapter are shown in Table 1 [36].

Table 1. A comparison of several different BCI hybrid systems.

Paper #	Hybrid Type	System Organization	Improvement	Number of Subjects	Classification
[15]	ERD, SSVEP	Simultaneous	Accuracy significantly improved compared to ERD and slightly better than SSVEP	14	LDA
[16]	ERD, SSVEP	Sequential	False positive rate was reduced	6	FLDA
[27]	ERD, SSVEP	Sequential	Application of BCI for FES triggering was improved	3	Filters and thresholds
[28]	ERD, SSVEP	Simultaneous	Feedbacks were added to the work done in [15]	12	LDA

Table 1. cont.

Paper #	Hybrid Type	System Organization	Improvement	Number of Subjects	Classification
[29]	P300, SSVEP	Sequential	Improved ITR	10	FLDA and BLDA
[30]	P300, SSVEP	Sequential	New application (smart home)	3	SVM
[31]	P300, ERD	Sequential	Improvement in application (wheelchair control)	2	Frequency analysis
[32]	P300, ERD	Sequential	Expand control functions in virtual environment	4	SVM and FLDA
[33]	P300, ERD	Simultaneous	Increase reliability	4	Fisher's discriminate analysis
[34]	ERD, NIRS	Simultaneous	Improvement in classification accuracy and performance	14	LDA
[35]	EEG, EMG	Simultaneous	Improvement in performance	12	Frequency analysis and Gaussian classifier
[36]	ERD, EOG	Simultaneous	Improvement in classification accuracy, reduction in number of electrodes and training time	3	Frequency analysis
[37]	ERD, EOG	Sequential	Improvement in performance	7	LDA

1.5.2 SSVEP-based BCI combined with other types of BCIs

In [15], the proposed hybrid was evaluated during the task and was applied under three conditions: ERD BCI, SSVEP BCI, and ERD-SSVEP BCI. During the ERD BCI task, two arrows appeared on the screen. When the left arrow appeared, subjects were instructed to imagine opening and closing their left hand. For the right arrow, subjects imagined opening and closing the right hand. In the SSVEP task, subjects were instructed to gaze at either left (8 Hz) or right (13 Hz) LED depending on which cue appeared. In the hybrid task, when the left arrow was shown, subjects were imagining the left hand opening and closing while gazing at the left LED simultaneously. The task was similar for the right arrow. Results show the average accuracy of 74.8% for ERD, 76.9% for SSVEP, and 81.0% for hybrid. The number of illiterate subjects, who achieved less than 70% accuracy [37] , reduced to zero from five using the hybrid approach.

A hybrid SSVEP/ERD BCI was introduced in [16] for orthosis control application. The SSVEP-based BCI was utilized for opening the orthosis at the activating stage, and an ERS-based BCI was used as a switch to deactivate the LEDs that were mounted on the orthosis for SSVEP evocation in the resting stage. The SSVEP-based stage entails four steps for opening and closing the orthosis completely. Frequencies 8 and 13 Hz LEDs were used for the opening and closing tasks, respectively. During training sessions, subjects were instructed to close the brain switch. Then, they were instructed to open and close the orthosis by gazing at the LEDs mounted on the orthosis. In the next stage, the SSVEP-based BCI was turned off by opening the brain switch. This switch was kept open during the resting period. At the end of the resting period, the brain switch was closed, and SSVEP task was repeated. After this experiment, subjects undertook the SSVEP-based BCI task alone and the LEDs were flickering during the resting period. For SSVEP detection, the power density spectrum was used. For the activity period the true positive rate and false positive rate were measured and for resting period the false positive rate was measured. It was shown that false positive rate was reduced by more than 50% when hybrid BCI was utilized.

SSVEP and ERD were combined in [38] to make a two-stage hybrid BCI system for triggering a Functional Electrical Stimulation (FES) system. In the first stage, SSVEP was presented for object selection. For evoking SSVEP, three LEDs with 15, 17 and 19 Hz frequencies were considered. The EEG was acquired from O1, O2, and Oz channels while considering Cz as a reference. The object selection task represented three basic grasps: palmar, lateral and precision grasp. For the analysis, Oz channel was chosen as the SSVEP activity in this channel and it was more noticeable compared to other channels. For SSVEP detection, Butterworth's band pass filters were used to separate frequency bands and a threshold for each subject was fixed manually. After selecting one of the three grasp options based on SSVEP, the next task was reaching movement in which ERD-based BCI was used. EEG signals for this task were recorded from the C3 channel. The Cz channel was used as the reference point. The signal was filtered utilizing Butterworth's band pass filters. The detection algorithm was based on the real-time mu and beta band-power estimation. The signal was compared with the manual adjusted threshold and a drop under the threshold was considered as a movement command. 98.1% accuracy was achieved in the SSVEP stage. Using mu and beta bands, 100% and 98.1% accuracy were achieved, respectively. This study showed that the presented hybrid BCI can be considered as one of the appropriate combinations for FES triggering application.

In [39], subjects found the hybrid BCI slightly more difficult than non-hybrid BCIs and ERD and SSVEP were combined for a simultaneous hybrid task. Bipolar channels C3, Cz, C4, O1, and O2 were utilized for EEG recording. After training sessions, in the online run for SSVEP task, a cue pointed to the top LED which was flickering with 8Hz and then pointed to the bottom 13 Hz LED. Subjects received a real-time feedback from a rectangular appearing on the screen. During the ERD task, a cue pointed to the top of the screen and subjects imagined the opening and closing of both hands. When the cue pointed to the bottom of screen, subjects were instructed to imagine moving both feet. In the hybrid condition both tasks were done simultaneously. The data from the training sessions was used for setting up the LDA classifier. The cross-validation classification accuracy was calculated for both online and the training sessions. In the training sessions, mean classification accuracy was 79.9%, 98.1%, and 96.5% for ERD, SSVEP, and hybrid condition respectively. The analysis of the online performance showed that the mean classification accuracy was 76.9%, 99.1%, and 95.6% for ERD, SSVEP, and hybrid condition. For the same conditions ITR was 3.2, 6.1, and 6.3 bits per min. In another analysis, the ERD and SSVEP features were classified separately in the hybrid BCI which showed that subjects were not doing only one of the tasks. Based on a questionnaire two subjects indicated that hybrid BCI was much more difficult and their performance declined compared to the SSVEP condition. Four subjects indicated that there was not any difference in difficulty of the hybrid condition compared to two other conditions and their performance stayed the same or improved in the hybrid condition. Overall, from the questionnaire the hybrid condition was moderately more difficult. Comparing the results of this experience with the previous one, [15], improvement was seen in the ERD results as the performance of the task had been changed (right hand versus left hand movement imagination in the previous study and both hand versus both feet movement imagination in this study). Other results such as the lower accuracy in ERD condition and the higher performance in SSVEP condition were consistent. The accuracy in the hybrid BCI is not significantly different from the SSVEP condition. By changing the classification or the combinations of the features improvement in results may appear. However, the reliability of the system is improved as the SSVEP BCI is added to the conventional ERD BCI system.

For subjects with low performance with ERD or in the case of fatigue, the SSVEP BCI is appropriate option.

1.5.3 P300-based BCI combined with other types of BCIs

A possible combination for a hybrid BCI is P300 and motor imagery (MI)-based BCI [40-42]. The basic concept in this type of hybrid is based on the features of P300 and ERD/ERS in control applications. P300 is a reliable BCI type for selecting one item out of several items and can be used for discrete control commands. On the other hand, due to the low degree of freedom presented by MI-based BCI this type of BCI is more efficient for continuous control commands. These two types of BCIs can be joined to present more complicated control commands in one task.

In [40], for controlling a wheelchair in a home environment several approaches using different BCI techniques were introduced. The wheelchair control commands were divided into three steps.

Step 1) ***Destination Selection:*** In this task, the user should select the destination of the wheelchair motion by selecting one of the items among a list of destinations. To implement this control command, an accurate and reliable interface is needed and false acceptance rates should be as low as possible. For this task, a P300 BCI presented at a screen was utilized. The experiments on healthy subjects showed a response time of about 20 seconds, the false acceptance rate of 2.5% and the error less than 3%. The results showed that P300 was an appropriate option for the interface, but there are a couple of points to be considered: First, all subjects were healthy. For users with severe disability, the accuracy of the results may differ. Second, there is concern about the applicability of the interface, if it is proper for daily use. A more applicable situation should be considered for evaluating this approach.

Step 2) ***Navigation:*** An autonomous motion control was introduced for this step. The destination was selected and the wheelchair started its motion toward the destination following virtual guiding paths. A proximity sensor was considered for stopping the wheelchair facing obstacles.

Step 3) ***Stopping Command:*** For this control command the interface needs to be fast, reliable and have a low false acceptance rate. Two approaches for a stopping command were presented. The first approach was the fast P300 in which, on the screen, there is only one item "The Stop" and the task is the detection of user's intention. Experimental results showed reduction in response time. However, increase in false acceptance makes this approach inapplicable. The second approach was to use a mu-beta BCI. The position of a cursor was considered for presenting the visual feedback for the mu-beta BCI system and the control of the cursor was based on an arm movement imagination. Results showed approximately the same response time as the fast P300 approach but for false acceptance, a rate of zero was achieved. Since the low false acceptance rate and fast response are the most important needs for this type of BCI, it seems that mu-beta BCI is a more reliable system for this application.

In [41], different states and control commands needed for operating the system were controlled in a virtual environment. P300/MI hybrid BCI was used for operating the system. Two sequential states covered the areas of the virtual environment, navigation, and device control state. The interface strategy is explained as follows. For navigation, MI BCI was used with the continuous control commands limited number of commands. By imagination of left and right hand movement, control commands were issued. The position in the virtual environment was updated by each control command.

In the device control state, the commands were discrete. By considering features of control commands and paradigms, an interface was developed. For this paradigm, the P300 oddball paradigm was considered. When the area coverage changed to the device control state, the MI command detection stopped and the controller switched to system state. The system state then switched to device control state automatically. The P300 BCI presented the control panel to subjects. A switch for navigation happened by the selection of the 'quit' command using the P300 oddball paradigm. If the 'quit' was not detected after 6 commands, the controller would switch to the system state automatically.

In [41], experiments were performed by four subjects. To evaluate the hybrid approach, the experiment was also implemented for P300 and MI BCIs separately. 22 testing runs were considered in three blocks: 1) A block for hybrid control testing, 2) A block for MI-based navigation, and 3) A block for P300-based device control. Three tasks with a combination of navigation and device control commands were considered for evaluating the hybrid control strategy.

In block presenting MI-based navigation, the tasks were the same, with the difference that in the device control state areas, the device control panels were not evoked. In the third block, navigation was not available and two of the tasks were tested for P300 BCI evaluation. The online accuracy was used for comparing different approaches. Comparing the P300 task in the hybrid BCI and the single P300 BCI showed reduction in the accuracy of the hybrid strategy. The accuracy for two of the subjects reduced in MI part of the hybrid BCI compared to the single MI BCI. However, by utilizing the hybrid BCI, more complicated tasks can be accomplished in a virtual environment.

In [42], P300 and ERD were introduced to be components of the hybrid BCI in robotic control decision applications. Parallel and asynchronous classifications were introduced. The system task was to detect the intended pattern. Classification accuracy was evaluated during the experiment, which was considered for presenting the hybrid. Sixty trials were presented to four subjects: thirty trials for P300 presentation and thirty trials for MI. During the second thirty trials, the P300 stimuli were also presented but the subjects were not supposed to pay any attention to the stimuli.

1.5.4 P300-based BCI combined with SSVEP-based BCI

P300 and SSVEP BCI were introduced as hybrids in an asynchronous BCI system in [26]. It seems the P300 and SSVEP combination worked well as the stimuli for evoking both patterns which can be shown on one screen simultaneously. The P300 paradigm considered in this study is a 6x6 speller matrix based on the original P300 row/column paradigm introduced by Farwell and Donchin [13]. Only one frequency is allocated for the SSVEP paradigm. The background color was flashed with a frequency slightly less than 18 Hz. The background color change facilitates the SSVEP detection. During the classification, P300 and SSVEP signals were separated by a band pass filter. The SSVEP was utilized as a control state (CS) detection. When the user was gazing at the screen, the SSVEP was detected and it was assumed that the user intended to send a command. The system detected the P300 target selection and CS simultaneously.

For SSVEP detection, the mean PSD in the narrow band near the desired frequency and the PSD in the wider range near the desired frequency were utilized in an objective function [26]. These values were subtracted from each other and divided over the PSD value from the wide band and the function value was compared to a specified threshold. During the data acquisition the channels for acquiring EEG signals were not fixed for all subjects.

For P300 classification, FLDA or BLDA were utilized [43, 44]. The experiment was presented as an offline and online test. Ten subjects participated in the experiment. In the offline test, forty characters were presented for detection, which were divided into four groups. For better evaluation, SSVEP was presented only to two groups out of four groups. In CS, subjects were instructed to count the number of times they distinguished the highlighted character. In the non-control state (NCS), subjects were instructed to do a mental task like multiplication of two numbers and relax with closed eyes.

For four out of five subjects, the accuracy was improved insignificantly during the presence of SSVEP and P300 detection was not determinate. Between the ten character's detection there was a break of a certain time which was due to the subject pressing a keyboard button. When the NCS time was almost finished, an auditory cue alerted subjects. Average classification accuracy of 96.5% and control state detection accuracy of 88% with the ITR of 20 bits/min were achieved during the offline test. The online test was presented under a semi synchronous condition. The experiment consisted of blocks with five rounds, for detecting each character. SSVEP detection for at least three out of five runs showed the control state detection by the subject and P300 was detected during the control state. If the control state was not detected, the '=' character would be shown on the screen. The break time and the auditory alert were the same as the offline test. An average control state detection accuracy of 88.15%, a classification accuracy of 94.44%, and an ITR of 19.05 bits/min were achieved during the online test.

P300 and SSVEP combination was also introduced to control smart home environments in [25]. P300-based BCI was used for controlling the virtual smart home environment and SSVEP was implemented as a switch for the P300 BCI operation. Results from this experiment show that P300 is suitable for discrete control commands and SSVEP is suitable for continuous control signals. The hybrid BCI achieved high accuracy and reliability in all subjects.

1.5.5 Other combinations

A type of hybrid BCI that uses EEG and NIRS [45] was introduced by [46]. Coyle *et al.* in [4] introduced an approach of utilizing NIRS as an optical BCI. In [46], EEG and NIRS measurements were utilized simultaneously for ERD-based BCIs. In this study, the experiment consisted of 2 blocks of motor execution and 2 blocks of motor imagery. For all blocks both EEG and NIRS were measured simultaneously. The increase in concentration of oxygenated hemoglobins (HbO) and decrease in concentration of deoxygenated hemoglobins (HbR) were measured using NIRS. The global peak cross-validation accuracy for each subject was considered for evaluation of the hybrid BCI. The mean classification accuracies of HbO, HbR, and EEG for executed movement tasks were 71.1%, 73.3%, and 90.8%. For motor imagery tasks they were 71.7%, 65.0%, and 78.2%. The mean classification accuracies of EEG/HbO, EEG/HbR, and EEG/HbO/HbR for executed movement tasks were 92.6%, 93.2%, and 87.4%, and for motor imagery tasks were 83.2%, 80.6%, and 83.1%, respectively. It was shown that the combination of EEG and NIRS improved the classification accuracy in both MI and executed movement tasks.

However, the information transfer rate may decrease. This type of hybrid BCI may enhance the performance of subjects who are not able to use EEG-based BCI properly.

The NIRS-based BCI was used as a brain switch for a SSVEP BCI system [35]. The objective was to open and close an orthosis. One subject with four runs performed an experiment. A 60 sec break was considered between two runs. For starting a command, the optical BCI was utilized as a switch for SSVEP BCI starting point. By using a switch false positives were detected during the first two runs but in the third run the performance was improved and only one false positive occurred. In the last run the performance was perfect with 100% accuracy.

EEG and EMG were fused to devise a hybrid BCI in [47]. EEG signals were recorded through 16 channels. EMG activities were recorded from channels over the flexor and extensor of the right and the left forearms. Two classifiers were used for EEG and EMG and the probabilities from these classifiers were used for controlling the BCI feedback. In the first approach of this experiment, a switch with weights equally balanced between the two classifiers was implemented between the input channels as the fusion of EEG and EMG. In the second approach, the Bayesian fusion method was utilized. Two conditions were considered for EEG and EMG separately and four conditions for the fusion of EEG and EMG depending on the increase of muscular fatigue. The accuracy for EEG activity alone was 73% and for EMG activity alone was 87%. In the first approach the accuracy was 90% for 10% attenuation due to the fatigue, 90% for 50% attenuation, 85.1% for 90% attenuation and it was decreased to 73% due to the increase of muscular fatigue.

Results had the same trend in the second approach with smaller standard deviation (SD). The accuracy was approximately 92% for 10% attenuation, 92% for 50% attenuation, and 60.4% for 90% attenuation. In the third condition, the accuracy achieved was less than the accuracy in EEG BCI and this is because of the assumption of fixed value sources in the Bayesian fusion technique calculations. Utilizing multimodal fusion techniques led to enhancement in performance reliability.

Since the majority of people with disabilities can have control on their eye movement, the EOG signals could be an appropriate option as input signals for BCI system. EEG and EOG combination was introduced to make a hybrid BCI [48]. In this study, EOG and EEG signals were taken from two channels and were utilized simultaneously. The technique in generating control commands based on EEG/EOG hybrid BCI is explained as follows.

The 'turn left' and 'turn right' control commands were derived from EOG signals based on the right/left eye gazing pattern. Subjects performed maximum right and left eye gazing, and the positive and negative potential were recorded respectively. 75% of the recorded amplitudes were considered as the threshold for the right and left eye. If the amplitude recorded from the right eye during the trials was greater than the threshold related to the right eye, the 'turn right' command was detected. For the 'turn left' control command detection, the absolute value of the negative potential recorded from the left eye should be greater than the related threshold. If both values were less than the related threshold values, the 'no action' control command was detected. Classification accuracy of 100% was achieved for 'turn left' and 'turn right' control commands. Average accuracy of 95% was achieved for 'no action' control command. The 'forward', 'no action', and 'completely stop' control commands were detected from EEG.

The parameter used for deriving the control commands from the EEG was PSD in the alpha and beta band. A threshold was considered for comparison to the maximum PSD detected from the alpha and beta band. Three subjects in three trials and 50 control commands in each trial performed experiments. At the beginning of the test software calibration was performed by the subjects. The maximum PSD in alpha band was recorded from the subjects with closed eyes and 75% of the PSD from the calibration was considered as threshold. For the 'completely stop' command, the subjects were instructed to close their eyes to increase the alpha activity. Then the maximum PSD in the alpha band was compared to a threshold. If the maximum PSD was greater than the threshold, the 'completely stop' command was issued. For the 'forward' control command, the subjects were instructed to think about moving forward. If the maximum PSD recorded in the beta band was greater than the maximum PSD recorded in the alpha band, the 'forward' control was issued. The 'no action' control command was issued if the maximum PSD in the beta band was less than the maximum PSD in the alpha band and both were less than the threshold.

The average classification accuracy over the whole trials was 100% for 'completely stop' and 87% for 'forward' control commands. The 'no action' control command was common in both EEG and EOG control command detection parts and the average classification accuracy of 95% was related to the both parts of the task. The interface implementation and the feedback were presented by employing the test on a toy truck. In addition to high classification accuracy, small number of electrodes and short training time showed the advantage of introduced hybrid.

In another approach [49], a self-paced BCI system was combined with an eye-tracker system to establish a self-paced hybrid BCI [35]. In this system, for cursor control, an eye tracker was utilized by detecting the user's eye gaze. A BCI was utilized for clicking on a selected item on computer screen. Subjects were instructed to first gaze at an intended letter on the screen to select it, then for click on the selected letter based on BCI. EEG was recorded from the cortex area with 15 electrodes. For EOG, two pairs of electrodes were used. In addition, four pairs of electrodes were used for recording facial muscle activities, from which the facial muscle artefacts can be detected. PSD of 30 combinations of bipolar EEG channels was computed based on Fast Fourier Transform (FFT). For feature selection, stepwise LDA was considered [50]. Then, the features were classified with LDA and adaptive LDA and for more improvement moving average.

For removing EOG and EMG artefacts from the EEG signal, an algorithm was proposed in [51], which showed improvement in the performance of the introduced self-paced hybrid BCI [49]. Stationary wavelet transform and an adaptive threshold mechanism were used in the proposed algorithm. Results were evaluated based on two types of data; real EEG signals with simulated artefacts (semi-simulated EEG signals) and real EEG signals. In semi-simulated EEG signals, signal distortion was decreased and in real EEG signals, the true positive rate was increased using the proposed algorithm.

To overcome limitations and disadvantages of conventional BCIs, different BCI systems or BCI and non-BCI systems can be combined to form a "hybrid BCI". Hybrid BCIs have been used for different applications such as 2-D control of a cursor, target selection, and virtual environment.

There are several advantages of sequential combination when one of the BCIs is used as a switch or different BCIs are used for different tasks sequentially. When combined sequentially, complicated tasks can be distributed to several stages in series. For each stage a specific BCI can be used. An example of this approach is a virtual environment application [25]. Based on the required type of control commands, different BCI systems can be implemented. In [16], one BCI (ERD) was used as switch for another BCI (SSVEP) and the false positive rate was decreased for this sequential hybrid BCI. However, the main advantage of the simultaneous combination is that in general the accuracy can be improved if the BCIs are combined appropriately for all subjects. With adaptive pattern recognition algorithms, a hybrid system can adapt to subjects based on their performance. In addition, classification methods can use more BCI outputs. Hybrid BCIs combining different systems simultaneously may be more complicated than a single BCI and more difficult to be accepted by all users. Therefore, the paradigm design of a hybrid BCI plays very important role in overall performance of the system. Similarly, when a BCI system is combined with a non-BCI, which is not based on EEG signals, the system performance can be improved. In general, in a hybrid BCI, the complexity of the system paradigm is increased compared to a non-hybrid BCI. Therefore, the use of hybrid systems might be more complicated from the user's point of view. Thus, in designing a hybrid system paradigm, the complexity and user acceptability are important performance criteria to be considered carefully. Another consideration for the user acceptability is the number of channels used in a hybrid BCI system.

In conclusion, although hybrid BCIs have shown great improvement in several performance criteria such as accuracy and information transfer rate, complexity of the system and user acceptability should be reported as important performance criteria of hybrid BCI systems. With the current trend in introducing hybrid BCIs, we will soon see more than two BCI systems combined sequentially or simultaneously. It is also possible to combined BCIs in a combined sequentially/simultaneously approach. This will create a network of BCIs which cannot be distinguished as sequential or simultaneous any more.

This thesis research study is focused on the spelling application based on two common types of BCI systems for this application, i.e., P300 and SSVEP approaches. Experiments were done on SSVEP and P300 separately and as also as a combined system. The SSVEP and P300 were designed as a simultaneous combination. The performance and the accuracy of the spellers were evaluated and compared.

Chapter 2. METHODS

2.1 Data Acquisition

2.1.1 Equipment

The data used for the experiments performed for this thesis was acquired using Guger Technologies (g. tec) products [52] including; g. GAMMA cap, g. USB amp, g. GAMMA box, and g.STIM box. MATLAB and Simulink were the software utilized for performing and processing the experiments. For repetitive stimulus, LEDs with white light color were utilized. The equipment utilized in this research are shown in Figure 12.

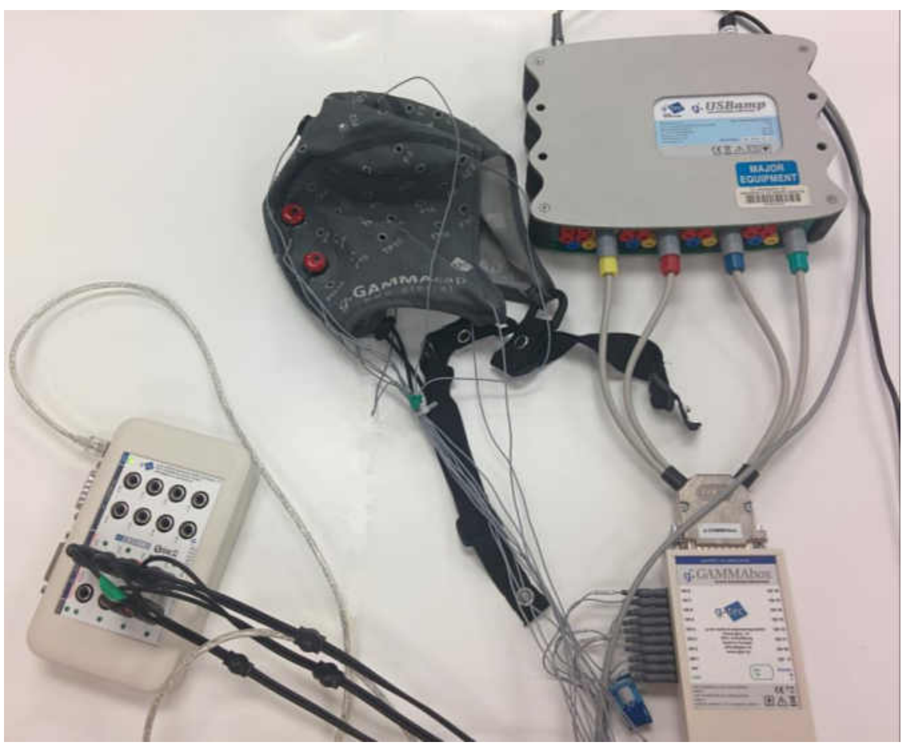


Figure 12. Equipment utilized for data acquisition.

2.1.2 Data

The biomedical signal used for the experiments is EEG which was acquired through surface electrodes using g. GAMMA cap. For the SSVEP spelling test, three channels; PO7, Oz, and PO8, were considered for recording the EEG, FPZ was considered as the ground and data from electrode placed on the right mastoid as the reference. For the subjects performed experiment based on SSVEP, P300 and hybrid Spelling paradigm experiment, 8 channels; Fz, Cz, P3, Pz, P4, PO7, Oz, and, PO8 were utilized for data acquisition. The electrodes position was based on 10-20 system [19].

2.2 Signal Processing

2.2.1 SSVEP Detection

EEG was passed through 60 Hz notch filter. The difference EEG from channels OZ and PO8 (OZ-PO8) with 256 Hz as sampling frequency rate was considered as the data to have the further processing on. The reason behind choosing OZ-PO8 was that this selection of the bipolar channels has the most distinct high amplitude at the elicited frequencies based on offline analysis of pilot experiments. FFT was applied to the signal and the signal is passed through 6 subsystem blocks. The signal processing model is shown in Figure 13. In Figure 14 the preprocessing blocks and FFT blocks are shown.

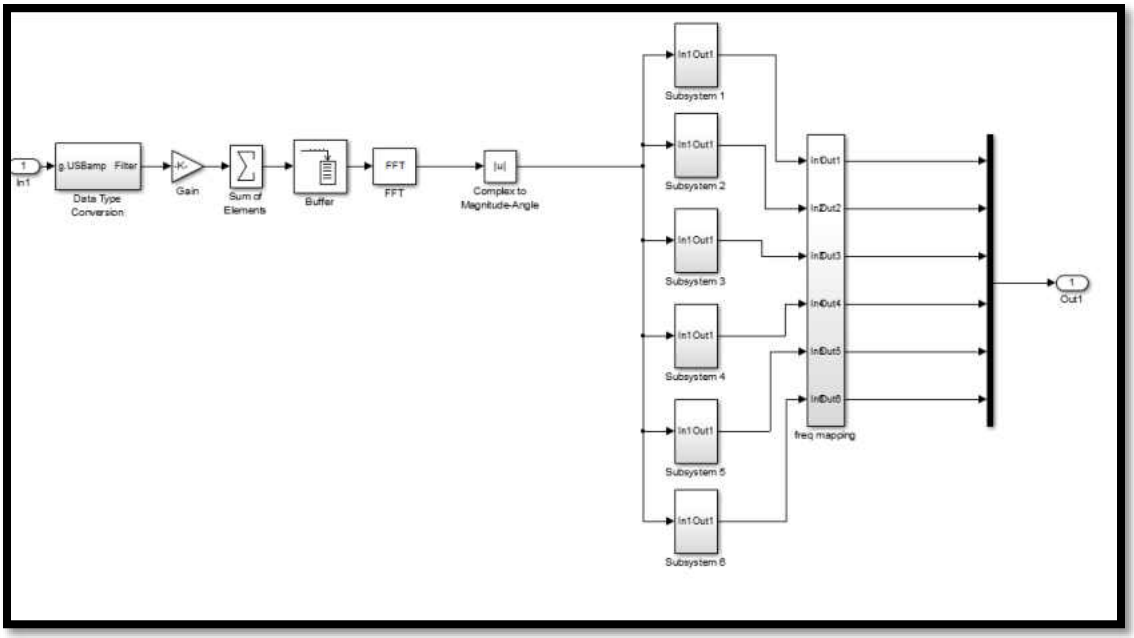


Figure 13. SSVEP signal processing block diagram.

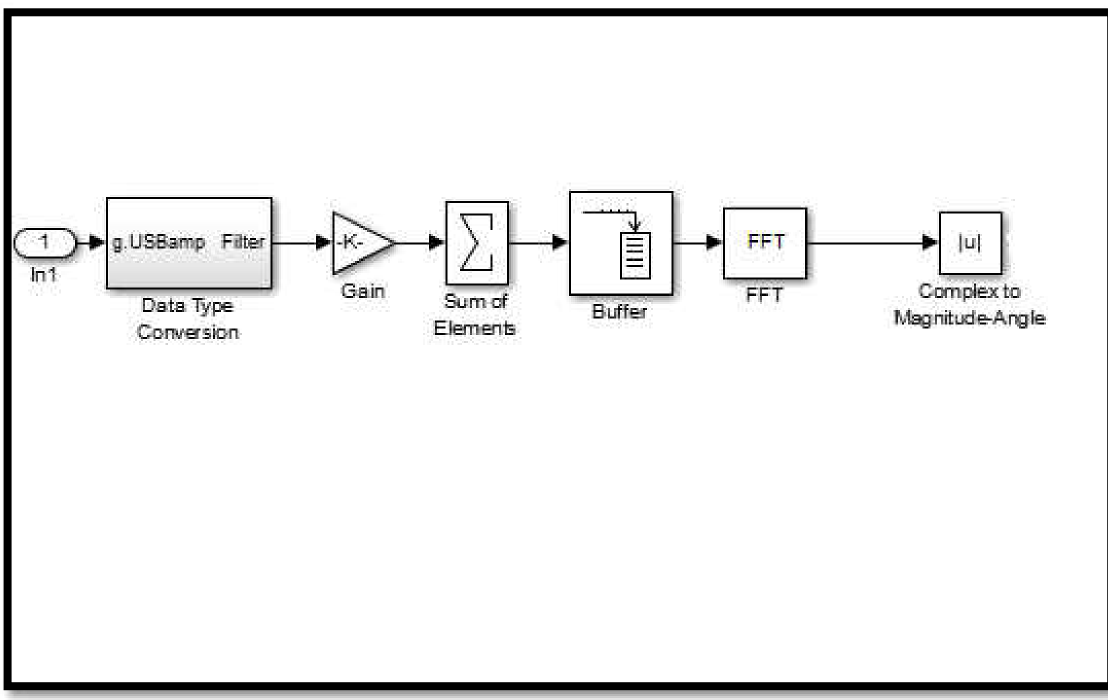


Figure 14. Block diagram showing calculating FFT.

The stimulus frequencies were defined as a vector ‘f’. In each subsystem block, one of the stimulus frequencies were considered for calculation. The amplitude of the narrow band of frequency ±0.2 Hz was considered. The calculation is shown in the following equation. The 'x' shows the number of each of the six intended frequencies and 4 is the window size.

$$Amplitude = [zeros((round((f(\mathrm{x}) - (.2)) * 4) + 2),1); ones(round((f(\mathrm{x}) * 4 + 4 * (.1)) - (f(\mathrm{x}) * 4 - 4 * (.1))) + 2,1); zeros(round(1024 - ((f(\mathrm{x}) + (.2)) * 4) - 1),1)]$$

The subsystem and the calculated amplitude as the 'gain' block are shown in Figure 15 and Figure 16 respectively. As it is shown in Figure 15, the intended frequency and 2 first harmonics are considered. The calculation of gain for the first and second harmonics (e.g., when $f(1)$ =17 Hz) is are shown in the following equations.

$$Amplitude = [zeros((round((2 * f(1) - (.2)) * 4) + 2),1); ones(round((2 * f(1) * 4 + 4 * (.1)) - (2 * f(1) * 4 - 4 * (.1))) + 2,1); zeros(round(1024 - ((2 * f(1) + (.2)) * 4) - 1),1)]$$

$$Amplitude = [zeros((round((3 * f(1) - (.2)) * 4) + 2),1); ones(round((3 * f(1) * 4 + 4 * (.1)) - (3 * f(1) * 4 - 4 * (.1))) + 2,1); zeros(round(1024 - (3 * f(1) + (.2)) * 4) - 1),1)]$$

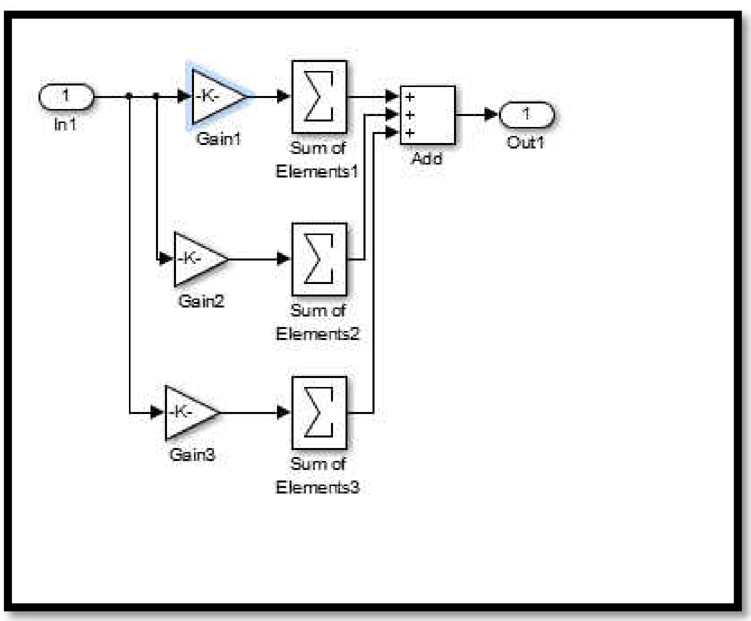


Figure 15.The block diagram of each subsystem.

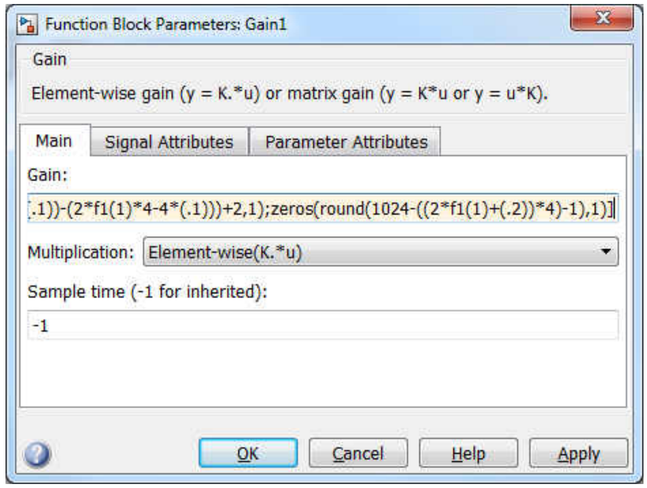


Figure 16. The calculated amplitude.

The output of each subsystem would enter the frequency mapping block which is shown in Figure 17.

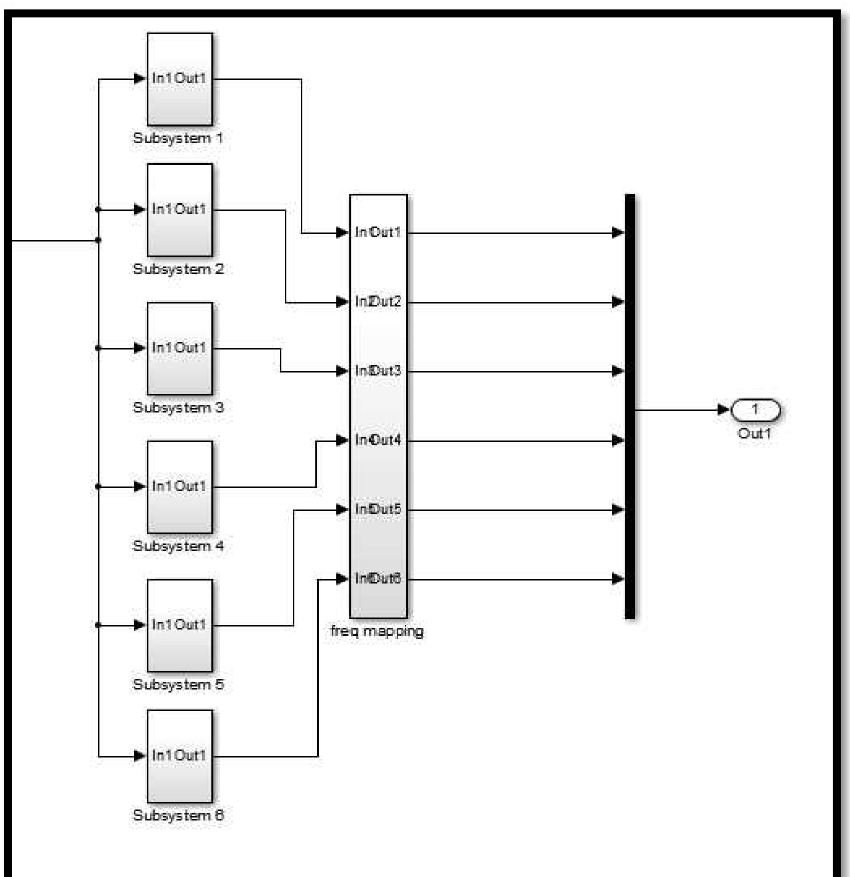


Figure 17. The frequency mapping block.

In the frequency mapping block the maximum of the six input would be determined and the frequency related to that would be shown. Other arrays of the ‘f1’ would be shown as zero. The processing in the frequency mapping block is shown in Figure 18. And the output of the SSVEP detection signal processing block is shown in Figure 19.

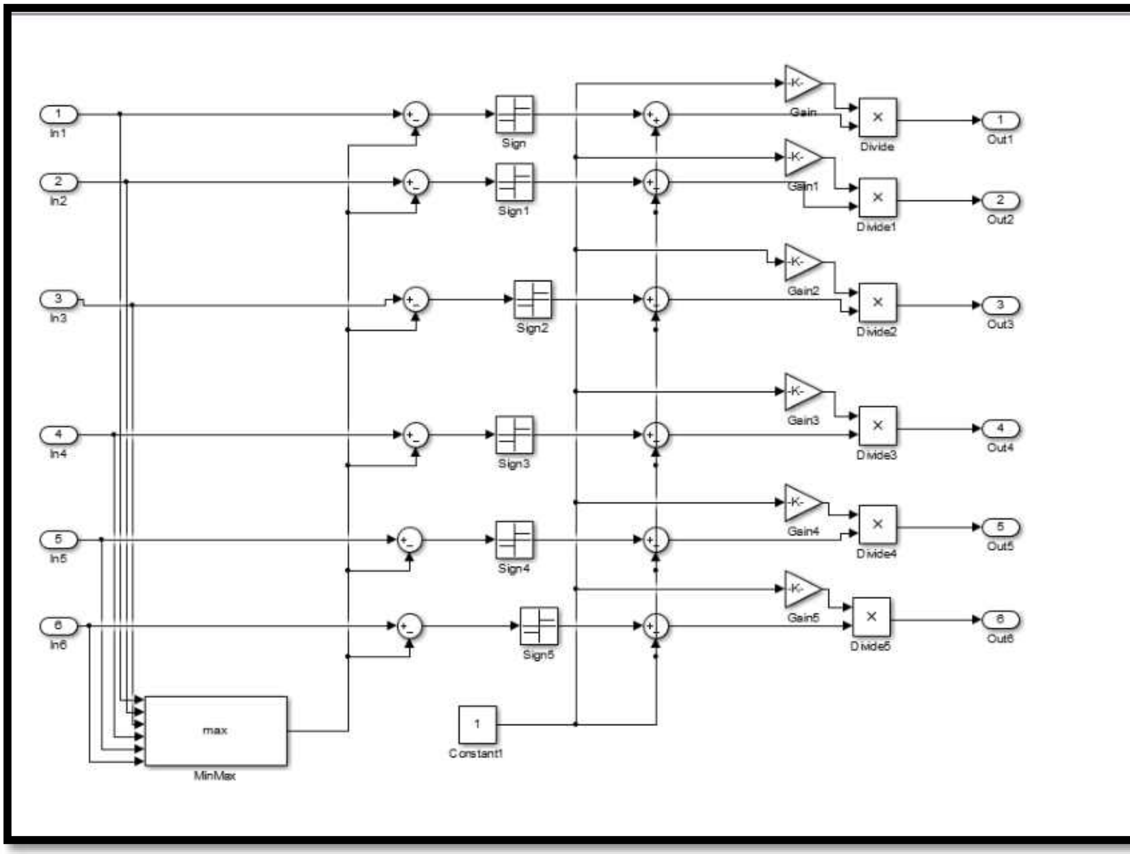
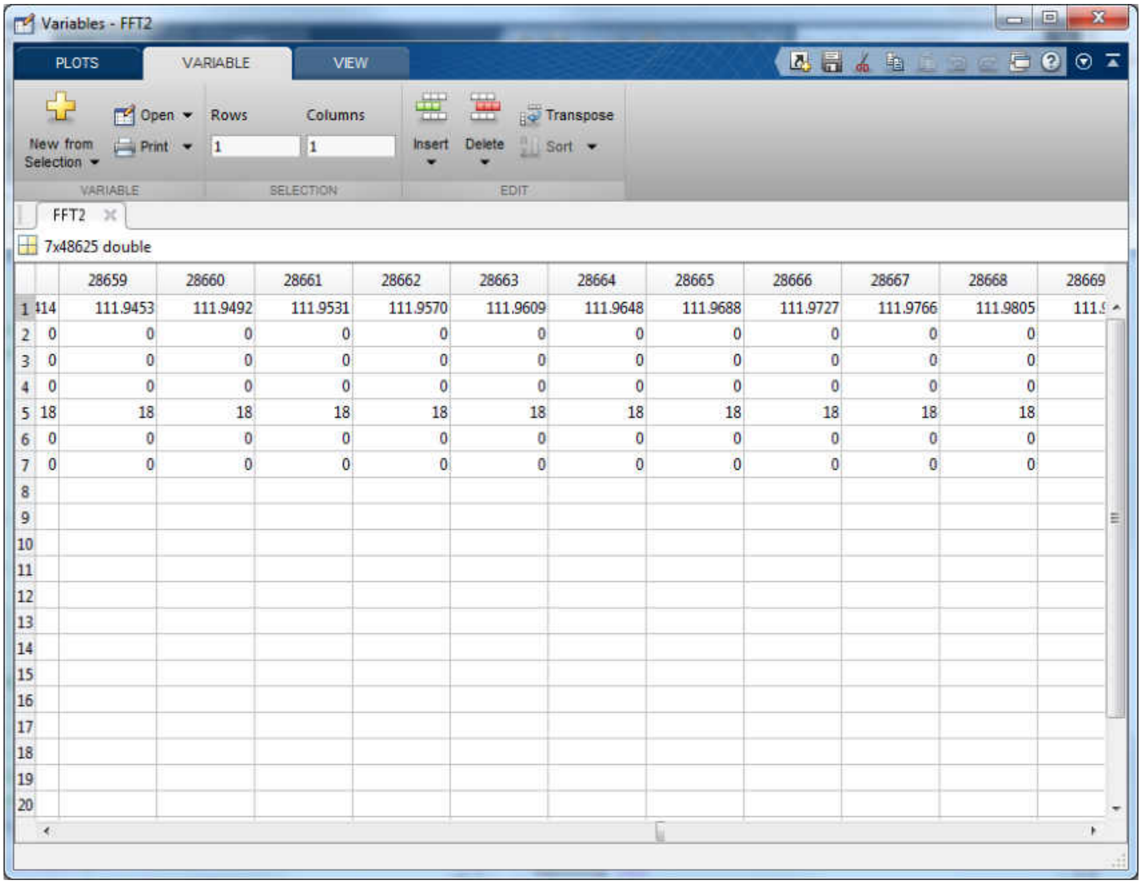


Figure 18. Frequency detection in frequency mapping block.



		28659	28660	28661	28662	28663	28664	28665	28666	28667	28668	28669
1	414	111.9453	111.9492	111.9531	111.9570	111.9609	111.9648	111.9688	111.9727	111.9766	111.9805	111.[illegible]
2	0	0	0	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	0	
5	18	18	18	18	18	18	18	18	18	18	18	
6	0	0	0	0	0	0	0	0	0	0	0	
7	0	0	0	0	0	0	0	0	0	0	0	
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Figure 19. Detected frequencies are shown as a column for each sampling time.

As the data shows, the output would present the frequency of the detected frequency. A 24 sec window size was considered for spelling each character, and as the window size was considered 4 sec. 6 detections were considered for each character, and the most detected frequecy was determind as the output frequency.The related region represented by the detected frequency was shown as the final output and related charater was shown on the display. In Figure 20, the identification number of detected regions are shown; 1, 2, 3, 4, 5, and 6.

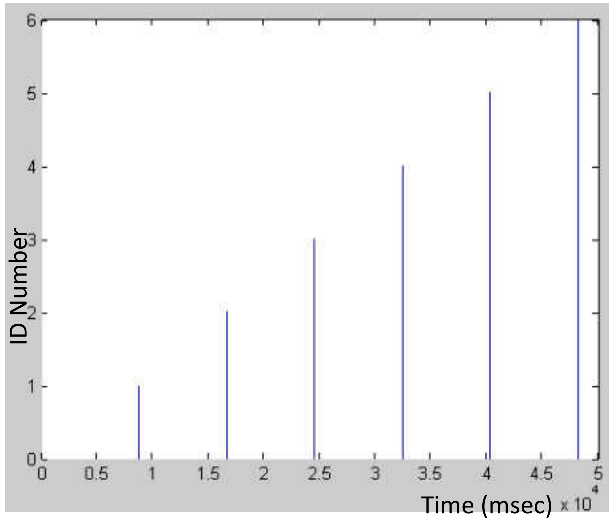

Figure 20. The identification number of detected regions.

2.2.2 P300 Detection

For P300 detection, data would pass through filter block and then downsample to 4, Figure 21, and the preprocessed data would enter the processing block. The classification method used in this research is LDA [25], which is a machine learning technique that uses linear combination of features that separates two or more types of events. The calibration was performed for each subject, using 'gbsanalyze' which is shown in Figure 22.

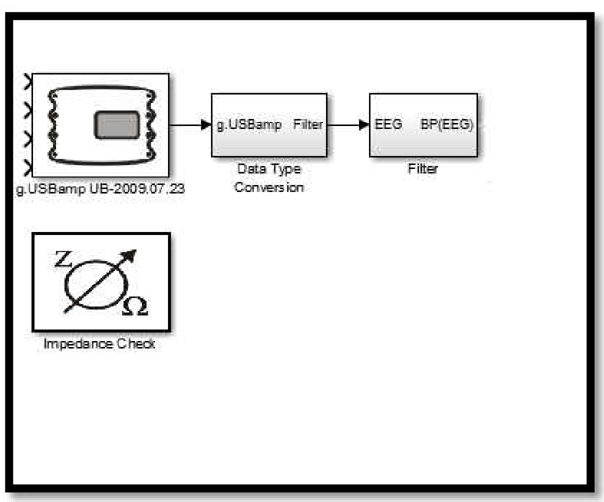

Figure 21 Pre processing for P300 detection.

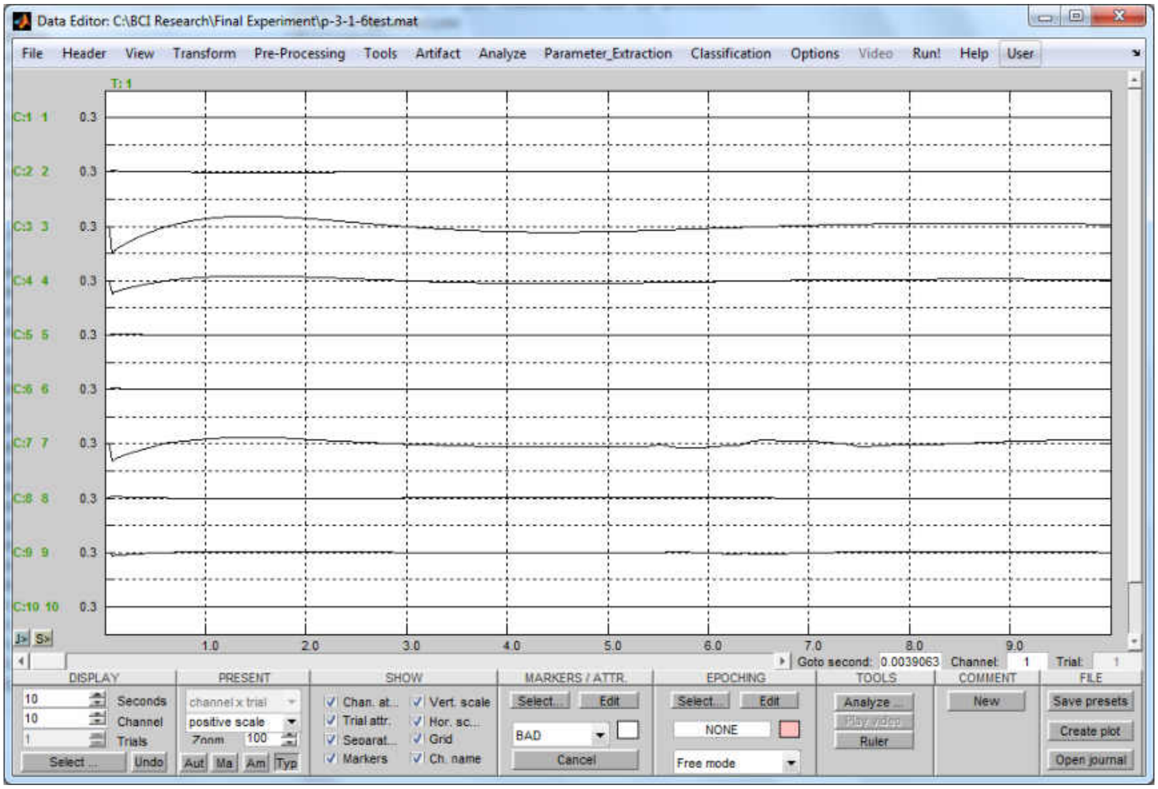

Figure 22. Loaded P300 file in gbsanalyze for LDA classification.

The same as SSVEP signal processing output, the output of the P300 signal processing was presented as the identification number of the detected region. Then the display as the character related to the detected region was displayed.

2.3 Paradigms

2.3.1 SSVEP-Based Spelling paradigm

The spelling paradigm utilized in this study was region-based spelling paradigm [53]. The spelling paradigm is designed with 49 characters, distributed in seven regions and has ‘copy spelling’ and ‘free spelling’ mode. For this study, the ‘copy spelling’ mode is utilized. Starting the paradigm, a keyboard would appear on the screen, the intended characters would be selected and the spelling screen would pop up. The spelling of each character happens in two levels. In the first level, the region of the intended character is selected and in the second level, the seven characters of the selected region are disperse in the same pattern of the first level and the character would be selected. The background color of the speller is black and characters color is white. The spelled character would be shown under the intended character. The spelling paradigm screen was projected on a white board with LEDs placed behind it. The LEDs placement is designed to be on the corner of the regions in level one and characters in the second level. The spelling paradigm set up, the keyboard display, and the two levels of the character spelling are shown in Figure 23, Figure 24, Figure 25, and Figure 26.

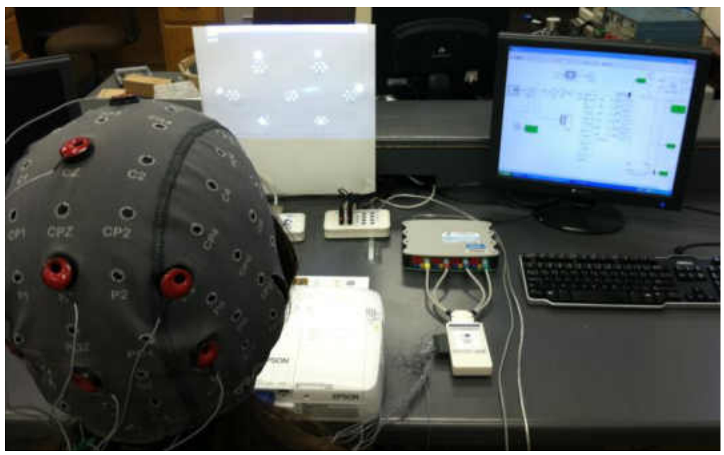

Figure 23. SSVEP-based spelling paradigm set up.

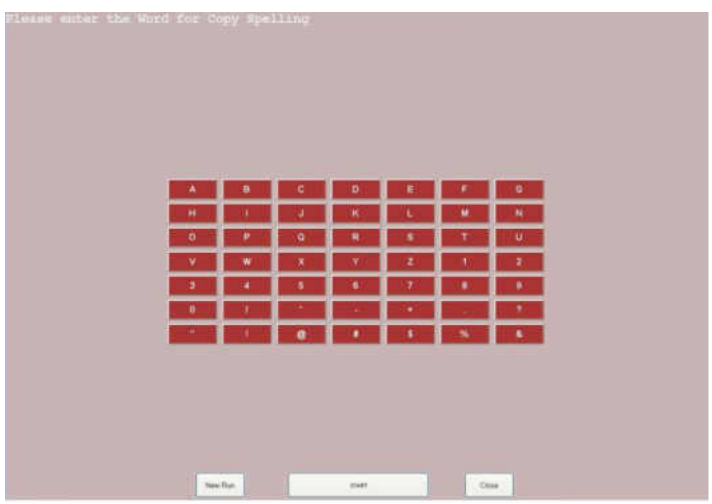

Figure 24. The keyboard display.

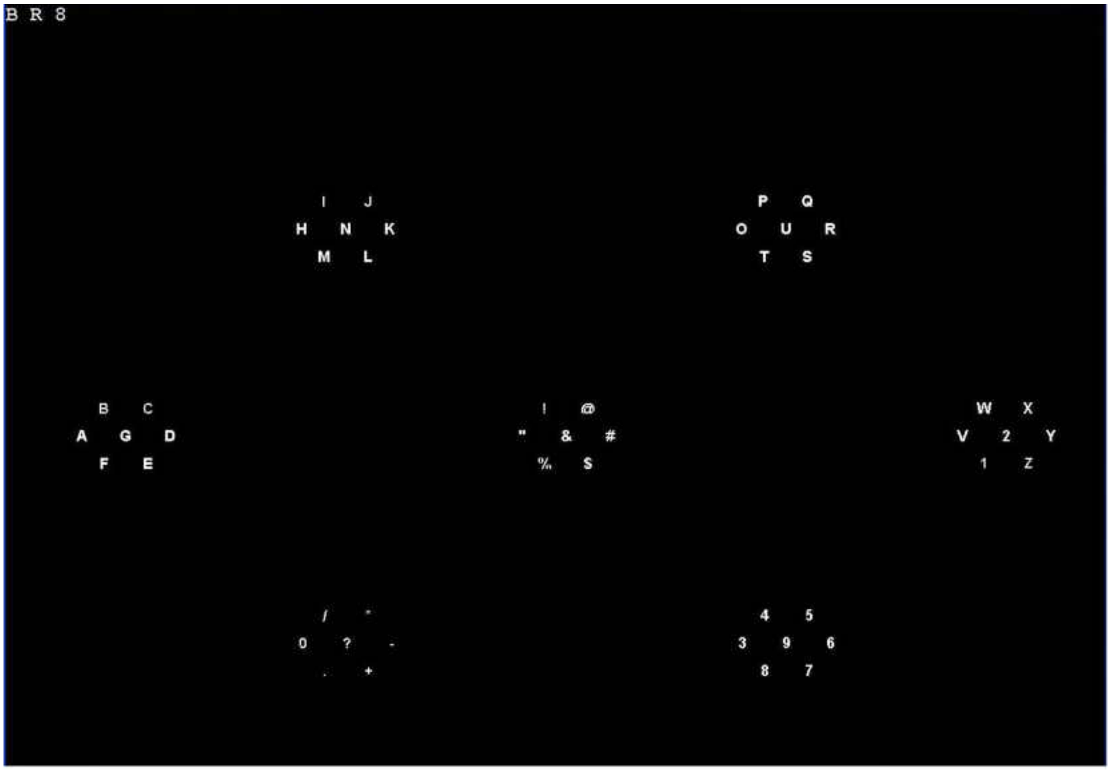

Figure 25. Level one of the character spelling.

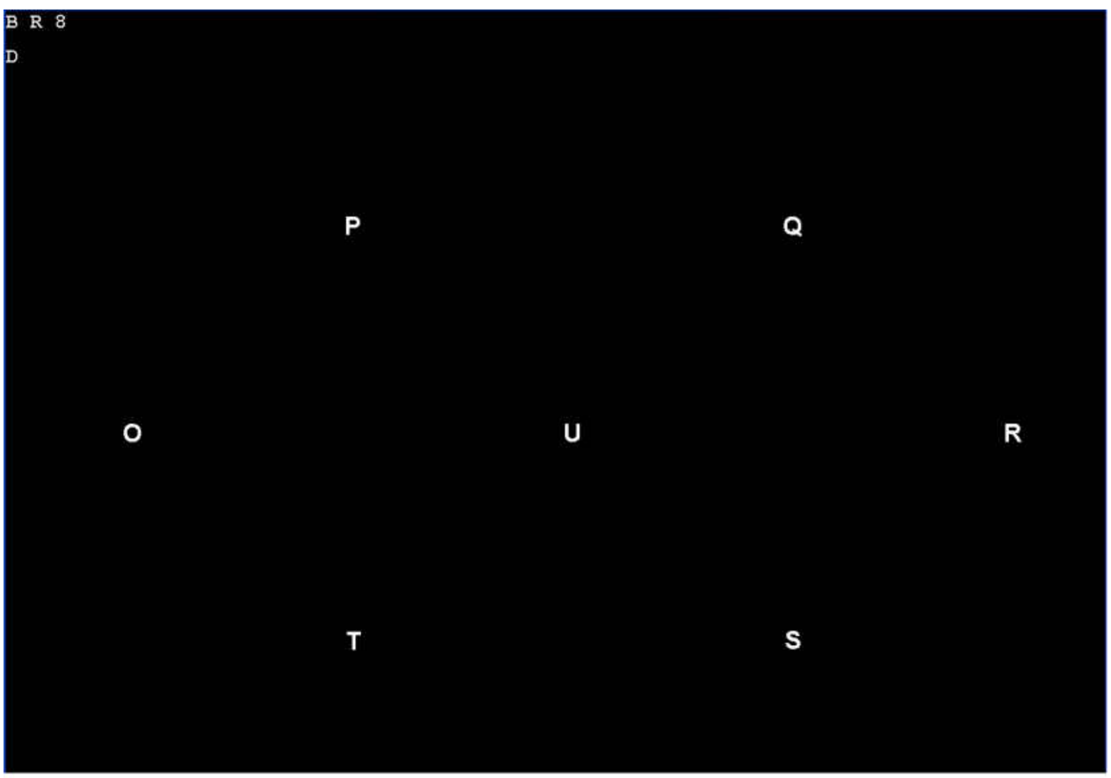

Figure 26. Level 2 of the spelling paradigm.

2.3.2 P300 Spelling Paradigm

The P300 region-based spelling paradigm [22] was utilized for experiments during this research. The distribution of characters and regions were the same as SSVEP Spelling paradigm. The P300 region-based spelling paradigm has two types based on the flashing stimulus. In the first type, the background of the regions flashed. In the second type, the characters flashed. In Figure 27, Figure 28, and Figure 29 the two types of paradigm and the Simulink model are shown.

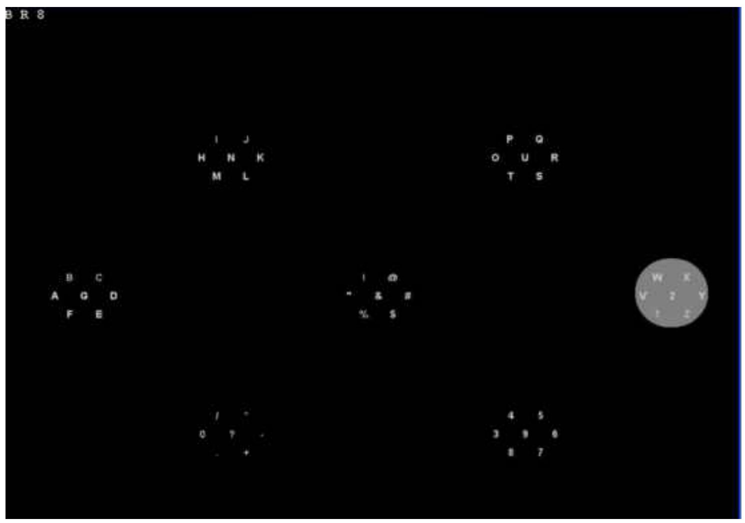

Figure 27. P300 region-based spelling paradigm with background flashing.

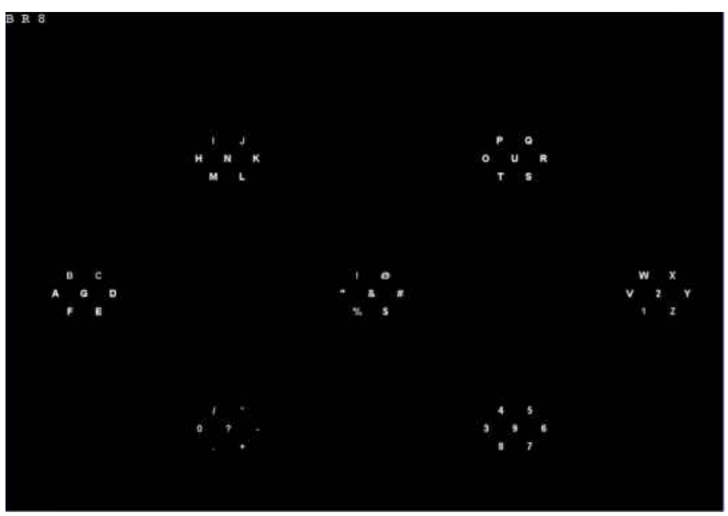

Figure 28. P300 region-based spelling paradigm with characters flashing.

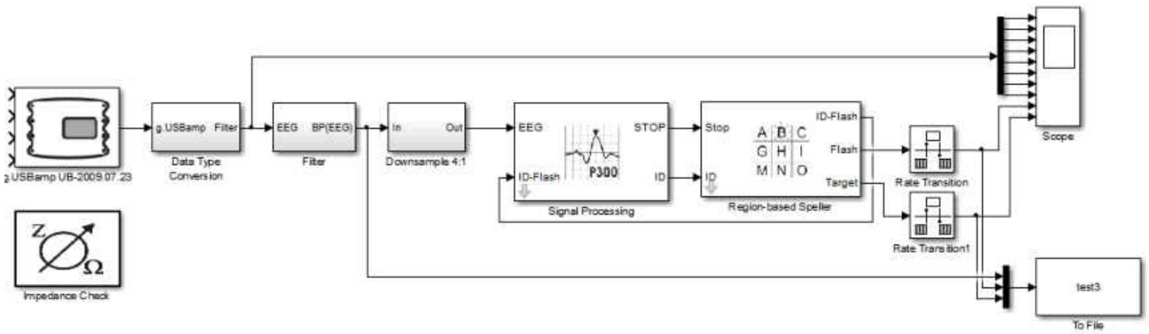

Figure 29. The P300-based spelling paradigm Simulink model.

2.3.3 Hybrid Paradigm

In the hybrid paradigm, the P300 region-based spelling paradigm was used and the LEDs placing behind the board were flashing. So both stimulus were performed at the same time. The Simulink model is shown in Figure 30. In this model EEG is processed through the P300 and SSVEP signal processing blocks. P300 and SSVEP signal processing blocks process the data simultaneously and send the identification number of the detected region at the same time. The output of both signal processing blocks are shown in Figure 31, as was displayed on the scope during the hybrid experiment, which is showing the identification number of detected region by both P300 and SSVEP signal processing blocks.

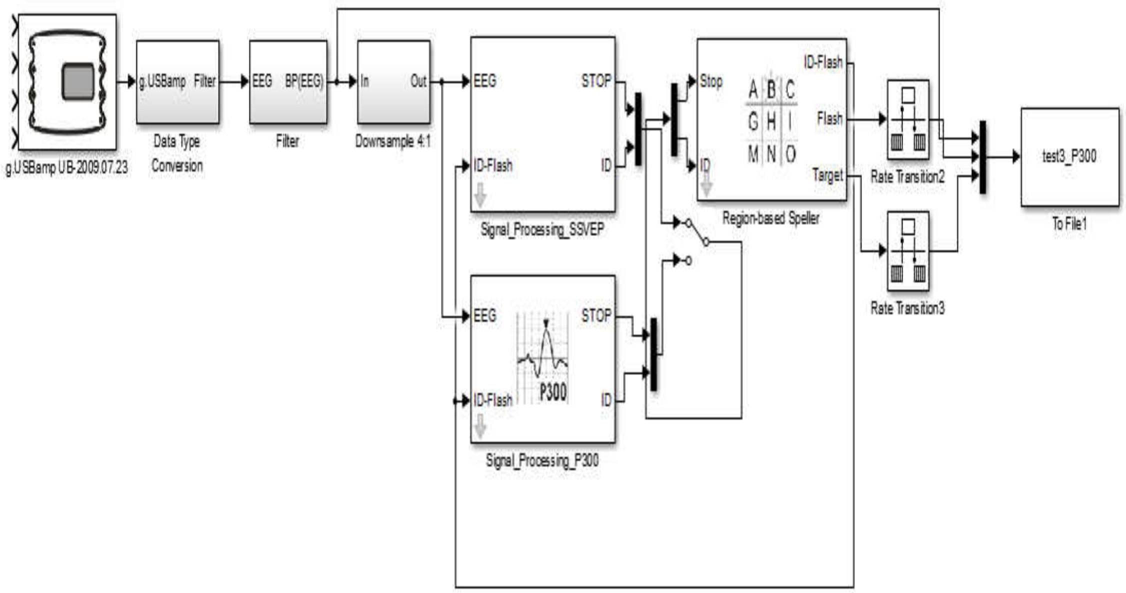

Figure 30. The Simulink model of hybrid spelling paradigm.

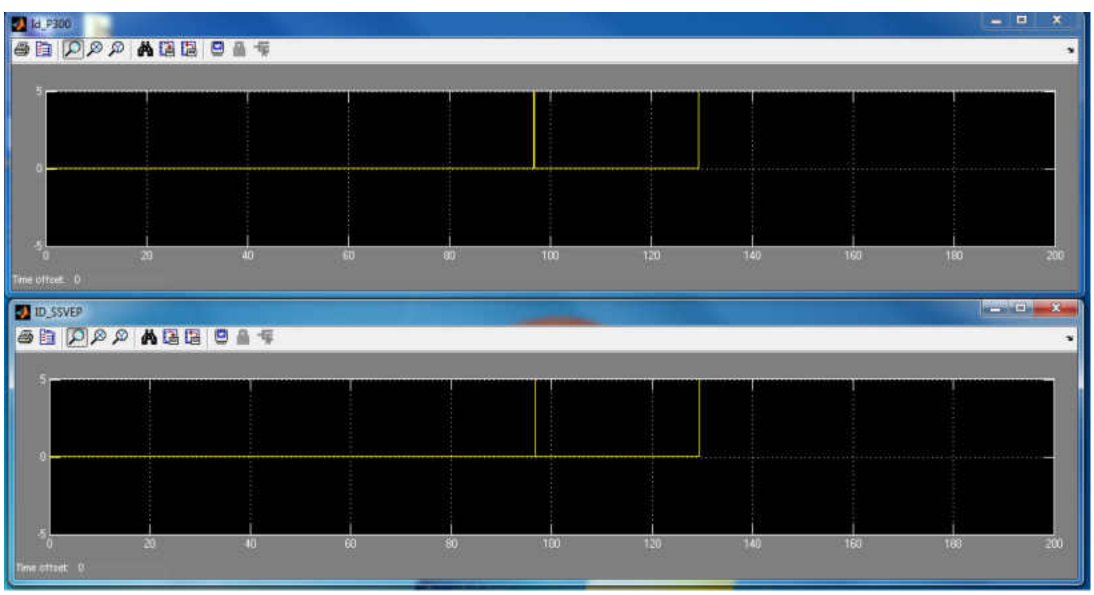

Figure 31. Identification numbers of detected regions by P300 and SSVEP.

Chapter 3. EXPERIMENTS AND RESULTS

In this chapter, the series of experiments performed during this study and their results are presented and discussed. Ethical approval for performing the experiment was obtained from the Institutional Review Board (IRB) from the University of North Dakota (UND). The IRB is responsible for ensuring that the rights and welfare of human subjects in social behavioral and biomedical research are protected. For experiments performed for this research the IRB approval number is IRB-201006-372 [54].

At the beginning, series of pilot studies were performed. Based on the analyzing the results of those experiments, the parameters for the SSVEP spelling paradigm were determined and the eventually results of the experiments performed for evaluation of hybrid P300 and SSVEP-based spelling paradigms.

3.1 Pilot Experiments

Series of pilot experiments were performed intending to determine the channel combination, the range of eliciting frequency, and the window size of data for processing. Two subjects participated in the first experiment and for the rest of experiments one subject performed the tasks.

3.1.1 SSVEP Detection Testing - Initial Experiment

The experiment was done offline with low frequencies to check the SSVEP detection. The SSVEP eliciting paradigm was a board with six LEDs on it in a circular pattern. For this experiment the upper left LED was flashing and frequencies of 14, 18 and 20 Hz were selected. Each time, the subject task was to gaze at the flashing LED for 200 seconds. The window size for processing was 16 sec. The first 16 sec of data was eliminated as it was corrupted with noise. Large peaks were appeared around the frequency of 11 Hz which is related to alpha activities. By analyzing offline data, 100% accuracy in detection of eliciting frequencies was achieved.

3.1.2 Determining the Processing Window Size

This experiment was performed as an online test. The same frequencies were utilized, except the three upper half LEDs were flashing at the same time and the subject task was to look at one of them at a time. The test started with assigning 16 sec as the window size. As the SSVEP detection was successfully achieved the window size changed from 16 to 8 and from 8 to 4 seconds. The results remained consistent as the window size got smaller. Based on this experiment, it was concluded in considering 4 sec window size is large enough for processing the EEG data to detect the SSVEP frequencies.

3.1.3 Switching between Flashing LEDs

In this test, subject task was to switch from one LED to another one. 93.33% accuracy was achieved in the previous test with considering 4 sec for window size of the processing. However, this set of experiments were processed with 16 and 8 sec of window timing, as assuring that the detection of peaks was just affected with the transition between LEDs and the processing was performed with a large enough window time. In the first set of experiments, the window size was 16 sec and the time of experiments was 64 sec. In first round, the subject task was to gaze at LED flashing at 18 Hz for 48 seconds and shifting to LED with 14 Hz flashing rate for 32 seconds. In the next round of the test, the transition was from LED with flashing rate of 14 Hz to LED with 20 Hz flashing rate. In the third round, the task was to switch from LED with flashing rate of 20 Hz to LED with 18 Hz flashing rate. In the next round, the transition was among the three LEDs with the sequence of LEDs with 18-14-20 Hz. The task was repeated for switching from 14 to 20 Hz and from 20 to 14 Hz.

As achieving high accuracy while analyzing data with 16 sec window for processing, the window time was reduced to 8 seconds and 4 sec. All the rounds repeated with the same sequence of switching between LEDs. The results of all sets of experiments are shown in Table 2.The accuracy was reduced as the window size was reduced to 4 sec.

Table 2. Results of the switching between LEDs.

Sequence of LEDs (Frequency Hz)	Accuracy (%) with 16 sec of window size	Accuracy (%) with 8 sec of window size	Accuracy (%) with 4 sec of window size
18-14	100	100	93.33
14-20	100	66.66	87.5
20-18	100	100	75
18-14-20	100	71.43	80
14-20-14	100	100	60

3.1.4 Detecting High Frequencies

The goal in this experiment was to evaluate the detection of high frequencies. Three high frequencies; 36, 44, and 40 Hz were selected for the first, second, and third LEDs, respectively. The experiment had three rounds. In the first round, subject gazed at the first LED with 36 Hz flashing stimuli, and the higher peak was detected at the frequency of 36 Hz. In the second and third rounds, the subject gazed at the second and third LEDs and peaks were detected at 44 and 40 Hz respectively. The analysis for this experiment was done offline and the FFT spectrums for each round are shown in Figure 32, Figure 33, and Figure 34.

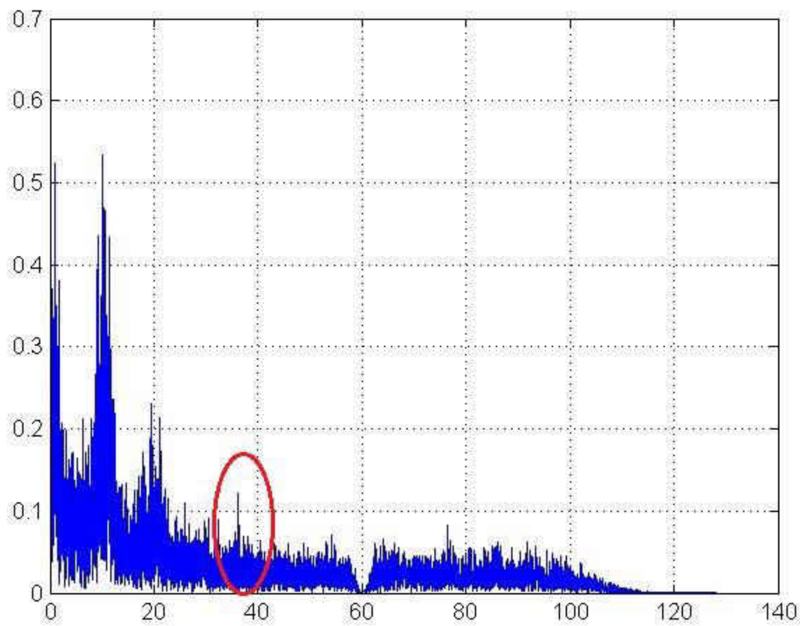

Figure 32. Frequency spectrum of the first round. Peak at 36 Hz is detected.

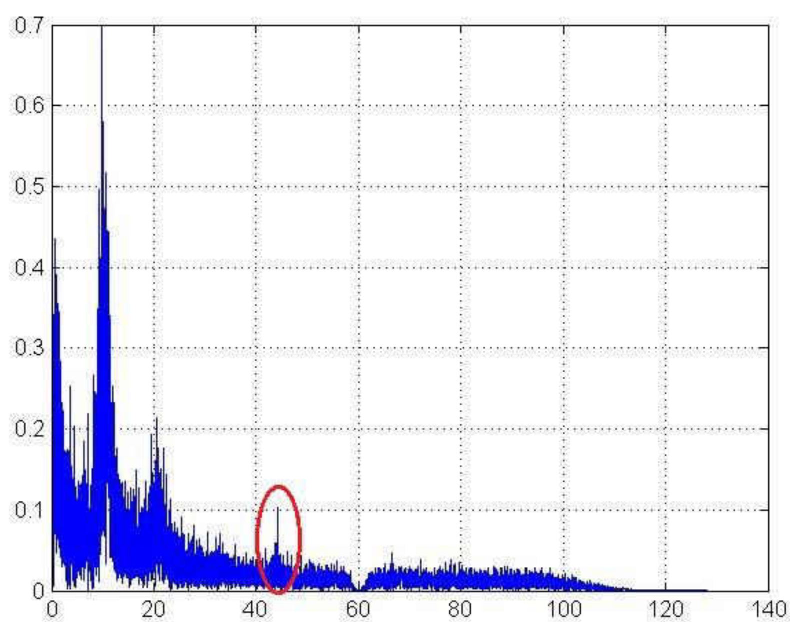

Figure 33. Frequency spectrum of the first round. Peak at 44 Hz is detected.

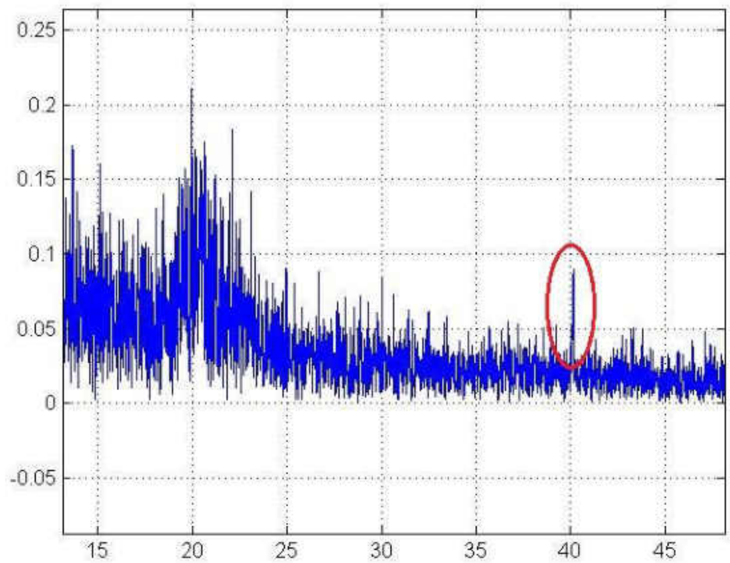

Figure 34. Frequency spectrum of the first round. Peak at 44 Hz is detected.

As it is shown in the frequency spectrum, at the frequencies close to 11 Hz the high peaks are detected related to alpha activity [1].

3.1.5 Determining the SSVEP stimulation board

In the previous tests, the LEDs were placed on a board. In this set of experiments, LEDs were placed behind a white board, and according to the accuracies achieved from the tests on the new board comparing to the basic board with LEDs placed on the board, the size of the holes on the board were determined. A black screen was projected on both boards to simulate the actual spelling board. In this experiment, it was tried to keep all the variables or environmental factors unchanged, and to see how changing the stimuli set up, affects the results. For the first step, 14 Hz was chosen as a flickering frequency. The test was done using the first board. The experiment resulted in detecting 14 Hz, 8 out of 8 times (100% accuracy). The same frequency was tested using the second board in the next round. 14 Hz was detected 4 out of 8 times. For the next round, the holes in the second board were enlarged and the experiment was repeated. In this round 14 Hz was detected 8 out of 8 times. By enlarging the holes the accuracy improved, so the size of the holes on the board was changed. The experiment continued using the first and the second board for 24 and 36 Hz. The three combinations of the three channels that the EEG signals were acquired were compared in the offline analysis and the FFT spectrums of the channels OZ and PO8 showed higher peaks at the intended frequency. The accuracy of the frequency detection is shown in Table 3 for 14 Hz and in Table 4 for 24 and 36 Hz.

Table 3. Average accuracy for 14 Hz.

Accuracy % Board I	Accuracy % Board II	Accuracy % Board II after enlarging the holes
100	50	100

Table 4. Average accuracy for 24 and 36 Hz.

Frequency (Hz)	Accuracy % Board I	Accuracy % Board II after enlarging the holes
24	100	100
36	87.5	100

In another series of the experiments, a black board was utilized for the tests. The effect of environmental condition was investigated in this experiment. The subject was seated in a dark room to determine the effect of the light on the results. The frequencies of 36, 38, 40, 42, 44, and 46 Hz were tested in this series of experiments. Subject did the task for the first four frequencies and had a break due to the fatigue caused by gazing at the flickering LEDs. After the break, the experiment was continued for 44 and 46 Hz three times with board II, but we were not able to detect the peaks at the intended frequencies for 46 Hz and with accuracy of 12.5% for 44 Hz. To justify that the failure to detect the frequencies was because of the frequencies, the test was repeated for 36 Hz, and 100% detection was achieved. The result for each frequency is shown in Table 5. The results show that the white board, second board, is more appropriate to consider as stimulating board. The black screen has better reflection on a white color board and subject was more comfortable doing the task in a dark room, with higher contrast of the LED lights and the room light.

Table 5. Average accuracy for three stimulating boards.

Frequency (Hz)	Accuracy % Board I	Accuracy % Boards II	Accuracy % Board III
36	100	87.5	100
38	87.5	87.5	75
40	75	62.5	50
42	12.5	62.5	25

These series of experiments show great potential in implementing SSVEP-based BCIs with high frequency. The frequencies up to 44 Hz were detected and stimulation board was determined. The higher the frequency, the harder would be to detect the peak [9] as the amplitude would be lower, and frequencies up to 44 Hz were detected. This shows that the SSVEP detection signal processing has high accuracy. After these series of experiment, a set of experiments was performed utilizing SSVEP for spelling paradigm application.

3.2 SSVEP-Based Spelling Paradigm

In this part of study, the SSVEP-based spelling paradigm was evaluated. Six healthy male subjects participated in this study. Three words; ‘BR8’, ‘C41’, and ‘*6B’, were selected, based on selecting all the 6 side regions. Each word was spelled in three trials. The LEDs were flashing as 17, 20, 23, 26, 29, 32 Hz for region one to region six, the side regions in a clockwise order, respectively. The EEG from OZ-PO8 channel was processed through a 4 sec window. The spelling paradigm was run 24 seconds for each character to be spelled for each level. Two male subjects participated in this part of the study. Allocating the frequencies to the LEDs in order to get high accuracy needs series of trial and error tests, as several parameters affect the accuracy of SSVEP peak detection. One parameter is the frequency of each LED. Several tests were performed to determine the frequencies for which the detection of SSVEP peaks has high accuracy. In the allocation of frequency for each LED, the frequencies of other LEDs should be also considered in a way that the frequencies of the adjacent LEDs should have a short range of interval. In the first set of selected frequencies, 17 Hz was allocated for the first LED and 32 Hz for the sixth LED. Results show that the LED with 17 Hz had the highest percentage of miss selection. Another parameter is the placement of the LEDs. The LEDs located straight to the subject's eye may create unwanted stimulus when subject eye's direction is to the other LEDs. The frequency for these LEDs should not be at the lowest range of the selected frequencies. The LEDs located on the sides may also create unwanted stimulus if the allocated frequency is not close to the other LEDs' frequencies. In designing the SSVEP spelling paradigm, the frequencies for each LED, the location of LED and the range of frequencies should be considered in frequency selection. The results of the first two subjects are shown in Table 6, Table 7, and Table 8.

Table 6. Accuracies of SSVEP detection for the first two subjects.

Subject	Accuracy 17Hz (%)	Accuracy 20 Hz (%)	Accuracy 23Hz (%)	Accuracy 26 Hz (%)	Accuracy 29 Hz (%)	Accuracy 32 Hz (%)
1	100	77.78	88.89	33.33	0	0
2	100	44.44	77.78	55.56	0	0
Avg.	100	61.11	83.33	44.44	0	0

Table 7. False positive rate of SSVEP detection for the first two subjects.

Subject	FPR 17Hz (%)	FPR 20Hz (%)	FPR 23Hz (%)	FPR 26Hz (%)	FPR 29Hz (%)	FPR 32 Hz (%)
1	55.55	2.22	0	0	0	0
2	33.33	2.22	26.66	0	0	0
Avg.	44.44	2.22	13.33	0	0	0

Table 8. Accuracies of SSVEP detection for each word.

Subject	Accuracy 'BR8'(%)			Accuracy 'C41' (%)			Accuracy '*6B' (%)		
	Trial1	Trial2	Trial3	Trial1	Trial2	Trial3	Trial1	Trial2	Trial 3
1	33.33	66.67	50	50	66.67	33.33	50	33.33	50
2	33.33	50	50	33.33	50	50	33.33	0	66.67
Avg.		47.22			47.22			38.39	

As the results show, the frequency of 17 Hz for the first LED creates high percentage of false positive rate. In despite of SSVEP peak detection at frequencies of 36, 44 and 40 Hz when three out of six LEDs were flashing. Detection of frequencies below 36 in previous tests, in this experiment selection of frequency set as 17, 20, 23, 26, 29, and 32 Hz results in zero detection of the peaks at 26, 29, and 32 Hz. After the first two subjects performed the test. The average accuracy of spelled words was in a close range which shows characters spelled do not affect the detection accuracy. The frequencies of the flickering LEDs were changed to 21, 23, 20, 18, 17, and 19 Hz. In this new selection of frequencies, the higher frequencies were allocated to the top LEDs and lower frequencies, which creates stronger stimulus, allocated to the lower LEDs. The frequencies of the adjacent LEDs were selected to be close to each other. For this series of experiments four male subjects participated. The results are shown in Table 9, Table 10, and Table 11.

Table 9. Accuracies of SSVEP detection for new set of frequencies.

Subject	Accuracy % for 21 Hz	Accuracy % for 23 Hz	Accuracy % for 20 Hz	Accuracy % for 18 Hz	Accuracy % for 17 Hz	Accuracy % for 19 Hz
3	100	77.78	44.44	100	100	88.89
4	66.67	55.56	33.33	66.67	100	66.67
5	44.44	33.33	0	55.56	44.44	44.44
6	55.56	33.33	33.33	44.44	77.78	22.22
Avg.	66.67	50	27.78	66.67	80.55	55.55

Table 10. False positive rate of SSVEP detection for new set of frequencies.

Subject	FPR % for 21 Hz	FPR % for 23 Hz	FPR % for 20 Hz	FPR % for 18 Hz	FPR % for 17 Hz	FPR % for 19 Hz
3	2.22	0	0	4.44	2.22	6.67
4	0	0	0	13.33	20	8.89
5	4.44	11.11	0	22.22	17.78	17.88
6	2.22	0	0	17.78	11.11	33.33
Avg.	2.22	2.78	0	11.55	10.22	13.35

Table 11. Accuracies of SSVEP detection for each word.

Subject	Accuracy % for 'BR8'			Accuracy % for 'C41'			Accuracy % for '*6B'		
	Trial1	Trial 2	Trial 3	Trial 1	Trial 2	Trial 3	Trial 1	Trial 2	Trial 3
3	100	66.67	83.33	100	66.67	100	83.33	83.33	83.33
4	83.33	66.67	66.67	33.33	66.67	66.67	50	83.33	50
5	33.33	50	83.33	50	16.67	0	33.33	0	83.33
6	100	66.67	33.33	66.67	16.67	16.67	33.33	16.67	33.33
Avg.		69.44			50			52.78	

As it is shown in the results, the false positive rate is in close range for the lower LEDs and upper LEDs as well. The average accuracy for spelling the intended words is not high, as number of subjects for this experiment was four, and two of them did not have high accuracy for SSVEP detection. For the next series of experiments, more subjects participated in the experiment to validate the results.

3.3 Hybrid Spelling Paradigm

As series of experiments were performed based on SSVEP spelling paradigm, in these series of experiments, SSVEP-based spelling paradigm, P300-based spelling paradigm and the hybrid spelling paradigm were evaluated. 10 subjects participated in these series of experiment. The task was to spell ‘BR8’, through SSVEP spelling paradigm, P300 spelling paradigm and in the last, hybrid spelling paradigm. The task for each paradigm was performed through three trials.

3.3.1 SSVEP-Based Spelling Paradigm

For the SSVEP spelling experiment, the frequencies were the same as previous experiment, 21-23-20-18-17-19 Hz, and also all other parameters. The average accuracy for spelling ‘BR8’ through three trials was calculated for each subject and the results are shown in Table 12. As the results show the average accuracy of 80% was achieved through SSVEP detection.

Table 12. SSVEP accuracy.

Subject number	Accuracy % Trial 1	Accuracy % Trial 2	Accuracy % Trial 3	Average %
1	100.00	100.00	100.00	100.00
2	100.00	100.00	83.33	94.44
3	50.00	75.00	50.00	58.33
4	50.00	83.33	50.00	61.11
5	75.00	83.33	100.00	86.11
6	100.00	100.00	100.00	100.00
7	75.00	75.00	50.00	66.67
8	50.00	50.00	83.33	61.11
9	83.33	83.33	100.00	88.89
10	83.33	83.33	83.33	83.33
Average	76.67	83.33	80.00	80.00

3.3.2 P300-based Spelling paradigm

After subjects performing the first task, the next step was to evaluate the test through the P300-based spelling paradigm [22] The parameters of the paradigm are; 150 msec for flash time, 100 msec for dark time, and 14 as number of flashes. The test went through three trials and the results are shown in Table 13. The average accuracy of 72.50 % was achieved.

Table 13. P300 accuracy.

Subject number	Accuracy(%) Trial 1	Accuracy(%) Trial 1	Accuracy(%) Trial 1	Average(%)
1	75.00	100.00	75.00	83.33
2	75.00	75.00	83.33	77.78
3	50.00	33.33	50.00	44.44
4	33.33	33.33	50.00	38.89
5	83.33	100.00	100.00	94.44
6	83.33	100.00	83.33	88.89
7	75.00	50.00	50.00	58.33
8	83.33	83.33	75.00	80.55
9	83.33	83.33	75.00	80.55
10	75.00	75.00	83.33	77.78
Average	71.67	73.33	72.50	72.50

3.3.3 Hybrid Spelling Paradigm

The last task was to spell ‘BR8’, and subjects were asked to focus on both flickering LEDs and random flashing regions. A sample of EEG signals recorded from 8 channels during the experiment is shown in Figure 35.

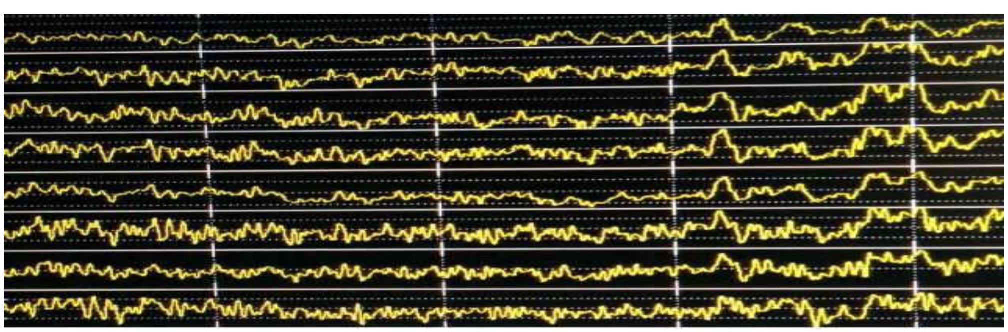

Figure 35. Recorded EEG.

The results from SSVEP signal processing block and P300 signal processing block are shown in Table 14 and Table 15.

Table 14. Results from hybrid/SSVEP signal processing block.

Subject Number	Accuracy % Trial 1	Accuracy % Trial 2	Accuracy % Trial 3	Average %
1	50.00	75.00	75.00	66.67
2	75.00	75.00	50.00	66.67
3	50.00	16.67	33.33	33.33
4	33.33	33.33	50.00	38.89
5	50.00	50.00	16.67	38.89
6	50.00	75.00	75.00	66.67
7	33.33	50.00	50.00	44.44
8	33.33	16.67	33.33	27.78
9	50.00	33.33	75.00	52.78
10	16.67	50.00	75.00	47.22
Average	44.17	47.50	53.33	48.33

Table 15. Results from hybrid/P300 signal processing block.

Subject Number	Accuracy (%) Trial 1	Accuracy(%) Trial 2	Accuracy(%) Trial 3	Average(%)
1	50.00	16.67	50.00	38.89
2	50.00	50.00	33.33	44.44
3	33.33	33.33	16.67	27.78
4	50.00	33.33	33.33	38.89
5	50.00	50.00	75.00	58.33
6	50.00	75.00	50.00	58.33
7	33.33	50.00	16.67	33.33
8	16.67	16.67	33.33	22.22
9	50.00	33.33	50.00	44.44
10	33.33	50.00	16.67	33.33
Average	41.67	40.83	37.50	40.00

As the results show, the average accuracy from P300 signal processing was 40.00% and from the SSVEP processing was 48.33 %, which shows decreasing comparing to SSVEP and P300 results. This shows the results from each of the speller. The detected region from both SSVEP and P300 was compared for each character, and if either of the processing systems had detected the intended region, the output was considered as the correct response. The decision making is shown in Figure 36, for the results from the first trial of the subject one. And the results calculated for all subjects are shown in Table 16. As the results show the average of 64.39% is achieved. For better comparison, the average accuracy achieved from SSVEP, P300 and hybrid speller for each subject is shown in Table 17. As the results show, the average accuracy in SSVEP is higher than P300 speller and the hybrid speller shows lower average accuracy.

BCI Type	DetectedRegion	DetectedRegion	DetectedRegion	DetectedRegion	DetectedRegion	DetectedRegion	Average %
SSVEP	T	F	F	F	T	T	50
P300	F	F	T	T	F	T	50
Hybrid	T	F	T	T	T	T	83.33

Figure 36. The calculated average for hybrid speller.

Table 16. Results for hybrid speller.

Subject Number	Accuracy % Trial 1	Accuracy % Trial 2	Accuracy % Trial 3	Average %
1	83.33	75.00	90.00	82.78
2	75.00	75.00	75.00	75.00
3	50.00	50.00	33.33	44.44
4	50.00	50.00	75.00	58.33
5	75.00	75.00	75.00	75.00
6	50.00	83.33	83.33	72.22
7	50.00	75.00	50.00	58.33
8	33.33	33.33	50.00	38.89
9	83.33	50.00	83.33	72.22
10	50.00	75.55	75.00	66.67
Average	60.00	64.17	69.00	64.39

Table 17. Average accuracies from SSVEP, P300 and hybrid speller.

Subject Number	Accuracy % SSVEP speller	Accuracy % P300 speller	Accuracy % hybrid speller
1	100.00	83.33	82.78
2	94.44	77.78	75.00
3	58.33	44.44	44.44
4	61.11	38.89	58.33
5	86.11	94.44	75.00
6	100.00	88.89	72.22
7	66.67	58.33	58.33
8	61.11	80.55	38.89
9	88.89	80.55	72.22
10	83.33	77.78	66.67
Average	80.00	72.50	64.39

3.4 Questionnaire and Evaluation Form

Before performing the experiments subjects filled out a questionnaire form about their general feeling and medical condition. All the subjects had no pre-existing medical condition or allergies. After performing the experiments, an evaluation form was filled out by the subjects. The 5.75 was the average level of general tiredness and fatigue after performing the experiments (the scale was from 1 to 10). The average level of focus ability was 7.1 at the beginning of the experiment and was decreased to 6.5 by the end of performing the task. The average level of complexity for performing SSVEP speller experiment, P300 speller experiment, and hybrid speller experiment were 3.3, 3, and 6.1 respectively. Results show that hybrid task was more complex to perform than P300 or SSVEP spelling.

Chapter 4. CONCLUSION

4.1 Conclusion

The average accuracy achieved from SSVEP spelling paradigm was 80.00 % and was higher than the P300 spelling paradigm which was 72.5%. The high accuracy for SSVEP spelling paradigm shows that this type of BCI is appropriate for spelling application and even has more promising future for spelling application as it shows higher accuracy than the P300 speller.

The accuracy of detection from SSVEP and P300 processing for the hybrid speller was 48.33% and 40.00% respectively which leads to overall accuracy of 64.39 %. The increase in hybrid accuracy compared to individual accuracies of SSVEP and P300 shows that if SSVEP and P300 are combined appropriately the overall hybrid accuracy can be increased. However, the accuracies of SSVEP and P300 in the hybrid speller were decreased compared to the conventional SSVEP and P300 speller. The reason of this decrease is the distraction caused by one visual stimulus (SSVEP/P300) on the other one (P300/SSVEP). Therefore, the design of the speller has a significant role in the performance of the speller. In this proposed design, the LEDs flashing light intensity makes it hard for subjects to follow the P300 flashes. Focusing on both task was quite hard as the P300 flashes distracted the subjects from gazing at the flickering LEDs and the task got more complicated for subjects to perform in the hybrid speller.

4.2 My Contributions

My contribution for this research was to design SSVEP speller paradigm and hybrid speller. More specifically I contributed the following:

- Conducted pilot experiments to determine the parameters for SSVEP speller paradigm, such as flashing frequencies, location of LEDs, processing window size.
- Designed, implemented, and conducted experiment for a new SSVEP speller BCI.
- Designed, implemented, and conducted experiment for a new hybrid speller BCI.
- Compared P300, SSVEP and a hybrid P300/SSVEP speller paradigms.

As the result of research conducted in this thesis, the following journal paper, book chapters, and conference papers were published.

1. **S. Amiri**, R. Fazel-Rezai, and V. Asadpour, "A review of hybrid brain-computer interface systems," *Advances in Human-Computer Interaction,* [online], vol. 2013 Article ID 187024, 8 pages, 2013. doi:10.1155/2013/187024.
2. **S. Amiri**, A. Rabbi, L. Azinfar, and R. Fazel-Rezai, "A Review of P300, SSVEP, and Hybrid P300/SSVEP Brain-Computer Interface Systems," in *Brain- Computer Interface Systems, Brain-Computer Interface Systems - Recent Progress and Future Prospects*, Ed. Dr. Reza Fazel-Rezai, InTech, Chapter 10, 2013.

3. S. Gavett, Z. Wygant, **S. Amiri**, and R. Fazel-Rezai,"Reducing human error in P300 speller paradigm for brain-computer interface," In *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, pp. 2869-2872. IEEE, 2012.

4. **S. Amiri,** and R. Fazel-Rezai, "A Review of Hybrid BCI Systems," in *Neural Interface Conference (NIC), The 40th Neural Interface Conference*, Salt Lake City, UT, June, 2012.

5. L. Azinfar, M. Ravanfar, E. Kim, **S. Amiri**, and R. Fazel-Rezai**,** "EEG Channel Optimization Based on Differential Evolutionary Algorithm for BCI Application**."** in *the Fifth International Brain-Computer Interface Meeting*, DOI: 10.3217/978-3-85125-260-6-152, June, 2013.

4.3 Future Work

Redesigning the hybrid speller to a sequential hybrid BCI can be considered as an approach for enhancing the performance of the speller. In this design, SSVEP system task can be considered as a switch to on/off the P300 flashing. Another design can be utilizing SSVEP system for adding more options to the speller, such as the 'backspace' or 'space' keyboard. This proposed design is shown in the Figure 37. In this design, both P300 and SSVEP systems can be utilized simultaneously, and only using 2 LEDs as a SSVEP stimulus, make the task less complicated for users. Improving the decision making system based on each BCI system can be considered as another approach as the future work of this study.

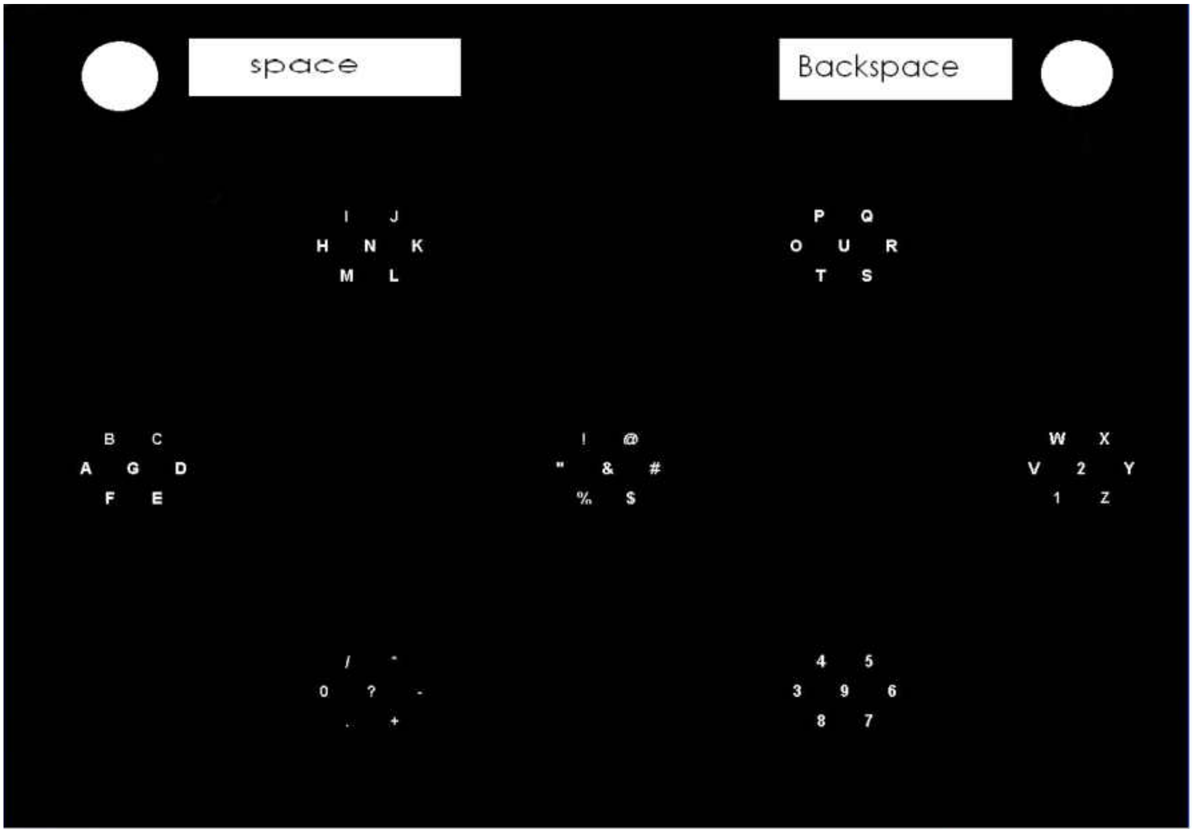

Figure 37. The proposed design for hybrid speller.

APPENDICES

APPENDIX A – BIOMEDICAL RESEARCH INFORMED CONSENT FORM

Informed Consent

Research Project Title: Brain-Computer Interface (BCI)

Researchers: Dr. Reza Fazel-Rezai, Scott Gavett, Zachary Wygant, Setare Amiri, Christopher Cunningham

This consent form, a copy of which will be left with you for your records and reference, is only part of the process of informed consent. It should give you the basic idea of what the research is about and what your participation will involve. If you would like more detail about something mentioned here, or information not included here, you should feel free to ask. Please take the time to read this carefully and to understand any accompanying information.

a. Purpose of the research:

The purpose of this study is to spell the characters / numbers using BCI speller. This will be accomplished by recording electroencephalogram (EEG) signals (brain signals) from a control group in a normal, everyday setting on a predetermined computer and running the program called p300 based BCI speller, and will be monitored by qualified professionals (University of North Dakota faculty). This research will help determine the speed and accuracy of a speller program based on p300 potentials as well as provides a new visual paradigm towards brain-computer interface research. The overall accuracy and speed of typing would be increased based on this research and beneficial to the people with disabilities to spell faster and less hectic way.

b. Research procedures:

Before starting the test you should sit on a chair in front of a computer screen and we will explain the experimental process to you as well as the tasks you should perform before the test. The task is to simply looking at the seven regions consisting of seven different sets of letters, characters and numbers, while each character set / region is being flashed or intensified for a particular amount of time. Later, we place the electrode cap on your head and the experiment begins whenever you confirm that you are completely comfortable and ready to begin

Participant's initial ________________________ Page 1 of 4 testing. During the experiment, the characters/ letters which you want to speller will be flashed on a computer screen distributed over seven regions, in a random sequence, and you will count how many time your particular character set flashes. Meanwhile, your brain signals are captured and transferred to the computer for further analysis. There are only four variations of these tests, each one resulting in a minimum duration of 20-30 minutes. The tests are carried out until the last character set flashes on the screen. The preparation time for the instruments take about 10 – 15 minutes and the whole procedure takes about 90 – 120 minutes. Before and after the experiments you would be asked to complete a questionnaire form which includes multiple choice questions and questions regarding the comfort level during the experiment and any other suggestions you may have to improve the process. The questionnaire form should take approximately 5 – 10 minutes to be answered. The questionnaire explores the strength and weakness of the experiment from the user's point of view and it gives us the scope of improvement in a very short span of time. However, you are not obligated to complete the questionnaire form or the experiment. You may inform us to stop the test and let you exit the laboratory under any circumstances. Furthermore, in the case where the data is corrupt, your decision to retest is voluntarily.

c. Risks and Benefits:

In this experiment the brain signals are recorded and transferred to the computer. This process will be done using "g.tec P300 Spelling Device with g.USBamp and Simulink V2.09a." (www.gtec.at/) hardware and software which have been guaranteed to protect subjects from all types of power related hazards. Very minor risks are involved in this study. After completing a segment of testing, you may feel fatigued, drowsy, claustrophobic and or frustrated. On the other hand, this research has the benefit of improving the accuracy and speed of the spelling device for paraplegic persons.

d. Recording devices:

In this study, we will use the g.tec's newest high-end and high performance active electrode system for non-invasive electrophysiological derivations called g.GAMMAbox® which collects your brain signal activity during testing. These signals will be stored on a computer's hard disk anonymously and will be analyzed later.

Participant's initial ______________________ Page 2 of 4

e. Assurance of Confidentiality:

In this experiment, the data including the recorded signals and questionnaires will be collected and stored separately in confidential and safe place at our laboratory and advisor's office for a minimum of three years. Your information will never be shared anywhere unless with your written permission.
We have one computer in our laboratory located in Harrington Hall 120 D specifically for our research purpose where the digital data will be stored. This computer is password-protected and nobody has access to it except the main researchers. The paper forms including the letters of consent and questionnaires will be kept safely in a cabinet (which is locked by the faculty advisor, Dr. Reza Fazel) located in the primary investigator's office. Our lab is also safely equipped by a key entry with limited access.
The title of data will be the date and the time of running the experiment. However, in case of giving the feedback we need to know whose subject the data associates with. For this purpose, we will specify the subject's name corresponding to the data in a different file and store it somewhere in our password-protected and absolutely safe computer.
All of the data will be completely destroyed at the end of the research. However, they will be kept at least for a minimum of 3 years. Data means paper forms and digital raw data which will be shredded by a paper shredder and will respectively be erased from the computer and only the results will be kept. Results, on the other hand, only include the final outcome of the research, the number of subjects, their average age and their gender.

f. Feedback

We can provide you the results of the experiment upon your request after analyzing the data. It is not possible to give you any feedback immediately after the test. In case of need of feedback, you may complete the "feedback request" form to request a summary of the results of your experiment. The feedback will be printed on paper with the "University of North Dakota" letterhead.

g. Assurance of Voluntary Participation

Participant's initial ______________________ Page 3 of 4

Your participation in this research is voluntary. Therefore, you can withdraw from the project at <u>anytime</u> without any consequence. You can contact us via one of the emails mentioned below to withdraw from the test any time prior to the experiment. Furthermore, you can stop the administration of the test in the middle of it through verbal communication to the supervising researcher.

Your signature on this form indicates that you have understood, to your satisfaction, the information regarding participation in the research project and agree to participate as a subject. You are free to withdraw from the study at any time, and /or refrain from answering any questions you prefer to omit, without prejudice or consequence. Your continued participation should be as informed as your initial consent, so you should feel free to ask for clarification or new information throughout your participation. If you have any questions or concerns, please contact the principal researcher, Dr. Reza Fazel-Rezai:

Reza Fazel-Rezai, Ph.D., EIT, IEEE Senior Member
Assistant Professor
Address: Department of Electrical Engineering
Upson Hall II Room 160 N
243 Centennial Drive Stop 7165
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Email: rezafazel@mail.und.edu
URL: http://www.ee.und.edu/html/research/biomed.html
Phone: 1-701-777-3368

This research has been approved by the University of North Dakota Institutional Review Board (IRB). If you have any concerns or complaints about this project you may contact the above-named person or the IRB Secretariat at (701) 777-4279. A copy of this consent form has been given to you to keep for your records and reference.

Participant's Signature ____________________ Date ______________

Researcher and/or Delegate's Signature__________________Date ______________

Participant's initial ________________________ Page 4 of 4

APPENDIX B – BCI SUBJECT QUESTIONNAIRE

Subject ID: ______________

Brain Computer Interface Subject Questionnaire

Please circle the best response.

1. Overall, how are you feeling today? One being the worst and 10 being the best.
   1 2 3 4 5 6 7 8 9 10
2. Do you feel well rested?
   Yes No
3. Do you feel stressed?
   Yes No
4. Can you sit at a computer performing tasks for up to 1 hour?
   Yes No
5. Do you have any pre-existing medical conditions that require specific medical attention?
   Yes No
   If yes, please explain ____
6. Do you have any allergies?
   Yes No
   If yes, please list____

_______________________ Participant's Signature

__________________ Today's Date

APPENDIX C – SUBJECT EVALUATION FORM

Subject Evaluation form

Date and Time: ____________________

Experiment No. ___________________

Subject ID: _______________________

All the questions are on the scale from 1 to 10, 1 being the weakest and 10 being the strongest.

1. Circle the level of general tiredness you feel after this experiment?

   1 2 3 4 5 6 7 8 9 10

2. Circle the level of eye fatigue you feel after this experiment?

   1 2 3 4 5 6 7 8 9 10

3. Circle the level of ability for focusing on the task at the beginning of the experiment.

   1 2 3 4 5 6 7 8 9 10

4. Circle the level of ability for focusing on the task at the end of the experiment.

   1 2 3 4 5 6 7 8 9 10

5. Circle the level of complexity of performing the first task.

   1 2 3 4 5 6 7 8 9 10

6. Circle the level of complexity of performing the second task.

   1 2 3 4 5 6 7 8 9 10

7. Circle the level of complexity of performing the third task.

   1 2 3 4 5 6 7 8 9 10

APPENDIX D – SSVEP TEST PLAN

SSVEP Test plan

Have subject read and sign the consent form and fill out the questionnaire.

1. Put EEG cap on subject and plug in the electrodes
   1.A. FPZ goes to GND
   1.B. Ear clip goes to right mastoid
   1.C. PO7 goes to Channel 6
   1.D. Oz goes to Channel 7
   1.E. PO8 goes to Channel 8
2. Use abrasive gel and Q-tips in each electrode
3. Use the conductive gel from the syringe to put gel under the electrodes
4. Open MATLAB
5. Open the 'SSVEP Experiment' directory, and open the 'SSVEPExp.mdl' file
   5.A. Make sure the settings are correct
      5.A.i. Double click on the SSVEP Signal processing box and check to see if the following are correct
         5.A.i.a. Buffer length [ms] – 10000ms
         5.A.i.b. Number of flashes - 22
         5.A.i.c. Number of channels – 6
      5.A.ii. Run the init.m file and see if the followings are correct
         5.A.ii.a. Mode – Copy Spelling
         5.A.ii.b. Flash time [ms] – 100
         5.A.ii.c. Dark time [ms] – 55.8
         5.A.ii.d. F1=[17 20 23 26 29 32]

   5.B. Click on the start simulation button
   5.C. Click on the characters to spell the word "TEST"
   5.D. Click 'START'
   5.E. Have the subject try not to blink too often or grind their teeth this interferes with the EEG, have the subject sit 1 meter from the computer screen
   5.F. Show the subject their EEG and show them what happens when they blink and grind their teeth. (this also is the time to see that all the electrodes have a good connection)
6. Reopen the 'SSVEPExp.mdl' file
   6.A. Change the mat files name
      6.A.i. Mat files should follow the format xx-y-z-1, xx-y-z-2, xx-y-z-3, xx-y-z-4, xx-y-z-5, xx-y-z-6, which xx shows the subject number, y shows which word is spelled, and z shows the number of trial
      6.A.ii. In this round y=1
   6.B. Click on the characters to spell the word 'BR8'
   6.C. Click 'START'

6.D. When the run is done, repeat the experiment for 2 more trials. Before starting each run, change the mat files name according to the number of trial.

7. Repeat from stage '6'
   7.A The word 'C41' would be spelled in this round
   7.B. In this round y=2
8. Repeat from stage '6'
   8.A The word '*6B' would be spelled in this round
   8.B. In this round y=3
9. Have the subject fill out the subject evaluation form
10. Make sure all papers are filled out and put them in the subject's folder
11. Clean the EEG cap and let it dry for the next use

APPENDIX E – BCI TEST PLAN

BCI Test plan

Have subject read and sign the consent form and fill out the questionnaire.

1. Put EEG cap on subject and plug in the electrodes
   - 1.A. FPZ goes to GND
   - 1.B. Ear clip goes to right mastoid
   - 1.C. Fz goes to Channel 1
   - 1.D. Cz goes to Channel 2
   - 1.E. P3 goes to Channel 3
   - 1.F. Pz goes to Channel 4
   - 1.G. P4 goes to Channel 5
   - 1.H. PO7 goes to Channel 6
   - 1.I. Oz goes to Channel 7
   - 1.J. PO8 goes to Channel 8
2. Use abrasive gel and Q-tips in each electrode
3. Use the conductive gel from the syringe to put gel under the electrodes
4. Open MATLAB
5. Open the 'Final Experiment' directory and open 'SSVEP2Exp.mdl' file
   - 5.A. Make sure the settings are correct
     - 5.A.i. Double click on the SSVEPSignal processing box and check to see if the following are correct
       - 5.A.i.a. Buffer length [ms] – 10000ms
       - 5.A.i.b. Number of flashes - 22
       - 5.A.i.c. Number of channels – 6
     - 5.A.ii. Run the init.m file and see if the followings are correct
       - 5.A.ii.a. Mode – Copy Spelling
       - 5.A.ii.b. Flash time [ms] – 100
       - 5.A.ii.c. Dark time [ms] – 55.8
       - 5.A.ii.d. F1= [21 23 20 18 17 19]
   - 5.B. Click on the start simulation button
   - 5.C. Click on the characters to spell the word 'Test'
   - 5.D. Click 'START'
   - 5.E. Have the subject try not to blink too often or grind their teeth this interferes with the EEG, have the subject sit 1 meter from the computer screen

5.F. Show the subject their EEG and show them what happens when they blink and grind their teeth.

5.G. Reopen the 'SSVEP2Exp.mdl' file

5.H. Change the mat files name

5.H.i. Mat files should follow the format s-xx-z-1, s-xx-z-2, s-xx-z-3, s-xx-z-4, s-xx-z-5, s-xx-z-6, which xx shows the subject number, and z shows the number of the trial

5.H.ii. Click on the characters to spell the word 'BR8'

5.H.iii. Click Start

5.H.iv. When the run is done, repeat the experiment for 2 more trials. Before starting each run, change the mat files name according to the number of the trial

5.H.v. Clear the workspace

6. Open 'P300Exp.mdl' file

6.A.i. Double click on the P300Signal processing box and check to see if the following are correct

6.A.i.a. Buffer length [ms] – 800ms

6.A.i.b. Number of flashes - 6

6.A.i.c. Number of channels – 8

6.A.i.d. Classification method – Linear Discrimination Analysis

6.A.ii. Double click on the P300Speller box and check to see if the following are correct

6.A.ii.a. Mode – Copy Spelling

6.A.ii.b. Flash time [ms] – 150

6.A.ii.c. Dark time [ms] – 100

6.B. Click on the start simulation button

6.C. Click on the characters to spell the word 'Test'

6.D. Click 'START'

6.E. For this calibration period have the subject spell the word 'Test' six times then you will load the .mat file for the calibration process.

6.F. Type in 'gbsanalyze'

6.F.i. File >> Load Data >> pxx-t.mat

6.F.ii. Sampling rate [Hz] – 256

6.F.iii. User >> P300_LDA_MultiFile_Batch_8ch_256Hz

6.F.iv. User >> P300_LDA_SingleFile_Batch_8ch_256Hz

6.F.v. Wait for the files to load then close the window

6.G. Change the mat files name

6.G.i. make sure to record the regions that were selected these can be found after the word is spelt in the main MATLAB command window

6.G.ii. Mat files should follow the format p-xx-z-1, p-xx-z-2, p-xx-z-3, p-xx-z-4, p-xx-z-5, p-xx-z-6, which xx shows the subject number, and z shows the number of the trial

6.H. Click on the characters to spell the word 'BR8'

6.I. Repeat the experiment for three times.

7. Open 'HybridExp.mdl' file
    7.A.i. Double click on the P300Signal processing box and check to see if the following are correct
        7.A.i.a. Buffer length [ms] – 800ms
        7.A.i.b. Number of flashes - 6
        7.A.i.c. Number of channels – 8
        7.A.i.d. Classification method – Linear Discrimination Analysis
    7.A.ii. Double click on the P300Speller box and check to see if the following are correct
        7.A.ii.a. Mode – Copy Spelling
        7.A.ii.b. Flash time [ms] – 100
        7.A.ii.c. Dark time [ms] – 150
    7.B. Change the mat files name
        7.B.i. Mat files should follow the format h-xx-z-1, h-xx-z-2, h-xx-z-3, h-xx-z-4, h-xx-z-5, h-xx-z-6, which xx shows the subject number, and z shows the number of the trial
    7.C. Click on the characters to spell the word 'BR8'
    7.D. Click on the start simulation button
    7.E. Repeat the experiment for three times
8. Have the subject fill out the subject evaluation form
9. Make sure all papers are filled out and put them in the subject's folder
10. Clean the EEG cap and let it dry for the next use

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