بسم الله الرحمن الرحيم

ADAPTIVE STIMULATION FREQUENCIES SELECTION FOR EFFECTIVE DETECTABLE STEADY STATE VISUAL EVOKED POTENTIAL RESPONSES

By (Hadi Mohammad Alshamrani)

A thesis submitted for the requirements of the degree

of Master of Science in Computer Science

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This thesis has been approved and accepted in partial fulfillment of the requirements for the degree of Master of Science in Computer Science

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Dedication

My dear Father, Mother, Wife, brothers, my work's administrator and my friend (Fares A. Ghaleb) who gave me his time to finalize this work, and insisted to develop this topic which support Saudi's citizen in future precisely in Technology field with great love and appreciation

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By the help of ALLAH, I prepared this thesis for the Master of Science Degree in Faculty of Computing and IT (Computer Science).

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Adaptive Stimulation Frequencies Selection for Effective Detectable Steady State Visual Evoked Potential Responses

Hadi Mohammad Alshamrani

Abstract

Brain Computer Interface (BCI) is an interaction method that permits a user to control external devices by his brain signals. One of the most used BCI systems is the Stead-State Visual Evoked Potential systems (SSVEPs). In SSVEP systems, the user looks at a visual stimulus flickering at fixed frequency. The generated brain signal has fundamental frequency as the frequency of the visual stimulus flickers. However, the stimulus frequency depends on the user and on the state of the user.

In order to make SSVEP more usable, an adaptive frequency selection algorithm is needed, and this is the objective of this master research work. To this end, two algorithms were proposed in this work. The first one is based on the idea of scanning all possible frequencies and select the best one based on the classification error rate. The second one is based on the idea of monitoring the classification error rate in real time. When the classification error rate exceeds a predetermined threshold, the system will automatically switch to another frequency.

The two proposed algorithms are implemented and tested in on-line. The obtained results show clearly better performance of proposed adaptive SSVEP system than the non-adaptive SSVEP system. In addition, second proposed algorithm shows better results comparing with the first proposed algorithm.

As a future work, a method will be developed to select the threshold of the classification error rate in adaptive SSVEP systems. In addition, the proposed adaptive SSVEP algorithms will be used in real applications.

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Chapter 1

Introduction

Brain-computer interfaces (BCIs) provide a direct communication between the brain activities and the computer [1]. BCIs are based on detecting and classifying specific patterns activities among brain signals that are associated with specific task or event [2]. The most common tasks used in BCIs are selective attention [3,4,5].

Selective attention paradigm uses external auditory stimuli [6], somatosensory stimuli [7], or visual stimuli [8] to generate appropriate brain signals. The visual stimulator commonly consists of flashtube/light-emitting diode (LED) flickering targets [9]. The flickering frequency of each LED can be controlled independently by a programmable logic device. Using such a stimulator, a 48-target BCI was reported in [10]. The number of stimulation targets varies between one and 64, which leads to a range of system performance. Generally, a system with more targets can achieve a higher ITR. For example, in tests of the 13-target and two-target systems, the subjects had an average Information Transfer Rate (ITR) of 43 and 10 b/min, respectively [11], [12]. However, because a stimulator with more targets is also more exhausting for users, the number of targets should be considered according to a tradeoff between system performance and user comfort. In addition, the optimal number of stimuli also depends on the usable bandwidth of SSVEPs, which is subject specific [11].

1.1Research Objectives

The goal of this research is to develop and test adaptive algorithms to select the appropriate frequencies that produce the most effective detectable SSVEP response. Accordingly, to achieve our goal, the objectives of this study would be:

- Understanding in detail the properties of the SSVEP stimuli for BCI [13].

- Developing adaptive algorithms to select the appropriate frequencies that produce the most effective detectable SSVEP response [14, 15].
- Implementing a prototype as a proofing of the concept.
- Performing experiments to compare performance of SSVEP-based BCI using non-adaptive algorithms and adaptive algorithms .

1.2 Literature Review

Steady State Visual Evoked Potentials (SSVEP), as shown in Figure 1, is the response of human brain to the visual stimulus with high frequency [16].

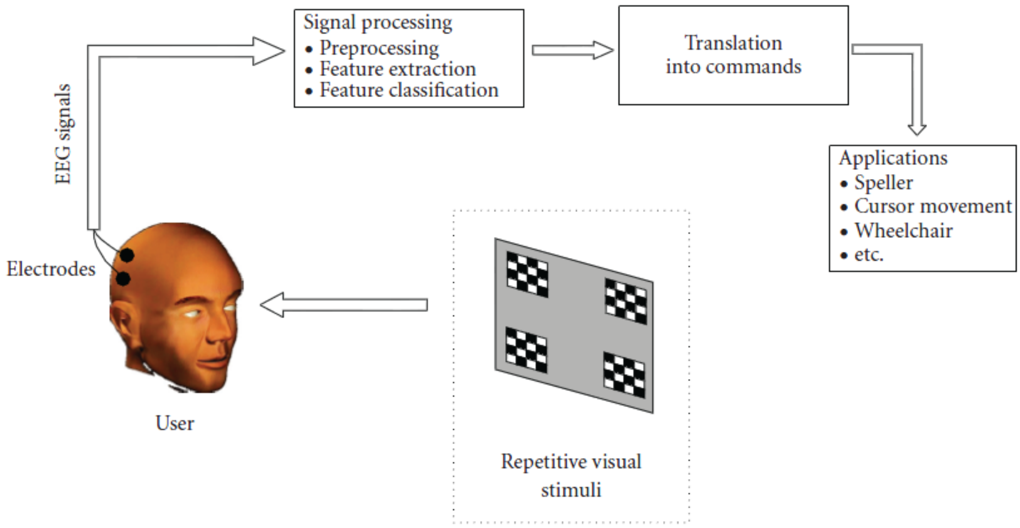


Figure 1: Functional model of an SSVEP-based BCI [13].

A Steady-State Visual Evoked Potential (SSVEP) is a resonance phenomenon arising mainly in the visual cortex when a person is focusing his/her visual attention on a light source flickering with a frequency above 6 Hz [16].

The SSVEP can be elicited up to at least 90 Hz and could be classified into three ranges: low (up to 12 Hz), medium (12-30) and high frequency (> 30 Hz). In general, the SSVEP in low frequency range has larger amplitude responses than in the medium range. Thus, the lower frequencies are easier to detect [17].

The high-frequency SSVEP ranges have the advantage of a minimum visual fatigue caused by flickering, making the SSVEP-based BCI a more comfortable and stable system. At the same time, these frequencies experience the weakest SSVEP that make the SSVEP detection a more difficult task and requires computationally expensive algorithm [18].

This thesis aims to develop and test adaptive algorithms to select the appropriate frequencies that produce the most effective detectable SSVEP response.

1.3 Research Project Design & Methodology

In this research, we plan to follow below methodology :

- Building background on the following subjects:
  - Studying signal processing algorithms for SSVEP-based BCI.
  - Studying the Emotiv toolkit.
- Analysis:
  - Analyzing the effect of using different visual stimuli.
  - Analyzing the effect of different frequencies in visual stimuli.

1.4 Thesis Objective

Transfer rate for any BCI application depends on three factors such as:

- Number of selections
- Accuracy
- Speed

This thesis aims to develop and test adaptive algorithms to select the appropriate frequencies that produce the most effective detectable SSVEP response.

1.5 Design and Implementation

Designing and implementing a SSVEP-based system with non-adaptive frequencies selection algorithm and adaptive frequencies selection algorithms.

1.6 Testing

The implemented SSVEP-based system will be tested on normal persons using non-adaptive frequencies selection algorithm and adaptive frequencies selection algorithms . The performance of the two cases will be compared.

1.7 Thesis Motivation

- The target of the BCI technology is the spinal core injury patients who can not communicate using their normal physical limbs or voice commands. The major objective of this thesis is to help those patients by giving them the ability to communicate and control applications in the easiest way .
- The quick growth in research and technique in development of BCI.

1.8 Thesis Organization

This thesis presents a Brain Computer Interface system based on Adaptive Stimulation Frequencies Selection for Effective detectable SSVEP Response.

In the second chapter, the BCI will be explained in detail and will describe the different methods for measuring BCI activities and will list the several signals that can be generated from the brain with the comparison between these signals.

In the third chapter, some of the previous BCI studies and researches which are based on steady state visual evoked potential (SSVEP) will be described.

The fourth chapter discusses two methods to be used in adaptive BCI . The first one consists of training the subject for all possible frequencies and select the most appropriate frequencies for each subject. This method will be called “Optimal Training SSVEP System”. The second method starts training and on-line running using initial frequencies. During the on-line running, the classifier error rate is monitored. Once the error rate exceeds a predefined threshold, another frequencies will be selected and used in training and on-line running. This method will be called “Adaptive On-line SSVEP System.”

In the fifth chapter, discussion will take place by comparing Adaptive Stimulation Frequencies Selection for Effective Detectable SSVEP Responses system with non-adaptive SSVEP.

Finally, the last chapter will present the conclusion of this work and the future work that has to be implemented in the future to improve the presented Adaptive Stimulation Frequency for effective SSVEP system.

Chapter II
Brain Computer Interface

2.1 Introduction

Brain Computer Interface (BCI) is a communication and control channel that is based on direct measurement of brain activity rather than the physical movement by interfacing brain signals to the computer and translating brain electrical activities into messages or commands which can be used in several computer applications such as spelling, cursor control, games and virtual environment control which will be useful and helpful for patients who are severely paralyzed.

BCI Technology has several advantages such as safety which means there is no risk to the patients brain or body while they are using it, painless, providing information more quickly than physical movement way and easy to use for the paralyzed people. Like any other technology, it also has some disadvantages and limitations. To name a few, it is not 100% accurate, not portable until now, requires surgery or electrode cap, works poorly in the real world environment, and needs training.

BCI attracts attention from many multidisciplinary fields such as:

- Neuroscience, understanding of the nervous system including the brain from, the biological and computational view.
- Physiology, understanding of the brain activities.
- Biomedical Engineering, understanding BCI hardware and how it can be connected or how to work with it.

- Computer Science, to implement BCI software and adding some of artificial intelligence algorithms to be more easy and helpful for the patients.

2.2 BCI Approaches

There are three types of BCI such as follow:

2.2.1 Invasive BCI

Invasive BCI research has targeted repairing damaged sight and providing new functionality to paralyzed people (Gerhardt, 2006). Electrodes for Invasive BCI system are set directly into the grey matter of the brain during neurosurgery. As they rest in the grey matter, electrodes produce the highest quality signals but are prone to scar-tissue build-up, causing the signal to become weaker or even lost as the body reacts to the foreign object in the brain (See Figure 1.1).

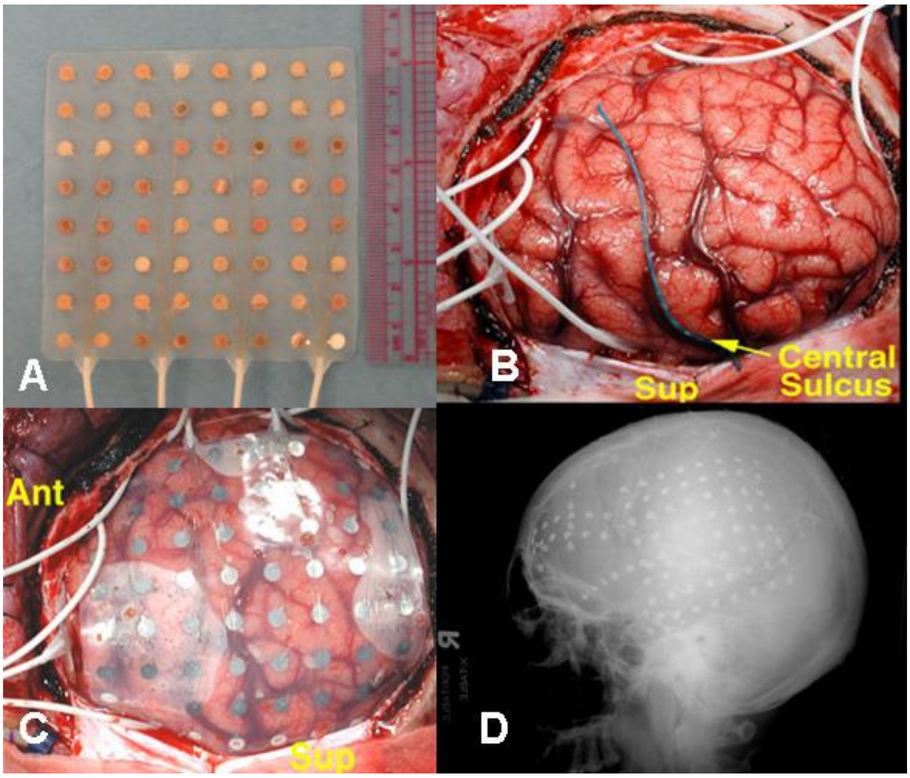


Figure 2.1: Invasive BCI (Gerhardt, 2006)

2.2.2 Partially Invasive BCI

Electrodes for partially invasive BCI are implanted inside the skull but rest outside the brain rather than among the grey matter. They produce better resolution signals than non-invasive BCIs where the bone tissue of the cranium deflects and deforms signals and have a lower risk of forming scar-tissue in the brain than fully-invasive BCIs (Gerhardt, 2006).

2.2.3 Non-Invasive BCI

In the non- invasive BCI system the electrodes are placed externally on the scalp and the signals produced from the brain activity can be recorded by these electrodes on the skull Algorithms then translate the bio-potential into instructions to direct the computer which will help people with brain injury to communicate with defined external devices without need to use the normal pathways such as speech or motion (See Figure 1.2).

Figure 2.1: Non Invasive BCI Electroencephalography (EEG) Electrodes Cap (Gerhardt, 2006)

2.3 BCI Structure

BCI systems like any other communication and control system, has an input, output and other components that translate from input (brain signal) to output (device commands) (Bashashati et al., 2007). BCI systems consist of the following structure (See Figure 2.3):

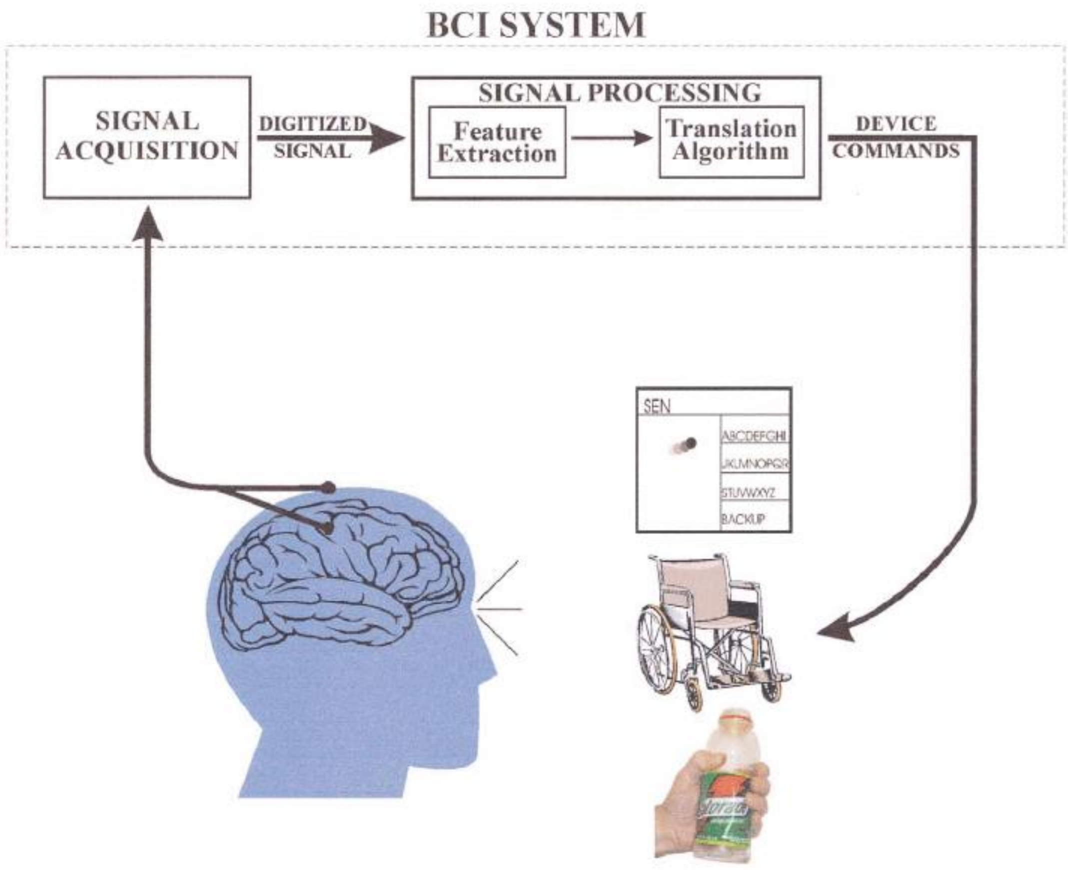


Figure 2.2: BCI Structure (Wolpaw et al., 2002)

2.3.1 Signal Acquisition

Brain signals will be recorded in this step as an EEG signal from the surface of the brain if it is a non-invasive BCI or neuronal activity recorded within the brain if it is an invasive BCI. In the signal-acquisition part of BCI operation, the chosen input is acquired by the recording electrodes, amplified, and digitized.

2.3.2 Feature Extraction

The digitized data from the previous step is passed through a filter to clean it from the artifacts such as the power supply 60HZ noise, EMG artifacts that refer to the muscle movement and electroocular gram (EOG) artifact that refer to the eyes movement. After that, the relevant information from this data is extracted.

2.3.3 Translation Algorithm

Translates the features into control message and commands to control several devices such as wheelchair, computer. The translation algorithm uses several classifiers such as linear classification methods (e.g., classical statistical analyses) or nonlinear ones (e.g., neural networks).

2.3.4 Output Device

For most current BCIs, the output device is a computer screen and the output is the selection of targets, letters or icons displayed on it. This output is the feedback that the brain uses to maintain and improve the accuracy and speed of communication.

Chapter III

Steady State Visual Evoked Potential

3.1 Introduction

BCI have grown over the years to become an integral part of the computer background necessary for the diverse fields of science and engineering. There are many kinds of BCI. Several Chinese Researchers started more than one decade ago to extend Steady State Visual Evoked Potential (SSVEP) by introducing the concept of Brain Computer Interface (BCI) for which the virtual telephone keypad needed in the BCI can be *dispensed with.* Soon, there was surge of publications on SSVEP applications that included low bandwidth and correction control problems, theoretical analysis of SSVEP problems, derivation of BCI proofs.

In this chapter, we concentrate only on the SSVEP application to BCI. We review, explain, assess, and extend the use of SSVEP in defining and manipulating BCI. We achieve a better understanding of this use by translating the SSVEP terminology to conventional or more familiar representations of BCI, and by explicitly identifying the bases on which the SSVEP expressions of the BCI are constructed.

The SSVEP methodology is not competitive to the Adaptive Steady State Visual Evoked Potential (ASSVEP) methodology for adaptive solutions of small problems, where the ASSVEP methodology has the definite advantage of conceptual simplicity and pictorial insight. The ASSVEP methodology, however, is not intended for larger problems where static solutions are not feasible and automated solutions are needed. Here, both the SSVEP and ASSVEP methodologies can be used.

3.2 Review of Related Literature

Current BCI systems are relatively low bandwidth devices, offering maximum information transfer rates of 5-25 bits/min at best which may take several minutes to input simple word to computer. In addition BCI systems are error prone with rate 10% to 30% for either false positive error which refers to selecting the incorrect choice or false negative error which refers to missing the correct choice. For both error types, BCI systems need error detection with error recovery and correction techniques to handle these errors [11, 12].

Authors in [14] presented a Brain Computer Interface based on Steady State Visual Evoked Potential (SSVEP). It was demonstrated as a virtual telephone keypad in the computer monitor with thirteen buttons explore as ten digits 0-9, BACKSPACE, ENTER and on/off, each button having different frequency. Users enter their required phone number putting their gaze at these buttons (e.g., Fig. 3.1). They used SSVEP in the BCI since it is recording non-invasive signal, which eliminates the need for intensive training to use and it has high information transfer rate which was 27.15 bits/min, an average for all subjects [12].

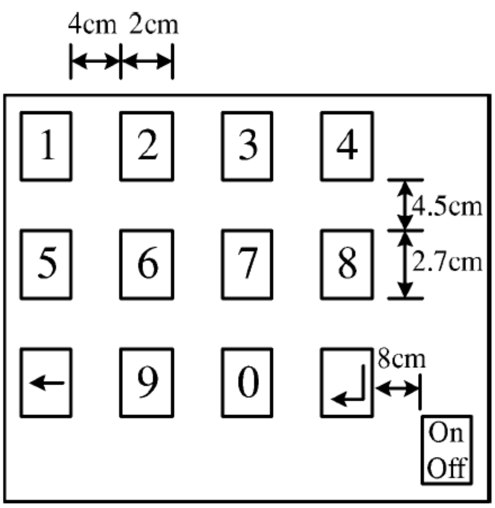


Figure 3.1: BCI Virtual Telephone Keypad [12]

This BCI system was tested on thirteen subjects who entered their required phone numbers by gazing eyes at the numbers and a beep was sent out from the loudspeaker of the computer after each selection and the result was displayed on the monitor which allowed the user to verify if they entered the correct number and delete any incorrect selection by gazing at the backspace button. The computer was connected to the modem. Once the subject selects the 'enter' button, the entered number will be dialed. The on/off button was designed to control the start and stop of the stimuli which mean that the twelve buttons start flicker once user select on/off button to be sure that user start dialing the phone number and which reduce the false positive error. This telephone system was successful for eight out of the thirteen subjects and no false positive error occurred during the testing period.

They demonstrated how to accelerate and enhance accuracy of brain computer interface by proper selection of the stimulus frequency in SSVEP BCI systems, and using COMB filtering of the electroencephalogram (EEG) signal prior to performing the Discrete Fourier transform (DFT) with substantial increase of the SSVEP signal to noise ratio, can be achieved [13]. They investigated that the benefits of using COMB filtering is to suppress noise and artifacts whose spectral components do not coincide with the stimulus fundamental frequency and its harmonics. COMB filtering is a well-known technique for luminance and chrominance components separation in color TV decoders and helps to separate the color signals from the black and white, providing a higher resolution or sharper picture. In this BCI system, there are twelve fields of different flicker frequencies displayed as a virtual telephone keypad 0-9 numbers, Enter and backspace Keys. If the user focuses his/her sight to one of these flickering buttons, the amplitude of the corresponding flicker frequency component of the EEG spectrum will increase. We studied five different layers which are EEG acquisition, Pre-processing, Windowing FFT, Post processing and Analysis and SSVEP Detection [11-13].

After testing this system, they conclude that selecting the proper stimulus frequency in SSVEP BCI system such that they correspond with DFT frequency samples and using COMB filtering of the EEG signal previous to performing the DFT substantial enhancement of the SSVEP can be achieved. Their research showed that signal to background noise is doubled in most cases and showed how this enhancement increased the speed and accuracy to the BCI [20].

Note that in the last studies showed a wearable BCI system. It consists of two parts: the first part is the hardware which they studied as Kimera that consists of two layers of hardware architecture. The second part of the system is the software which the last researchers called Bellerophonte for the graphical user interface management, protocol execution, data recording, transmission and processing [14-15]. The implementation of this BCI system is based on SSVEP applied to two state selections using standard monitor with a couple of high efficiency frequency LEDs. EEG signals are recorded from the O1 and O2 electrodes according to the 10-20 International System of electrodes placement. BCI system is based on supervised classifier implemented through a multi- class Conical Discriminate Analysis (CDA) with a continuous real time feedback and required a proper initial training period which consists of nine phases of fifteen seconds equally distributed among three stimulus: screen center fixation (NULL event), left stimulus (command A) and right stimulus fixation (command B) (e.g., Figure 3.2).

Figure 3.2: A Detail of BCI Simple Setup Screen Center and the Two LEDs Left and Right [14].

In passing, experiment presented a similar technology as previously presented by Kimera and Bellerophone system but with four commands instead of two commands only (up, down, left and right). This BCI system algorithm was based on supervised multi class classifier implemented by combining different binary Regularized Linear Discriminate Analysis (RLDA) classifiers [12, 14]. It is also a system based on a supervised translation algorithm and the protocol consisting of three main functioning modes:

3.2.1 Training Mode

This mode acts as a data acquisition stage to record useful information for the later supervised classifier. This mode is achieved by guiding the user through the interface by vocal instructions and mobile center cue on the center of the screen where the user gazes alternatively to the different light source.

3.2.2 Meta-Training Mode:

The user is asked to focus his gaze on a practical source light while the signal is processed and identified continuously by the online translation algorithm. Switching from one stimulus to another occurs only after the system identifies the command related to the target source. Together with the current estimated commands (LEFT, RIGHT, UP, DOWN, NULL) the number of false positive and correct assignment were presented and consciously update the GUI (See Figure 3.3).

3.2.3 Testing Mode

The BCI system performs continues real time classification of the signal, translating the estimated intention in a control command. In this configuration, both stimuli related biofeedback and latency were active.

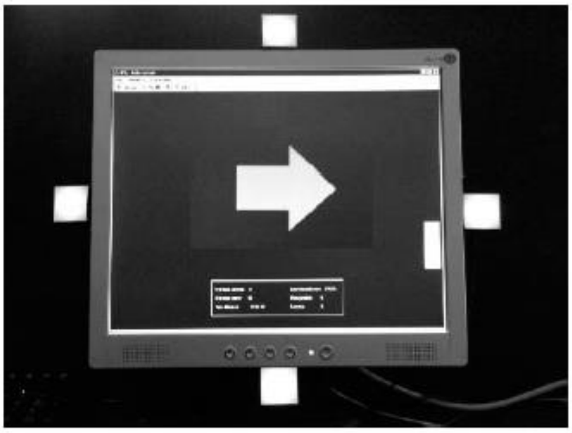


Figure 3.3: The GUI and the Stimulation Unit during Meta-Training Phase [14].

After testing the system on five healthy subjects the system showed good robustness against false positive and achieved accuracy during meta-training between 80% and 100% and the average speed was 10-15 commands per minute. As result of these findings, this BCI system provided a reliable, smart and low cost BCI system.

In 2006, Kim Dremstrup Nielsen, Alvaro Fuentes Cabrera, and Omar Feix do Nascimento described BCI system based on SSVEP which studied seven healthy subjects using a 3 X 3 matrix flickering squares numbered from 1 to 9. Stimulation frequencies used were 5.0, 7.08, 7.73, 8.5, 10.63, 12.14, 14.16, 17.0 and 9.44 Hz in order for each box 1 to 9. They were displayed on a CRT computer screen with a refresh rate of 85 Hz. Subjects were instructed to enter their phone number, birth date and numbers from one to nine by focusing their gaze on the appropriate squares on the computer screen. They then select the next number after they hear the spoken number whether or not it matched with the desired number. Each phone number or birth date was selected three times while numbers from one to nine were selected four times. EEG signals were recorded from Oz electrodes and referred to the left ear lobe sampled at 500 Hz using a 0.5 high pass filter, 75 Hz low pass filter and 50 Hz. EEG data acquisition was done using Nuamp 40 channel system, stimulation, data collection, feature extraction and detection were done using C++ programming language.

Online extraction of SSVEP features classification was done using Fast Fourier Transform (FFT) based on non-averaged periodograms of 2048 samples. Symbol selection is based on first, second and third harmonics. If the amplitude is below a defined threshold, it means no symbol is selected. The result extracted from seven subjects showed 79.7% of the trials were correctly detected with a resulting signal rate of 9.3 characters per minute.

In 2007, Ola Friman, Thorsten Luth, Ivan Volosyak and Axel Graser presented an online spelling BCI application based on SSVEP and tested on eleven healthy subjects to spell word BRAINCOMPUTERINTERFACE which in previous off line studies has shown significantly improved classification performance [17].

3.3 Spelling BCI System

Spelling BCI system is displayed to the user in two different layouts. The first layout is Row Column layout which requires two selections from the user to reach their desired letter. User must select the row then the column of the corresponding letter. The second layout is Rhombus layout by which a cursor moves right, left, down, up from the center to reach the desired letter, after which, cursor returns back to the center once a letter is selected (e.g., Figure 3.4).

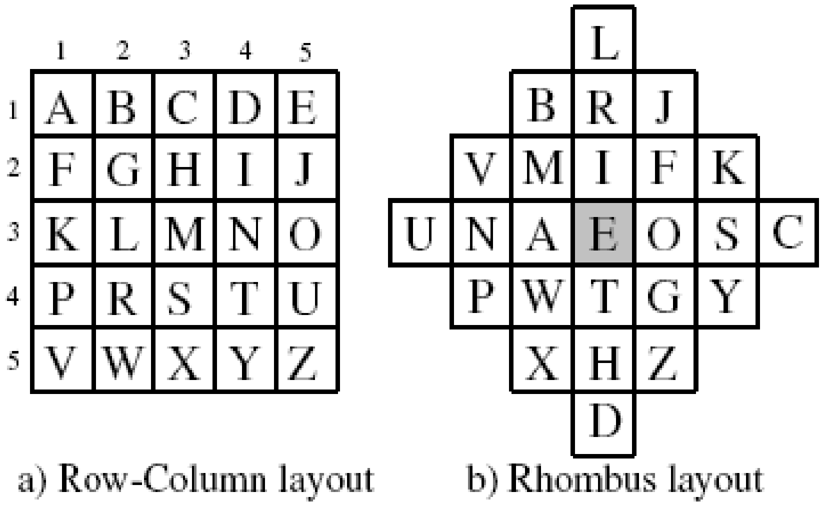


Figure 3.4: Spelling Layout [18].

The EEG signal was recorded from 6 gold EEG electrodes placed over the visual and parietal cortex; 2 electrodes at position Oz, Pz according to the international 10-20 system, and 4 electrodes 2.5 cm above and under the position O1 and O2 and refer to a ground electrode passed at position Fz. The measured signals were amplified using a g.Bsamp amplifier from g.tec and filtered through analog high pass and low pass filters cut off frequencies of 0.5 Hz and 32 Hz. The average information rate of this on-line spelling application was 27 bits/minute and the probability of correctly classifying the user's attention was estimated to be 97.5%.

Gernot R. Muller-Purtz and Gert Pfurtscheller presented a 2-axis hand prosthesis, asynchronously (self-based) controlled with 4 class SSVEP based BCI. The hand prosthesis attach with four red lights(LED) at the fingers, index finger to turn right, fifth finger to turn left and at the forearm, there are two lights - first one to open the hand and the second one, to close it. All these lights flicker continuously with different frequencies 6, 7, 8 and 13 Hz. (See Figure 3.5) [16-19].

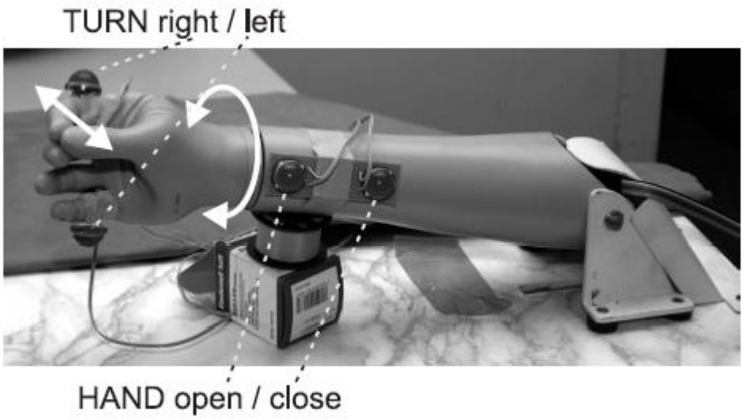


Figure 3.5: Hand Prosthesis With Mounted Lights [16].

3.4 EEG Signal

The EEG signal for this system is recorded from the electrodes O1 and O2 based on 10-20 international electrode system and the ground electrode was placed at position Fz. The EEG amplifier settings were 0.5 Hz and 30 Hz for the bandpass, the notch filter 50 Hz was on and the sensitivity was 50V and the sampling rate was 256 Hz.

The test for this system was done on four healthy subjects by instructing them to focus on the flickering lights. From second 0 to 2, the subjects had to look on a blank screen. From second 2 to 6, a written instruction is displayed on the screen with a short beep left, right, open, close with each command having specific color indicating to the subjects which flickering light to the subject to focus on. A long beep is heard indicating a correct classification and absence of the beep for a wrong classification. The accuracy of the online classification for this BCI system was between 44% and 88%.

Zhonglin Lin, Chagshui Zhang, Wei Wu and Xiaorong Goe introduced canonical correlation analysis (CCA) to analyze the frequency component of the SSVEP in EEG. They employed CCA to extract frequency feature in EEG, as well as to select channels for analysis. After that, recognition strategy for SSVEP based BCI was proposed [19].

CCA is a multi-variable statistical method and it is used when there are two sets of data, which may have some underlying correlation. CCA finds a pair of linear combinations called canonical variables, such that the correlation between the two canonical variables is maximized. After that, it was found out that the second pair which is uncorrelated with the first pair has a next highest correlation. The process of constructing canonical variables continues until number of pairs of canonical variables equal number of variable in the smaller set. CCA works on two sets of variables and in this work, the first set are the signals recorded from several channels within local region and second set are from stimulus signals. In this work and for comparison, they also implemented the power spectral density based analysis (PSDA) which utilized fast Fourier transform in its calculation and which might be sensitive to Signal Noise Ratio (SNR).

After testing this system, they concluded that the used signals in PSDA approach had a very high SNR and the area that generated the SSVEP was very small while the use of signal within a broader area in the CCA approach can introduce more noise and negatively affect recognition accuracy. Like any other approach, there are some problems such that they only use the largest co-efficient of CCA because it transmits most information and this will help in ideal conditions which does not cover the fact since EEG signals may be affected by noise or may discontinue phase transition which will cause information to spread across in more than one co-efficient. This was a point of future reference for them in studying how efficiently they can use more than one co-efficient; also how they can use the linearity of the user's visual pathway of the brain which is not matching the multiple neural mechanism and how they can plan to explore using the projection in CCA subspaces other than only the coefficient.

Tilmann Kluge and Manfred Hartmann proposed a different estimator for the analysis of SSVEPs. In contrast to previously published Power Spectral Density (PSD) estimator which is non-coherent measures for the signal power in narrow frequency band. In this study, they presented a phase coherent estimate that takes into account both amplitude and phase of Fourier series coefficients. The EEG signal was recorded from two electrodes and the used band-pass filter between 0.3Hz and 100Hz and a notch filter at 50Hz. Analog to digital conversion was performed using a data acquisition card with a sampling rate of 256 Hz and 6-bit resolution [15, 18-19].

In this approach three different experiments were performed:

1- Two stimuli flickered with two different reversal rates of 10Hz and 12 HZ, respectively.
2- Two stimuli flickering both at 10 Hz but with different relative phase. A phase difference of 144 degree corresponding to two frames on the TFT was used
3- Similar to the second one, but stimuli flickered at 12Hz and the phase difference was 180 degree

When they presented this study, they found many advantages of using coherent estimator rather than using non-coherent PSD estimator such as the increasing discrimination reliability since noise can be reduced to the in-phase component which improves the SNR significantly. Another advantage for using phase coherent estimator is to be given the ability to discriminate stimuli of the same frequency that are presented with a specific time shift which helps to increase the number of degrees of freedom for stimuli design and make the system design more easier. It is also more helpful specially when generating SSVEP BCI with TFT displays where number of frequencies that can be created is very limited.

In 2007, Ola Friman, Ivan Volosyak and Axel Graser presented six different methods namely: Average Combination, Native Combination, Bipolar Combination, Laplacian Combination, Minimum Energy Combination and Maximum Contrast Combination for detecting steady state visual evoked potentials using multiple EEG signals for achieving high information transfer rates with high detection accuracy by finding combinations of electrode signals that cancel strong interference signal in EEG data [17]. There are several advantages for this presented methodology which are fully online, no calibration data for noise estimation, feature extraction or electrode selection is needed. These methods were tested on 10 subjects to evaluate new methods and compared with the standard techniques and results from these six different visual simulation frequencies could be discriminated with an average classification accuracy of 84%.

The best detection accuracy was achieved with the minimum energy method which utilized an SSVEP model to produce uncorrelated channels containing minimal energy from nuisance signals.

Chapter 4

Adaptive Brain Computer Interface

4.1 Introduction

In order to take into account the subject's state in SSVEP quality systems, two methods are proposed in this thesis. The first one consists of training the subject for all possible frequencies and selecting the most appropriate frequencies for each subject. This method will be called "Optimal Training SSVEP System" and it will be discussed in Section 4.3. The second method starts training and on-line running using initial frequencies. During the on-line running, the classifier error rate is monitored. Once the error rate exceeds a predefined threshold, other frequencies will be selected and used in training and on-line running. This method will be called "Adaptive On-line SSVEP System" and it will be discussed in Section 4.3. Before explaining the adaptive methods, the general non-adaptive SSVEP system is explained in the following section.

4.2 Non-Adaptive SSVEP System

The proposed non-adaptive SSVEP system consists of two checkerboards working at different frequencies as shown in Figure 4.1.

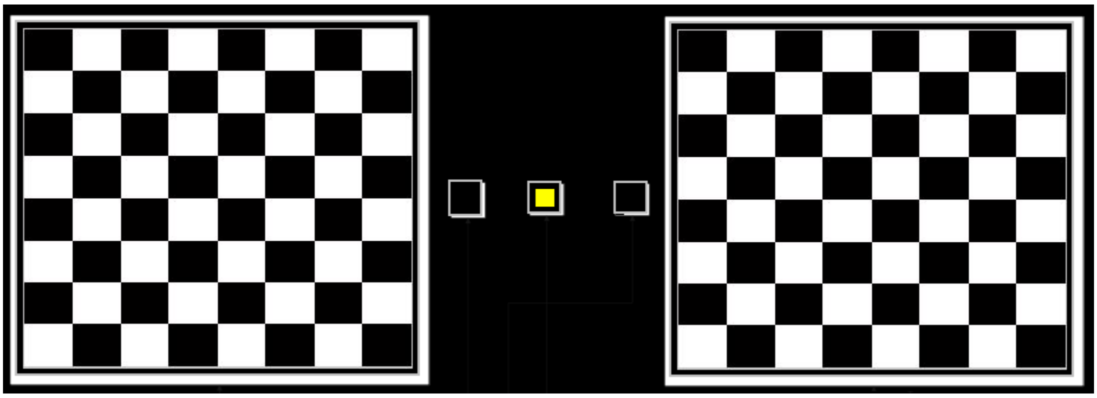


Figure 4.1 Proposed 2-class visual stimulation system.

A subject looks at specified checkerboard indicated by the yellow square beside it. The generated EEG signal is recorded using EPOC Emotiv headset with fourteen sensors (and two grounds) distributed over the scalp as shown in Figure 4.2.

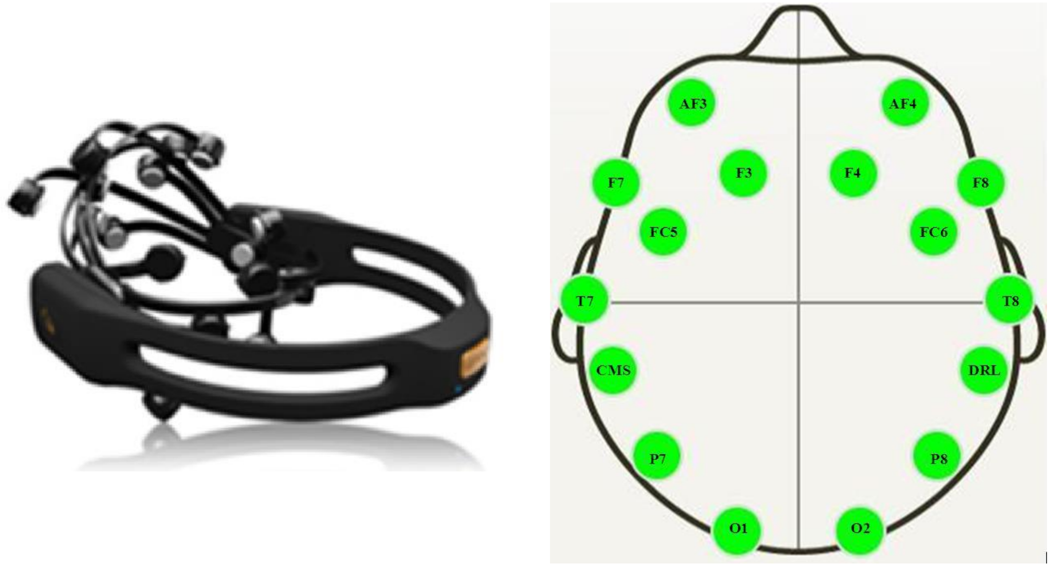


Figure 4.2 Signal acquisition unit: the Emotiv EPOC headset (Left) and the location of electrodes relative to the head (Right).

In order to extract features from recorded EEG signal, the recorded EEG signal is firstly filtered by 10 order Butterworth filter between 2 Hz and 30 Hz. Then two channels are constructed from the fourteen EEG signals using a correlation method. EEG segments corresponding to left and right flickers are extracted from constructed channels. Each segment is divided into 1 second segments and Fast Fourier

Transform (FFT) is applied on each 1 second segments. Finally, the values of FFT of each 1 second segment at working frequencies and their harmonics are extracted to form the feature vector.

The obtained samples, feature vectors and their classes are divided into training and test groups using 10-fold cross-validation method. The training samples are used to train linear classifier and the test samples are used to test the trained classifier error rate.

4.3 Optimal Training SSVEP System

In 2-class adaptive training SSVEP system, the admissible frequencies are randomly distributed in pairs as shown in Table 4.1. The frequencies are selected according to the screen refresh rate, which is 60Hz.

Table 4.1 Distribution of possible frequencies in pairs

Pair	P1	P2	P3	P4	P5	P6
F1 (Hz)	4.29	4.62	5	5.45	6	6.67
F2 (Hz)	7.5	8.57	10	12	15	20

The subject is trained for each pair of frequencies and the classification error rate is registered for each pair. Then the frequency pair of least error rate is chosen for on-line running. The flowchart of the proposed method is shown in Figure 4.3.

Table 4.2 shows the error rate of each frequency pair of a subject. It is clear that the pair with least error rate is the pair P2 which corresponds to frequencies F1 = 4.62 Hz and F2 = 8.57 Hz.

Table 4.2 Frequency pairs and error rate of a subject

Pair	P1	P2	P3	P4	P5	P6
ER1 %	30	20	70	40	40	80
ER2 %	30	20	15	25	25	30
ER1+ER2%	60	40	85	65	65	110

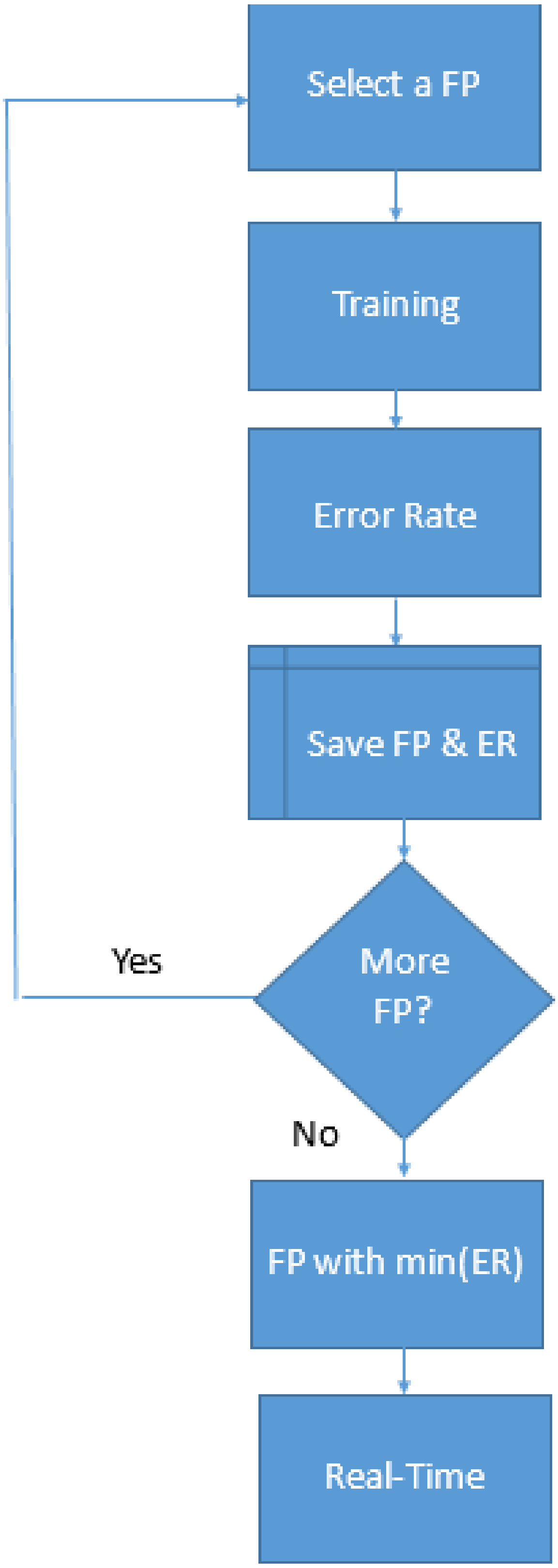


Figure 4.3 Flowchart of optimal training SSVEP system

4.4 Adaptive On-line SSVEP System

In 2-class adaptive on-line SSVEP system, the system starts training with a random frequency pair. Then this frequency pair is used in on-line running. At the same time, the error rate is monitored in real time. Once the error rate exceeds a predefined threshold, another frequency pair is randomly selected. Figure 4.4 show the flowchart of the proposed method.

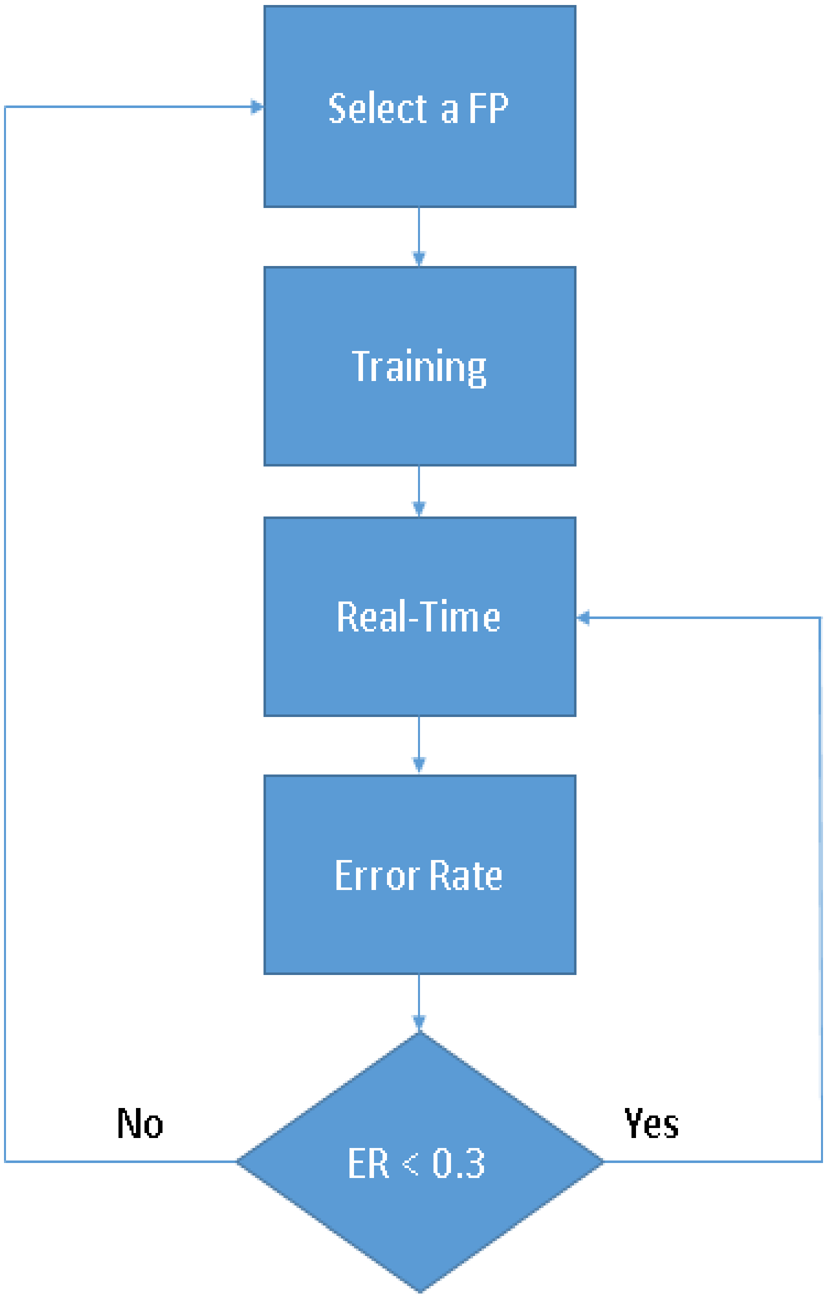


Figure 4.4 Flowchart of adaptive on-line SSVEP system.

Figure 4.5 shows the frequency pair in real time with error rate for a subject. The error rate threshold is set to 0.3 (30%).

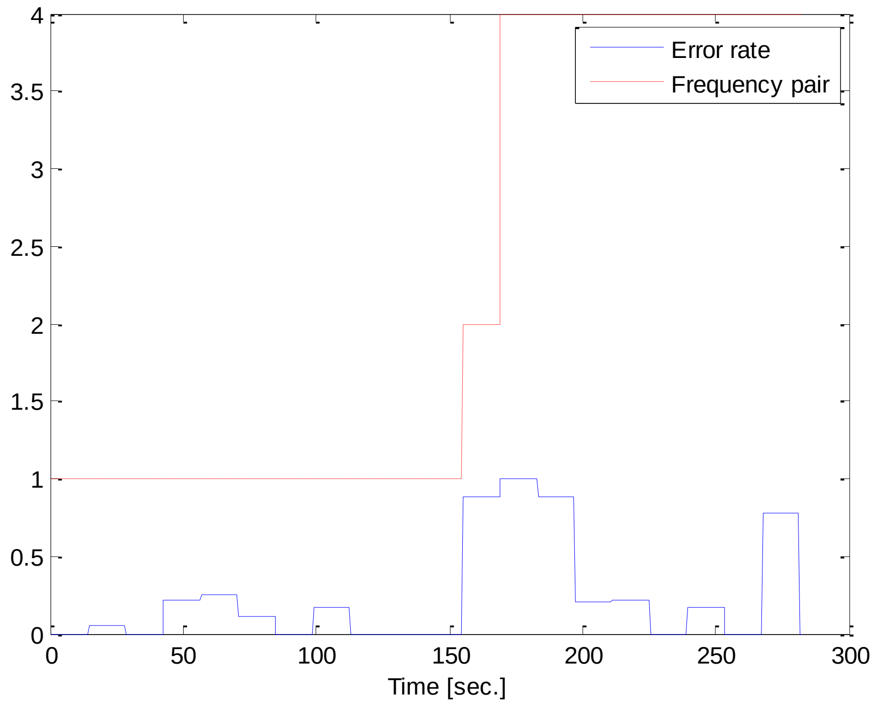


Figure 4.5 Frequency pairs and error rate of a subject.

All obtained results and their discussion are given in next chapter.

Chapter 5

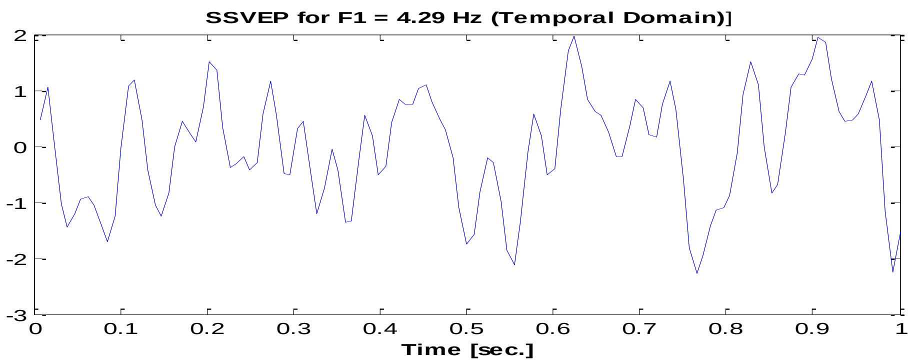
Results and Discussion

5.1 Introduction

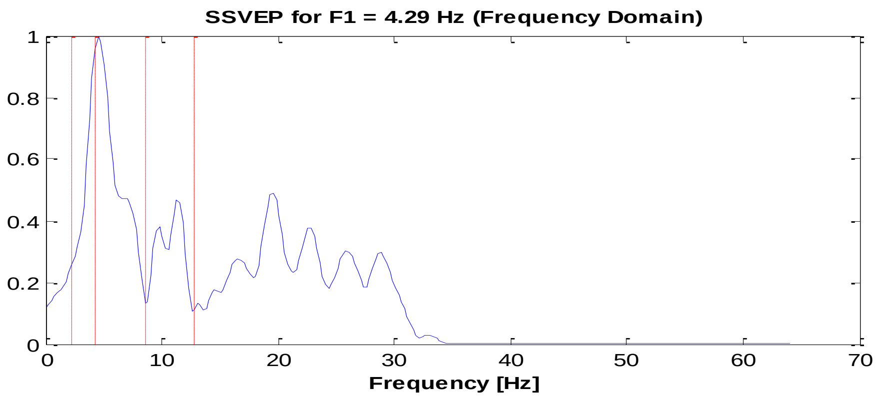
This chapter is devoted to the results of applying the two proposed methods explained in previous chapters on two subjects. The subjects are normal male with ages between 25 and 45 years. First, the results of non-adaptive SSVEP system is presented.

5.2 Results of Non-Adaptive SSVEP Method

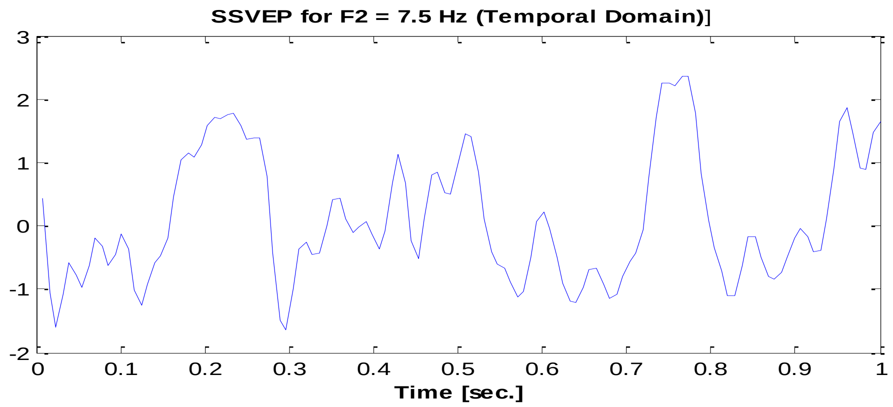
Non-adaptive SSVEP method explained in Section 4.1 is applied on two subjects. Figures 5.1 and 5.2 show the averaged EEG signals and their FFT for left and right checkerboards for the two subjects.



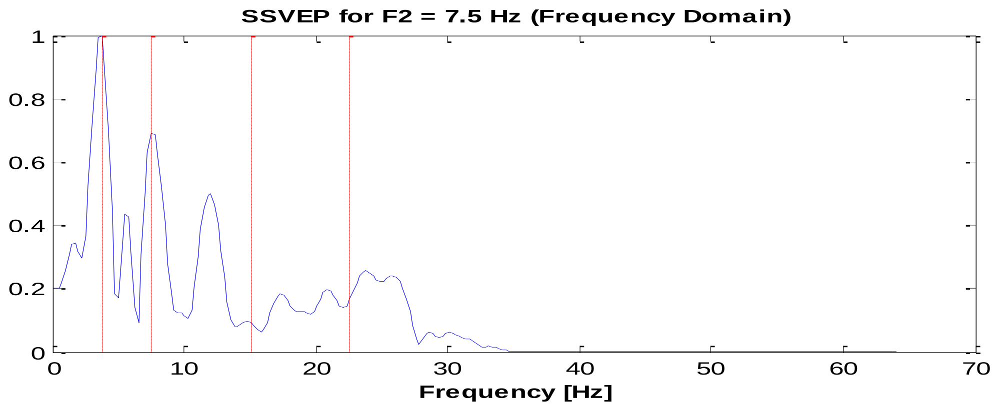
(a)



(b)

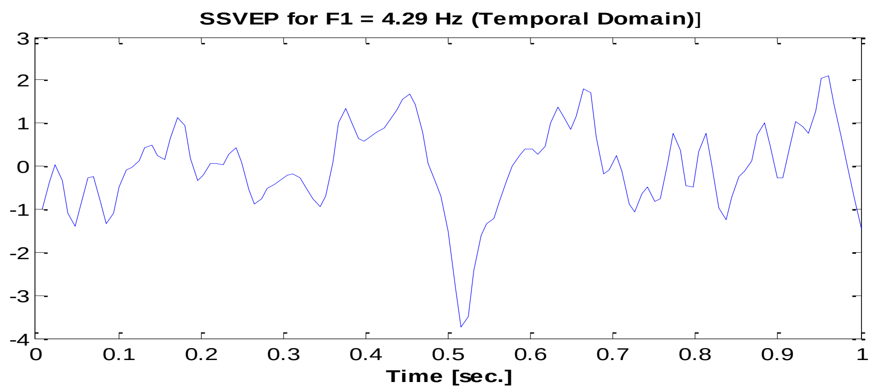


(c)

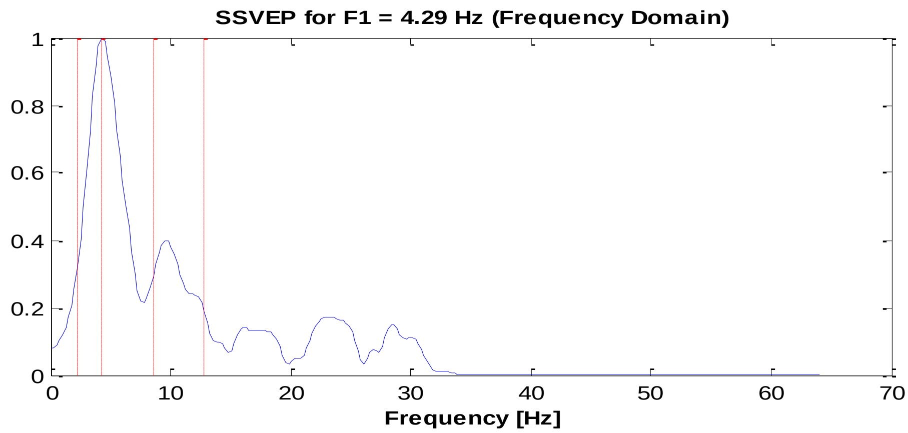


(d)

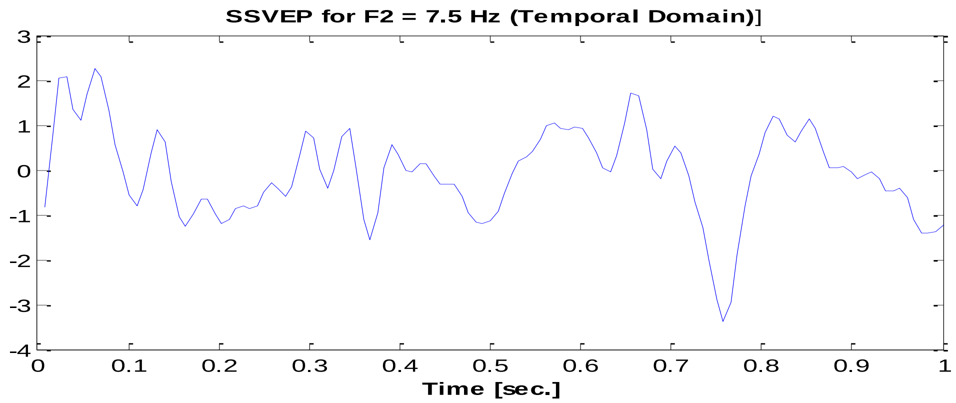
Figure 5.1 Averaged EEG signals and their FFT for left and right checkerboards for subject 1.


SSVEP for F1 = 4.29 Hz (Temporal Domain)]
Time [sec.]

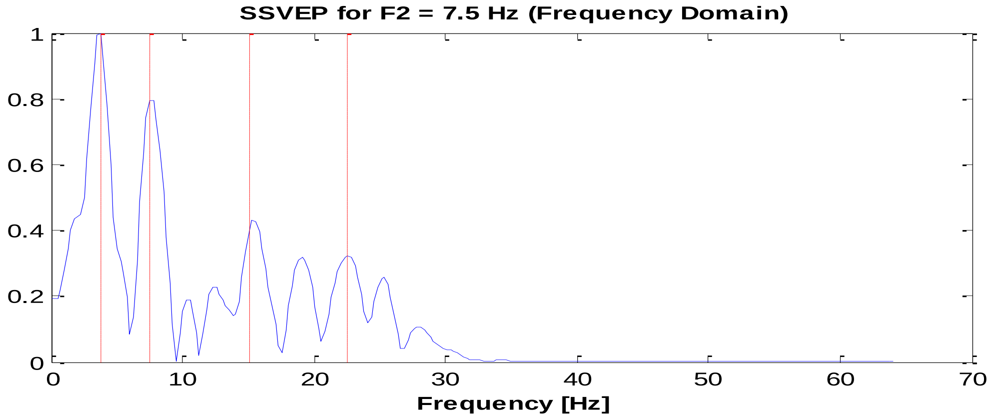
(a)


SSVEP for F1 = 4.29 Hz (Frequency Domain)
Frequency [Hz]

(b)


SSVEP for F2 = 7.5 Hz (Temporal Domain)]
Time [sec.]

(c)



(d)

Figure 5.2 Averaged EEG signals and their FFT for left and right checkerboards for subject 2.

The values of FFT of each segment at working frequencies and their harmonics are extracted from the feature vector. Table 5.1 shows some feature vectors for subject 1.

Table 5.1 some of feature vectors for subject 1

Segment	Feature Vector																Class
1	0.804363	0.102543	0.198196	0.155541	0.577931	0.857911	0.1512	0.090844	0.490836	0.027118	0.174782	0.096834	0.97763	0.21848	0.231461	0.282277	1
2	0.961674	0.471245	0.092402	0.039947	0.814005	0.443503	0.798657	0.372278	0.674493	0.400103	0.187257	0.474387	0.54017	0.415004	0.378617	0.6852	1
3	0.688543	0.45266	0.015987	0.426832	0.525245	0.500069	0.596147	0.664222	0.75201	0.090316	0.238738	0.196252	0.478224	0.463034	0.153665	0.302453	1
4	0.608946	0.72893	0.598748	0.322938	0.983851	0.949349	0.225069	0.26315	0.968229	0.349834	0.217751	0.25194	0.917486	0.42462	0.207951	0.103292	1
5	0.250281	0.651985	0.615468	0.81556	1	0.703262	0.796762	0.478	0.477062	0.579605	0.41594	0.643937	0.577507	0.577845	0.399477	0.226675	1
6	0.979462	0.423028	0.341225	0.199142	0.816525	0.853168	0.079083	0.360772	0.545819	0.530844	0.242605	0.0147	0.94096	0.035649	0.137455	0.174383	1
7	0.952623	0.46969	0.071752	0.291924	0.714688	0.210518	0.331157	0.511437	0.661518	0.396648	0.234712	0.052209	0.60923	0.590249	0.648636	0.265168	1
8	0.863226	0.305973	0.661096	0.288235	0.35355	0.428112	0.297949	0.226613	0.630787	0.755214	0.030936	0.133042	0.644589	0.030277	0.077542	0.363506	1
9	0.12603	0.604045	0.514124	0.089399	0.827258	0.724211	0.172844	0.271962	0.67907	0.223333	0.166372	0.147375	0.721223	0.235907	0.537905	0.278567	1
10	0.193678	0.482931	0.679543	0.152139	0.562939	0.765911	0.67792	0.268567	0.295019	0.870807	0.369543	0.237034	0.573171	0.748063	0.19747	0.214506	1
11	0.705967	0.780671	0.186697	0.174146	1	0.381944	0.273847	0.188183	1	0.051599	0.176615	0.080269	0.384352	0.521597	0.2309	0.056938	2
12	0.968003	0.315378	0.030406	0.05672	0.949219	0.367535	0.259152	0.099002	0.36982	0.086187	0.077298	0.046239	0.579482	0.322186	0.204125	0.072961	2
13	0.766727	0.275797	0.134234	0.061977	0.724915	0.257928	0.127039	0.147968	0.482388	0.142698	0.050981	0.016756	0.475998	0.208769	0.037557	0.036819	2
14	0.575759	0.834281	0.276907	0.187474	0.817576	0.858426	0.446316	0.434654	0.998858	0.379593	0.240185	0.093395	1	0.397026	0.388314	0.202296	2
15	0.960961	0.454234	0.346942	0.266555	0.86433	0.690564	0.399082	0.112194	0.59041	0.257662	0.038387	0.189917	0.817944	0.457034	0.229821	0.189008	2
16	0.874965	0.661933	0.140857	0.393315	0.800198	0.643658	0.08129	0.153867	0.915274	0.487183	0.468014	0.192982	0.792104	0.233059	0.0722	0.269242	2
17	0.871863	0.691135	0.144539	0.109632	0.951553	0.142452	0.109224	0.129931	0.822564	0.100938	0.130067	0.063707	0.371028	0.030382	0.045664	0.168972	2
18	0.201865	0.529069	0.616304	0.187957	1	0.855444	0.276371	0.143275	0.743314	0.2855	0.398022	0.254329	0.767789	0.279609	0.429441	0.043748	2
19	0.966702	0.221338	0.236366	0.360896	0.935652	0.809688	0.257028	0.075123	0.522614	0.684636	0.319	0.541365	0.904434	0.367195	0.234652	0.121004	2
20	1	0.251424	0.688202	0.79995	0.749349	0.777393	0.569758	0.442459	0.423272	0.606781	0.340303	0.26871	0.950793	0.422681	0.819272	0.398076	2

The obtained samples, feature vectors and their classes are divided into training and test groups using 10-fold cross-validation method. The training samples are used to train linear classifier and the test samples are used to test the trained classifier error rate. The following error rate is obtained for subject 1 and subject 2:

$$ER\_S1 = 0.3,\ ER\_S2 = 0.4$$

The obtained confusion matrix is:

$$CM\_S1 = \begin{bmatrix} 3 & 2 \\ 1 & 4 \end{bmatrix},\ CM\_S2 = \begin{bmatrix} 4 & 1 \\ 3 & 2 \end{bmatrix}$$

The following figure shows classified samples (red and green ones) and misclassified samples (black ones) for subject 1.

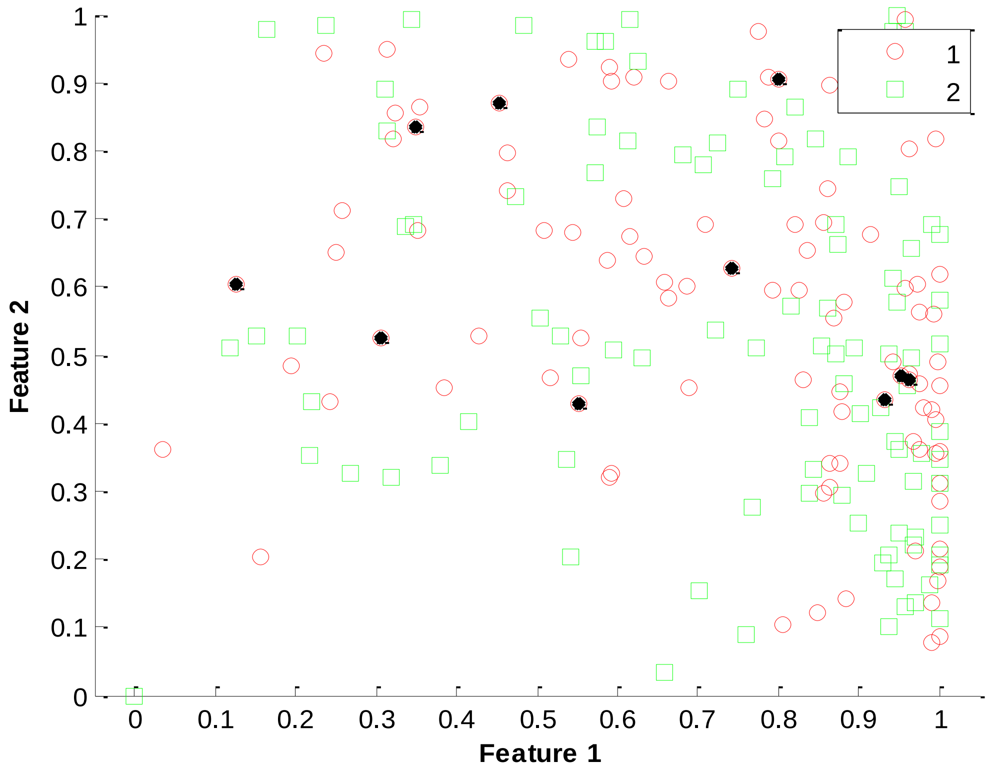
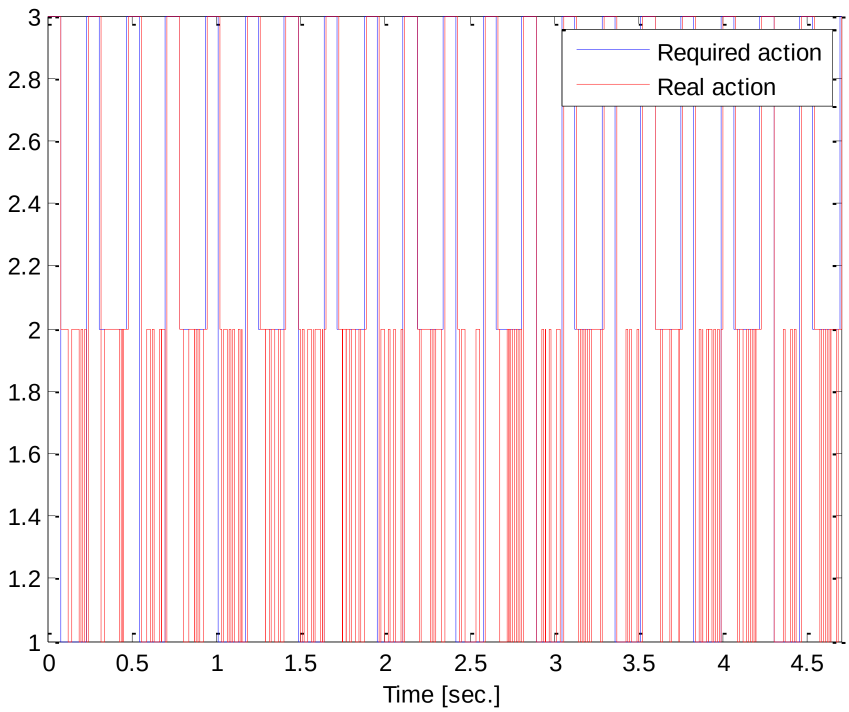


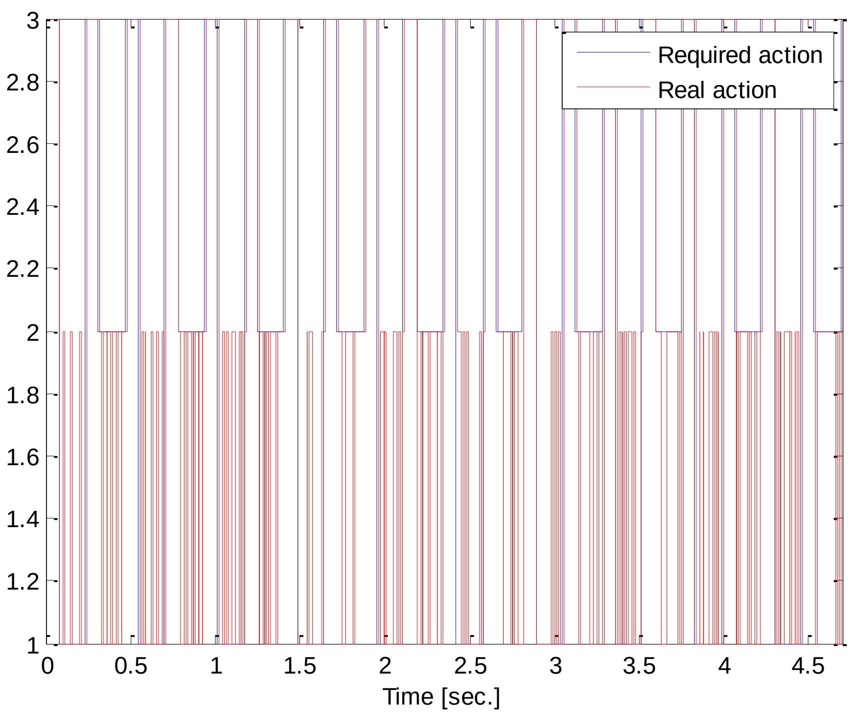
Figure 5.3 Classified and misclassified samples (black samples are misclassified).

The obtained classifier is applied in on-line experiment. The classifier output is shown in Figure 5.4. The averaged on-line error classification is

$$NA\_AER\_S1 = 0.3650,\ NA\_AER\_S2 = 0.3375 \quad (5.1)$$



(a) Subject1



(b) **Subject2**

Figure 5.4 Classifier output in on-line experiment.

5.3 Results of Adaptive Training SSVEP Method

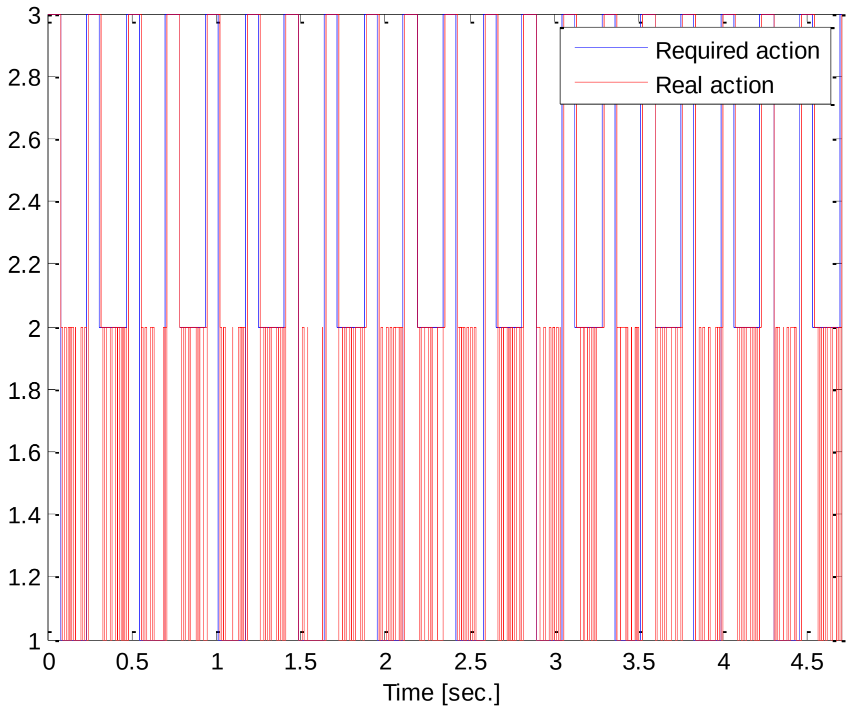
Adaptive training SSVEP method explained in Section 4.3 is applied on two subjects. Table 5.2 shows the obtained *best frequency pair* for each subject.

Table 5.2 Best frequency pair (FP) for each subject

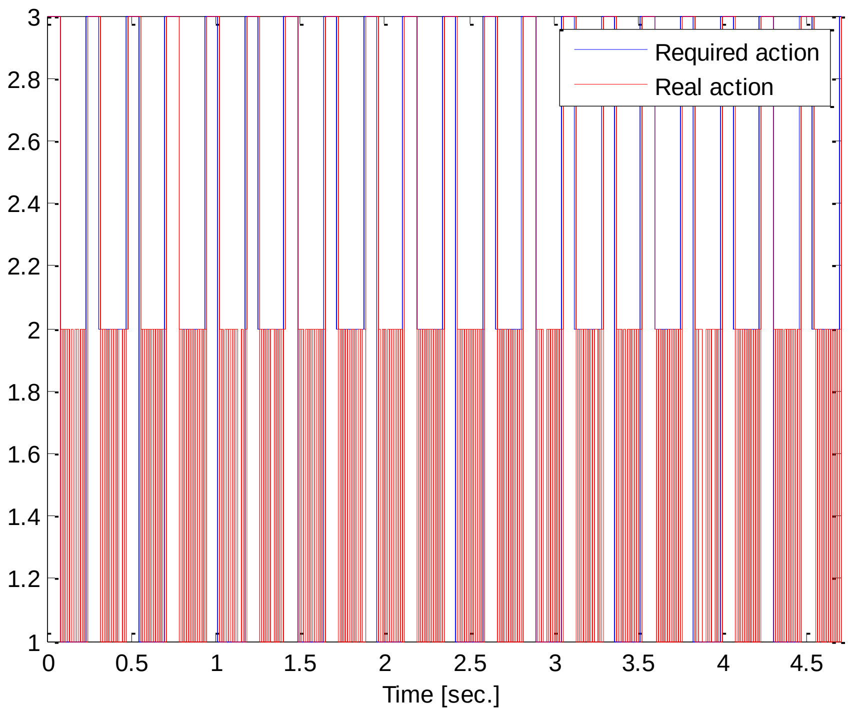
Subject	**S1**	**S2**
FP	P2	P4

The obtained frequency pairs are applied in on-line experiments. The classifier output is shown in Figure 5.5. The averaged on-line error classification is

$$AER\_TR\_S1 = 0.2375, \quad AER\_TR\_S2 = 0.3050 \quad (5.2)$$



(a) Subject1

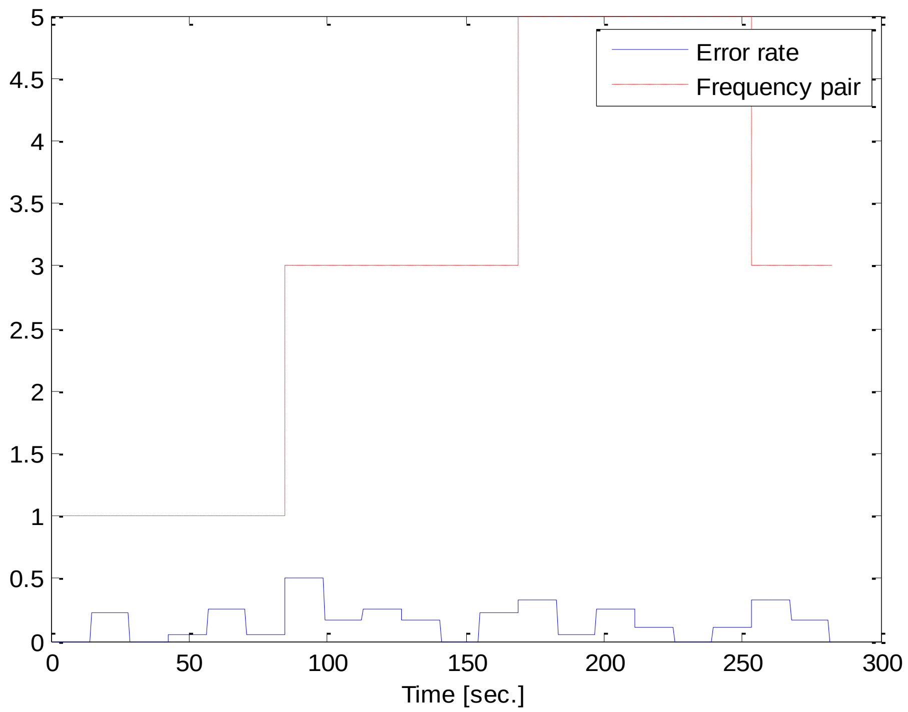


(b) Subject2

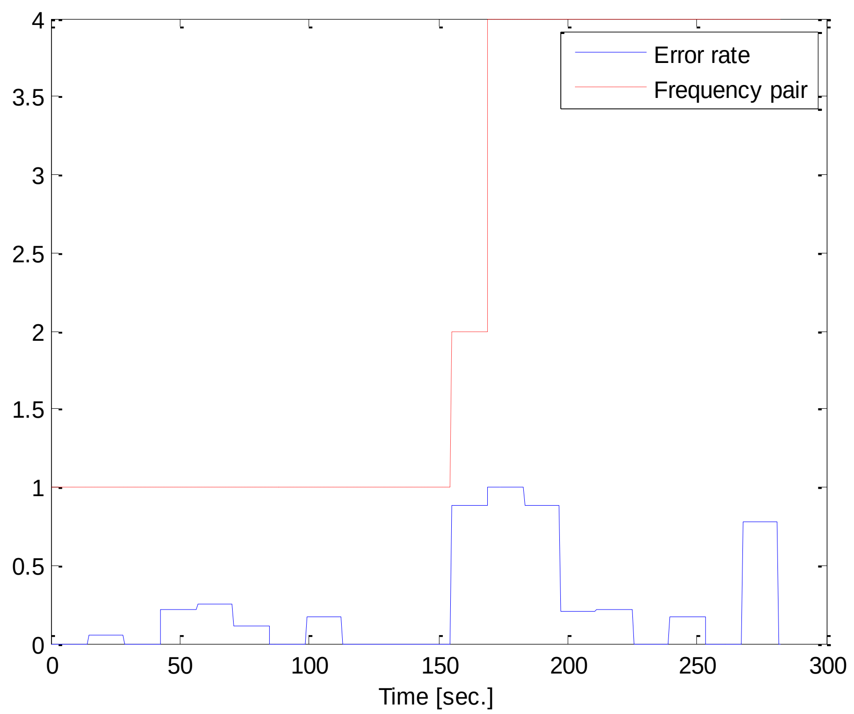
Figure 5.5 Classifier output in on-line experiment.

5.4 Results of Adaptive On-line SSVEP Method

Adaptive on-line SSVEP method explained in Section 4.4 is applied on two subjects. The following results are obtained. Figure 5.6 shows the error rates and the frequency pairs of each subject.



(a) Subject1

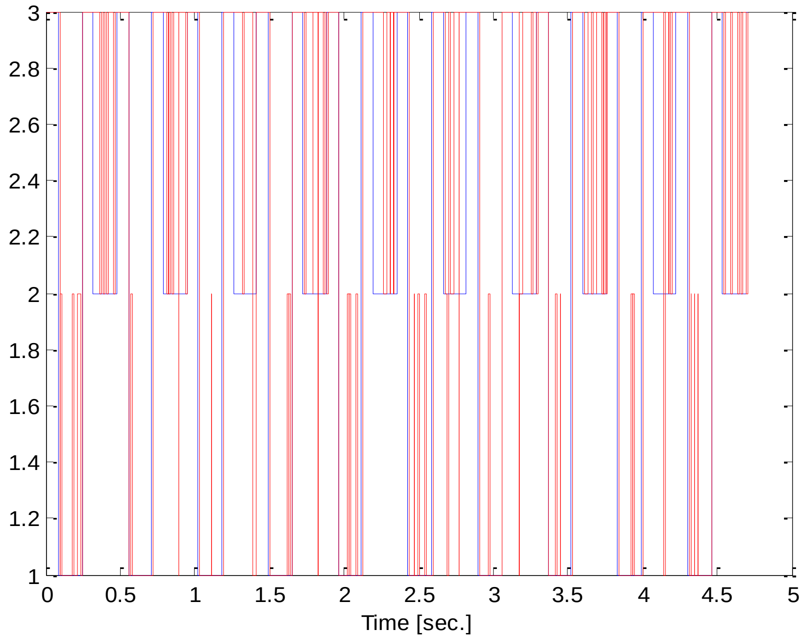


(b) Subject2

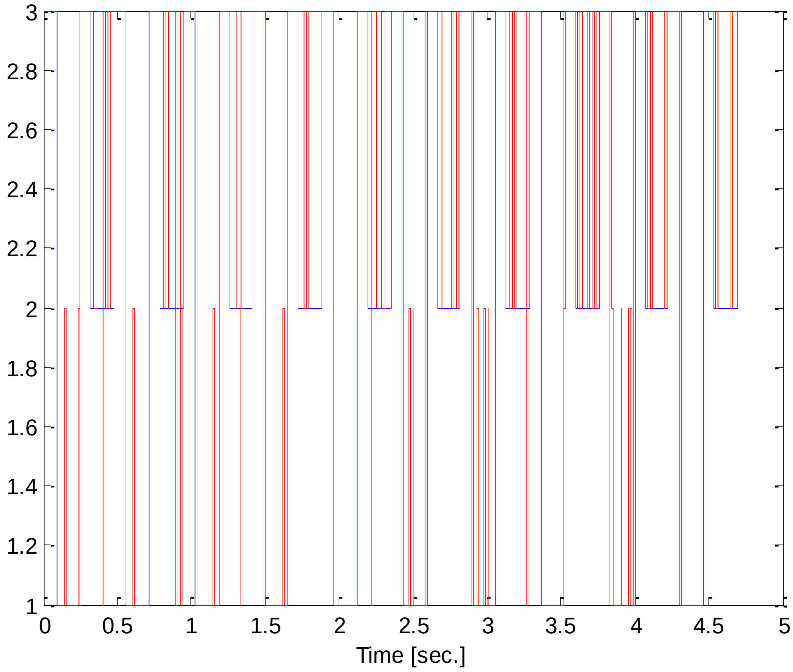
Figure 5.6 Error rate of on-line experiments of the two subjects.

The classifier output is shown in Figure 5.7. The averaged on-line error classification is

$$AER\_RT\_S1 = 0.1620, \quad AER\_RT\_S2 = 0.1974 \qquad (5.3)$$



(a) Subject1



(b) Subject2

Figure 5.7 Classifier output in on-line experiment.

5.5 Discussion

The obtained results show clearly better performance of proposed optimal and adaptive SSVEP systems than non-adaptive SSVEP system. From Equations 5.2 and 5.3, it is clear that adaptive on-line SSVEP method has better performance than optimal training SSVEP method.

The proposed methods will be applied on more subjects.

Chapter 6

Conclusions and Future Work

6.1 Conclusions

This thesis is a detailed exposition of the topic of solution of Adaptive Stimulation Frequencies Selection for Effective Detectable SSVEP Responses because it includes many exemplar methods of solving Steady State Visual Evoked Potential. These methods are of a great utility in many subareas of Brain Computer Interface such as wheelchair, Robots, and Multimedia. Other fields to which Adaptive Stimulation Frequencies Selection for Effective Detectable SSVEP Responses solving is applicable include biology, grammars, chemistry, law, medicine and spectroscopy.

In chapter 2, we defined the relationship for a set of elements in a BCI, then we tried to visualize BCI attract for many multidisciplinary fields.

Finally, we converted the output device to a computer screen, and the output is the selection of targets, letters or icons displayed on it. This output is the feedback that the brain uses to maintain and improve the accuracy and speed of communication.

Chapter 3 has presented previous works, and this thesis proposed system is based on Ming Cheng, Xiaorong Gao, Shangkai Gao,and Dingfeng Xu. We concluded that different visual simulation frequencies could be discriminated with an average classification accuracy of 84%.

In chapter 4, we presented a new method for obtaining the most compact form of the parametric general solution of a system of Adaptive BCI. The method is based on the use of the frequency and hence is an effective combination of adaptive frequency. The method starts by ordering to take into account the subject's state in SSVEP quality systems. Two methods are proposed in this chapter. The first one consists of training the subject for all possible frequencies and selecting the most appropriate frequencies for each subject. Second method starts training and on-line running using initial frequencies. During the on-line running, the classifier error rate is monitored. Once the error rate exceeds a predefined threshold, other frequencies will be selected and used in training and on-line running.

In chapter 5, the main idea is devoted to the results of applying the two proposed methods explained in previous chapters on two subjects. The subjects are normal male with ages between 25 and 45 years.

6.2 Future Work

The concepts and method developed herein can be utilized in various application areas of BCI [4, 6, 7, 12, ١٣, ١٤, ١٦, ١7, ١8]. In particular, an automated version of the present adaptive BCI solver can be applied in many reality areas. The ideas expressed herein can also be incorporated in the automated solution of large systems of BCI [41]. They can also be extended to handle Adaptive Stimulation Frequencies Selection For Effective Detectable SSVEP Responses.

The study undertaken in this thesis also paves the way to the explicit use of Adaptive Stimulation Frequencies Selection for Effective Detectable SSVEP Responses, the solution of Brain Computer Interface (BCI) in the frequency domain, and investigating a liaison between BCI and resiliency properties of Adaptive Stimulation Frequencies Selection for Effective Detectable SSVEP Responses.

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الاختيار التأقلمي لترددات التحفيز من أجل استجابات SSVEP قابلة للكشف بفعالية

هادي محمد علي الشمراني

الملخـص

تبدأ رسالة البحث هذه بتقديم شرح تعليمي مفصل لنوع جديد عظيم النفع من واجهة الحاسوب الدماغية (وح د)، من حيث كونها توفر اتصالات مباشرة بين أنشطة الدماغ والكمبيوتر. وتستند واجهة الحاسوب الدماغية (وح د) على كشف وتصنيف الأنشطة إلى أنماط محددة إلى إشارات المخ التي ترتبط بين مهمة أو حدث معين. ومن المهام الأكثر شيوعا في واجهة الحاسوب الدماغية (وح د) هي الانتباه الانتقائي.

يستخدم الانتباه الإنتقائي نموذج المؤثرات الخارجية السمعية، أو المحفزات الحسية الجسدية، أو محفزات بصرية لإشارات الدماغ المناسبة التي يتم توليدها حيث أن المشجع البصري يتكون عادة من محفزات فلاشية التي ينبعث منها ضوء الصمام الثنائي بهدف إحداث حركة أو فعل داخل الدماغ. بحيث أن تردد المشجع البصري لكل صمام ثنائي يمكن التحكم به بشكل مستقل من قبل أجهزة منطقية قابلة للبرمجة. وبإستخدام مثل هذه المشجعات سجلت واجهة الحاسوب الدماغية ٤٨-هدفا. حيث أن الأهداف التحفيزية تتراوح مابين واحد إلى ٦٤، الأمر الذي أدى إلى تحقيق مدى معين في أداء النظام. عموما، كلما زادت أهداف النظام كلما زاد معدل نقل المعلومات. على سبيل المثال في أنظمة أختبارات ١٣ هدفا وأنظمة أختبارات ٢ هدف وجد أن متوسط معدل نقل المعلومات ٤٣ و١٠ بت/دقيقة على التوالي. من ناحية أخرى، فإن زيادة عدد المحفزات مع مزيدا من الأهداف هو أيضا أكثر إرهاقا للمستخدم، لذا ينبغي النظر في عدد الأهداف وفقا لأداء المفاضلة بين الأداء والراحة للمستخدم. إضافة إلى ذلك، فإن العدد الأمثل من المحفزات يعتمد أيضا على عرض النطاق الترددي القابل للإستخدام من جهد الحالة المستقرة المثار بصريا، التي تحقق الهدف المطلوب.

بعد ذلك تم التطرق إلى تعريف واجهة الحاسوب الدماغية على أنها قناة الاتصال والتحكم التي تقوم على القياس المباشر لنشاط الدماغ بدلا من حركة التواصل الجسدي من قبل إشارات الدماغ إلى الكمبيوتر وترجمة الأنشطة الكهربائية في المخ إلى رسائل أو أوامر يمكن استخدامها في العديد من التطبيقات الحاسوبية مثل الهجاء ومراقبة المؤشر والألعاب والسيطرة على بيئة إفتراضية والتي سوف تكون مفيدة ومفيدة جدا للمرضى المعاقين.

حيث أن تكنولوجيا واجهة الحاسوب الدماغية (وح د) لديها العديد من المزايا ومن أهمها السلامة والتي تعني عدم وجود خطر على الدماغ أو أجسام المرضى كما أنها غير مؤلمة وسهلة الاستخدام من قبل المعاقين وتوفر المعلومات بسرعة أكبر من طريق الحركة العادية مثل أي تكنولوجيا أخرى. كما أن لديها بعض العيوب والقيود، على سبيل المثال لا الحصر، إنها ليست دقيقة ١٠٠% وليست محمولة حتى الآن.

كما أنها تجذب الاهتمام في العديد من المجالات والتخصصات مثل: (أ) علم الأعصاب، فهم الجهاز العصبي بما في ذلك الدماغ من وجهة النظر البيولوجية والحسابية. (ب) علم وظائف الأعضاء، وفهم أنشطة الدماغ. (ج) الهندسة الطبية الحيوية، فهم عتاد واجهة الحاسوب الدماغية وكيفية ربطها وكيفية العمل معها. (د)علوم الكمبيوتر لتنفيذ برامج واجهة الحاسوب الدماغية (و ح د) وإضافة بعض خوارزميات الذكاء الاصطناعي لتكون أكثر سهولة ومفيدة للمرضى.

إن برنامج جهد الحالة المستقرة المثار بصريا هو أحد تطبيقات واجهة الحاسوب الدماغية والتي تم التركيز عليها في هذه الرسالة، حيث قمنا باستعراض وشرح وتقييم وتوسيع استخدام جهد الحالة المستقرة المثار بصريا في تحديد ومعالجة واجهة الحاسوب الدماغية. فقد حققنا فهما أفضل لهذا الاستخدام من خلال ترجمة وشرح مصطلحات جهد الحالة المستقرة المثار بصريا، وتحديد الترددات التي يتم بناء واجهة الحالة المستقرة المثار بصريا من واجهة الحاسوب الدماغية.

تختلف منهجية جهد الحالة المستقرة المثار بصريا كونها لا تعتبر منافسة لمنهجية جهد الحالة المستقرة المثار بصريا التأقلمية في حلول التأقلم مع الترددات. كما ظهرت الحاجة إلى وجود حل آلي لاختيار الترددات بشكل تلقائي وهي الميزة التي نهدف إلى الوصول إليها من خلال جهد الحالة المستقرة المثار بصريا التأقلمية.

من أجل أن نأخذ بعين الاعتبار موضوع الجودة (وح د) في حال أنظمة جهد الحالة المستقرة المثار بصريا، فقد تم اقتراح طريقتين في هذه الرسالة. الطريقة الأولى تعتمد على تدريب المستخدم على جميع الترددات الممكنة وتحديد الترددات الأنسب لكل مستخدم. سيتم تسمية هذا الأسلوب "نظام (وح د) التأقلمي في التدريب " كما سيتم مناقشتها في القسم ٤،٣.

الطريقة الثانية يبدأ التدريب والتشغيل في الوقت الحقيقي ويتم تشغيلها باستخدام الترددات التي تم تسجيلها في الطريقة الأولى خلال الوقت الحقيقي على التوالي، ويتم رصد معدل الخطأ المصنف عندما تتجاوز نسبة الخطأ الحد الأدنى المحدد سلفا، وسوف يتم اختيار ترددات أخرى واستخدامها في التدريب والتشغيل في الوقت الحقيقي. سيتم تسمية هذه الطريقة " نظام (وح د) التأقلمي في الوقت الحقيقي". كما سيتم مناقشتها في القسم ٤،٣.

تتضمن هذه الرسالة ستة أبواب بيانها كما يلي:

- يحتوى الباب الأول على مقدمة سريعة للبحث تتضمن فائدة واجهة الحاسوب الدماغية والمعتمدة على اكتشاف وتصنيف أنماط محددة من خلال إشارات الدماغ المرتبطة بحدث أو حركة معينة، ويشرح الأهداف العامة له، ويعرض بعض الدراسات السابقة التي تتعلق بفكرة البحث، ويبين تصميم مشروع البحث ومنهجيته، والإشارة إلى آلية تنفيذ المشروع واختباره.
- في الباب الثاني تم تعريف واجهة الحاسوب الدماغية كما تم التطرق إلى مميزات هذه التقنية ومدى تأثيرها على مجالات العلوم والتطبيقات الأخرى، واشتمل أيضا على مناهج واجهة الحاسوب الدماغية وهيكلته حيث يشمل على المكونات الاساسية لأي نظام مدخلات (إشارة الدماغ) ومخرجات (أوامر) والمعالجة أو العمليات، حيث أعتبر اكتساب الإشارة كمدخلات، وأعتبر استخراج الخصائص وخوارزمية التحويل كمعالجة للإشارة، والأوامر الناتجة من معالجة الإشارة اعتبرت كمخرجات.

- اشتمل الباب الثالث على شرح جهد الحالة المستقرة المثار بصريا والتوسع في استخداماته في تعريف ومعالجة واجهة الحاسوب الدماغية. كما أشتمل على مقارنة بين جهد الحالة المستقرة المثار بصريا وجهد الحالة المستقرة المثار بصريا التأقلمي. كما تم استعراض واجهة الحاسوب الدماغية اعتمادا على جهد الحالة المستقرة المثار بصريا مع إعطاء بعض الأمثلة السابقة مثل لوحة مفاتيح الهاتف، وتوضيح كيفية عمل تسريع وزيادة الدقة في واجهة الحاسوب الدماغية بواسطة اختيار التردد المناسب. كما تم ذكر أوضاع خوارزمية التحويل حيث اشتملت على ثلاثة أوضاع (أ) وضع التدريب (ب) وضع التدريب الفوقي (ج) وضع الاختبار.
- في الباب الرابع تم تقديم طريقتين للحصول على واجهة الحاسوب الدماغية التأقلمية، تتكون الطريقة الأولى من تدريب المستخدم على جميع الترددات الممكنة واختيار التردد الأنسب له. الطريقة الثانية يبدأ التدريب في الوقت الحقيقي ويتم تشغيلها باستخدام الترددات التي تم تسجيلها في الطريقة الأولى خلال الوقت الحقيقي على التوالي. كما تم استعراض نظام جهد الحالة المستقرة المثار بصريا غير التأقلمي حيث يتم تسجيل اشارات الدماغ بواسطة جهاز EPOC Emotiv headset والذي يتكون من ١٤ جهاز استشعار.
- في الباب الخامس تم عرض النتائج التي تم التوصل اليها من خلال تنفيذ الطريقتين المقترحتين. حيث بينت النتائج فعليا وبشكل واضح أن جهد الحالة المستقرة المثار بصريا التأقلمي أفضل من جهد الحالة المستقرة المثار بصريا غير التأقلمي.
- يمثل الباب السادس خاتمة للبحث، حيث تم استعراض الهدف العام من هذا البحث، والخطوات التي تمت لإتمام هذه الدراسة، كما جرت الإشارة إلى محتوى هذا البحث وما يتضمنه من دراسة لاختيار الترددات بشكل تلقائي واستخداماتها. كذلك تمت الإشارة في نهاية هذا الباب إلى المسائل المقترحة للعمل عليها في المستقبل إن شاء الله.

الاختيار التأقلمي لترددات التحفيز من أجل استجابات SSVEP قابلة للكشف بفعالية

هادي محمد علي الشمراني

المستخلص

واجهة الحاسوب الدماغية (وح د) هي طريقة تفاعلية تمكن المستخدم من التحكم بالأجهزة الخارجية بواسطة إشارة دماغه. أحد أكثر أنظمة واجهة الدماغ الحاسوبية الأكثر استخداما هو جهد الحالة المستقرة المثار بصريا (ج ح م م ب). في نظام (ج ح م م ب) ينظر المستخدم في وميض المحفز البصري بتردد ثابت. الإشارة المتولدة من الدماغ لديها تردد أساسي كتردد الوميض المحفز بصريا. على أن التردد المحفز يعتمد على المستخدم وحالته.

ومن أجل جعل (ج ح م م ب) أكثر قابلية للاستخدام، نحتاج إلى خوارزمية لاختيار التردد التأقلمي، وهذا هو الهدف من رسالة الماجستير هذه. تحقيقا لهذه الهدف، تم اقتراح خوارزميتين لهذا العمل. الخوارزمية الأولى تعتمد على مسح جميع الترددات الممكنة واختيار أفضل تردد على أساس تصنيف معدل الخطأ. بينما تعتمد الخوارزمية الثانية على فكرة مراقبة تصنيف معدل الخطأ في الوقت الفعلي. عند تجاوز معدل الخطأ النسبة المحددة سابقا يقوم النظام باختيار تردد أخر بشكل تلقائي.

الخوارزميتين المقترحتين في هذه الرسالة تم تنفيذهما واختبارهما بشكل فعلي. النتائج التي تم الحصول عليها أظهرت بشكل واضح أن الأداء في نظام جهد الحالة المستقرة المثار بصريا التأقلمي أفضل من نظام جهد الحالة المستقرة المثار بصريا الغير تأقلمي. بالإضافة إلى أن الخوارزمية المقترحة الثانية أظهرت نتائج أفضل مقارنة مع الخوارزمية المقترحة الأولى.

وكعمل في المستقبل، سيتم تطوير طريقة نسبة تصنيف معدل الخطأ في نظام جهد الحالة المستقرة المثار بصريا التأقلمي. إضافة إلى أنه سيتم استخدام خوارزميات نظام جهد الحالة المستقرة المثار بصريا التأقلمي المقترحة في تطبيقات حقيقية.

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شكر وعرفان

من لايشكر الناس لايشكر الله

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اللواء سليمان بن عبدالعزيز اليحيى

اللواء محمد بن عايض الوهبي

اللواء سالم بن بخيت الزهراني

العميد محمد بن حسن الاسمري

العميد خلف الله بن عبيدالله الطويرقي

العميد فالح بن عبدالحميد الحازمي

العقيد سعيد بن محمد القحطاني

العقيد عبود بن محمد الحربي

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الاختيار التأقلمي لترددات التحفيز من أجل استجابات جهد الحالة المستقرة المثار بصريا القابلة للكشف بفعالية

إعداد

هادي محمد علي الشمراني

بحث مقدم لنيل درجة الماجستير في العلوم

(الحاسبات وتقنية المعلومات)

إشراف/ د. أنس محمد علي فتوح

كلية الحاسبات وتقنية المعلومات

جامعة الملك عبد العزيز – جدة

رجب ١٤٣٥ هـ / مايو ٢٠١٤ م