NEW APPROACH FOR DESIGNING cVEP BCI STIMULI BASED ON SUPERPOSITION OF EDGE RESPONSES

A THESIS SUBMITTED TO

THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE

OF BILKENT UNIVERSITY

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR

THE DEGREE OF

MASTER OF SCIENCE

IN

ELECTRICAL AND ELECTRONICS ENGINEERING

By

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January 2020

New Approach For Designing cVEP BCI Stimuli Based On Superposition of Edge Responses
By Muhammad Nabi Yasinzai
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We certify that we have read this thesis and that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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ABSTRACT

NEW APPROACH FOR DESIGNING cVEP BCI STIMULI BASED ON SUPERPOSITION OF EDGE RESPONSES

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January 2020

Electroencephalography (EEG) based brain-computer interfaces (BCIs) are widely used in the field of neural engineering, due to their portability, noninvasive nature, and high temporal resolution properties. Among the different BCI modalities, code modulated visual evoked potentials (cVEP) are very popular due to their high classification speed and accuracy. Over the years, various cVEP stimulus sequences have been designed aiming to increase the classification speed, accuracy, and the number of supported targets. This study is carried out in order to present a novel cVEP stimulus sequence designing methodology, which is purely based on characteristics of the actual brain responses to visual stimuli.

Seven male subjects participated in our study, and they were presented pulse-type visual stimulus sequences on a monitor with 60 Hz refresh rate (each bit of a stimulus sequence is presented for 16.67 ms). EEG was recorded using Brain Products V-Amp (16 channel) EEG Amplifier from O1, Oz, O2, P3, Pz, P4, P7, and P8 positions at the rate of 2000 sps and the recorded EEG was then bandpass filtered between 4 and 40 Hz. Electrode impedances were kept under 10 KOhms, and Canonical Correlation Analysis (CCA) was used to reduce the 8-channel data to a single signal. Matlab, along with psychtoolbox, was used for stimulus presentation on a PC with Ubuntu operating system.

In the first part of this study, our aim was to reconstruct the EEG response to pulse-type stimulus patterns by superposing the EEG responses to simple stimulus patterns. It is observed that the EEG response is only sensitive to the changes in the stimulus sequence, that is, to positive (change from Black to White) and negative edges (change from White to Black). The edge responses have a delay of around 50 ms, and these responses can be observed up to 350

ms after the edge. Furthermore, the magnitude of the positive edge response is much larger than the negative edge response. Edge responses for every person are unique, and they are also repeatable. The 7 subjects of our experimental study have an overall average correlation of 84% between the positive edge responses obtained with two weeks of separation. It is also interesting to know that edge responses for all of the subjects have a similar overall pattern.

A series of experiments are then carried out to determine how well the EEG responses can be predicted by superposition of the edge responses. The reconstructed and measured EEG responses are compared for different pulse widths, different pulse separations, and also for different pulse repetitions. It is observed that response to 1 and 2 bit wide pulses can be predicted accurately for all subjects with an average correlation of 70.3% and 68.1%, respectively. Further, for 1 bit wide pulses, if the separation between two pulses is 4 to 9 bits, the correlation between predicted and measured responses is above 51.5%. For 2 bit wide pulses, if the separation is between 3 and 9 bits, the correlation is above 53.4%. Furthermore, responses to repeating 2 and 3 bit wide pulses can be predicted with a correlation of up to 62.4% and 59.2% for 4 and 5 repetitions, respectively.

In the third part of this study, we constructed 120 bit stimulus sequences based on the constraints explained above and compared them with two other types of stimulus sequences in the context of a BCI speller application. The proposed BCI speller consists of 36 targets that are presented as a 6x6 matrix on the monitor screen at the refresh rate of 60 Hz, and the experiments are performed on seven healthy subjects. The classification results of our BCI speller follow our expectations based on the second part of our study; in that, for our proposed BCI stimulus sequences, the accuracy and ITR are recorded to be 95.5% and 57.19 bits/min, respectively, whereas for the other two types of codes, the classification accuracies are 6.94% and 10.53% with information transfer rates (ITR) of 1.7 bits/min and 10.53 bits/min, respectively.

Keywords: Brain-computer interface (BCI), Electroencephalogram (EEG), code-modulated visual evoked potential (c-VEP), Modeling, canonical correlation analysis (CCA).

ÖZET

KMGUP BBA UYARI TASARIMI İÇİN KENAR TEPKELERİNİN SÜPERPOZİSYONUNA DAYANAN YENİ YAKLAŞIM

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Elektroensefalografi (EEG) bazlı Beyin-Makina Arayüzleri (BBA) nöro-mühendislik alanında, taşınabilir olmaları, invaziv olmamaları, ve yüksek zamansal rezolüsyona sahip olmaları sebebiyle yaygın olarak kullanılmaktadırlar. Değişik BBA modaliteleri arasında, kod modülasyonlu uyarılmış potansiyeller (KMGUP), yüksek sınıflandırma hız ve doğrulukları dolayısıyla, çok popülerdir. Yıllar içinde, sınıflandırma hız ve doğruluğunu ve desteklenen hedef sayısını artırmak anamcıyla, çeşitli KMGUP uyarı dizinleri tasarlanmıştır. Bu çalışma, tamamen beynin görsel uyarılara verdiği tepkelerin özellikleri baz alınarak, yeni bir KMGUP uyarı dizini tasarımı metodolojisi sunmak amacıyla yapılmıştır.

Çalışmamıza katılan yedi erkek deneğe 60 Hz yineleme hızlı bir monitörden darbe-tipli görsel uyarı dizinleri sunulmuştur (uyarı dizininin her bir biti 16.67 ms süre tutmaktadır). EEG, Brain Products V-Amp 16-kanal EEG Amfisiyle O1, Oz, O2, P3, Pz, P4, P7, ve P8 pozisyonlarından 2000 örnek/saniye hızıyla kaydedilmiş ve 4Hz ila 40 Hz arasında bant-geçiren filtreyle filtrelenmiştir. Elektrot empedansları 10 KOhm altında tutulmuş, ve 8 kanal veri Kanonik Korelasyon Analizi (CCA) yöntemiyle tek sinyale indirilmiştir. Psychtoolbox ve bereberinde Matlab kullanılarak uyarı sunumu Ubuntu işletim sistemi içeren bir Kişisel Bilgisayarla gerçeklenmiştir.

Çalışmamızın birinci kısmında amacımız darbe-tipi uyarı dizinlerine olan EEG tepkelerini basit uyarı örüntülerine verilen EEG tepkelerinden süperpozisyon yoluyla oluşturabilmektir. EEG tepkelerinin sadece uyarı dizinindeki değişimlere yani pozitif (Siyahtan Beyaza dönüşme) ve negatif (Beyazdan Siyaha dönüşme) kenarlara hassas olduğunu gözlemledik. Kenar tepkeleri 50 ms gecikmeyle kenardan itibaren 350 ms boyunca sürmektedir. Pozitif kenar tepkesi negatif tepkeden

genlik olarak oldukça fazladır. Her deneğin kenar tepkeleri kendine özgüdür ve aynı zamanda tekrar edilebilirdir. Deneylere katılan 7 denekte iki hafta arayla elde edilmiş olan iki kenar tepkesi birbiriyle ortalamada %84 korelasyona sahiptir. Diğer taraftan deneklerin kenar tepkeleri genel hatlarıyla birbirlerine benzemektedir.

Daha sonra EEG tepkelerinin, kenar tepkelerinden süperpozisyon yoluyla ne kadar doğrulukla elde edilebildiğini sınamak için deneyler yapıldı. Oluşturulan ve kaydedilen EEG tepkeleri, farklı darbe uzunlukları, farklı darbe aralıkları ve de farklı darbe tekrarları için karşılaştırıldı. 1 ve 2 bit uzunluktaki darbelere olan tepkelerin sırasıyla %70.3 ve %68.1 korelasyonla oluşturulabildiği gözlemlendi. İlaveten, iki adet 1 bitlik darbenin arasındakı boşluğun 4 ila 9 bit arasında olması durumunda, oluşturulan ve ölçülen tepkeler arasındaki korelasyon %51.1'den fazla olmaktadır. 2 bit uzunluğundaki darbeler için ise iki darbe arasındaki boşluk 3 ila 9 bit arasındaysa, söz konusu korelasyon %53.4'ten yüksek olmaktadır. Tekrarlanan 2 ve 3 bit uzunluğundaki darbeler için, eğer tekrarlanma sayısı 4 veya 5 ise, EEG tepkeleri sırasıyla %62.4 ve %59.2 korelasyonla öngörülebilmektedir.

Çalışmamızın üçüncü kısmında, yukarıda gözlemlendiği belirtilen kısıtlamalar göz önüne alınarak hazırladığımız 120 bit uzunluğunda uyarı dizinlerini, ve diğer başka iki tip uyarı dizinlerini bir BBA heceleyici uygulamasında karşılaştırdık. 36 hedefe sahip olan BBA heceleyici 60 Hz yineleme hızlı bir monitör kullanılarak 7 deneyde uygulandı. Çalışmamızın ikinci kısmında elde edilen gözlemlerlerden beklenenlere uygun olarak, önerdiğimiz dizinlerle, sınıflandırma doğruluğu ve Enformasyon Transfer Hızı (ITR) sırasıyla %95.5 ve 57.19 bit/s olurken, diğer iki dizin tipiyle sınıflandırma doğruluğu %6.94 ve %10.53, ITR ise 1.7 bit/s ve 10.53 bit/s oldu.

Anahtar sözcükler: Beyin-Bilgisayar Arayüzü (BBA), Elektroansefalografi (EEG), kod-modülasyonlu görsel uyarılmış potansitel (KMGUP), modelleme, kanonik korelasyon analizi (KKA).

Acknowledgement

All praises and thanks to Almighty Allah; the ultimate source of all knowledge to mankind and for His endless blessings for humanity.

I want to express my gratitude to my family for their love, support, guidance, and for keeping their faith in me. Their support and presence give me the strength and courage to work hard and to chase my goals.

I am grateful to my supervisor Professor Yufus Ziya Ider (Department of Electrical and Electronics Engineering, Bilkent University) for believing in me. I am thankful for his guidance, support, cooperation, and constant feedback. His commitment to our project motivated me to push my limits and deliver my best.

I am very thankful to Kamilla Shah for her support, assistance, and for keeping faith in me. Her continued consultation and encouragement helped me a lot in achieving my goals.

I am thankful to the BCI group members, Abdul Waheed, Suleman Memon, and Toygun Basaklar, who have been great friends and mentors for their support and guidance.

I am grateful to Caner Yıldırım, Muhammad Hilal, Sina Gholizadeh, M. Anjum Qureshi, Salahuddin Zafar, M. Aamir Saeed and Daniyal Namdar for participating in the experiments.

I gratefully acknowledge the funding received from the Scientific and Technological Research Council of Turkey (TÜBİTAK) under Grant 116E153 during my MSc studies.

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Chapter 1

Introduction

1.1 Background

1.1.1 Brain-Computer Interfaces (BCIs)

BCI is a powerful communication system that provides a user, the capability to interact with the surroundings using brain signals [1]. The ability to control the environment based on brain electrical signals is a subject of interest for a long time. BCI has numerous applications in the real world, they include drowsiness detection of car drivers [2], controlling the position of computer cursor on the screen [3], finding the mental concentration levels [4], determining the emotions of a person [5] and typing using a visual keyboard [6]. The biggest beneficiaries of the BCI systems are the people with motor disabilities. BCI is helping them to interact with the environment using brain signals which involves minimal muscle movements [7]. EEG based BCI is very popular in the field of neural engineering because of their portability, non-invasive and the temporal resolution properties of the EEG. There are different types of BCI systems and every kind of BCI system uses different EEG control signals. Out of these BCI modalities, the most popular are event-related potentials (ERPs) and visually evoked potentials (VEPs) [8]. The popularity of ERP and VEP based BCI is due to the feasibility of these approaches in clinical practices along with their low training time and high information transfer rate, and because of these reasons they are the most researched approaches for BCI systems [9].

A BCI system consists of 5 stages. These stages are named as signal acquisition, signal preprocessing, feature extraction, classification, and control interface[10]. The general design of a BCI system is shown in Figure 1.1. In the signal acquisition stage, signals from the brain are recorded. These signals are due to the hemodynamic activity or electrophysiological activity of the brain. Hemodynamic activity accounts for events of difference in glucose delivery to the active and inactive neurons [11]. Glucose to the active neurons is delivered at a higher rate than the inactive neurons. As a result, the oxyhemoglobin ratio increases in the active region which can be easily distinguished. Whereas, electrophysiological activity is observed when the information from one neuron is passed to the other neuron using electrochemical transmitters [8]. In our study, we determine the electrophysiological activity of the brain by placing electrodes at different locations on the scalp, and the electrical signals generated by the brain electrophysiological activity are recorded from these electrodes.

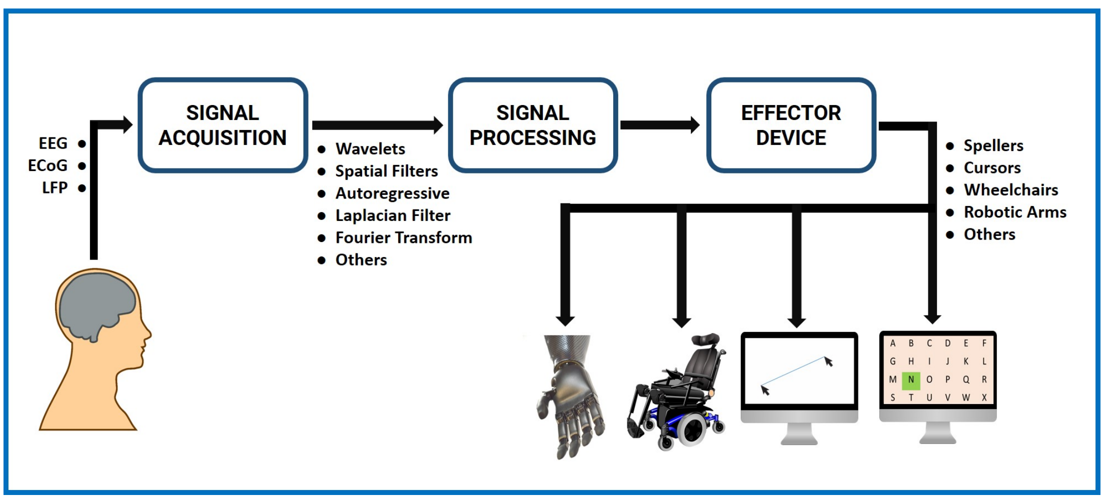

Figure 1.1: Flow diagram of a general BCI system

The second stage of the BCI system is the preprocessing stage where the signals acquired from all of the electrodes are filtered. In this stage, the signals can also be spatially filtered which further removes the noise and transforms multi-channel signals into a single-channel signal. Furthermore, the shape of the signal is also altered, which is then utilized by the feature extraction stage. In the Feature extraction stage, distinct informative features are extracted from the preprocessed EEG, which are then used for the task of classification. Acquiring good features is very important because EEG from the scalp is very noisy and it also includes noise from electrooculography (EOG) and electromyography (EMG) activity of the brain [7]. The acquired features are then used for the task of classification to determine the user intent. The classification stage decodes the command that needs to be executed based on the EEG acquired from the user. Finally, the control interface stage allows the user to interact with the surroundings. In this stage, a specific command is executed which is selected in the classification stage. The available commands for the user are based on the type BCI application, like spelling a word [6], controlling a wheelchair [12], and the cursor of a computer [3].

1.1.2 Electroencephalography (EEG)

EEG is a procedure that is performed to record and track the electrophysiological activity of the brain. These electrical signals are the result of the electrical impulses through the synaptic connections between the neurons. EEG based neurodiagnostic techniques are widely used in clinical diagnosis and brain research because of its low cost, noninvasive nature, portability, and high temporal resolution. Recording EEG is a very simple and easy process, and it is done by placing EEG electrodes on the scalp of the person. These electrodes detect the electrical signal generated by the electrophysiological activity of the brain. There are two different types of electrodes for acquiring EEG; they are wet electrodes and dry electrodes. A conductive gel is applied to the scalp of the subject when wet electrodes are used for acquiring the EEG. The gel acts as a bridge between the electrodes and the scalp lowering electrode-scalp contact impedance, whereas the dry electrodes do not require any gel. The EEG recording system is also very easy to operate. It consists of amplifiers, analog to digital converter, and a recording device (computer). EEG electrodes acquire the electrical signals from the scalp, which is amplified by the amplifier and then converted into a digital form using analog to digital converter (ADC). Amplifying the signal is necessary because the amplitude of the EEG signal is in millivolts, so it cannot be directly converted into digital form with high accuracy. The accuracy of the ADC is better when the input signals given to the ADC are amplified. The recorded signal is then stored in computer memory and can be displayed for visualization. Electrodes for most of the EEG acquisition system consist of a pre-amplification module immediately after the skin-contact pin of the electrode allowing the signal to be amplified before it is affected by additive noise between the electrodes and the amplifier. Such electrodes are called active electrodes. If the electrodes don't have any pre-amplification module then they are called passive electrodes. Further, the signal to noise ratio for the active electrodes is much better than the passive electrodes.

EEG signal acquisition setup consists of 3 types of electrodes, ground electrode, active electrodes, and a reference electrode. The recorded EEG signal is the potential difference between active electrodes and the reference electrode. However, the ground electrode is used to measure the differential voltage, which is utilized to reduce the noise from the reference and active electrodes. EEG can be recorded as uni-polar or bi-polar measurements. In unipolar measurements, the voltage difference of active electrodes to the reference electrode is recorded, whereas in bi-polar setup, the potential difference between two active electrodes is recorded. Most of the electrodes which are used for EEG acquisition contains small thick pins of silver chloride (AgCl)[13]. The amplitude of the EEG signal acquired from the skull of the subject is in millivolts, which is too low for ADC to convert it in digital form with reasonable accuracy. Therefore, it is amplified using a high gain amplifier of the order of x100000, which, as a result, gives an excellent digitized signal.

The EEG acquired from the scalp is very susceptible to noise generated from different muscle activities, due to this reason, having a good contact between the scalp and the electrode is very necessary. Usually, the impedance between the scalp and electrode is kept below 10 KΩ [14] for good signal quality and it is achieved by applying conductive gel between the scalp and the electrodes. This gel is responsible for making a low impedance bridge between the electrode and the scalp. The use of gel makes it a wet type electrode setup. However, dry electrode setup does not use any gel to improve the conductivity of electrode-scalp contact. Wet electrode setup provides a better EEG signal quality with low noise compared to the dry electrode setup, but it requires continuous maintenance. Regardless of the type of electrode used, the user should stay stationary while recording his/her EEG to minimize noise due to neuromuscular movements, and necessary steps should be taken to reduce the noise due to interference by both external and internal sources. The external sources include power lines whereas, thermal, flicker and burst noises are taken as internal noises [15].

Furthermore, EEG signals are divided into 5 categories based on the frequency range of these signal. These classes are named as delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ) rhythms. These different rhythms observed in the EEG corresponds to different activities or state of mind of the person. Delta band consists of the EEG signal components from 0 to 4 Hz. Delta rhythms are only observed in adults when they are in a state of deep sleep. Delta rhythms are very hard to monitor because of its low-frequency nature, and it can easily be distorted by the muscle movements of the neck and jaw [16]. EEG signal components in the range of 4-7 Hz are termed as theta band. Theta rhythms are generated due to the cognitive and concentration activities of a person [17]. An example of such an activity is performing mental calculations. The alpha band consists of the EEG components between 8-12 Hz. The amplitude of alpha rhythms is susceptible to an increase in the mental effort, and due to this reason, alpha rhythms are best observed when the person is relaxed or in the eyes-closed state [18]. Beta rhythms consist of frequencies between 12 to 20 Hz. They are observed in frontal and central lobe of the brain and these rhythms are due to the motor activities carried out by the brain [19]. EEG frequencies between 30-100 Hz are termed as gamma rhythms, and these are associated with specific perceptions or motor functions [20].

The placement of electrodes in our EEG setup is according to the International 10-20 EEG electrode placement system [21]. In this system, 2 reference points on the scalp are used to determine the relative positions of all of the electrodes. The first reference point is the nasion, at the center of the forehead, above the nose whereas, the other reference point is located at inion, which is under the bump at the back of the skull. The positions of the electrodes are marked as 10% and 20% at the transverse and median planes [21]. The locations of the electrodes are shown in Figure 1.2. The electrode position are named with letters, and each letter represents a specific region of the brain. For instance, C represents the central lobe, A- represents the ear lobe, P- the parietal lobe, Pg- the nasopharyngeal region, Fp- the frontal polar region, F- the frontal area and O- represents the occipital lobe of the brain.

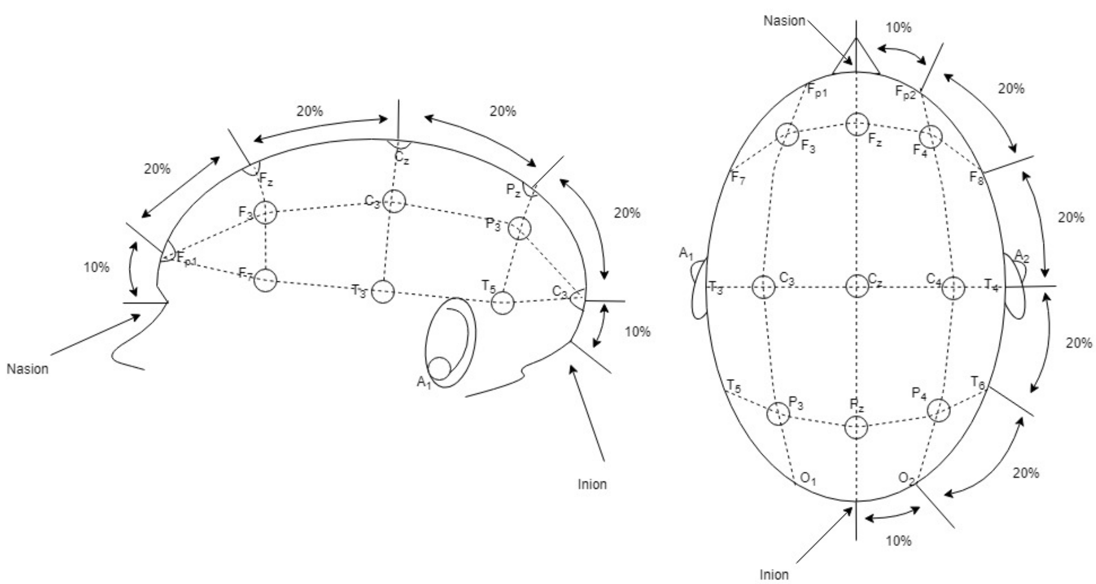

Figure 1.2: 10-20 International Electrode Placement System

1.1.3 Visual Evoked Potential (VEP)

VEPs are the electrophysiological signals generated in response to a visual stimulus and they are recorded by placing electrodes around the scalp near the visual cortex [22]. VEPs can be classified based on three different criteria, by the morphology of visual stimuli, by the frequency of visual stimuli, and by field of stimulation. According to the morphology of the visual stimuli, VEPs can be categorized based on flashing visual stimulation or by using graphic patterns in the visual stimulation such as a random-dot map, gate, and checkerboard lattice. According to the frequency, visual evoked potentials can be further classified into two types, steady-state visually evoked potentials (SSVEPs) and transient evoked potentials (TVEPs). The Evoked potential is SSVEP when the visual stimulus is periodic with a frequency of 6 Hz or above[8]. The analysis for SSVEP signals is carried out in the frequency domain. However, TVEP occurs when the frequency of the stimulus is less than 6 Hz [8] . Finally, according to the field of stimulation, VEPs can be classified into whole field VEPs, half field VEPs, and part field VEPs depending upon the area of the on-screen visual stimulus. For instance, a half field VEP stimulus will be induced if one half of the monitor is displaying the visual stimulus, and the other half of the monitor is not displaying any graphics, and the subject is looking at the center of the monitor screen. It is worth mentioning that different VEPs based visual stimulus patterns generate different EEG responses.

VEPs are generally used for the task of target classification, and due to this reason, the goal is to design the input stimuli in such a way to obtain orthogonal VEP responses for different targets in order to identify them with better accuracy. VEPs can be generated from visual stimulators of different types of light sources, with different color and brightness properties. However, the flashing pattern of the visual stimulus determines the type of the generated VEP response. Furthermore, SSVEP based BCI modalities can be further classified into code modulated VEPs (cVEPs), frequency modulated VEPs (f-VEPs), and time modulated VEPs (t-VEPs). cVEP are the evoked responses, generated in the visual cortex as a response to random binary sequences of a specified length [23]. The visual stimulus is flashed ON when the corresponding bit of the binary sequences is “1”, and the stimulus is flashed OFF when the corresponding bit in the sequence is “0”. t-VEPs are the EEG responses generated as a result of applying a visual stimulus sequence for each target that is orthogonal in time [8]. f-VEPs are the periodic EEG responses which can be observed in the occipital lobe when the stimulus for each target is flashed with distinct periodic frequencies [24].

1.1.4 Code-Modulated Visual Evoked Potential (cVEP)

In recent years, visually evoked potentials based on the cVEP modality have become very popular among the BCI community because of its promising classification accuracy and its capability to classify large number of targets per minute, quantified as information transfer rate (ITR) [25]. ITR is a standard measurement metric used in the BCI community for determining the overall speed of the BCI system. In cVEP based BCI system, the stimulus of each target is assigned with a pseudo-random sequence such that every target has its own distinct sequence [23]. The pseudo-random binary sequence has combinations of "0" and "1" only. These binary digits of the sequence represent the intensity levels of the visual stimulus; 0 represents low-intensity value (Black color) whereas, 1 represents high stimulus intensity (White color). The binary sequence can also represent different colors of the visual stimulus. For instance, Toygun et al. [26] used colored stimulus for cVEP based BCI application. In their study, 0 is represented by "Blue" colored flash, and 1 is represented by "Green" colored flash.

For cVEP based BCI, the EEG responses for all of the targets should be acquired to do classification. However, this will increase the training time if the responses for the targets are to be obtained individually. Generally, the sequence for one of the target is acquired, and the cVEP stimulus pattern for the rest of the targets are obtained by circularly shifting the target of the first pattern [23]. Each target of the visual stimulus then flickers according to its assigned pseudo-random sequence. As a result, cVEP responses are then observed in the EEG acquired from the visual cortex, depending on the target focused by the subject. In order to assign the stimulus patterns to the targets, m-sequences are generally preferred [23]. The idea of using m-sequences for cVEP based BCI is because m-sequences and their time-lagged versions are nearly orthogonal to each other. The auto-correlation of the m-sequence is similar to the impulse function. It is desired to have orthogonal EEG responses for the targets because it will make the task of classification easy; therefore, the responses from the m-sequences are assumed to be orthogonal. However, the human brain is nonlinear in nature, and the generated responses of the m-sequences and its time-lagged versions may not be orthogonal to each other [26] . The variable m, mentioned in m-sequence, defines the size of linear feedback shift register, which is required to generate m-sequence; furthermore, the formula $2^m - 1$ is used to determine the length of m-sequence [27].

The stimulus of the cVEP based BCI is usually presented on monitor screen, which is divided into a matrix based on the number of targets and each cell of the matrix is assigned to a specific target. The targets represent the different choices available for the subject to interact with the surroundings based on the BCI application. In BCI speller applications, the targets are assigned to letters, numbers, and other characters. The arrangement of the targets for our BCI speller application is shown in Figure 1.3. The background of every target is flickered based on its assigned stimulus sequence. The subject focuses on a particular target of choice, and the corresponding EEG response is then recorded on the computer.

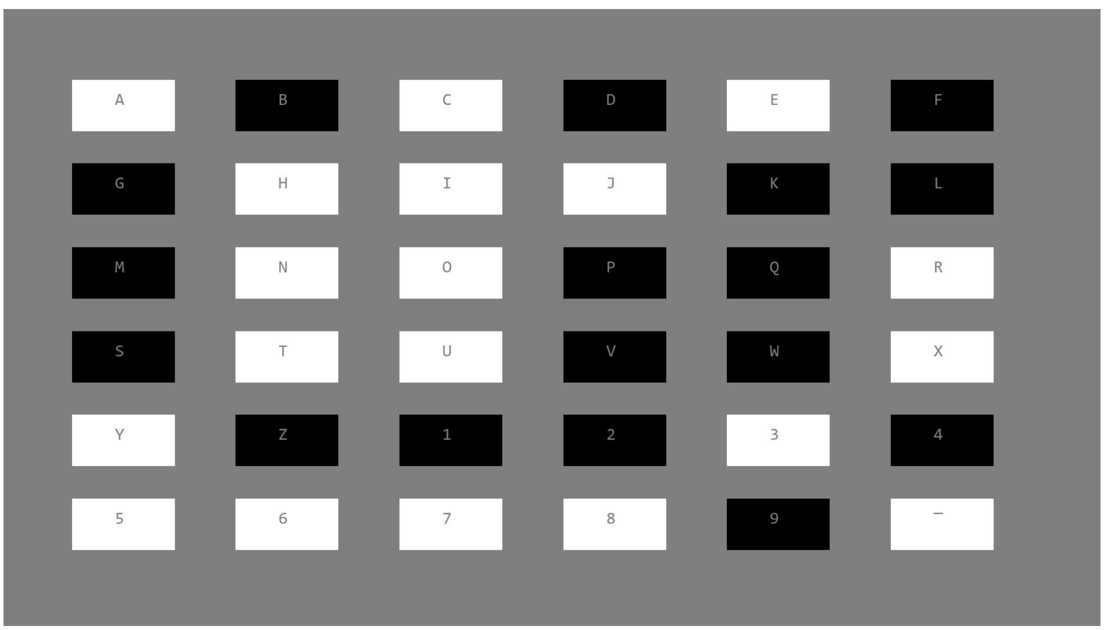

Figure 1.3: The Figure shows a single stimulus frame of cVEP BCI speller while the targets are flickering based on their assigned psedo-random sequence. The 36 stimulus targets are arranged in a 6x6 matrix, and each target is assigned to a letter/number/character. The targets are flashed black and white when the corresponding bit of the pseudo-random sequence is 0 and 1.

In cVEP, the flashing frequency of individual bits of the stimulus sequence is limited by the frequency of the monitor. The stimulus bits can be flashed at a frequency equal to the refresh rate of the monitor. Hence, each bit is displayed for the duration of a single frame. The majority of the cVEP BCI systems use 60 Hz as the stimulus frequency, which means each bit of the sequence is flashed for 16.667 milliseconds. Furthermore, the number of available targets in the cVEP BCI system depends on the length of m-sequence, longer the length of the sequence is the more target will be supported by the BCI systems but the information transfer rate of the BCI system will decrease. Hence, there is a tradeoff between the information transfer rate and the number of supported targets by the BCI application. Another method to increase the number of targets is to decrease the size of the circular shift, but this will impact the accuracy of the classifier. For instance, a 63 bit long m-sequence with a 2 bit shift is very popular and commonly used in cVEP BCI spellers, and it supports a total of 32 targets. The 63 bit m-sequence is generated using a linear feedback shift register, and it is then assigned to one of the 32 targets [28]. The stimulus sequences for the remaining 31 targets are obtained by circularly shifting the m-sequence by two bits successively.

During training, the EEG responses (also known as templates) for all of the targets are acquired. Let, the total number of targets in BCI speller is denoted by T. The EEG response for the m-sequence of length L is obtained for just one of the T targets by performing an experiment. The EEG is recorded for N trials, and the reference template for that target is obtained by taking the average over N trials. The templates for the rest of the targets (T-1) are obtained by circularly shifting the EEG template for that target [24]. This method of acquiring EEG responses for the targets is commonly used by the BCI community because it requires less training time. During testing, the subject focuses his/her gaze on any of the T targets (for one trial) and the corresponding EEG response is then correlated with the templates of all targets. Finally, the target with maximum correlation is selected.

1.1.5 Model Based Paradigms For BCI Design

BCI research is mainly focused on application-specific approaches, where the main goal is to increase target classification speed (ITR) and the accuracy of the classifier. Most of the BCI applications are designed without considering the actual nature of the brain. However, there are some studies which aim to model brain responses to random stimulus pattern, but they use machine learning approaches to predict the EEG responses from stimulus patterns which again does not provide any insight on how the brain responds to visual stimuli [29], [30]. Hence, the concept of making a cVEP BCI system based on the properties of brain responses to the visual stimulus pattern is still untouched.

However, researchers have focused on modeling the brain responses for transient and steady-state conditions for different visual stimuli. A physiological based corticothalamic model was proposed by Robison et al [31] . which aimed to model different features of EEG, including event-related potentials and discrete spectral peaks in all of the EEG frequency bands. Later, Roberts et al. [32] used the Robinson corticothalamic model to explain the nonlinear behavior of the cortical activity when the subject is presented with a periodic stimulus. Robinson's corticothalamic model was highly nonlinear with a large number of second-order filters along with feedback loops, making it very hard to learn the parameters for optimizing the model. In order to decrease the complexity, a linear model was proposed by Zhang et al. [33]. In this model second-order linear system was proposed to model the transient response of the SSVEP.

In 2018, Negal et al. [29] proposed a moving average model for predicting the EEG responses to arbitrary stimulus patterns. They also proposed an inverse model by which they predicted the stimulus pattern from the EEG. The reported accuracy and ITR values for BCI speller is surprisingly high. Later in 2019 [30], they used convolutional neural network models for classifying BCI targets and reported further improvement in the accuracy and ITR metrics. However, all of the methods mentioned above do not provide any insight about how the brain responses to different stimulus patterns. These model-based approaches for BCI applications have shown improvements in target classification accuracy and increase in information transfer rate. The parameters of the models are optimized during the training stage, and then the EEG responses for all of the targets are generated using the learned model. During the test stage, the acquired EEG response is correlated with the model-generated responses of all targets, and the target with the maximum correlation is chosen. The advantage of using model-based approaches includes reduced training time and increase the number of possible targets [29].

In section 1.1.4, we mentioned the use of m-sequences to reduce the training time. By using m-sequences, we perform experiment for only one target, and the EEG templates for the rest of the targets are obtained by circularly shifting the EEG template for that target. However, if arbitrary sequences are used for all of the targets, then for each target, an experiment should be performed to record their EEG responses, which will take a lot of time. This is where the model-based approaches come in to play. Hence, by using a model, EEG response can be predicted for an arbitrary number of stimulus patterns, and the number of BCI targets can be easily increased.

1.2 Objective And Scope

In the first part of our study, we aim to decompose the stimulus sequences into simple patterns and then reconstruct the EEG response for the stimulus sequences by superposing the EEG responses of the simple patterns. Hence, we decompose the stimulus sequences into positive and negative edges. Where positive edge corresponds to the change in stimulus color from black to white, and the negative edge corresponds to the change in stimulus color from white to black. This decomposition of the stimulus sequences is done based on the fact that EEG is sensitive to only the edges of the stimulus, and it will be explained in chapter 3.

First, we obtain the EEG responses for the positive and the negative edges, and then we predict the responses for any arbitrary sequences using superposition of the edge responses. The next task was to investigate how well the EEG can be reconstructed based on the structure of the stimulus sequences. A series of experiments are conducted with simple stimulus patterns to investigate the similarity between the actual and the generated EEG (Details on the experiments are provided in chapter 2). The main goal is to investigate to what extent does the superposition holds and to find out the necessary conditions on the structure of the stimulus sequences whose EEG response can be predicted with high accuracy.

In the third part of the study, we implement a superposition-based BCI application as mentioned above. A 36 target stimulus is used for the BCI speller where each target was assigned a 120 bit long binary stimulus sequence. During the training, the positive and negative edge responses are acquired, and the EEG response for all of the target stimulus sequences are predicted by the superposition of the edge responses. There different types of stimulus sequences are tested. Furthermore, one type of sequence is optimized according to the findings from the first part of the study. The goal here is to observe if there is a significant improvement in the classification accuracy of BCI application for this sequence type.

1.3 Organization Of Thesis

This thesis has 3 chapters: material and methods, results, and discussion/conclusion.

In chapter 2 (Materials and Methods), the experimental setup, EEG acquisition procedure, and the BCI system design are discussed in detail. Furthermore, it provides details of the experiments for recording the positive and negative edge responses. It also provides the details of the experiments where the predicted EEG is compared to the acquired EEG for simple stimulus patterns. Finally, a BCI speller based on the superposition model is discussed in detail.

In chapter 3 (Results), the results obtained from the experiments are analyzed. In this chapter, the acquired edge responses are discussed. It also discusses the proposed superposition model for predicting EEG responses to arbitrary stimulus patterns, and the predicted EEG for simple stimulus patterns are analyzed and compared with the recorded EEG. Finally, the performance of the BCI application in terms of classification accuracy and ITR is discussed.

In chapter 4, (discussion and conclusion) the general discussion is provided and the study is concluded.

Chapter 2

Materials And Methods

Information on the experimental setup and the different types of stimulus sequences designed for this study are provided in this chapter. Furthermore, this chapter also provide details on the training and testing process of the proposed BCI speller application.

2.1 Experimental Setup

A BCI speller application is designed for performing experiments, and the complete setup consists of two computers and an EEG amplifier. The visual stimulus is presented to the subject on one computer, while the EEG is recorded to the other computer. The EEG amplifier detects and amplifies the EEG signal from the brain and sends it to the computer where the EEG data is being recorded. Information on the subjects, experimental design, and procedures are discussed in the following subsections.

2.1.1 Participants

The study is carried out on 7 male participants with a mean age of 29.7 years and a standard deviation of 5.5 years. All the participants signed a written consent form, which has been approved by the ethical committee of Bilkent University. The participants were guided and informed about the nature of the experiments. All of the subjects had corrected or corrected to normal vision, with good mental health, and participants with any history of epilepsy, neurological disorders, migraines, and visual impairments were excluded before the start of the experiment to avoid complications. The subjects were also informed that flashing stimulus might cause epileptic seizures.

2.1.2 Stimulus Design Setup

Matlab environment, along with psychtoolbox [34] is used for designing the stimulus, and for displaying the stimulus, Dell Alienware (AW2518HF) monitor is used, which is a 25-inch LED monitor capable of displaying up to a frame rate of 240 Hz. However, our study is based on a 60 Hz refresh rate for each target, so the frame rate of the monitor is set to 60 Hz, and the resolution of the monitor is set to 1920 x 1080 pixels. Furthermore, the participants were seated in front of the monitor at a distance of 80 cm. The visual stimulus consists of 36 targets in total, and they are arranged in a 6 x 6 grid, as shown in Figure 2.1. Every target cell of the matrix is assigned to a letter, number or symbol, displayed at its center. Additionally, each target cell has a rectangular shape of 5.18 cm x 2.6 cm (180 x 90 pixels). The 36 stimulus targets include 26 upper case alphabet from A to Z, nine numbers from 1 to 9 and a "-" symbol (see Figure 2.1). During experiment, the targets are flashed between black and white, depending on their stimulus sequence. The color of a specific target is replaced with black when the corresponding bit of the stimulus sequence is 0, and it is replaced with white when the corresponding bit of the stimulus sequence is 1. Each bit of the stimulus is presented for a single frame, which is equal to 16.667 ms.

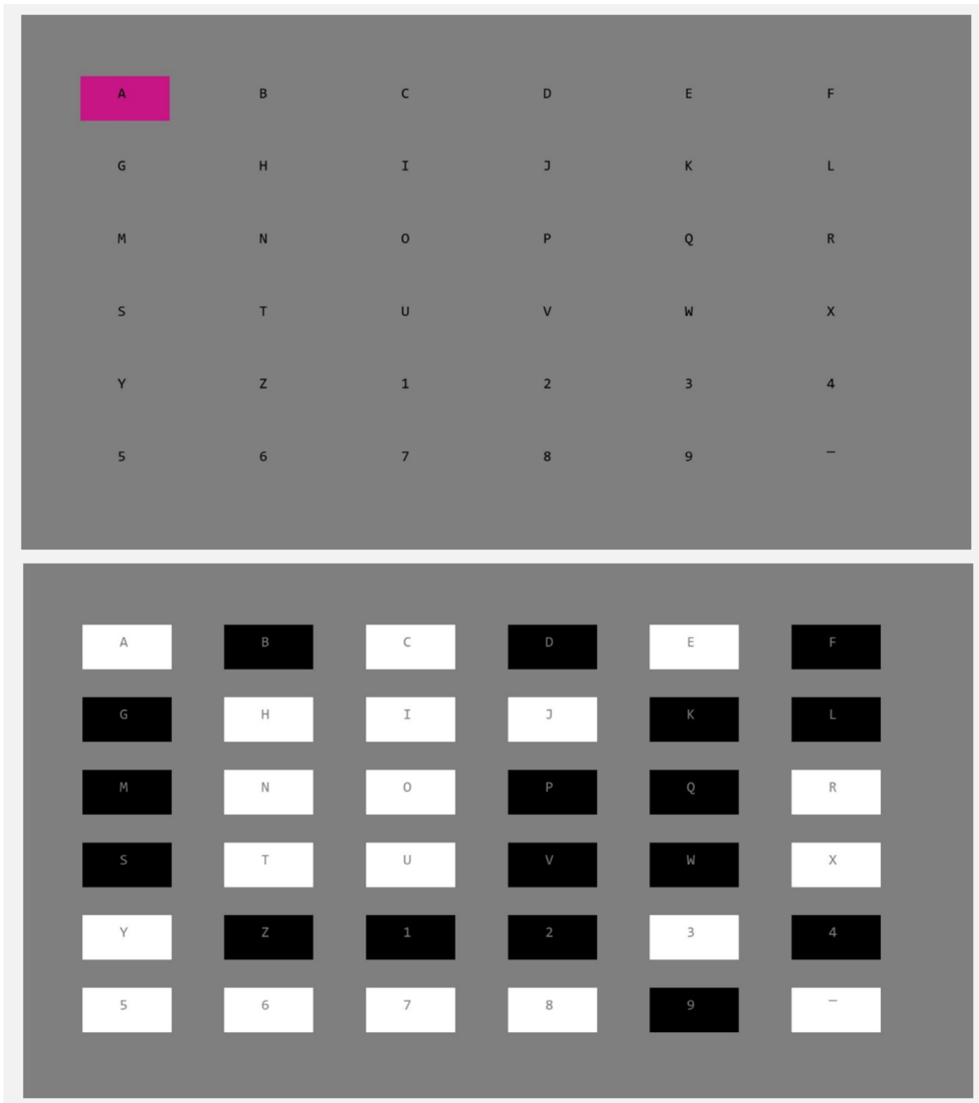

Figure 2.1: For a better understanding of our BCI speller stimulus, the above two frames are captured. The stimulus consists of 36 targets in total with the corresponding characters written in the center of each target. The frame on the top is captured before flickering the targets with the stimulus sequences. The pink rectangle guides the users to focus their gaze on the target A, and it will then disappear before the targets start flashing. Later, each target of the stimulus will start flashing according to its stimulus sequences. The bottom frame in the Figure is captured while each target is flashing according to their assigned stimulus sequence. All of the 36 targets of the stimulus are either black or white, depending upon the value of their particular sequence bit to be either a 0 or 1, respectively.

Ubuntu 18.04, with a low latency kernel, is used on the computer for the accurate timings of the visual stimulus patterns. We will refer to this computer as the stimulus computer in this document for ease in referral. The missed frame counter of psychtoolbox is monitored by displaying its value on the terminal at the end of the experiment to assure that no frames are dropped during the experiment. In order to find the accurate refresh rate of the monitor we used a pinhole diode circuit and we place it close to the monitor. A rectangular region on the monitor equal to the size of a single target was flashed between black and white. The actual refresh rate of the monitor was found to be 59.98 Hz [35]. While recording the EEG response to the visual stimulus, a marker signal is also passed from the stimulus computer into the EEG amplifier to keep track of the flashing (displaying time) time of each bit in the sequence. The marker signal plays a vital role for synchronization of the responses when the average EEG responses are to be obtained. We also conducted an experiment to find the exact delay between the frame updates and the marker pulse. This delay was measured to be 280 microseconds and can easily be ignored [36].

2.1.3 Data Acquisition

For recording EEG, V-Amp, 16 channel EEG amplifier (Brain Products, Gilching, Germany) is used at 2000 sampling frequency along with the actiCAP (EEG cap), which has 32 electrode placement positions designed according to the international 10-20 electrode placement system. A total of 8 active electrodes are used in the experiment located on occipital and parietal areas of the brain. Active wet electrodes are used to acquire the EEG from the O1, Oz, O2, P3, Pz, P4, P7, and P8. Furthermore, the reference electrode is placed on FCz location, and the ground electrode is placed above nasion at the center of the forehead. In order to have a good signal quality, the impedance of each electrode is set below 10 KΩ. The ImpBox (Brain Products, Gilching, Germany) was used to monitor the impedance of the electrodes. To record the EEG responses for the targets and the marker locations on the recording computer BCI2000 [37] along with fieldtrip [38] are used.

2.1.4 Data Preprocessing

After recording the EEG responses, the EEG signals were first filtered by using a 4-40 Hz bandpass filter. Then it was further passed through a 50 Hz notch filter to remove all of the remaining 50 Hz interference from the signal. Later, the average EEG responses were obtained by taking the mean over multiple trials of EEG responses by utilizing the synchronization markers.

The signals were also spatially filtered by using the coefficients obtained from canonical correlation analysis (CCA). The EEG responses from 9 stimulus sequences, mentioned in section 2.2.2 were used to find the CCA cofficients. These sequences are 120 bit long, and the EEG was recorded for 30 trials of these sequences. The length of a single trial of EEG response was 4000 samples, and the EEG data consists of 8 channels. So, for a single experiment (120 bit stimulus with 30 repetitions), the size of the acquired EEG is 8x120,000. Further, the average EEG responses of the 30 trials were obtained, and it was then replicated 30 times, and hence we get an overall averaged signal equal to the dimension of the unaveraged signal (8x120,000). The data was then arranged as a 2D array labeled as $\boldsymbol{X}$ and $\boldsymbol{Y}$ where $\boldsymbol{X}$ was obtained by concatenating the unaveraged data from 9 experiments. Similarly, $\boldsymbol{Y}$ was obtained by concatenating the repeated averaged signal from 9 experiments. Hence, the total length of $\boldsymbol{X}$ and $\boldsymbol{Y}$ becomes 8x1080,000. The purpose of CCA is to find the linear combination of the un-averaged signal $\boldsymbol{X}$ and the linear combination of the averaged signal $\boldsymbol{Y}$ such that the correlation between $\boldsymbol{X}$ and $\boldsymbol{Y}$ is maximized. The maximizing function of CCA is given in equation 2.1

$$\underset{W_x,W_y}{maximize}\, \rho(X,Y) = \frac{E[W_x^T X Y^T W_y]}{E[W_x^T X X^T W_x] E[W_y^T Y Y^T W_y]} \tag{2.1}$$

Whereas W_x is the weight vector for the variable $\boldsymbol{X}$, and W_y is the weight vector for the variable. $\boldsymbol{Y}$. The weight coefficients W_x (8×1) are the resulting spatial filter coefficients, and they are multiplied with the 8 channel EEG data to get a single channel spatially filtered EEG data. Spatial filtering improves the signal quality and makes the processing easy because of the reduction of 8 dimensional EEG signal to a single dimension. The "canoncorr" function is used in Matlab to find the spatial filter coefficients.

2.2 Stimulus Sequences

Three types of experiments were conducted in our study with different stimulus sequences. In the first type of experiment, EEG responses to long stimuli pulses were obtained. The stimulus sequences for the first type contains alternating binary levels (1 and 0) with a random number of bits for each level. In the second type of experiment, EEG responses were acquired for 9 different 120 bit stimulus sequences with simple patterns. Whereas, in the last type, a BCI speller application was tested for three different types of stimulus sequences. The stimulus sequences designed for each type of experiment will be discussed in their respective subsections below. However, the experimental setup and the preprocessing steps are the same for all of them.

2.2.1 Long-Pulse Stimulus Patterns

In the first type of experiment, EEG responses are recorded for long-pulse stimulus sequences, as shown in Figure 2.2. It should be noted that the stimulus sequences are presented as waveforms rather than binary sequences for ease in understanding. A low value of the waveform corresponds to the black color of the stimulus, whereas a high value corresponds to the white color of the stimulus pattern. EEG responses are acquired for these 3 stimulus waveforms with different pulse widths, as shown in Figure 2.2 from just one subject. Furthermore, the positive and negative pulses for these stimulus sequences are repeated for 100 trials. In the first stimulus sequence, the width of the positive and negative pulse is 250 ms + V, where V is a uniform random variable from 0-125 ms. Hence, for each positive and negative pulse in this sequence, the pulse width is randomly chosen between 250 ms - 375 ms in order to remove any artifacts which might be observed if the stimulus sequence was periodic. Similarly, for the second stimulus sequence, the size of the pulse is randomly chosen between 375 ms - 555 ms, and the size of each pulse of the third sequence is randomly chosen between 500 - 750 ms.

It should be noted that the length of each pulse is displayed in milliseconds (see Figure 2.2), but the actual stimulus sequences are represented in bits, and a single bit corresponds to 16.667 ms. In other words, a single bit is displayed on the monitor for 16.667 ms, which means the stimulus sequence is time discretized with the 16.667 ms as smallest display time for a single bit in the sequence. Hence the total length of the stimulus sequence will always be a multiple of this interval. Consider the first stimulus pattern (see Figure 2.2a); initially, a random value between 250 ms - 375 ms is generated for each positive and negative level of the waveform. Later, N number of bits are appended to the sequences in such a way that the actual pulse width ($N \times 16.667ms$) is equal to or greater than the randomly chosen value. For instance, consider a positive pulse has to append the sequence and 301 ms is randomly chosen for the width of the pulse. The sequence will be appended by 19 ones, which is around 316.6 ms ($19 \times 16.667ms$). We do not append it with 18 ones because the width will become 300 ms ($18 \times 16.667ms$) which is smaller than the randomly chosen width (301). Furthermore, the index of the start of the positive and negative levels of the stimulus sequences are recorded, which will help in synchronizing the EEG acquired for multiple trials of pulses in order to get the average EEG pulse response correctly.

The stimulus sequences provided in Figure 2.2, were assigned to the target A, whereas, the rest of the stimulus targets were assigned randomly generated sequences. The subject was asked to focus his gaze on letter A and the EEG data resulting from the three experiments (see Fig 2.2) was saved on the recording computer. Later, it was preprocessed, and then the averaged responses for the positive and negative pulses were obtained. The average EEG was obtained for only the fixed width of the pulse, which is 250 ms, 375 ms, and 500 ms for stimulus sequences in Figure 2.2a, 2.2b, and 2.2c, respectively.

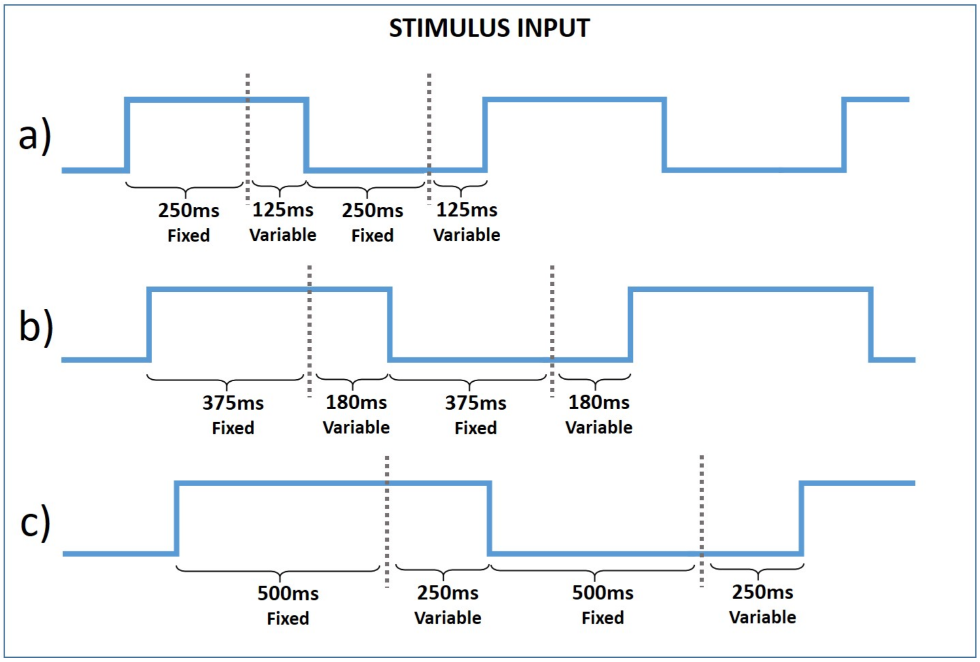

Figure 2.2: Three long-pulse stimulus sequences are used for acquiring EEG from one subject; a) The individual pulse of the stimulus has fixed width of 250 ms along with uniform random width between 0 - 125 ms. b) Positive and negative pulses has 375 ms fixed and 180 ms variable width. c) The pulses in sequence has 500 ms fixed width and 250 ms variable width.

Later, for all of the 7 subjects in our study, the stimulus sequence shown in Figure 2.3 is used for acquiring the EEG response to long-pulses. Here a stimulus pattern with alternating pulses of 1's and 0's with a width of $500ms + V$ for each pulse was employed where V is a uniform random variable between 0 and 250 ms. Note: this is the same waveform as the one given in Figure 2.2c. The stimulus sequence designed for obtaining the long-pulse response for 500 ms wide pulses (see Figure 2.3) consists of 20 positive and negative pulses. A total of 8 such stimulus sequences are generated randomly, so in total, there are 160 positive and negative pulses in the 8 stimulus sequences. Training is done in 8 individual sessions to record the edge responses, and in each session, the subject is presented with one of the 8 stimulus sequences. As we know for each positive and negative pulse, the initial width of 500 ms is fixed, and the rest is randomly generated. Therefore, the acquired EEG responses are truncated up to 500 ms for each pulse, and then these responses are averaged to remove the additive noise. During training, these sequences are assigned to target A, whereas the sequences for the remaining targets are generated randomly. Furthermore, the subjects are instructed to focus their gaze on the target A, and the corresponding EEG is then recorded on the recording computer.

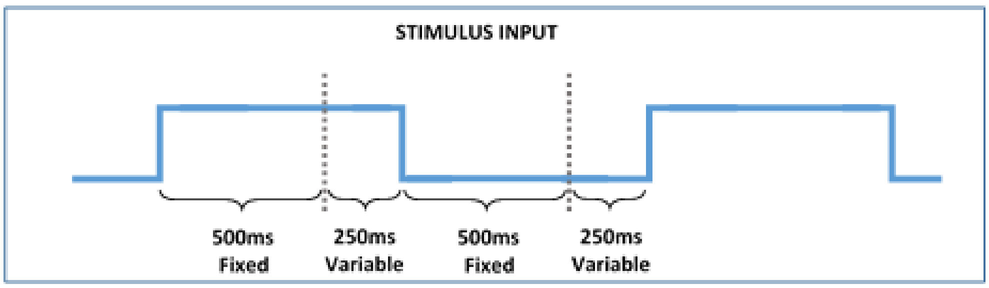

Figure 2.3: long-pulse stimulus sequence waveform designed for recording positive and negative pulse responses of 7 subjects. The initial width of 500 ms for each pulse is kept fixed whereas, the remaining width is randomly chosen betwene 0 and 250 ms.

2.2.2 Stimulus Sequences with Simple Patterns

In the second type of experiment, EEG responses are recorded for stimulus sequences with generic pulse patterns to carryout three different studies. These studies are discussed in detail in chapter 3. In the first study, EEG responses resulting from different pulse widths in the stimulus sequence are investigated. Whereas, in the second study, the EEG is recorded for different separation distances between the pulses. Finally, in the third study, stimuli with pulse repetitions are investigated. A total of 9 different stimulus sequences are prepared to carry out these studies, and each stimulus sequence consists of 120 bits, presented at 60 Hz frame rate of the monitor. Hence, a single trial of the stimulus sequence will take two seconds to complete. Furthermore, the stimulus patterns are repeated for 30 trials to get a good averaged signal. Therefore, the total time for recording the EEG of a single stimulus sequence takes 1 minute, and the total experiments for this study take about 9 minutes. All of the 9 stimulus sequences are assigned to target A while recording their EEG responses, whereas, the remaining targets are assigned randomly-generated binary stimulus sequences. Furthermore, the subjects are instructed to focus their gaze on target A before starting the experiment.

2.2.2.1 Stimulus Sequences With Different Pulse Widths

In this study, EEG responses are recorded for stimulus sequences comprising of pulses with different widths (see Figure 2.4). The stimulus sequences for this study are named as PW15 and PW69 for ease in referral. Furthermore, the stimulus sequence PW15 covers the pulse width of 1 bit up to 5 bits, whereas the width of 1 bit is equal to 16.667 ms, which is the time for displaying a single frame on the monitor screen. Similarly, the stimulus code PW69 covers the pulse widths of 6 to 9, as shown in Figure 2.4.

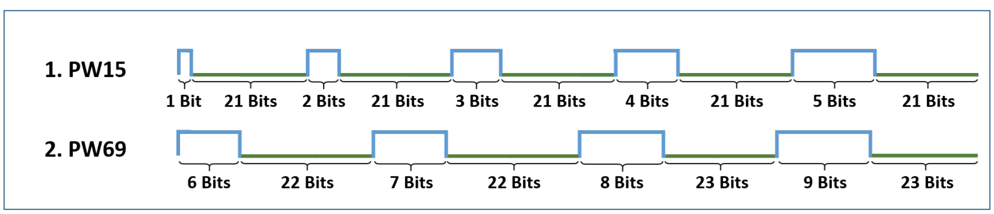

Figure 2.4: 120 bit stimulus sequences, including pulses of different width, are shown in this Figure. The blue regions of the waveforms represent the pulses, which are under investigation. The stimulus sequences are named PW15 and PW69, and they include pulse widths of 1-5 and 6-9, respectively. The green sections of the stimulus represent the regions where no pulse is applied. The widths of all of the sections of the stimulus sequences are mentioned in bits where 1 bit is equal to 16.667 ms.

2.2.2.2 Stimulus Sequences With Different Pulse Separation

In this study, EEG responses are recorded for stimulus sequences comprising of patterns of two pulses with different separation spacing between the pulses. This study is further divided into 2 parts, and the detail of this study is given in chapter 3. In the first part of this study, EEG responses are acquired for different separation intervals between 1 bit wide pulses. The stimulus design for this study is shown in Figure 2.5. Two stimulus sequences of 120 bits are designed for the study, named as PS15W1 and PS69W1. The width of the pulses in the stimulus sequence is kept fixed (equal to 1 bit), whereas the separation distance between the pulses change. PS15W1 sequence covers pulse separation distance of one 1 bits up to 5 bits (16.667 ms to 83 ms), and PS69W1 covers the pulse separation distance of 6 to 9 bits (100 ms to 150 ms). The stimulus waveform patterns under study are shown in blue color, whereas green color represents regions where no pulses are applied.

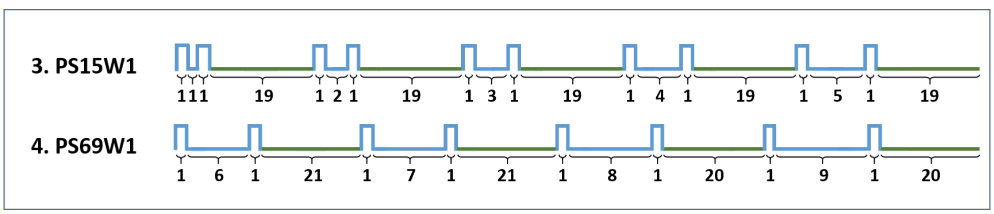

Figure 2.5: This Figure displays 120 bit stimulus sequences for recording EEG data for different separation intervals between 1 bit wide pulses. The stimulus sequences are named PS15W1 and PS69W1, which include pulse separations of 1-5 and 6-9 bits, respectively. The length of each pulse and the separation distance are mentioned below each sequence.

In the second part of this study, EEG responses are recorded for different separation intervals between 2 bit wide pulses. Two 120 bit stimulus sequences covering pulse separation distances of 1-5 and 6-9 bits are designed for this experiment (see Figure 2.6). The PS15W2 sequence covers pulse separation distance of one 1 bits up to 5 bits (16.667 ms to 83 ms), and PS69W2 covers the pulse separation distance of 6 to 9 bits (100 ms to 150 ms). The stimulus waveform patterns for this study are shown in blue color (see Figure 2.6), whereas the green segments of the waveform represent the regions where no pulse is applied.

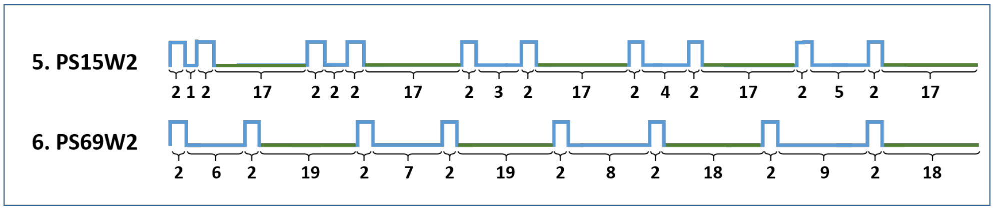

Figure 2.6: This Figure displays 120 bit stimulus sequences for recording EEG data for different separation intervals between 2 bit wide pulses. The stimulus sequences are named PS15W2 and PS69W2, which include pulse separation intervals of 1-5 and 6-9 bits, respectively. The length of each pulse and the separation distance are mentioned below each sequence.

2.2.2.3 Stimulus Sequences with Pulse Repetitions

In this study, EEG is recorded for different numbers of repetitions of the pulses. This study is further divided into 3 sections depending upon the width (1 bit, 2 bit, and 3 bit) of the pulse, and the details of this study are provided in chapter 3. In the first part of this study, the EEG is recorded for different repetitions of 1 bit wide pulse. The stimulus sequence for this experiment is shown in Figure 2.7. The sequence is named PR36W1 for ease in referral, and it covers from 3 up to 6 repetitions of 1 bit pulses. Furthermore, the separation distance between the pulses is 366 ms (22 bits). Note: the stimulus pattern does not cover 2 repetitions of the pulses because it is already covered in section 2.2.2.2, so there is no need to find the EEG response for this pattern again.

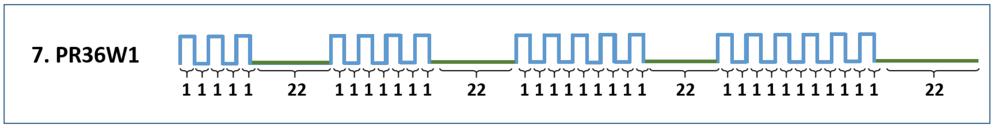

Figure 2.7: This Figure displays 120 bit stimulus sequences for recording EEG data for different repetitions (3 to 6 repetitions) of 1 bit wide pulses. The stimulus sequence for this experiment is named as PR36W1. The blue segment of the waveform represents the pulse repetition patterns under investigation, whereas the green-colored regions of the waveform represent the regions where no pulse is applied.

In the second part of the experiment, EEG is recorded for the stimulus sequence with repetitions of 2 bit wide pulses, as shown in Figure 2.8. The stimulus sequence is named PR35W2 for ease in referral, and it covers from 3 up to 5 repetitions of pulses. Note: the stimulus pattern does not cover the pulse repetition of two because it is already included in section 2.2.2.2. Furthermore, to get a better separation distance between the stimulus patterns with pulse repetitions, only 3 patterns are being added into the sequence.

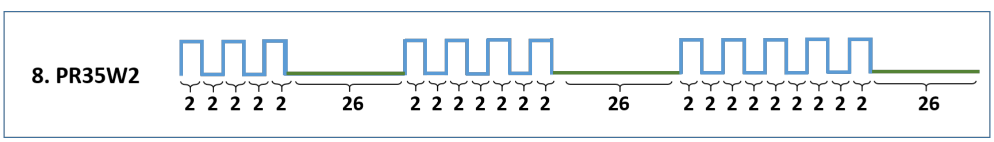

Figure 2.8: This Figure displays 120 bit stimulus sequences for recording EEG data for different repetitions (3 to 5 repetitions) of 2 bit wide pulses. The stimulus sequence for this experiment is named as PR35W2. The blue segment of the waveform represents the pulse repetition patterns under investigation, whereas the green-colored regions of the waveform represent the regions where no pulse is applied.

In the third part of the experiment, EEG is recorded for the stimulus sequence with repetitions of 3 bit wide pulses, as shown in Figure 2.8. The stimulus sequence for this experiment is named PR24W3 for ease in referral, and it covers from 2 up to 4 repetitions of 3 bit wide pulses. Furthermore, the separation distance between the pulses is 433 ms (26 bits).

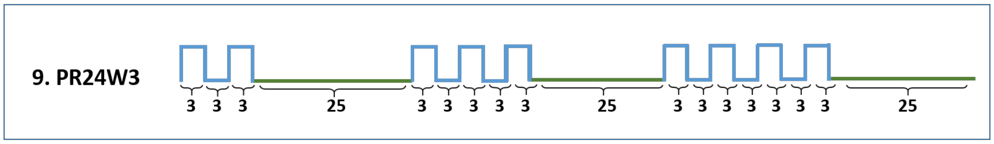

Figure 2.9: This Figure displays 120 bit stimulus sequences for recording EEG data for different repetitions (2 to 4 repetitions) of 3 bit wide pulses. The stimulus sequence for this experiment is named as PR24W3. The blue segment of the waveform represents the pulse repetition patterns under investigation, whereas the green-colored regions of the waveform represent the regions where no pulse is applied.

2.2.3 Stimulus Sequences For BCI Speller

In the third type of experiment, we tested a BCI speller with 3 different types of stimulus sequences. The stimulus for the BCI speller consists of 36 targets which are assigned to their respective letter/number/symbol. Furthermore, the target stimulus sequences for the BCI speller are 120 bit long, and they are presented at 60 Hz frame rate. The 3 different codes tested for the BCI speller are named as Pulse Position Modulated (PPM) Sequences, 7-in-15 Change Random (7-in-15CR) Sequences and Superposition Optimized Pulse (SOP) Sequences.

The PPM sequences consist of single bit pulses, randomly separated by a distance of 1 bit up to 4 bits. Note, 1 bit distance is the time to display a single frame which is 16.667 ms as discussed in section 2.1.2 in detail. On the other hand, 7-in-15CR sequences are randomly generated, and it consists of 7 changes in every 15 bits of the stimulus. In other words, in every 15 bits of the stimulus sequence, the number of changes (from 0 to 1 and 1 to 0) should be equal to 7. This code was proposed by Nagel [29] and was reported to have better classification accuracy compared to randomly generated stimulus sequences. Finally, the SOP sequences are proposed based on our study. To generate such a code, we first selected 16 different small sequence patterns. They include 1 bit pulse followed by 5 up to

10 bit zeros, 2 bit pulse followed by 5 up to 10 bit zeros, 3 and 4 repetitions of 2 bit pulses followed by 5 bit zeros and finally, 3 and 4 repetitions of 3 bit pulses followed by 5 bit zeros. Hence, in total there are 16 different patterns to choose from, and the SOP sequences are generated by randomly picking up these patterns and truncating the final pattern to 120 bits. The stimulus sequences assigned to the target A for all of the three types of sequences mentioned here are shown in Figure 2.10

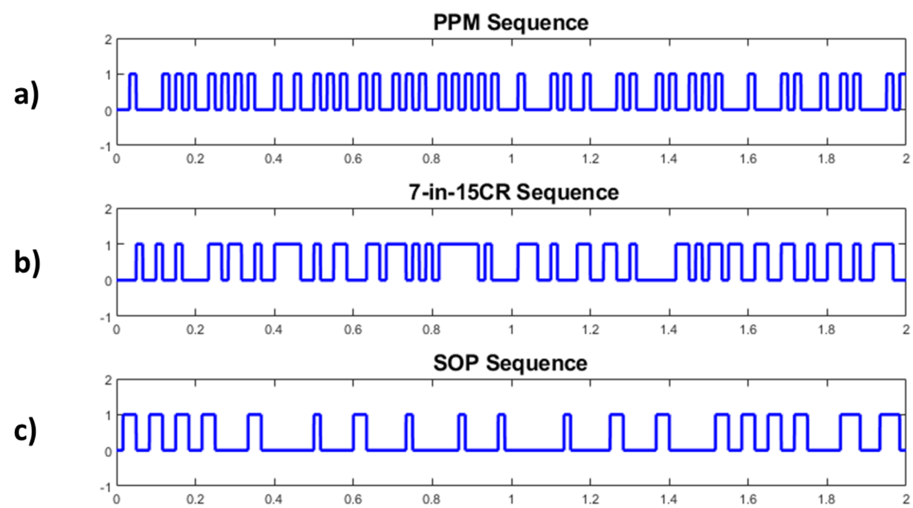

Figure 2.10: In this Figure three different types of stimulus sequences assigned to the target A of our BCI stimulus are plotted. Figure a) provides an illustration for PPM Sequence, b) for 7-in-15CR Sequences, and c) for SOP sequences.

2.3 BCI Training And Testing

Training for the BCI speller requires the EEG responses acquired from the long pulses, as shown in Figure 2.3 . After recording the EEG responses from the long pulses, these responses are used to predict EEG responses for all of the targets in the BCI application, as explained in the result section. During the test phase, the subject is asked to spell 35 letters and numbers in sequence from A-Z and 1-9. The stimulus sequence for each target is repeated for 2 trials and then averaged to improve the EEG signal quality. During testing the acquired EEG is compared with the generated EEGs of all targets and the target, which has the maximum correlation with the acquired EEG is chosen.

The performance of the BCI speller is measured in terms of accuracy, and information transfer rate metrics. Accuracy of the BCI system is defined by the number of targets classified by the subject correctly divided by the total number of targets (alphabets/numbers) spelled by the subject. Information Transfer Rate (ITR) is a standard performance metric defined in equation 2.2.

$$ITR = \frac{60}{T} \times (log_2 N + P log_2 P + (1-P) log_2 \frac{1-P}{N-1}) \tag{2.2}$$

Where $\boldsymbol{P}$ is the accuracy of the BCI speller, $\boldsymbol{N}$ is the number of symbols in the spellers and $\boldsymbol{T}$ is the time interval for selecting a single target. The time $\boldsymbol{T}$ includes the flashing time of the stimulus plus the gaze shifting time for each target. As the stimulus consists of 120 bits so it takes 2 seconds for the sequence to complete furthermore, the sequence is repeated for 2 trials so the total time of flashing for one target will become 4 seconds. In our BCI speller, we have set the gaze shifting time to 1 second. Hence, For our BCI speller, T is 5 seconds.

Chapter 3

Results

3.1 EEG Response To Long Pulses (Obtaining The Edge Responses)

EEG responses recorded for the 3 stimulus patterns (see Figure 2.2) for one subject are provided in Figure 3.1. In Figure 3.1a, the EEG is averaged starting from the positive pulses for a length of 250 ms, 375 ms, and 500 ms for the stimulus patterns shown in Figures 2.2a, 2.2b, and 2.2c, respectively. Similarly, Figure 3.1b provides the results of a similar analysis carried out for negative pulses. It can be observed that the response for the positive and the negative pulses acquired for different pulse lengths are almost the same. From Figure 3.1, it can be observed that the EEG responses for the pulse width of 250 ms and 375 ms are the truncated versions of the EEG response of 500 ms pulse width. Furthermore, the response for the positive and the negative pulse dies of around 350 ms after the start of the edge. Therefore pulse width of 375 ms is a sufficient choice for acquiring pulse responses whereas, 500 ms pulse width is more than enough for obtaining the pulse responses. The results presented in Figure 3.1 shows that EEG responses only depend on the positive and negative edges of the stimulus pattern rather than the stimulus pattern as a whole. The positive edge response and negative edge response is also called as onset response and offset response, respectively and in this thesis these names would be used interchangeably.

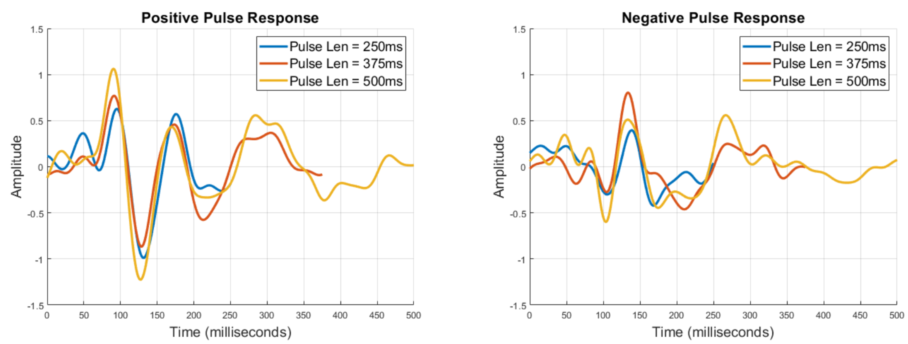

Figure 3.1: a) Positive pulses responses for pulse widths of 250 ms, 375 ms, and 500 ms are presented as blue, red, and orange colored signals. b) Negative pulse responses for 250 ms, 375 ms, and 500 ms of pulse widths are shown in blue, red, and orange colors.

Edge refers to a change in stimulus pattern; when the stimulus sequence changes from 0 to 1, it is termed as a positive edge (onset of the stimulus), and when it changes from 1 to 0, it is called a negative edge(off set of the stimulus). We have already mentioned that 0 represents the black color of the stimulus, and 1 represents the white color of the stimulus. Hence, the edge occurs when there is a change in the stimulus color. An onset occurs when the stimulus changes its color from black to white, and an offset occurs when the stimulus changes its color from white to black. Edge responses serve as the building blocks of our model for predicting EEG responses for arbitrary stimulus patterns, discussed in detail in section 3.3. Therefore, obtaining positive and offset responses with minimal noise is our priority.

The acquired edge responses for each of the seven subjects are shown in Figure 3.2. To be on the safe side, we decided to record the edge responses for a stimulus pulse width of 500 ms to ensure that the edge responses are acquired perfectly. It can be observed that both the positive and offset responses have a delay of around 50 ms, and the responses diminishes around 350 ms after the edge. The prominent region for the edge response is between 50 ms up to 200 ms. It can be noted that for all of the subjects, EEG has a common overall pattern. However, the EEG response of each subject deviates significantly from the average response over all subjects (see Figure 3.2). Additionally, it can also be noted that the onset response is much larger than the offset response.

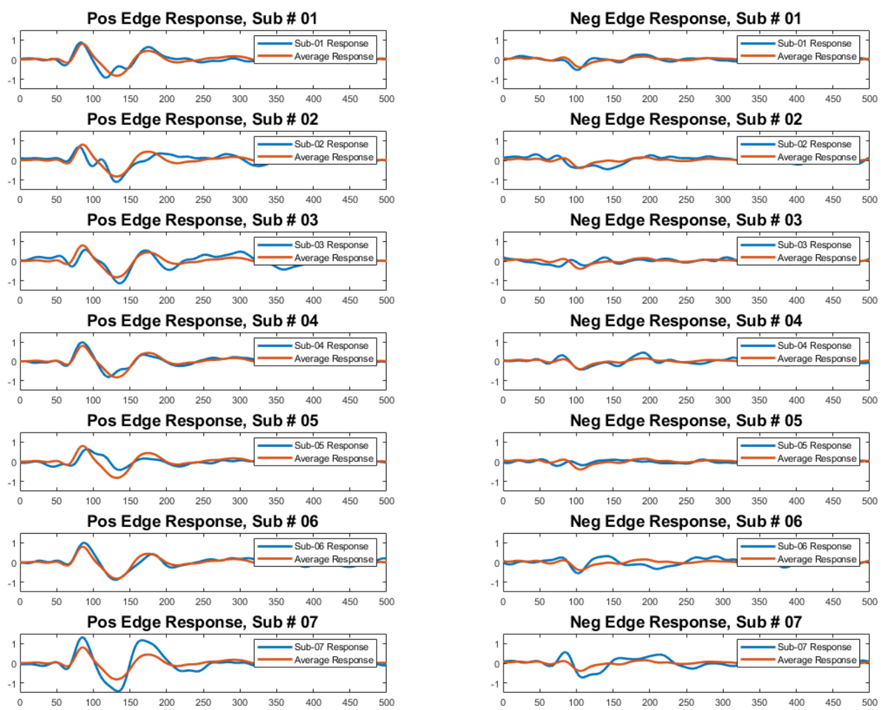

Figure 3.2: The signals on the left represent the onset responses for each subject, whereas the signals on the right represent the offset responses. The blue signals are the individual onset and offset responses of the subjects. However, the red signals are the averaged onset and offset responses over all subjects.

3.2 Repeatability Of The Edge (onset and offset) Responses

It is interesting to know about the similarity of the edge responses acquired from two separate experiments at different times. Therefore, we conducted a second experiment to record the edge responses for all of the 7 subjects. The second experiment was conducted 2 weeks after the first experiment. The onset and offset responses for each subject acquired from the two different experiments are given in Figure 3.3. It can be observed that the edge responses for each person are the same, even if these responses are acquired at different times. From Figure 3.3, it can be witnessed that the onset responses for subject 6 acquired from the two experiments shows less similarity. However, the edge responses for the other six subjects are very similar.

The onset responses acquired from the two experiments has a correlation of 0.90, 0.82, 0.93, 0.86, 0.81, 0.61, and 0.96 for subject 1, 2, 3, 4, 5, 6, and 7 respectively. For the offset responses the correlations are 0.79, 0.80, 0.44, 0.82, 0.04, 0.67 and 0.87. The small correlation values for the offset responses are because of the low signal to noise ratio due to the low amplitudes of the offset responses. The average root mean square value (RMS) of onset response for experiment 1 and 2 are 0.303 and 0.289, respectively. However, the average RMS value of offset response for experiment 1 and 2 are only 0.149 and 0.160, respectively.

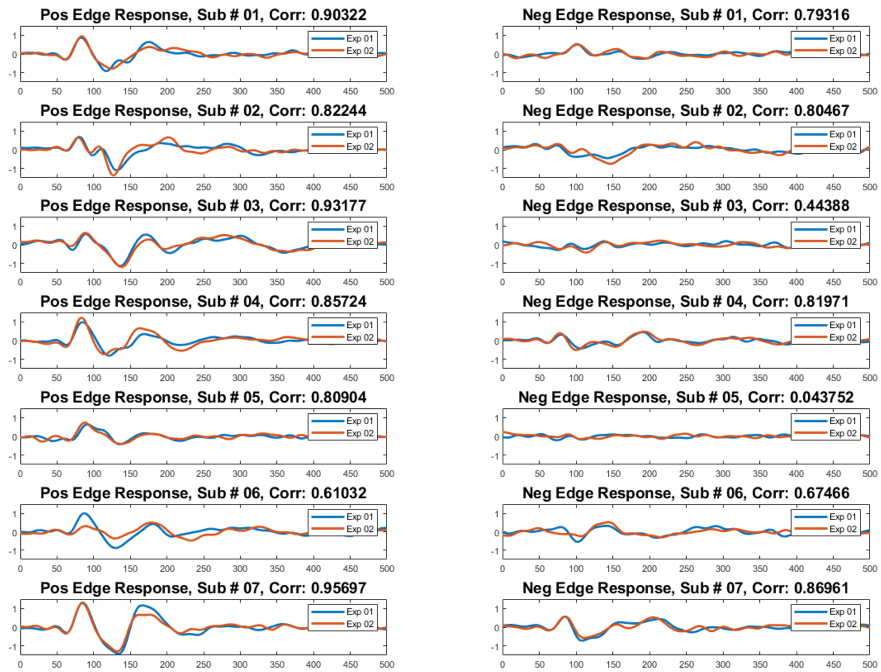

Figure 3.3: The signals on the left represent the onset responses for each subject, whereas the signals on the right represent the offset responses for each subject. Furthermore, the blue and red signal represents the onset and offset response acquired form experiment 1 and experiment 2, respectively.

3.3 Superposition Based Model For Prediction cVEP Responses

If the system responds only to the edges of the stimulus sequence and if the system is linear, then it should be possible to predict EEG responses to arbitrary stimulus patterns by appropriately shifting and adding the edge responses. Therefore, we have developed a superposition-based model for predicting the EEG responses to arbitrary stimulus patterns, and in section 3.4 we investigate to what extent this model can predict EEG responses. First, the onset and offset responses are acquired correctly, and then the EEG responses to arbitrary stimulus patterns are predicted. The process of predicting EEG response employs shifting of the edge responses to the corresponding location of these edges in the stimulus pattern and then adding up these shifted edge responses. This superposition-based model is illustrated in Figure 3.4.

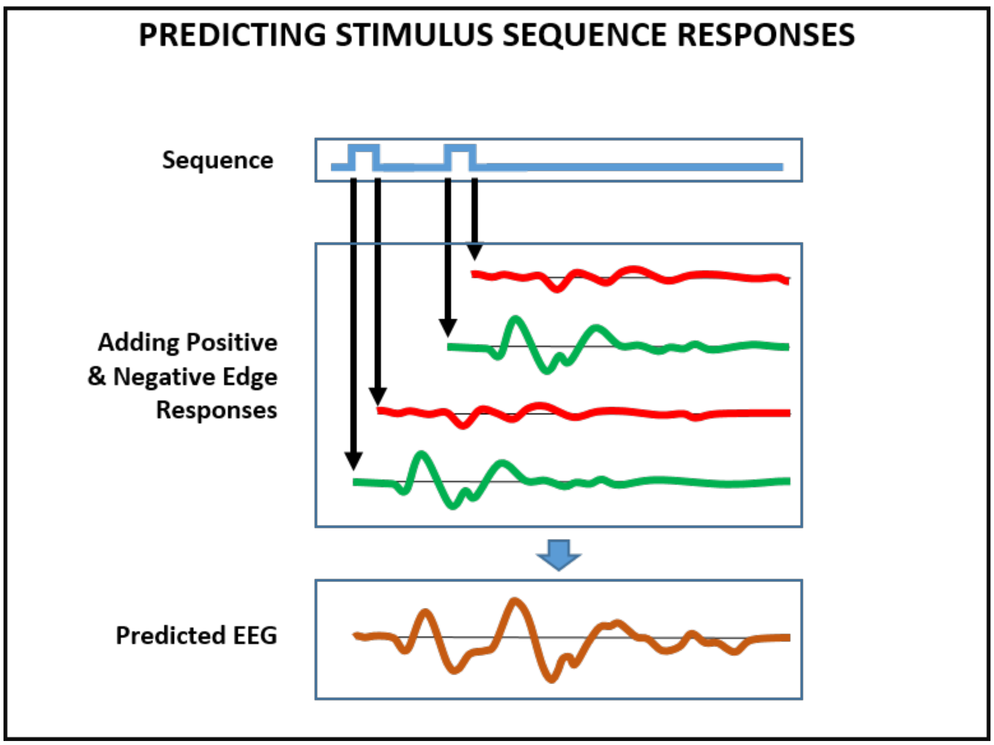

Figure 3.4: This Figure illustrates the process of predicting the EEG response of a simple stimulus pattern using the superposition-based model. The blue waveform represents the stimulus pattern, and it consists of 2 pulses only. The green and red signals are the onset and offset responses that are added based on their location in the sequence to get the predicted EEG (orange signal).

3.4 Model Prediction Performance For Simple Stimulus Patterns

The performance of the superposition-based model is evaluated for simple stimulus patterns discussed in section 2.2.2. The predicted EEG and recorded EEG are compared for these stimulus patterns, and their correlations are obtained. This study is divided into three parts, as we have mentioned before. In the first part, the prediction performance of the superposition model is investigated for a single pulse of different widths. The second part discusses the model prediction performance for different separations between two pulses. Finally, in the third part, the model prediction performance for repetitive pulses is investigated.

3.4.1 Prediction Performance For Different Pulse Widths

In this study, the recorded and generated EEG responses for the stimulus patterns with different pulse widths are compared for 7 subjects. The generated and recorded EEG responses of subject 1 for the stimulus sequences PW15 (for 1-5 bit wide pulses) and PW69 (for 6-9 bit wide pulses), mentioned in section 2.2.2.1 are given in Figure 3.5. From Figure 3.5 it can be observed that as the pulse width is increased from 1 to 9 bits the correlation drops from 0.634 to 0.316. The correlation values for 1 bit and 2 bit wide pulses are 0.634 and 0.643, respectively, which are much higher than the values obtained for 3-9 bit wide pulses. Hence, if the stimulus sequences contain only 1 and 2 bit wide pulses, then the EEG response for such sequence can be predicted with high accuracy.

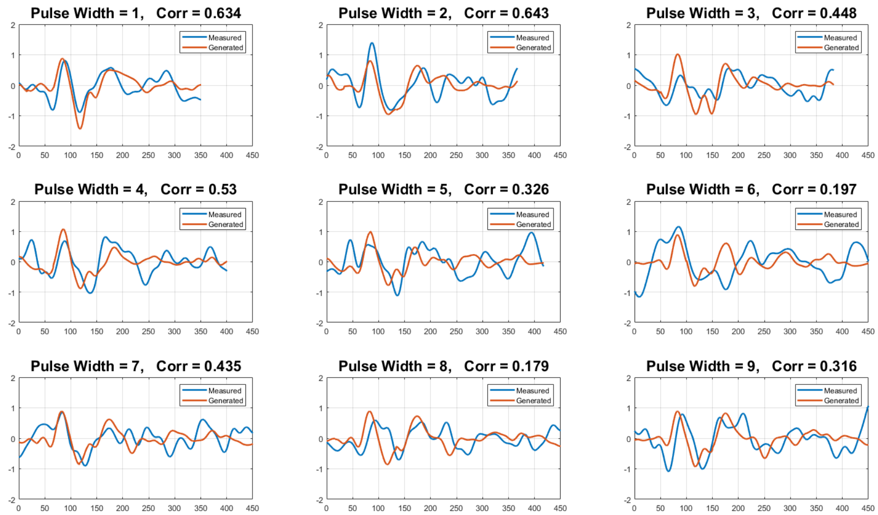

Figure 3.5: Comparison of the generated and observed EEG responses for various pulse width sizes ranging from 1 to 9 bits. The pulse widths are mentioned above each figure along with the correlation value. The blue signals are the measured EEG response, whereas the red signals are generated EEG response.

Table 3.1 provides the correlation values between the observed and the generated EEGs for 7 subjects. Subjects 1, 2, 3, 6, and 7 have maximum correlation of 0.643, 0.757, 0.836, 0.795, and 0.812, respectively, for 2 bit wide pulses. Furthermore, 1 bit wide pulse has the second-highest correlation for these subjects, and the correlation values are 0.634, 0.736, 0.641, 0.793, and 0.731 for subjects 1, 2, 3, 6, and 7, respectively. In the case of subject 4, a maximum correlation of 0.767 is obtained for a pulse width of 1 bit. However, for subject 5, a maximum correlation of 0.662 is recorded for 9 bit wide pulse. In general, it can be inferred that as the pulse width is increased, the correlation between the actual and the generated EEG decreases. Overall the subjects have maximum correlation value of 0.700 for 1 bit wide pulses, and the second-highest correlation value of 0.680 is for 2 bit wide pulse. The overall correlation of the subjects then drops to 0.542 as the pulse width is increased to 9 bit. Repeated measures ANOVA test shows that there is significant difference among the correlations obtained for different pulse widths ($p < 0.001$). Detailed results for repeated measured ANOVA is given in

Appendix C. Furthermore, when paired t-test was applied to pairwise compare different pulse widths, we observed that the correlations for 1 and 2 bit wide pulses are similar. As the width of the pulse is increased further, the correlations become significantly different from the pulses of narrow widths and they become similar to the correlations obtained from the pulses of higher widths. All of the results for the paired t-test is provided in appendix C. Therefore, we arrive at the understanding that by using 1 bit and 2 bit pulses in the stimulus sequences for the BCI system, the classification accuracy will improve.

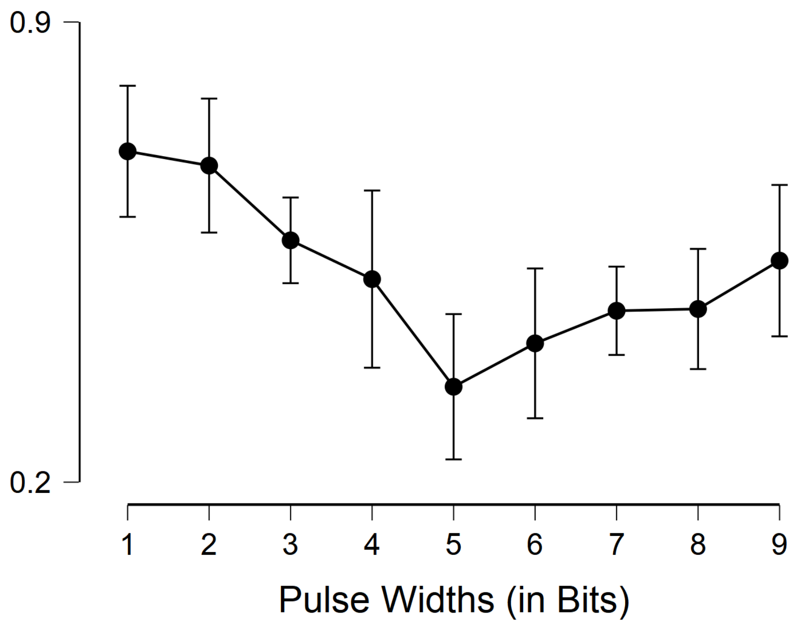

Figure 3.6: Graph for average correlation values for different pulse widths overall subjects.

Figure 3.6 provides the graph for the average correlation values for different pulses widths, overall subjects. The upper and lower bounds shown in the Figure represents the upper and lower limits of the confidence interval. Again it is clear that 1 bit and 2 bit pulses should preform better.

Table 3.1: Correlation values between generated and recorded EEG responses of 1-9 bit stimulus pulses are provided in this table. The rows of the table provided information on the individual subject, whereas the data for different stimulus pulse widths are provided in columns of the table. The last row of the table contains the average correlation values for 1-9 bit pulse widths overall subjects.

	Correlation Pulse Widths								
Sub NO	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
01	0.634	0.643	0.448	0.530	0.326	0.197	0.435	0.179	0.316
02	0.736	0.757	0.676	0.277	0.261	0.528	0.555	0.544	0.678
03	0.641	0.836	0.517	0.573	0.467	0.566	0.430	0.560	0.563
04	0.767	0.468	0.532	0.553	0.319	0.143	0.414	0.303	0.357
05	0.599	0.447	0.493	0.504	0.088	0.458	0.290	0.409	0.662
06	0.793	0.795	0.647	0.463	0.427	0.392	0.468	0.588	0.477
07	0.731	0.812	0.668	0.664	0.574	0.606	0.667	0.710	0.742
Avg	**0.703**	**0.681**	**0.568**	**0.509**	**0.345**	**0.411**	**0.460**	**0.463**	**0.537**
std	**0.074**	**0.164**	**0.093**	**0.120**	**0.157**	**0.181**	**0.119**	**0.183**	**0.165**

3.4.2 Prediction Performance For Different Pulse Separations

In this study, the generated and observed EEG is compared for different separation distances between the two pulses. This study is divided into 2 parts; in the first part, EEG responses are compared for different separations between 1 bit wide pulses. Whereas, in the second part, the pulse separation is studied between 2 bit wide pulses. Figure 3.7 provides the generated and observed EEG responses of stimulus patterns with different separation intervals between 1 bit wide pulses for subject 1. The separation distance between the adjacent 1 bit pulses in the stimulus sequence was changed from 1 to 9 bits and the stimulus sequences PS15W1 and PS69W1 are used for this study. Details on the stimulus sequences are provided in section 2.2.2.2. From Figure 3.7, it can be observed that as the separation between 1 bit wide pulses are increased from 1 to 9 bits the correlation increases from a low value of 0.335 and reaches a maximum of 0.724

(for 6 bit separation) and then slowly falls to 0.473 (for 9 bit separation). Hence, it can be inferred that if the stimulus sequence for subject 1 consists of more than 5 bits separation between the pulses, the generated EEG from the model will be more accurate.

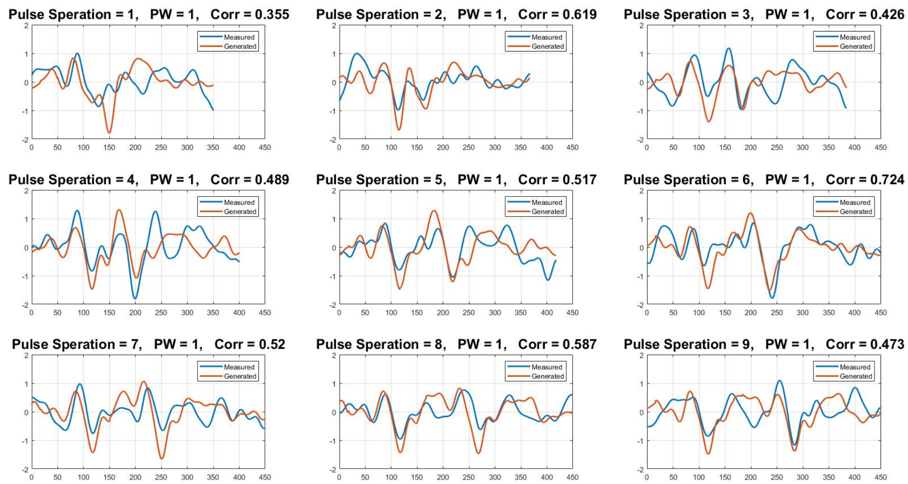

Figure 3.7: Comparision of the acquired and generated EEG responses for different separation intervals (from 1 bits to 9 bits) between 1 bit wide pulses of Subject 1. The signals in blue are the recorded EEG responses, and the red signals represent the generated EEG response from the superposition-based model. Information on the pulse separations, pulse width, and correlation values are provided above each graph.

Table 3.2 provides the correlation values for all of the seven subjects. It can be observed that when the separation distance between stimulus pulses is small, the accuracy of predicting its EEG response is low, and when the separation is increased, the prediction accuracy improves. The overall average correlation for the subjects is around 0.3 for pulse separation of 1, 2, and 3 bits. The correlation improves to 0.554 when the separation between the pulses is 4 bit. Furthermore, the correlation is recorded to be around 0.6 for pulses with more than 4 bit separation. Repeated measures ANOVA test shows that the null hypothesis of having equal means for the columns of Table 3.2 is to be rejected (p = 0.013). The detailed results for this hypothesis is provided in Appendix C. Furthermore pairwise comparisons using paired t-test shows the means of that columns 4, 5, 6, 7, 8 and 9 are similar to each other and columns 1, 2 and 3 has significant difference from column 6, so in general choice of 4 to 9 bit separation between 1 bit pulses seems reasonable. The details of these results are provided in Appendix C. Therefore, it can be inferred that in general, if the separation between 1 bit pulses of the stimulus is 4 or more, its EEG response can be predicted with high accuracy.

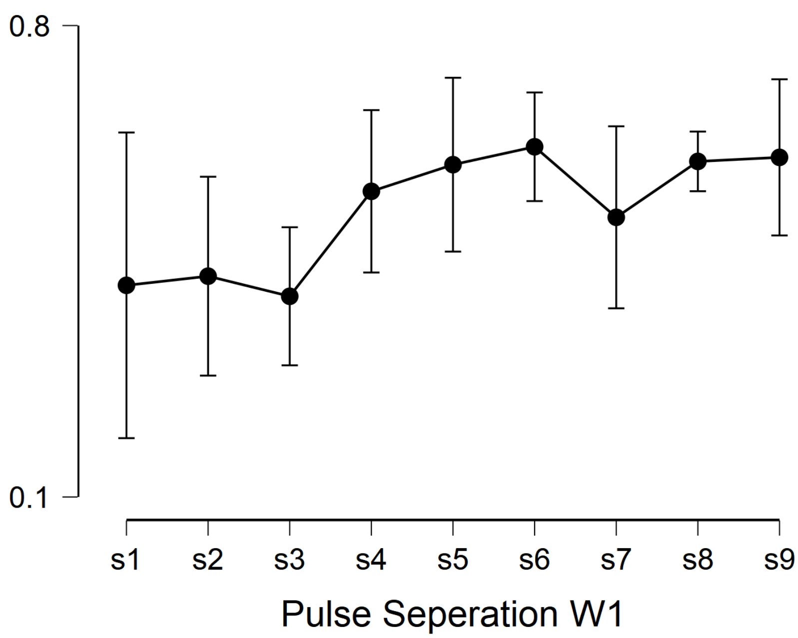

Figure 3.8: Graph for average correlation values for different separations between 1 bit wide pulses, overall subjects.

Figure 3.8 provides the graph for the average correlation values for different separations between 1 bit wide pulses, overall subjects. The upper and lower bounds shown in the Figure represents the upper and lower limits of the confidence interval. Again it is clear that if the pulse separation is greater than 3 bits the prediction should be better.

Table 3.2: Correlation values between generated and recorded EEG responses of 1-9 bit separations between 1 bit pulses, for all 7 subjects, are provided in this table. The rows of the table provided information on the individual subject, whereas the data for different separation between pulses are provided in colums of the table. The last row of the table contains the overall average correlation values for 1-9 bit separations between pulses.

	Correlation Pulse Separation (W1)								
Sub NO	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
01	0.335	0.619	0.426	0.489	0.517	0.724	0.520	0.587	0.473
02	0.699	0.449	0.274	0.415	0.468	0.671	0.559	0.596	0.728
03	0.481	0.489	0.733	0.682	0.765	0.701	0.759	0.703	0.753
04	0.091	0.473	0.222	0.577	0.313	0.374	0.507	0.511	0.561
05	0.507	0.321	0.230	0.336	0.688	0.593	0.258	0.455	0.507
06	0.601	0.378	0.406	0.595	0.591	0.533	0.265	0.639	0.387
07	0.166	0.266	0.495	0.783	0.812	0.744	0.739	0.697	0.821
Avg	**0.414**	**0.428**	**0.398**	**0.554**	**0.593**	**0.620**	**0.515**	**0.598**	**0.604**
std	**0.223**	**0.118**	**0.181**	**0.154**	**0.176**	**0.132**	**0.200**	**0.092**	**0.163**

In the second part of this study, the generated and recorded EEG responses are compared for stimulus patterns with 1 to 9 bit separations between 2 bit wide pulses. Figure 3.9 provides the generated and observed EEG responses of stimulus patterns with different separation intervals between 2 bit wide pulses for subject 1. The separation distance between the adjacent 2 bit pulses in the stimulus sequence was changed from 1 to 9 bits, and the stimulus sequences PS15W2 and PS69W2 are used for this study. Details on the stimulus sequences are provided in Section 2.2.2.2. It can be observed from the figure that as the separation between 2 bit wide pulses is increased from 1 to 9 bits, the correlation increases from a low value of 0.358 and reaches a maximum of 0.761. The correlation for 2 bit separation is 0.475, and the correlation is greater than 0.6 for the separation of more than 2 bits. Hence, it can be inferred that if the stimulus sequence for subject 1 consists of more than 2 bits separation between 2 bit wide pulses, the EEG response will be predicted with higher accuracy.

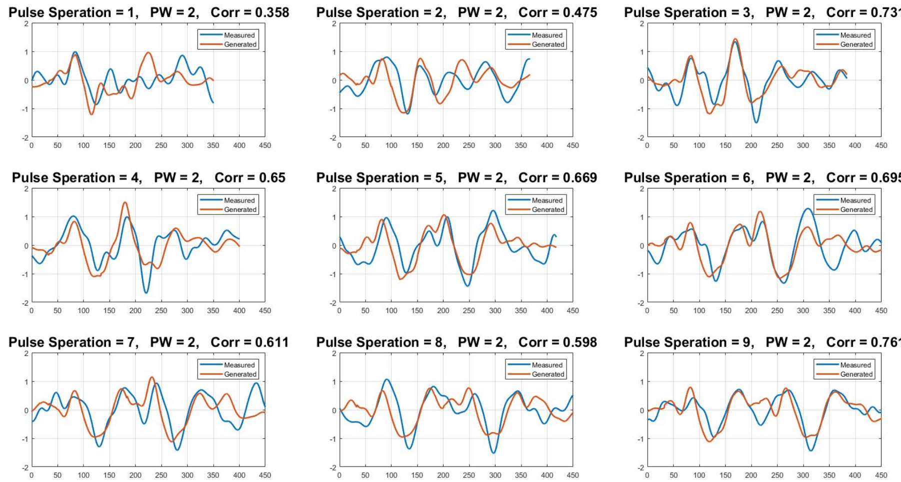

Figure 3.9: Comparison between measured and generated EEG for different separation lengths between 2 bit wide pulses. The blue signal is the measured response whereas the red signal is the generated response. The pulse separation values are mention above each plot along with the pulse width size and the correlation values between generated and measured signals.

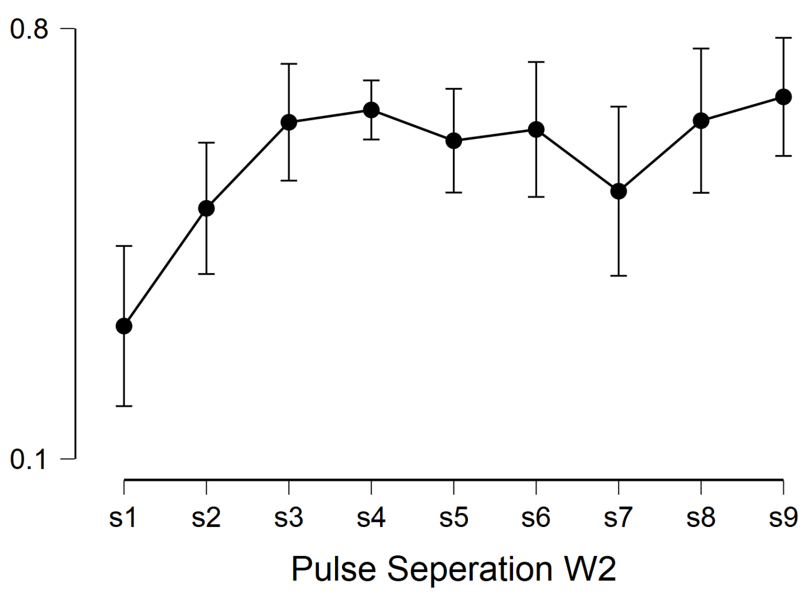

Figure 3.10: Graph for average correlation values for different separations between 2 bit wide pulses, overall subjects.

Table 3.3 provides the correlation values of the generated and observed EEG responses to different stimulus patterns, with 1 to 9 separations, between 2 bit pulses. The average correlation for a separation of 1 bit is 0.316, and it increases to 0.648 as the separation between the pulses is increased to 3 bits, and from 3 bit up to 9 bit small variations in the correlations are observed. Repeated measures ANOVA test shows that the null hypothesis of having equal means for the columns of Table 3.3 is to be rejected ($p = 0.001$). The detail results for the repeated measures ANOVA test can be found in appendix C. Furthermore pairwise comparisons using paired t-test shows the means of that columns 3, 4, 5, 6, 7, 8 and 9 are similar to each other and columns 1 and 2 has significant difference from column 3, 4 and 9. The results for the paired t-test are provided in appendix C. Therefore, it can be inferred that if the separation between 2 bit pulses is greater than 2 bits, the EGG responses resulting from the individual pulses will have less overlap, so the generated EEG response will have a high correlation with the observed EEG response.

Figure 3.10 provides the graph for the average correlation values for different separations between 2 bit wide pulses, overall subjects. The upper and lower bounds shown in the Figure represents the upper and lower limits of the confidence interval. Again it is clear that if the pulse separation is greater than 2 bits the prediction should be better.

Table 3.3: Correlation values between generated and recorded EEG responses of 1-9 bit separations between 2 bit pulses, for all 7 subjects, are provided in this table. The rows of the table provided information on the individual subject, whereas the data for different separation between pulses are provided in columns of the table. The last row of the table contains the overall average correlation values for 1-9 bit separations between pulses.

	Correlation Pulse Separation (W2)								
Sub NO	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
01	0.358	0.475	0.731	0.650	0.669	0.695	0.611	0.598	0.761
02	0.238	0.431	0.477	0.619	0.694	0.596	0.671	0.641	0.771
03	0.360	0.634	0.574	0.632	0.661	0.718	0.704	0.513	0.588
04	0.409	0.605	0.693	0.623	0.403	0.345	0.361	0.725	0.656
05	0.282	0.505	0.702	0.608	0.515	0.659	0.450	0.554	0.482
06	0.473	0.518	0.674	0.779	0.733	0.734	0.349	0.643	0.737
07	0.093	0.385	0.682	0.762	0.648	0.704	0.602	0.877	0.827
Avg	**0.316**	**0.508**	**0.648**	**0.668**	**0.618**	**0.636**	**0.535**	**0.650**	**0.689**
std	**0.125**	**0.089**	**0.090**	**0.072**	**0.116**	**0.136**	**0.147**	**0.121**	**0.121**

3.4.3 Prediction Performance For Different Pulse Repetitions

Finally, in the third study, the recorded EEG responses for the stimulus patterns with a different number of pulse repetitions are compared with the generated EEG acquired from the superposition based model. This study is further divided into three parts depending upon the width of the pulse (1 bit, 2 bit, and 3 bit wide). The EEG response for different repetitions of 1 bit stimulus pulse is given in Figure 3.11. It can be noted that for all stimulus patterns, the correlation between the generated and the observed EEG responses is very low. For different repetitions of 1 bit pulses, the distance between the consecutive pulses is only 16.7 ms (1 bit), so the EEG responses of these pulses overlap in a destructive manner, giving a poor overall EEG response. Hence, if the stimulus sequences includes repetitions of 1 bit pulses, then the EEG is predicted by the model with poor accuracy.

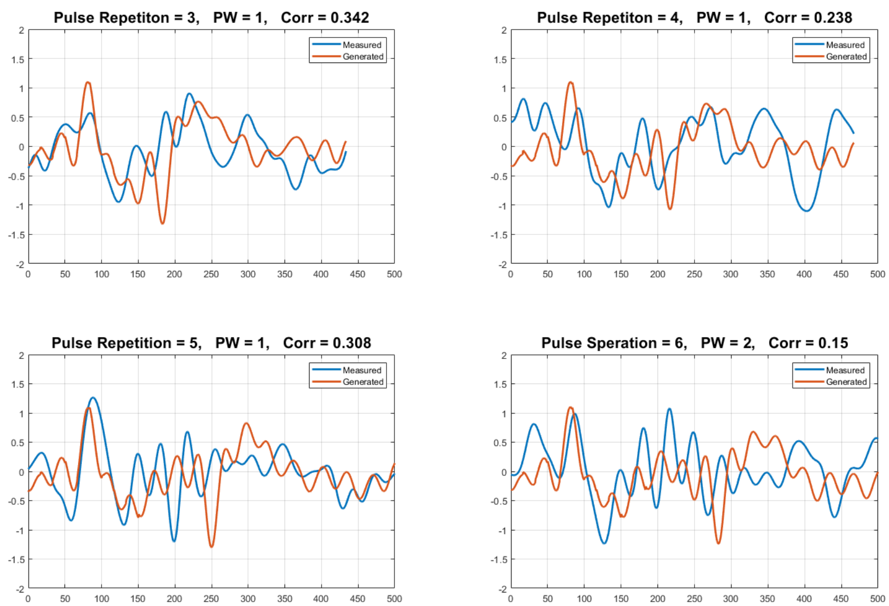

Figure 3.11: Comparison between measured and generated EEG for 3, 4, 5 and 6 repetitions of 1 bit pulse. The blue signal is the measured response whereas the red signal is the generated response. The number of pulse repetitions is mention above each plot along with the pulse width size and the correlation values.

The correlation values for different repetitions of 1 bit wide pulses are given Table 3.4. It can be observed that for 2, 3, 4, 5, and 6 repetitions of 1 bit wide pulses, the correlation of the overall subject is low (0.411, 0.287, 0.185, 0.157, and 0.170 for 2, 3, 4, 5, and 6 repetitions of 1 bit wide pulses) because of the destructive superposition of the individual pulses responses. However, subject 6 has a surprisingly high correlation for two repetitions of 1 bit pulse, but still, the overall correlation for subject 6 decreases as the number of repetitions increases. The repeated measures ANOVA indicates significant difference between different repetitions with a p value of 0.03. However pairwise paired t-tests do not show any significant difference between the columns (at 5% significance level). The details of the repeated measures ANOVA test and paired t-test are provided in Appendix C. Therefore, if the stimulus sequence includes repetitions of 1 bit wide pulses, the generated EEG response from the model will be less accurate.

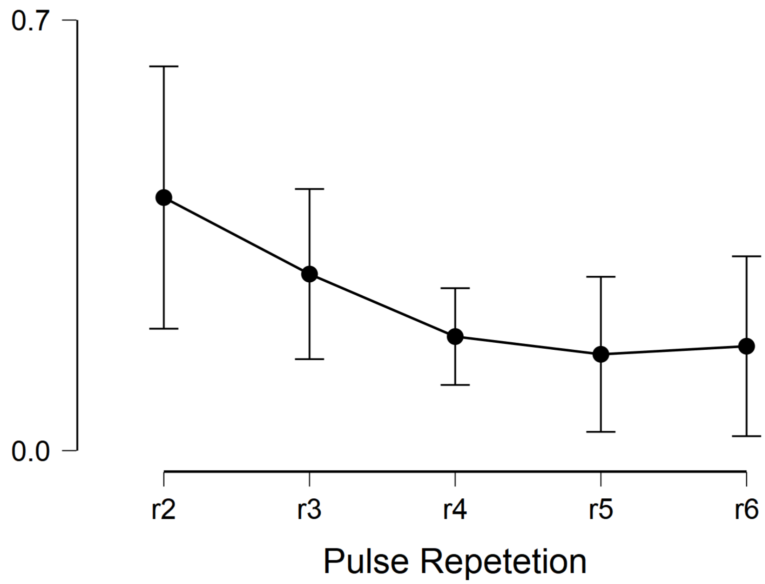

Figure 3.12: Graph for average correlation values for different repetitions of 1 bit wide pulse, overall subjects.

Figure 3.12 provides the graph for the average correlation values for different repetitions of 1 bit wide pulse, overall subjects. The upper and lower bounds shown in the Figure represents the upper and lower limits of the confidence interval. Again it is clear using different repetitions of 1 bit pulse will result in low classification accuracy.

Table 3.4: Correlation values between generated and recorded EEG responses of 2, 3, 4, 5, and 6 repetitions of 1 bit wide pulse for 7 subjects are provided in this table. The rows of the table provides information on the individual subject, whereas the data for different repetitions of 1 bit pulse is provided in columns of the table. The last row of the table contains the overall average correlation values for 2, 3, 4, 5, and 6 repetitions of 1 bit wide pulse.

	Correlation Pulse Repetition (W1)				
Sub No	**2**	**3**	**4**	**5**	**6**
01	0.335	0.342	0.238	0.308	0.150
02	0.679	0.372	0.074	0.094	0.045
03	0.481	0.404	0.328	0.011	0.090
04	0.091	0.416	0.077	0.239	0.064
05	0.507	0.197	0.249	0.156	0.306
06	0.601	0.177	0.116	0.029	0.093
07	0.166	0.101	0.216	0.259	0.440
Avg	**0.411**	**0.287**	**0.185**	**0.157**	**0.170**
Std	**0.219**	**0.126**	**0.098**	**0.117**	**0.148**

The EEG response of the first subject for the 3, 4, and 5 repetitions of a 2 bit pulse is given in Figure 3.13. It can be noted that for all stimulus patterns with repetitions of 2 bit pulse, the correlation between the generated and the observed EEG response is very high (above 0.675). Unlike 1 bit pulses, as discussed above, here the correlation between the observed and the predicted EEG is high because of the constructive superposition of the individual pulse responses. The distance between two consecutive pulses is 33.4 ms, which seems good enough for subject 1.

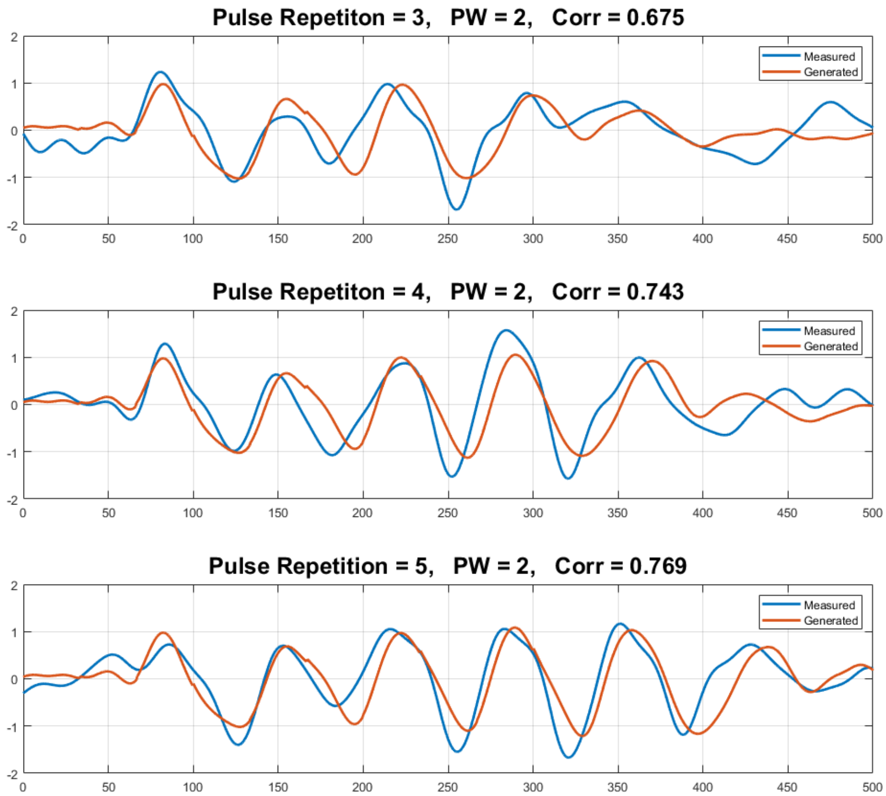

Figure 3.13: Comparison between measured and generated EEG for 3, 4, and 5 repetitions of 2 bit wide pulse. The blue signals are the measured responses, whereas the red signals are the generated responses. The number of pulse repetitions is mention above each plot along with the information on pulse width and the correlation value.

The correlation values for 2, 3, 4, and 5 periodic repetitions of 2 bit wide pulses are given Table 3.5. It can be noted that correlation values are high for most of the subjects. However, for subject seven, 3 repetitions of 2 bit wide pulse have a very low correlation (0.32) between the predicted and the generated EEG. Furthermore, subject 7 showed an overall low correlation for all of the pulses, and this is because of the unique shape of the onset and offset responses for subject 7 (EEG responses for different people are different). Repeated measures ANOVA indicates that correlations for different repetition are significantly different ($p <$

0.01). Pairwise paired t-test results indicate that although for all repetition cases the average correlations are higher than 0.507, the correlation for 4 and 5 repetitions are significantly higher than 2 and 3 repetition cases. The detailed results for the repeated measures ANOVA and paried t-test are provided in appendix C. In general, if the stimulus sequence contains 4 or more repetitions of 2 bit wide pulses, the generated EEG response can be predicted using the superposition-based model with high accuracy.

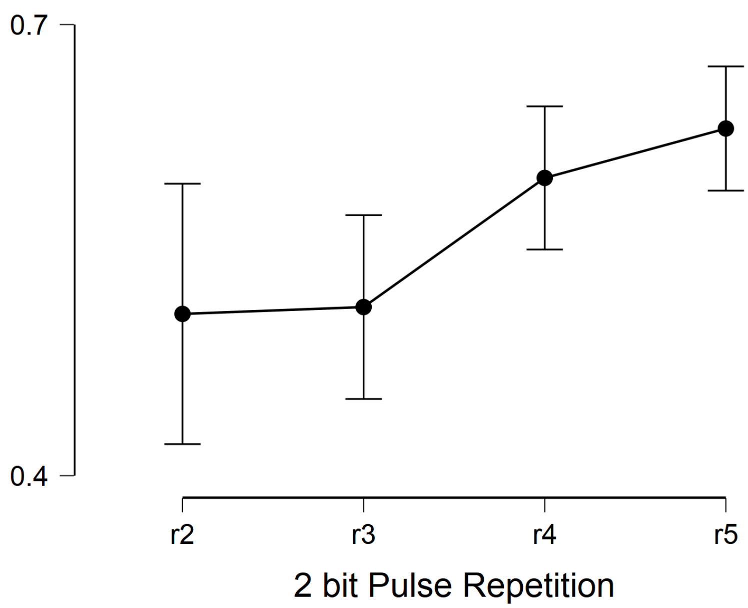

Figure 3.14: Graph for average correlation values for different repetitions of 2 bit wide pulse, overall subjects.

Figure 3.14 provides the graph for the average correlation values for different repetitions of 2 bit wide pulse, overall subjects. The upper and lower bounds shown in the Figure represents the upper and lower limits of the confidence interval. Again it is clear that the EEG can be predicted accurately if 4 and 5 repetitions of 2 bit wide pulse is used.

Table 3.5: Correlation between generated and recorded EEG responses of 2, 3, 4, and 5 repetitions of 2 bit wide pulse for 7 subjects are provided in this table. The rows of the table provided information on the individual subject, whereas the data for different repetitions of 2 bit pulse is provided in columns of the table. The last row of the table contains the overall average correlation values for 2, 3, 4, and 5 repetitions of 2 bit wide pulse.

	Corr Pulse Repetition (W2)			
Sub No	**2**	**3**	**4**	**5**
01	0.475	0.675	0.743	0.769
02	0.431	0.540	0.516	0.551
03	0.634	0.456	0.517	0.647
04	0.605	0.644	0.733	0.699
05	0.505	0.416	0.616	0.614
06	0.518	0.534	0.638	0.729
07	0.385	0.320	0.423	0.407
Avg	**0.508**	**0.512**	**0.598**	**0.631**
Std	**0.089**	**0.126**	**0.119**	**0.123**

The EEG responses of subject 1 for 2, 3, and 4 repetitions of a 3 bit wide pulses is given in Figure 3.15. It can be noted that for all stimulus patterns with repetitions of 3 bit wide pulse, the correlation between the generated and the observed EEG response is high for subject 1. Hence, for subject 1 if the stimulus sequence includes periodic repetitions of 3 bit patterns, the generated and the predicted EEG would be quite similar.

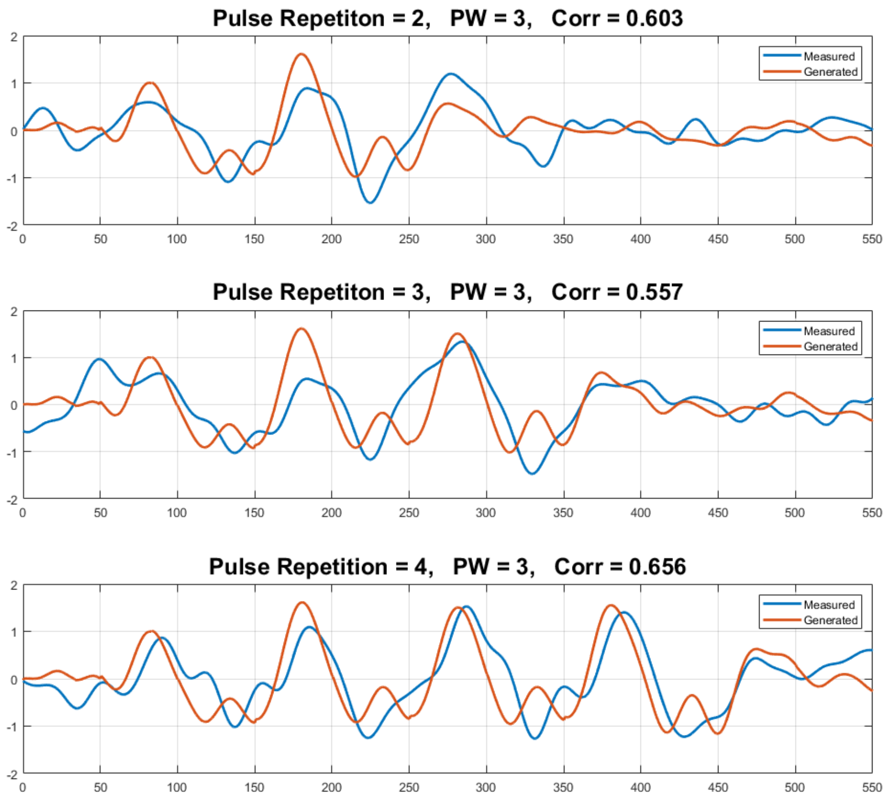

Figure 3.15: Comparison between measured and generated EEG for 2, 3, and 4 repetitions of 3 bit wide pulse. The blue signals are the measured EEG responses, whereas the red signals are the generated EEG responses. The number of pulse repetitions is mention above each plot along with the information on pulse width and the correlation value.

The correlation values for 2, 3, and 4 repetitions of 3 bit wide pulses are given in Table 3.6. It can be observed that correlation values are high for most of the subjects. However, again subject 7 showed an overall low correlation for all of the pulses repetitions. Furthermore, the overall average correlation of subjects is quite high for all repetitions of 3 bit wide pulses. For the repetition of 3 bit pulses it is found from repeated measures ANOVA that all repetition cases are statistically the same ($p = 0.16$) and the average correlations are higher than 0.58. Pairwise comparisons also do not show any significant difference between the correlations of different repetition cases. The detailed results of repeated measures ANOVA and paired t-test are provided in appendix C. Therefore, if the stimulus sequence contains repetitions of 3 bit wide pulses, the generated EEG acquired from the superposition-based model will be more accurate.

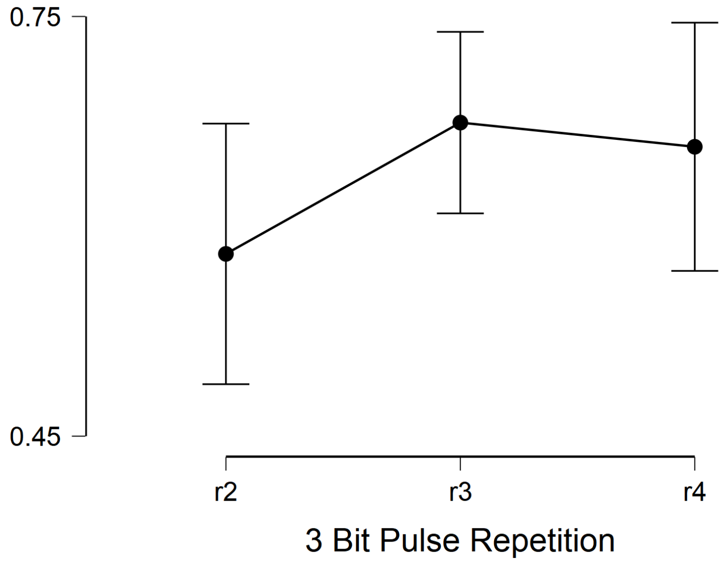

Figure 3.16: Graph for average correlation values for different repetitions of 3 bit wide pulse, overall subjects.

Figure 3.16 provides the graph for the average correlation values for different repetitions of 3 bit wide pulse, overall subjects. The upper and lower bounds shown in the Figure represents the upper and lower limits of the confidence interval. Again it is proved that if the stimulus includes repetitions of 3 bit wide pulses then the EEG can be predicted with better accuracy.

Table 3.6: Correlation between generated and recorded EEG responses of 2, 3, and 4 repetitions of 3 bit wide pulse for 7 subjects are provided in this table. The rows of the table provided information on the individual subject, whereas the data for different repetitions of 3 bit pulse is provided in columns of the table. The last row of the table contains the overall average correlation values for 2, 3, and 4 repetitions of 3 bit wide pulse.

	Correlation Pulse Repetition (W3)		
Sub No	**Reps = 2**	**Reps = 3**	**Reps = 4**
01	0.603	0.557	0.656
02	0.725	0.822	0.804
03	0.596	0.576	0.484
04	0.406	0.696	0.724
05	0.519	0.634	0.422
06	0.525	0.712	0.688
07	0.688	0.722	0.820
Avg	**0.580**	**0.674**	**0.657**
Std	**0.108**	**0.092**	**0.152**

3.5 Model Prediction Performance For Long Stimulus Sequences

In this study we investigate the prediction performance of the superposition-based model for three different 120 bit stimulus sequences mentioned in section 2.2.3. The first stimulus sequence is called Pulse Position Modulated (PPM) Sequences, and it consists of only 1 bit pulses along with 1 to 4 bit separations between the pulses. According to the study carried out in section 3.4, we observed that for better EEG prediction, the separation between 1 bit pulses should be greater than or equal to 4 bits, so it is expected to have low prediction accuracy for PPM sequences. Figure 3.17a provides the comparison between the generated EEG response and the 2 trials averaged EEG response of PPM sequence for subject

3. Furthermore, the generated and recorded EEG has a correlation of -0.035, which is pretty low. The second type of sequences are called 7-in-15 Change Random (7-in-15CR) Sequences, and it contains 7 changes for every 15 bits of the sequence. The details on this stimulus sequence are provided in section 2.2.3. The generated, and the acquired EEG responses for this stimulus sequence are compared in Figure 3.17b and the correlation between the generated and recorded EEG for subject 3 is 0.345, which is much better than the PPM sequence. The third type of sequence is the Superposition Optimized Pulse (SOP) Sequences, and the design of this sequence is based on the study conducted in sections 3.4. For instance, It was observed that the superposition-based model performs better; if only 1 and 2 bit wide pulses are used, if the separation between the pulses is equal to or greater than a specific length (4 and 2 bits for 1 and 2 bit wide pulses, respectively), if the stimulus has repetitions of 2 and 3 bit pulses. All of these constraints are met for the SOP and the details on the design this sequence is given in section 2.2.3. The generated and the acquired EEG responses for subject 3 are compared in Figure 3.17c . The correlation between the generated and acquired EEG is 0.552, which is much higher than the other two types of sequences.

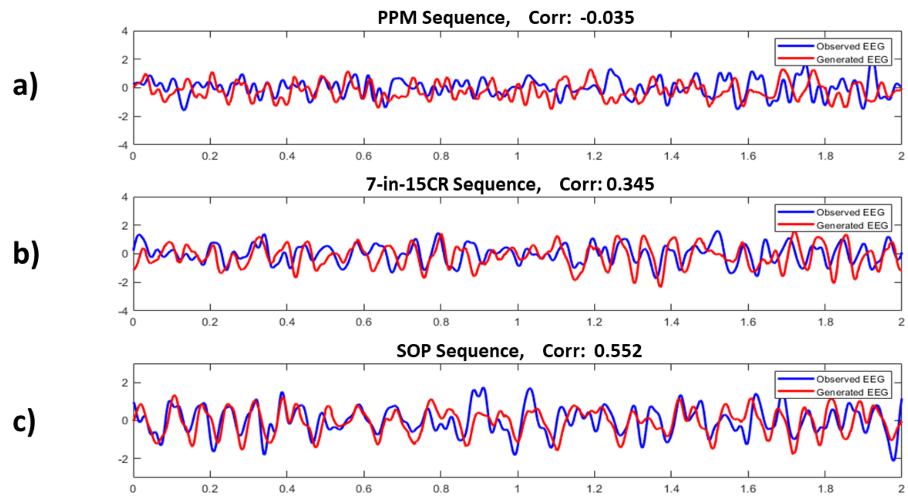

Figure 3.17: Comparison of the generated and the measured EEG responses for three types of stimulus sequences (assigned to the target A of the BCI speller). The observed signals are the average responses of 2 trials. Blue signals are the recorded EEG responses, whereas the signals in red, are the generated EEG responses. The 3 stimulus sequences are; a) PPM Sequence, b) 7-in-15CR Sequence, and c) SOP Sequence.

Table 3.7 provides the correlation values between the generated EEG and the observed EEG of the three types of stimulus sequences provided in Figure 2.10. The EEG for each of the stimulus type is recorded for 2 trial and the observed EEG is the average of the two trials. The overall subject correlation for the PPM sequence is the lowest (only 0.026), whereas the overall correlation for the 7-in-15CR sequences is around 0.244, which is better than PPM sequences. However, the overall correlation of SOP sequences is much better than the other two types of sequences, and it is measured to be 0.324. It should be noted that the negative correlation values are considered as 0's for finding the average correlation of overall subjects. The correlation for SOP sequences for subject 5 is only 0.007, which is very different from all the other subjects where SOP sSequences have high values. Therefore, a BCI application using SOP sequences should perform better than the other two types of sequences.

Table 3.7: This table provides correlation values between the generated and observed EEG response of 7 subjects for PPM sequence, 7-in-15CR sequence, and SOP sequence. The last row provides the overall correlation values for the three types of stimulus sequences.

Sub No	PPM Sequence	7-in-15CR Sequence	SOP Sequence
01	-0.057	0.419	0.505
02	0.106	0.156	0.165
03	-0.035	0.345	0.552
04	0.012	0.195	0.433
05	-0.064	0.111	-0.007
06	-0.087	0.486	0.422
07	-0.525	-0.044	0.190
Avg	**0.026**	**0.244**	**0.324**
Std	**0.201**	**0.187**	**0.207**

As mentioned before, Figure 3.17c provides a comparison for the generated, and recorded (two trials averaged) EEG response for the SOP stimulus sequence given in Figure 2.10c. However, the two trials averaged EEG signal cannot be considered as a good, considering the low SNR of the EEG signals. We performed some more experiments in which the SOP sequence is presented to subjects 1, 3, 5, and 7 for sixty trials, and the observed response is obtained by averaging EEG from these trials. The correlation values of the subjects are recorded to be 0.778, 0.741, 0.482, and 0.332 for subject 1, 3, 5, and 7, respectively which are much better than the correlations obtained for 2 trials averaged EEG (0.505, 0.552, -0.007, and 0.19 for 1, 3, 5, and 7, respectively).

Figure 3.18 provides the generated and 60 trials averaged EEG of the SOP sequence for subject 3. The SOP sequence is given in Figure 2.10c. It can be noted that the generated and observed EEG responses are highly correlated. Furthermore, the generated EEG response has accurately captured the major variations and the location of the peaks. However, there is slight difference in the amplitude of the peaks between the generated and observed EEG responses.

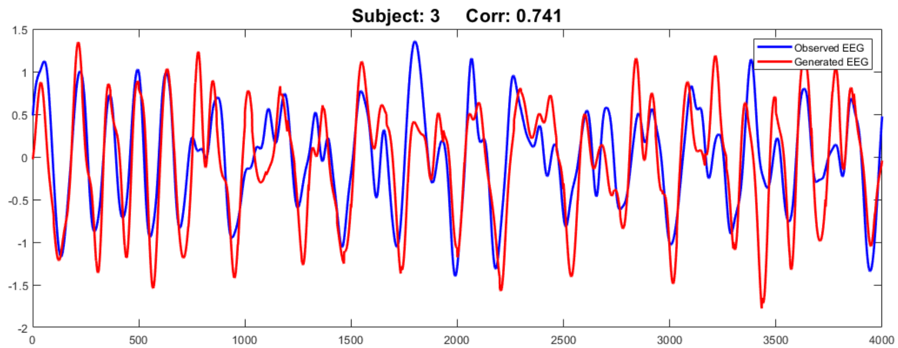

Figure 3.18: This figure provides a comparison of the generated and the measured EEG responses of SOP sequence for subject 3. Blue signals are the recorded EEG responses, whereas the signals in red, are the generated EEG responses.

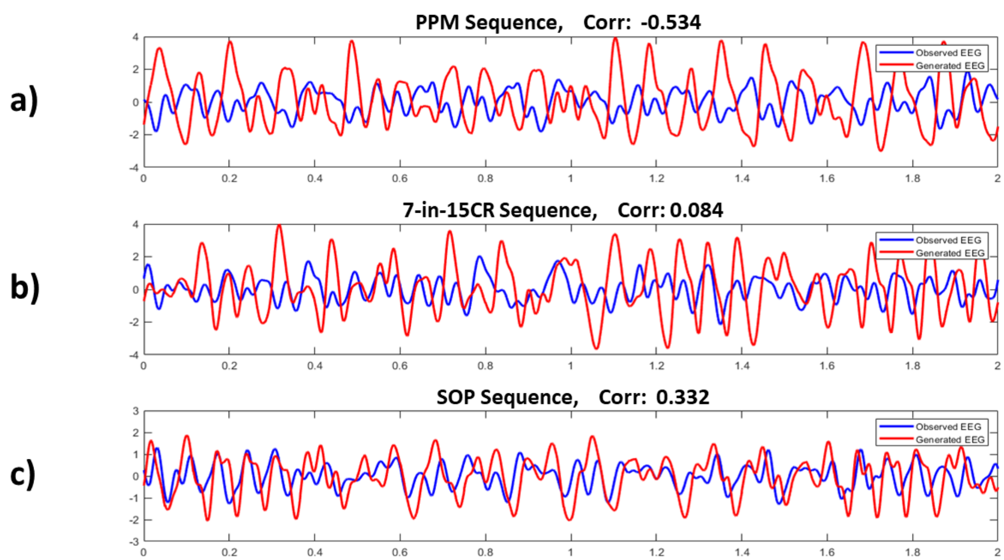

Figure 3.19: This Figure provides a comparison of the generated and the measured EEG responses of subject 7, for three types of stimulus sequences. Blue signals are the recorded EEG responses, whereas the signals in red, are the generated EEG responses. The 3 stimulus sequences are; a) PPM Sequences, b) 7-in-15CR Sequences and c) SOP Sequences.

Figure 3.19 provides the comparison between the generate and observed EEG responses for the 3 stimulus types given in Figure 2.10. The EEG responses for each type of stimulus sequence are recorded for 60 trials and then averaged for getting the observed EEG response. The correlation for the PPM sequences, 7-in-15CR sequences, and SOP sequences are -0.554, 0.084, and 0.332. This Figure provides a confirmation that PPM sequences and 7-in-15CR sequences will perform poorly than SOP sequences if used in a BCI application. Note: negative correlation are taken as zeros.

In general, it can be said that the superposition-based model is not very successful for obtaining the EEG response for all stimulus patterns, there are nevertheless some pulse combinations for which it is reasonably successful. Therefore, if the stimulus sequences follow these constraints, then its EEG response can be obtained with better accuracy. In the next section, we use the three stimulus sequences in our BCI speller application, and we will compare their performance by their classification accuracy and ITR.

3.6 BCI Results

Table 3.8 provides the accuracy and ITR values of the BCI application using the three stimulus types for each subject. For all of the subjects the PPM sequences performed the worst with an overall accuracy and ITR of 6.94% and 1.7 bits/min, respectively. The performance of the 7-in-15CR sequences was comparatively better than the PPM sequence with an average accuracy and ITR of 27.75% and 10.53 bits/min, respectively. Finally, as expected, the SOP sequences performed the best with an accuracy of 95.9% and ITR of 57.19%, respectively. It can be easily notice for all of the subjects the SOP sequences give the best results with high accuracy and ITR values. The PPM sequences performed the worst for all of the subjects with very low ITR and accuracy values. Furthermore, the first subject has overall better performance for all of the stimulus types than other subjects. In general we may conclude, although from the comparison results of just 3 sequence types, that sequences which do not obey the rules that we have identified in the previous sections, poorly perform.

Table 3.8: Accuracy values of BCI application using 3 different types of stimulus sequences.

	PPM Sequences		7-in-15CR Sequences		SOP Sequences	
Sub No	**Acc (%)**	**ITR (bits/min)**	**Acc (%)**	**ITR (bits/min)**	**Acc(%)**	**ITR (bits/min)**
01	37.14	11.93	94.29	54.73	100	62.04
02	0	0	14.29	2.18	100	62.04
03	2.86	0	22.86	5.25	100	62.04
04	0	0	20.0	4.13	91.4	51.67
05	5.71	0.21	17.14	3.10	88.54	48.82
06	2.86	0	20.0	4.13	100	62.04
07	0	0	5.71	0.21	91.4	51.67
Avg	**6.94**	**1.7**	**27.75**	**10.53**	**95.9**	**57.19**
Std	**13.48**	**4.496**	**29.86**	**19.55**	**5.19**	**6.125**

Chapter 4

Discussion And Conclusion

In this study, we investigated the EEG response to simple stimulus pulse sequences in order to find the basic characteristics of the visual system as observed through the EEG. We observed that the brain responds only to the changes in the stimulus sequence, that is, EEG response is only induced when the visual stimulus intensity changes from Black to White or from White to Black, denoted as the positive (onset of the stimulus) and negative edges (offset of the stimulus), respectively. It is also noted that the EEG response is more prominent for the positive edge, whereas, the response for the negative edge is comparably low. We also found that the edge responses for each person are unique, and they are also repeatable even if they are acquired on different days. Furthermore, the EEG responses for all of the subjects have a common overall pattern. We performed experiments using simple stimulus patterns and determined the accuracy of predicting the EEG responses to these patterns using superposition of the edge responses. It was observed that based on some constraints on the shape of the stimulus sequence, the EEG responses are predicted with high accuracy. Later, we used this superposition concept in a BCI application and proposed target sequences that are made up of combinations of acceptable simple patterns. We then confirmed that if certain constraints on the stimulus patterns are met, the BCI application will give much better classification results.

The human brain is a complex and nonlinear system, and however, most of the cVEP based BCI applications are designed without considering the characteristics of brain responses. In conventional m-sequence based BCI systems, the EEG responses to circularly shifted versions of an m-sequence are formed by circularly shifting its EEG response [28]. Such systems assume that circularly shifting the input sequence causes circular shifting of the output EEG response. The m-sequence based BCIs are successfully and widely used. The BCI application based on the moving average model of the 250 ms window proposed by Negal et al. also performed quite well in predicting EEG response from stimulus sequences, and it shows that cVEP responses can be modeled by a moving average model at least for the purposes of a BCI application [29]. In our study, we have gone one step further to understand the system better and have investigated how well the brain complies with the superposition property. This is the first study to investigate the nature of brain responses to different visual pulse sequences to show that the brain responses follow superposition under certain constraints on the stimulus pattern. The observations are then used for designing optimum sequences for BCI.

One might think that imposing constraints on the structure of the stimulus sequences will limit the total number of targets that can be supported by the BCI system. Undoubtedly, the number of possible targets would indeed decrease. However, it still is a huge set, and a large number of targets can be introduced based on such stimulus sequences. Furthermore, we have performed experiments for only a few stimulus patterns, and we determined how well the EEG responses can be predicted for these stimulus patterns using the superposition principle. The stimulus patterns that have better prediction accuracy are selected, and the sequences are constructed based on these patterns in our study. Further studies can be carried out, and superposition property can be tested for many other patterns, and the patterns which can be predicted accurately can be introduced in the stimulus sequences, and as a result, it would increase the number of possible targets. The number of targets supported by our proposed BCI application is much higher than the number of sequences in a BCI based on m-sequences, where it supports only a limited number of targets depending on the length of the stimulus sequence. Furthermore, the proposed BCI application has a short training time because the training is done only for acquiring the edge responses, which are then used to generate the responses for all of the targets.

Out of the seven subjects that we have studied, six of them had very similar edge responses. Therefore, it may be conjectured that a universal edge response can be used for BCI without having to obtain the edge response of every subject. However, at this stage, until further studies are undertaken in this respect, we suggest that for every individual, a training session must be undertaken to establish his/her unique edge responses.

It should be noted that the EEG response of a stimulus sequence can be observed up to a duration of 350 ms, as we have discussed in the results section. In our BCI speller application, we are consecutively repeating the stimulus sequence two times in order to record the EEG responses for two consecutive trials, and the EEG responses from these two trials are averaged to improve the signal quality. However, the initial 350 ms data for the EEG response of the first sequence trial will get corrupted because there is no stimulus sequence before it. Therefore, we suggest using the last 350 ms of the stimulus sequence in front of the first sequence. It will prevent the starting 350 ms of the EEG response from getting corrupted and will further improve the accuracy of the BCI speller.

The EEG response from the brain mostly depends on the positive and negative edges of the stimulus sequence. Further, these responses have an initial delay of around 50 ms, and the response can be observed up to 350 ms after the edge. Furthermore, the edge responses appear to be similar to the step response of a low order system. Hence, further studies can be carried out in order to develop a model for the system. If such a model is found to be successful (applicable), then the training phase would comprise a parameter identification procedure. In our BCI application, we determined the similarity between the recorded EEG and generated EEGs of all targets using correlation. However, other methods can be used instead. For instance, from Figure 3.18, it can be observed that the predicted and recorded EEG have peaks near one another. Hence, they can be compared based on the location of these peaks.

The results that we have obtained not only serve for better design of BCI experiments but also shine light on the workings of the visual system regarding its linearity and shift-invariance properties. We hope that our results will give insight to researchers who deal with the fundamental aspects of the visual system in addition to application-oriented research such as BCI studies.

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Appendix A

Data Acquired During the Experiments

All of the experimental data acquired for this study is uploaded on the BCI harddrive of our lab and saved in the folder named “Superposition based BCI Speller”. The initial test experiments and their analysis codes are provided in the subfolder named “Initial Testing”. The stimuli sequence used in these initial experiments contains simple patterns and they were carried out to find the nature of EEG response to the visual stimulus. The main experiments for this study are given in a subfolder named “ExperimentData” and it contains the data for 7 subjects. Two separate experiments are performed on each subject and for the second experiment the folder name is given a prefix of “$_2$”. Hence, in the ExperimentData folder, the Sub01, Sub02, Sub03, Sub04, Sub05, Sub06, and Sub07 contains the experimental data of the first experiment and Sub01_2, Sub02_2, Sub03_2, Sub04_2, Sub05_2, Sub06_2 and Sub07_2 includes the experimental data of the second experiment of subject 1, subject 2, 3, 4, 5, 6 and 7 respectively. Each folder containing the subject data has a log file, which mentions the name of the subject, the type of experiment and the electrode impedance of the subject. Furthermore, in the ExperimentData folder, we have added an excel sheet (Superposition based BCI Results) which has the accuracy and information transfer rate of all of the subjects. Note, we have also included the experimental data in the CD submitted along with this thesis.

Appendix B

Software Used in Experiments and in Post-processing

The BCI setup is run on two separate computers: stimulus computer and recording computer. The stimulus computer is responsible for displaying the stimulus sequences for all targets to the subject and Matlab scripts are written for this task. These scripts are included in the CD with the name “Superposition based BCI Stimulator.zip”. Furthermore, Matlab scripts are written for the recording computer to acquire the EEG from the amplifier, these scripts are also included in the CD as a zipped file with the name ”Superposition based BCI Recorder.zip”.

Appendix C

Repeated Measures ANOVA and Paired t-test

C.1 Stimulus With Different Pulse Widths

The results of repeated measures ANOVA test and pairwise paired t-test on correlations obtained for different pulse widths are shown in the Tables given below.

Table C.1: Repeated measures ANOVA test on the correlations obtained for different pulses widths.

	SumSq	DF	MeanSq	F	pValue
(Intercept):Measurements	0.7428	8	0.0928	7.6067	1.6429e-06
Error(Measurements)	0.5859	48	0.0122		

Table C.2: Pair wise paired t-test on the correlations obtained for different pulses widths (PW). In this table, 1 shows that the data comes from different distribution, and 0 shows that the data is from the same distribution (at 5% significance level).

PW	1	2	3	4	5	6	7	8	9
1		0	1	1	1	1	1	1	0
2	0		0	0	1	1	1	1	0
3	1	0		0	1	1	1	0	0
4	1	0	0		1	0	0	0	0
5	1	1	1	1		0	1	0	0
6	1	1	1	0	0		0	0	1
7	1	1	1	0	1	0		0	0
8	1	1	0	0	0	0	0		0
9	0	0	0	0	0	1	0	0	

Table C.3: P-Values of Pair wise paired t-test on the correlations obtained for different pulses widths (PW).

PW	1	2	3	4	5	6	7	8	9
1		0.7479	0.0016	0.0160	0.0006	0.0096	0.0009	0.0119	0.0658
2	0.7479		0.0721	0.0696	0.0002	0.0034	0.0030	0.0067	0.1059
3	0.0016	0.0721		0.3963	0.0075	0.0350	0.0118	0.0764	0.6193
4	0.0160	0.0696	0.3963		0.0245	0.2888	0.5049	0.6484	0.6943
5	0.0006	0.0002	0.0075	0.0245		0.4510	0.0309	0.1023	0.0621
6	0.0096	0.0034	0.0350	0.2888	0.4510		0.4359	0.1616	0.0036
7	0.0009	0.0030	0.0118	0.5049	0.0309	0.4359		0.9320	0.2519
8	0.0119	0.0067	0.0764	0.6484	0.1023	0.1616	0.9320		0.1536
9	0.0658	0.1059	0.6193	0.6943	0.0621	0.0036	0.2519	0.1536	

C.2 Stimulus With Different Separations between 1 bit wide pulse

The results of repeated measures ANOVA test and pairwise paired t-test on correlations obtained for different separations between 1 bit wide pulses are shown in the Tables given below.

Table C.4: Repeated measures ANOVA test on the correlations obtained for different pulse separations between 1 bit wide pulses.

	SumSq	DF	MeanSq	F	pValue
(Intercept):Measurements	0.4488	8	0.0561	2.7829	0.01296
Error(Measurements)	0.9676	48	0.0202		

Table C.5: Pair wise paired t-test on the correlations obtained for different pulse separations between 1 bit pulses (PS1). In this table, 1 shows that the data comes from different distribution, and 0 shows that the data is from the same distribution (at 5% significance level).

PS1	1	2	3	4	5	6	7	8	9
1	0	0	0	0	0	0	0	0	0
2	0		0	0	0	1	0	1	0
3	0	0		1	1	1	0	1	1
4	0	0	1		0	0	0	0	0
5	0	0	1	0		0	0	0	0
6	0	1	1	0	0		0	0	0
7	0	0	0	0	0	0		0	0
8	0	1	1	0	0	0	0		0
9	0	0	1	0	0	0	0	0	

Table C.6: P-Values of Pair wise paired t-test on the correlations obtained for different separations between 1 bit wide pulses (PS1).

PS1	1	2	3	4	5	6	7	8	9
1		0.8899	0.8848	0.3044	0.1289	0.0552	0.4724	0.0866	0.1423
2	0.8899		0.7097	0.1669	0.1402	0.0270	0.3277	0.0250	0.0824
3	0.8848	0.7097		0.0236	0.0131	0.0079	0.1025	0.0036	0.0265
4	0.3044	0.1669	0.0236		0.5816	0.3783	0.5275	0.2726	0.4447
5	0.1289	0.1402	0.0131	0.5816		0.6125	0.3906	0.9343	0.8815
6	0.0552	0.0270	0.0079	0.3783	0.6125		0.1633	0.6196	0.7923
7	0.4724	0.3277	0.1025	0.5275	0.3906	0.1633		0.2023	0.0596
8	0.0866	0.0250	0.0036	0.2726	0.9343	0.6196	0.2023		0.9131
9	0.1423	0.0824	0.0265	0.4447	0.8815	0.7923	0.0596	0.9131	

C.3 Stimulus With Different Separations between 2 bit wide pulse

The results of repeated measures ANOVA test and pairwise paired t-test on correlations obtained for different pulse separations between 2 bit wide pulses are shown in the Tables given below.

Table C.7: Repeated measures ANOVA test on the correlations obtained for different pulse separations between 2 bit wide pulses.

	SumSq	DF	MeanSq	F	pValue
(Intercept):Measurements	0.77103	8	0.09637	7.3629	2.4356e-06
Error(Measurements)	0.62831	48	0.01309		

Table C.8: Pair wise paired t-test on the correlations obtained for different pulse separations between 2 bit pulses (PS2). In this table, 1 shows that the data comes from different distribution, and 0 shows that the data is from the same distribution (at 5% significance level).

PS2	1	2	3	4	5	6	7	8	9
1		1	1	1	1	1	0	1	1
2	1		1	1	0	0	0	0	1
3	1	1		0	0	0	0	0	0
4	1	1	0		0	0	0	0	0
5	1	0	0	0		0	0	0	0
6	1	0	0	0	0		0	0	0
7	0	0	0	0	0	0		0	0
8	1	0	0	0	0	0	0		0
9	1	1	0	0	0	0	0	0	

Table C.9: P-Values of Pair wise paired t-test on the correlations obtained for different separations between 2 bit wide pulses (PS2).

PS2	1	2	3	4	5	6	7	8	9
1		0.0011	0.0008	0.0008	0.0041	0.0056	0.0502	0.0064	0.0025
2	0.0011		0.0249	0.0197	0.1431	0.1176	0.7097	0.0880	0.0448
3	0.0008	0.0249		0.6112	0.6593	0.8567	0.2089	0.9616	0.5160
4	0.0008	0.0197	0.6112		0.2391	0.5147	0.0980	0.6616	0.5849
5	0.0041	0.1431	0.6593	0.2391		0.5676	0.1661	0.6437	0.1563
6	0.0056	0.1176	0.8567	0.5147	0.5676		0.1381	0.8580	0.4435
7	0.0502	0.7097	0.2089	0.0980	0.1661	0.1381		0.1882	0.0527
8	0.0064	0.0880	0.9616	0.6616	0.6437	0.8580	0.1882		0.3448
9	0.0025	0.0448	0.5160	0.5849	0.1563	0.4435	0.0527	0.3448	

C.4 Stimulus With Different Repetitions of 1 bit wide pulse

The results of repeated measures ANOVA test and pairwise paired t-test on correlations obtained for different repetitions of 1 bit wide pulses are shown in the Tables given below.

Table C.10: Repeated measures ANOVA test on the correlations obtained for different pulse separations between 2 bit wide pulses.

	SumSq	DF	MeanSq	F	pValue
(Intercept):Measurements	0.32518	4	0.081296	3.2185	0.029995
Error(Measurements)	0.60622	24	0.025259		

Table C.11: Pair wise paired t-test on the correlations obtained for different of 1 bit wide pulse (PR1). In this table, 1 shows that the data comes from different distribution, and 0 shows that the data is from the same distribution (at 5% significance level).

PR1	2	3	4	5	6
2		0	1	0	0
3	0		0	0	0
4	1	0		0	0
5	0	0	0		0
6	0	0	0	0	

Table C.12: P-Values of Pair wise paired t-test on the correlations obtained for different repetitions of 1 bit wide pulse (PR1).

PR1	2	3	4	5	6
2		0.2374	0.0481	0.0754	0.0817
3	0.2374		0.1591	0.1032	0.2768
4	0.0481	0.1591		0.6400	0.7765
5	0.0754	0.1032	0.6400		0.8157
6	0.0817	0.2768	0.7765	0.8157	

C.5 Stimulus With Different Repetitions of 2 bit wide pulse

The results of repeated measures ANOVA test and pairwise paired t-test on correlations obtained for different repetitions of 2 bit wide pulse are shown in the Tables given below.

Table C.13: Repeated measures ANOVA test on the correlations obtained for different repetitions of 2 bit wide pulse.

	SumSq	DF	MeanSq	F	pValue
(Intercept):Measurements	0.080398	3	0.026799	6.0311	0.0049883
Error(Measurements)	0.079984	18	0.0044436		

Table C.14: Pair wise paired t-test on the correlations obtained for different repetitions of 2 bit wide pulse (PR2). In this table, 1 shows that the data comes from different distribution, and 0 shows that the data is from the same distribution (at 5% significance level).

PR2	2	3	4	5
2		0	0	1
3	0		1	1
4	0	1		0
5	1	1	0	

Table C.15: P-Values of Pair wise paired t-test on the correlations obtained for different repetitions of 2 bit wide pulse (PR2).

PR2	2	3	4	5
2		0.9274	0.0837	0.0174
3	0.9274		0.0144	0.0061
4	0.0837	0.0144		0.1916
5	0.0174	0.0061	0.1916	

C.6 Stimulus With Different Repetitions of 3 bit wide pulse

The results of repeated measures ANOVA test and pairwise paired t-test on correlations obtained for different repetitions of 3 bit wide pulse are shown in the Tables given below.

Table C.16: Repeated measures ANOVA test on the correlations obtained for different repetitions of 3 bit wide pulse.

	SumSq	DF	MeanSq	F	pValue
(Intercept):Measurements	0.034933	2	0.017466	2.1593	0.15812
Error(Measurements)	0.097065	12	0.008088		

Table C.17: Pair wise paired t-test on the correlations obtained for different repetitions of 3 bit wide pulse (PR3). In this table, 1 shows that the data comes from different distribution, and 0 shows that the data is from the same distribution (at 5% significance level).

PR3	2	3	4
2		0	0
3	0		0
4	0	0	

Table C.18: P-Values of Pair wise paired t-test on the correlations obtained for different repetitions of 3 bit wide pulse (PR3).

PR3	2	3	4
2		0.0802	0.2257
3	0.0802		0.6917
4	0.2257	0.6917	