ENHANCEMENT AND OPTIMIZATION OF A MULTI-COMMAND-BASED BRAIN-COMPUTER INTERFACE

by

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A sub-culture that
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ABSTRACT

Brain-computer interfaces (BCI) assist disabled person to control many appliances without any physically interaction (e.g., pressing a button). BCI systems are still very limited especially with reliable application because, the mechanism of human-brain responses are not sufficiently understood. Steady-state visual evoked potential (SSVEP) is brain activities elicited by synchrony evoked signals that are observed by visual stimuli paradigm. The observant signals of SSVEP are presented as harmony oscillation responses provoked by gathering brain activities occupied in quest electroencephalography (EEG). These occupation signals contain fundamental frequencies and harmonics described by amplitude, magnitude and phase corresponding to base-frequency of visual stimulation. In this dissertation were addressed the problems which are oblige more usability of BCI-system by optimising and enhancing the performance using particular design. The prototype design includes SSVEP methodology paradigms of brain activities. Main contribution of this work is improving and increasing the reliability of brain reaction response of SSVEP paradigm depending on two focal approaches: (1) achieving maximum cortical brain responses to use further in BCI applications as multiple commands depending on visual stimulation which constrained by multiple frequency, different dynamic colours, regular/irregular paradigms, changing levels on duty-cycle and multi-patterns. Those various stimulation paradigms reveal growth activity by increasing the measurable SSVEP signals that enhance brain waveform responses based-BCI technologies; (2) developing adaptive sensitive algorithm to extract the features of weak SSVEP response from non-stationary signal that stimuli by aperiodic flicker oscillations using multi-threading process. In this study used variety visual stimulation that exploited the foundation of SSVEP to distinguish reveal features of brain responses. The approaches demonstrate the optimal frequency that achieves a maximum response from brain cortical. Furthermore, the presented work concerns three different dynamic colours that assess diverse effects on brain activities, allowing an improved and enhanced system design based on the lassitude of BCI users. Additional, this study applies a new paradigm of regular/irregular based-stimulation to explore the influences of brain response that directly increment the BCI-commands; beyond visual stimulations provide different duty-cycles and multiple patterns in specific condition to present pragmatic and continuous brain responses. These attribute are rendered methodology to enhance performance the BCI system. The research study has engaged offline analysis topography to reveal the features of human-brain capability by

discriminating between response activities based on SSVEP fundamentals. Similarly, a configuration and setting of all empirical studies has considered a symmetrical balance in each individual experimental study. Consequently, a promising result achieves greater applicability based on brain response that increased the BCI-command numbers and enhances the extrication of SSVEP response signals. In general, substantial differences between stimulation states that contributed many valuable characteristics in BCI-system performance. The outcome results suggest a particular design of SSVEP-BCI based system that provides the possibility of a more highly accurate and reliable system without user training. This result could lead to robust BCI application-based brain response estimates in unsupervised clinical and e-home environment settings, as well as in other challenges of brain-technology tasks in the service of society.

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LIST OF ABBREVIATIONS

AIB	Analogy Input Box
ALS	Amyotrophic Lateral Sclerosis
AVP	Average-voltage Process
ANOVA	One-way Analysis of Variance
BL	Baseline
BW	Brainwave
BCI	Brain-computer interface
BSS	Blind Source Separation
BMI	Brain–machine Interface
BPF	Band Pass Filter
CS	Cognitive-status
CBF	Cerebral Blood Flow
CCA	Canonical Correlation Analysis
CRT	Cathode Ray Tube
CSF	Cerebrospinal fluid
CNS	Severe central nervous system
CMR	Common Mode Rejection
CMS	Common Mode Sense
DS	Detection Signal
DBG	Donoghue's Brain-gate
DFT	Discrete Fourier Transformation
DRL	Driven Right Leg
DSP	Digital Signal Processing
DWT	Discrete Wavelet Transform
DNI	Direct Neural Interface
EEG	Electroencephalography
ECG	Electrocardiogram
EOG	Electrooculography
EMG	Electromyography
ERP	Event Related Potential
FFT	Fast Fourier transform
FIR	Finite Impulse Response
fMRI	functional Magnetic Resonance Imaging
FPGA	Field-programmable Gate Array
GUI	Graphic User Interface
HF	High-frequency
HT	Hilbert Transform
HCI	Human-computer Interaction
HPC	High Performance Computing
HPF	High Pass Filter
ICA	Independent Component Analysis
IFT	Inverse-Fourier Transform
ICP	Intracranial Pressure
ITR	Information Transfer rate

LF	Low-frequency
LED	Light-emitting Diode
LDA	Linear Discriminant Analysis
LGN	Lateral Geniculate Nucleus
LPF	Low Pass Filter
MT	Middle Temporal
MF	Medium-frequency
MEG	Magneto-encephalogram
MDD	Multi-dimensional Data
MRI	Magnetic Resonance Imaging
MMI	Mind-machine Interface
MND	Motor Neurone Disease
MVS	Multi-variate Sources
MDDP	Multidimensional-data Projection
NF	Nyquist Frequency
NTL	Non-time-locked
NIRS	Near Infrared Spectroscopy
PT	Phase-tagged
P300	P300-evoked Potential
PCB	Print Circuit Board
PET	Positron Emission Tomography
PTT	Phase-tagged Trigger
QAD	Quadrature Amplitude Demodulation
RHY	Rhythm-waveform
S.D.	Standard Deviation
SC	Stability Coefficient
SCPs	Slow Cortical Potentials
STI	Synthetic Telepathy Interface
SNR	signal-to-noise Ratio
SVM	Support Vector Machine
SSVP	Steady-state Potential
SSVEP	Steady-state Visual Evoked Potential
SWDA	Step-wise Discriminant Analysis
TM	Time-locked
TBI	Traumatic Brain Injury
TLE	Time-locked-event
TTD	Thought-translation Device
VEP	Visual Evoked Potentials
WT	Wavelet Transform
WPSD	Welsch-power Spectral Density

Chapter 1

Introduction

Brain-computer interface (BCI) is shared boundary across systems that obtained two separate units are represent on human-brains and certain machine such as computer system to exchange interaction information. The brain is the human-control centre that responds to observation and processes certain reactions. Different parts of the human-brain (lobes) are stimulated when a person focuses attention on a flickering spotlight, which creates an electric potential signal that reflects the neural firing of brain cells. These potential signals can be observed through recording signals based on electroencephalography (EEG). This technique of EEG is widely used to gather brain activity and providing an excellent temporal resolution, which is adorn as a non-invasive technique based on BCI system. The recorded signals from neurons are enabled to control definite actions using BCI methodology. The BCI structure is containing of communication system used the compute-system based-software/hardware co-design. These kind paradigms allow control of any electronic device, such as wheelchair-motorised, prosthetic limb, or any other elec.-device. The steady-state visual evoked potential (SSVEP) is a classified as responses that presents the influence of brain activities which attractive with external visual stimuli. In this dissertation were focuses on increasing the number of brain reaction responses by optimising and enhancing the feature of extractions using SSVEP paradigms. In additions, different empirical approaches have been described based on diverse categories, such as multifarious frequencies, three different colours, several duty-cycle levels, and multiple patterns, which thereby affect to increase the BCI commands and enhance to adapt algorithm that extract reaction based-multiple computing.

1.1 Research Motivation

Some serious diseases such as spinal cord injury (SCI) or amyotrophic lateral sclerosis (ALS) restrict the human-neural pathway-system. Nowadays, support disabled people to control the electronic/electronic machines, such as a computer, wheelchair and artificial-limb using (gaze tracking technique system or control stick held between the teeth) which are allow to control and enabled to move cursor computer monitor. However, not all these devices are convenient to use. Therefore, there are good alternative input devices based on brain-computer interface (BCI) that establish a control system depending on direct communicate channel between machine and human-brain. The BCI technique is assist the incapacitated-person and increase the productivity of healthy people based on brain technology. In BCI systems, the human-brain response signals are processed and acquired to extract specific features that reflect the user's intent. These features are translated into certain reaction based-BCI commands to activate device operations.

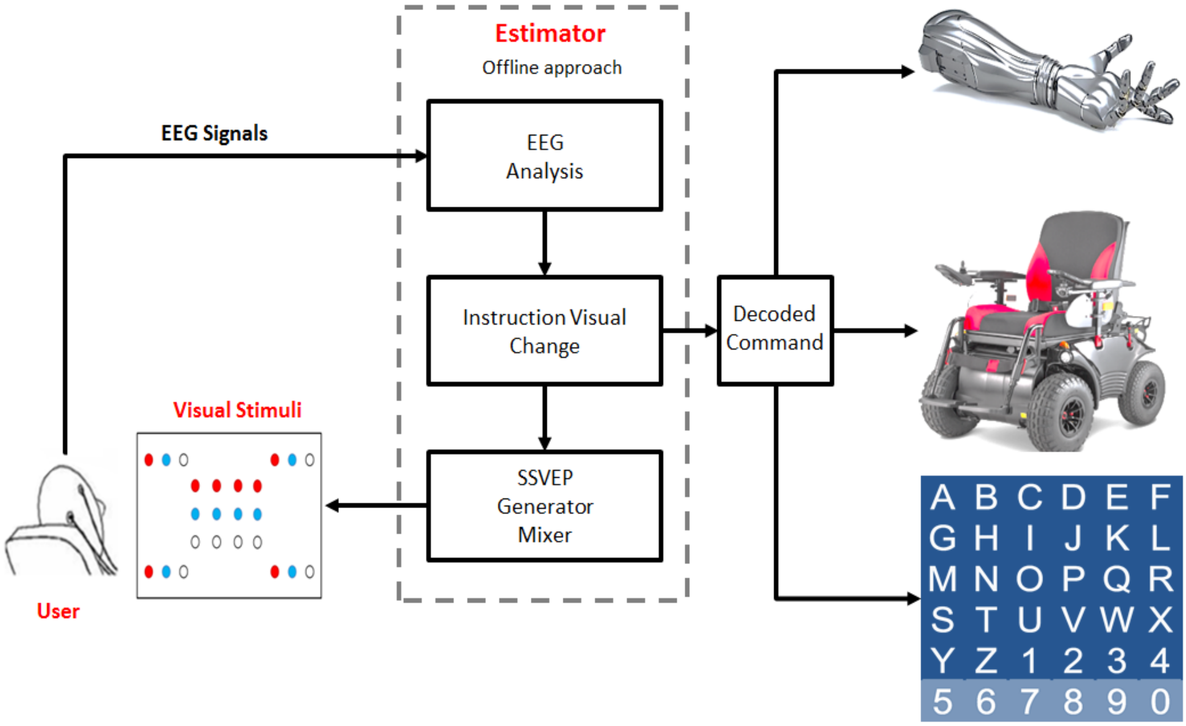


Figure 1.1: Common structure of based brain-computer interface (BCI) system [170]

This contribution work of this dissertation is motivated to employ the BCI technique to improve brain responses by increasing reaction-command number based-system; however is enhancing the feature extraction based on multiple analysis approaches. Figure 1.1 shows the main structure of BCI system, which includes the stimulation panels of visual stimuli and gathered brain activities to amplify and digitize the signals. The brain response activities are extracted and translated into different commands by a decoded the pertinent of EEG signals. Those BCI-reactions are representing a control commands signals, which are dominate on certain device, such as wheelchair (motorised), or prosthetic-limb controller or speller alphabet device. Particular, the EEG raw signal has commonly used to recognize and extracting the dynamic responses of brain activities. One such a method based on the steady-state visual evoked potentials (SSVEP), which is represented the extraction brain responses paradigm. The SSVEP paradigms can be recorded during visual stimulus, which is directed effect on brain responses with respect to frequency of flicker-light. Since the visual stimulator plays an important role, it can be presented on a computer screen using flashing spotlights or flickers grids of (LEDs) that allow to consider different stimulation parameters such as pattern, frequency and position. However, the present flickers of standalone lights/LED is more flexible than a computer monitors because, the number refresh/frame of screen-monitor is always limited by flicker frequency and non-stability that restricted by refresh rate of monitor type. Therefore, the LEDs flicker (light/spots) with band of frequency and pattern with respect of phase-tagged triggers (PTT) is support to indict the temporal and phase of that response. The promising assessment of existing SSVEP based BCI systems cannot realize full potential signals due to difficulties of low signal to noise ratios (SNRs) extraction based on a single trial of gathered EEG signals. Although, the multiple trials are prevented to increase the number of BCI commands because time evoked stimuli signal with respect to EEG recording; however, decreasing EEG electrodes based on brain region is optimally more convenient which are typically used in BCI-systems

1.2 General Problems Statements based on BCI techniques

Brain-computer interface (BCI) researchers invariably face substantial problems. In general, any types of non-invasive BCI design system still a way to achieve a robust reaction of brain responses based on BCI-system design, due to several important issues, namely:

- The feature of signal response is uncompleted extraction and hard-classification that restrict incoming results especially when increasing the BCI reaction commands
- Low signal-to-noise-ratios (SNRs) based on single-stimulus-trial which essentially require a long-time that exhausts the BCI user from intent onset recognition
- Inadequate of brain response to recognition due to undesirable signal of inter-brain activities of artifacts that decreased reaction command numbers based-BCI design

- Demand more pay-attentions on stimulation paradigm to evoke powerful brain activity which generates fatigue and neglect because of distortion response signals
- Continuous attentiveness procedure will lead to increase exhaust and fatigue the BCI-user after few work-hours operation that minimal distractions the brain activities
- Bulky and expensive equipment which are employed to build a BCI system leads to a complicated computational analysis of extraction features and difficult configuration and usability

1.3 SSVEP Paradigm Problems based on BCI techniques

In this study, have been concerned the brain reaction response signals, which are exploited based on steady-state visual evoked potential (SSVEP) paradigms. The SSVEP response is elicited from the brain cortex. However, this paradigm easily extracts features from brain activity responses, which are dependent on synchrony by observing flickering of visual stimuli. Additionally, the SSVEP approach provides a good advantage based-BCI design, because this type of paradigm affords a high brain response in terms of executed time and conversely with other paradigm types. Correspondingly, the disadvantages revealed in SSVEP paradigm based on BCI tetralogy are summarised by:

- Strenuous to adjust and setup the adequate flicker (spot light) of based on band of multiple-frequency in each stimuli to evoke strong SSVEP response signal
- The stimuli of flicker LEDs are closely to each other which prompt higher eye artifacts and increase user fatigue
- Reduce the electrodes numbers of acquisition data which are acquired from brain-lobes lead to confer a decent insight signals that enhanced the BCI performance
- Need to understand of perception on SSVEP mechanisms that enhancement the reaction of brain responses to increase commands based-BCI system
- Extraction signal feature using a complicated method based on signal processing process with respect to parametrization of frequency that increased the analysis and extraction time
- Existing SSVEP-based paradigm have not sufficient ability to realize the desired potential signals, due to a weak occupier protrusion of brain responses that are gathered from complicated EEG signals based on a single-trial stimulation

1.4 Contribution and Addressing Problems

In these empirical studies were depending on existing SSVEP response signals with a low-cost BCI prototype that has used 24 flicker LEDs representing as flicker spotlight. A multiple stimulations paradigm has been used in order to evoke a sufficiently robust, measurable brain response. These paradigms cover most visual stimulation, which are extracted from brainwaves based on activity and response; however, reduce the tiredness and fatigue of BCI-users that are increased the artifacts and restrict extract feature to enhance performance. In addition, most brain-computer interface is implementing as system that have fulfil the main criteria based on BCI categories [5]. The thesis addresses the existing problems, which are described in the previous sections. Therefore, a practical design of BCI prototype was created to remove obstacles artifacts and engage to extract feature based on offline analysis. This contribution work is present a laboratory research that proved a new approach based-BCI design. The outcome results pursuing the aims of this thesis contribution that are presented in two main objectives:

- Evaluate to optimise a different stimulus paradigms that achieve a maximum cortical response at different brain region to be further used in BCI-applications based on various empirical studies. Estimate a paradigm that used different frequency, diverse colours, regular/irregular of periodic and non-periodic stimulation evoked signals; however, easement dissimilar duty-cycle levels; in addition evaluate a multiple patterns stimulation effect. All these experimental studies have been implemented to increase and enhance the measurable signal that contents a SSVEP-response, which substantially incremented the BCI-command numbers based on the reaction of brain activities. Thus experiments are reveal growth to use in brain technologies based on the these contribution of different studies
- Improve adaptive extract algorithm that depends on multi-thread process using new approach. This assessment is discipline a parallel computing to overcome the problems of execution time and extract a weak protrusion SSVEP response. The high-speed computational is robust analysis that used to disentangle reactions from massive non-stationary EEG signals in terms of execution time consumption. High performance computing (HPC) was evaluated based on BCI techniques, and implement the algorithm to improve the processing based on a large amount of EEG dataset dependent on multi-thread processing with open source-library (OpenMP)

The experimental studies and stimulation setup stabilized production the provocation signals to represent consequence brain activities, which rapidly change according to visual stimuli. The promising assessment of the main hypothesis pursued items that are needed to increase the number of BCI reaction-commands, subsequently compatible to use in BCI-system, which can be recognized as certain commands corresponding to brain activities. The substantial SSVEP problems based BCI addressed in this contribution work are as follows:

- Reduce the numbers EEG channels that are used of gathering active responses at sensory cortex region of occipital-lob of brain: optimize pre-design a new BCI based-SSVEP paradigm that used a minimal number of unipolar EEG channels (see chapter 3, section 3.1)
- Objectively measured the EEG signals to find out the optimal stimulation frequency towards selection of effect band frequency that provides a higher amount of brain activities based-SSVEP response; and minimize visual obstruction though evoke-process of SSVEP at different frequencies (chapters 3 and 4, sections 3.2, 4.1)
- Estimates latencies of time delayed based on the dynamic-time analysis to increase BCI active-commands and decrease distortion of responses using a three different colour stimulus; and exploit the influence on brain activity with respect to phase shifts of each stimuli actions (see chapter 4, sections 4.2 and 4.3)
- Achievement a robust signal of SSVEP response based on diverse duty-cycle level stimulation; and evoked brain activities by proposing three different stimuli duty-cycle paradigms that are adapted to comfortable the BCI users; however, enhance the extracted signal feature by removing the artifacts using ICA technique and high response filter such as finite impulse response (FIR) (see chapter 5, section 5.1)
- Evaluate strong measurable signal based-SSVEP response using regular/irregular paradigms and multiple pattern stimulations, leading to a novel dynamic brain responses that increases amount of BCI-command (see chapter 4 and 5, sections 4.3 and 5.2)
- Instead to decrease execution time of extraction and analysis, evaluate algorithm based on high performance computing (HPC) with multi-thread processing depend on OpenMP lead to high-speed computational performance on large amount of EEG dataset (see chapter 5, section 5.3)

Table 1.1 describes the summarized comparison between the new approaches, which are presented in this thesis and previous research work. However, the thesis presents the objectives pursued as two main goals directions:

Table 1.1: Comparison between approaches based on this thesis and previous work

Employed Material	This Thesis Work	Previous Work
Brain locations Sensor	Yes base brain region of : ▪ Frontal ▪ Partial left/right- temporal ▪ Occipital	Yes base brain region of : ▪ Frontal ▪ Partial left/right- temporal ▪ Occipital
Decreased number of EEG Channels	Yes, employed Three-electrodes without references	Yes, at least nine-electrodes without references
Minimize eye and other interference artifacts	Yes, ICA based technique and FIR filters	Not all studies have been employed
Study of SSVEP properties	▪ Frequency response curves and power ▪ Time dynamic based SSVEP ▪ Duty-cycle Effect of SSVEP responses	No
Regular/Irregular stimuli effect	Yes, based Frequency and Time Domains analyses and extraction	No
Colour SSVEP Stimuli to increase commands and reduce user fatigues	Yes, using three Colours based stimuli	No
Increased number of SSVEP Commands based BCI	Yes, 4 – 24 Commands based SSVEP	Yes, 1 – 4 Commands based SSVEP
Stimuli a Multiple patterns based SSVEP	Yes, more than 12 patterns have been used	No
Clustering the SSVEP response based multiple and single core process	Yes single core and multiple using OpenMP as HPC	Consider a single Core
SSVEP based BCI ITR	No	Yes

1.5 Organization of Dissertation and Structural

The thesis contents six chapters that described approaches and results; however, the appendix and related-work that conclude important information based on research that organized as follows:

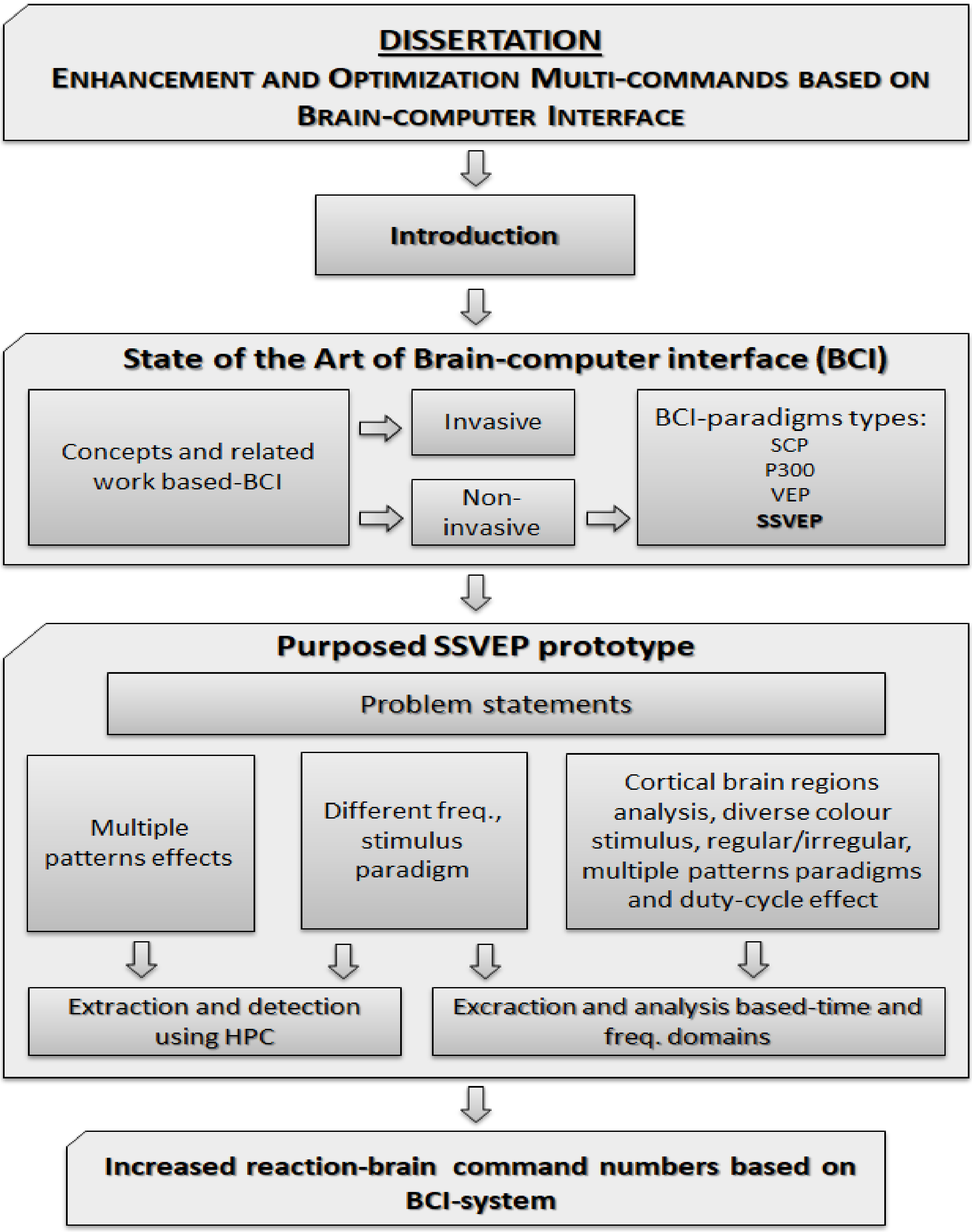


Figure 1.2: Dissertation structure illustrating research path

Chapter 2: Surveys the state of the art and outline of EEG gathering signal techniques, by exploring background knowledge. This chapter also introduces extract information regarding brain-interfacing technology through essential EEG acquisition signals based-design BCI systems. In addition, the chapter focuses on the concept of classified brainwave that including structure and extraction method.

Chapter 3: Discusses the adaptive efficiency of visual stimulus system, which is describes by a low-cost prototype that used 24 flicker-dot employed with all experiments. The propose design of prototype based on SSVEP of BCI-system is including the hardware equipment and software even tools that configured with different stimulus performance. In addition, data acquisition of raw EEG signal, which is scheduled recording based on individual time and stored as accumulated template technique. However, utilise pre-processing to clean-up the accumulate raw-data from any artifacts then stored again as new-dataset. Furthermore, explore the brain region regarding variant band frequency which exposure an adequate response with respect to SSVEP paradigm.

Chapter 4: Explore the efficient of visual stimulus with different evoked signals through stimulation LED-flicker paradigms, which provide a different characteristic based on analysis of brain activity. The SSVEP response is elicited by existing iterate stimulus flicker at set of frequencies. The frequency at three bands of low frequency (LF), medium frequency (MF) and high frequency (HF) are direct exploit SSVEP responses with respect brain activities. This chapter discusses the effective frequency band that provides a stronger brain activity response. Beyond the stimuli frequency bands, the influence of three colours on brain activities directly affecting SSVEP responses is debated. Furthermore, two contrasting stimulation paradigms are presented as regular/irregular to discover the oddball/flicker and orderly/flicker effect on the brainwave, depending on brain activities. The criteria of frequency, colour and oddball paradigms are all applied to diverse experiments to determine response contiguous to a range of parameters that yield optimally strong and broadest level based SSVEP response paradigms.

Chapter 5: This chapter inspects three empirical studies that discuss brain influence based on duty-cycle and multiple patterns based on extracted signals of SSVEP responses. The SSVEP are increasingly used in brain–computer interface techniques. The duty-cycle study is explored at three intensity levels of flicker LED, which are a deliberately deceptive effect in three different stimuli session to analysis of extracted feature from brainwaves. Furthermore, employing a novel multiple patterns technique supports the analysis methodology in respect of execution time to distinguish between detected phases of each stimuli pattern. The multiple patterns technique based BCI requires extraction of a specific signal of SSVEP response from a huge dataset. This problem has been solved by analysing datasets in parallel on multiple processor cores using the OpenMP standard for shared memory programming [xxx159]. However, the high performance computing (HPC) based on BCI presents a reasonable solution that has improved the rapid process of a large amount of dataset dependent on multiple threads of processor-cores that are used with the open source library of Open Multi-processing (OpenMP).This thesis focuses on an integrated approach to enhance and optimise SSVEP response based brain-computer interface technology. Figure 1.2 illustrates the dissertation structure in investigating brain activity, continuous visual flicker stimulation with ordinary LEDs. In addition to discussion, the results were applied to designing a prototype that optimised paradigms using several stimuli models (Chapter 4 and Chapter 5). In this work, assorted novel concepts are introduced and different innovations explored, in order to construct an acceptable new type of BCI-system that is efficient as a user-friendly based brain-computer interface technique

1.6 Achievements Summary

The thesis has achieved a substantial enhancement and optimization of the SSVEP based paradigms that extract cortical visual responses using signal processing algorithms, as well as achieving superior reliability of multiple command summarised in the following a main conclusions:

- Evaluation of stimulation paradigms using ordinary 24-LEDs showed measurable SSVEPs signal to be elicited and a reliable prototype design dependent on a single-trial provided brain activities according to the evoked responses. However, user training based setup and configuration were unnecessary; since the setup evoked SSVEP within some factors dependent on the topic research, (see section 3.1.1).
- The SSVEP responses depending on paradigms were estimated by selecting diverse brain-regions at frontal, partial left/right-temporal and occipital sensor cortex brain locations to reduce electrodes, although compacting the strength, reproducibility and stationarity (see section 3.1.2)

- Performed the SSVEP dynamic response signals based onset delays at the first peaks, and stationarity waveforms were strongly dependent on stimulation of multiple frequencies based on analysis of brain waveform bands, (see sections 4.2.1, and 4.3.1)
- Assessment SSVEP signal based frequency domain providing responses respect to spectral analysis at 2Hz – 35Hz for flicker LED stimuli were studied to extract the optimal frequency range which are determined by 5Hz – 13Hz, referred to (see sections 3.2.1, and 4.1.2)
- Throughout stimulation based six-variant frequencies were compared at (2, 4, 8, 10, and 12Hz) which were overlaid on alpha-band of brain waveform; whereas, 10Hz response exhibited the fastest stimuli-onsets and maximum signal stability, (see section 4.1.2)
- A new paradigm based on single-trial using phase-tagged trigger (PTT) variability value was found by offline analysis; furthermore, supplemental measurement of sensitive SSVEP signal according to stimuli-onset was shown. This approach provided energy based measure of FFT and ERP analyses methods, (see section 4.2.1)
- Onset stimulation based on single-trial SSVEP responses were achieved and detected between 0.05 second and 0.5 second which is evaluated using a multiple colour oscillation paradigms; however, the different phases were given as new attitude based-ERP waveform which measured based-latencies, (see section 4.2.1)
- Due to the colour stimuli based SSVEP of BCI design the visual field obstruction was substantially reduced as long-term of user fatigue, (see section 4.2.1)
- Assessment was made of two different paradigms by regular/irregular, which offered important features of stability and reliability responses respect to desirable extraction methods, (see section 4.3.1)
- Estimates were made of the distribution energy of fundamental frequency and harmonic in SSVEP based duty-cycle effect, which improves user comfort and attentions during the sessions, (see section 5.2)
- The behavioural multiple-stimuli patterns on brain waveforms were realized using spectral power analysis and phase shifting signal extraction based-approach, (see sections 4.2, and 5.2)
- Improved analysis was applied based on computational algorithm design using the HPC to compute and recognition based-patterns in comparison and sliding-windows approach, (see section 5.3)

1.7 List of Publication based Thesis Contributions

Most results in this thesis work were published in conferences and journals as follows:

- New Paradigms for Brain Computer Interface Based on SSVEP, 2014 World Symposium On Web Applications and Networking, ISBN: 978-0-9940194-1-7
- Exploiting a Short-Terms Adaptation: In Brain Computer Interface Based on Steady State Visual Evoked Potential, 2014 NNGT: International Journal of Information Systems, ISSN Online: 2356-5888
- Beyond Pure Frequency and Phases Exploiting: Color Influence in SSVEP Based on BCI, Computer Technology and Application 5 (2014)
- Discriminate the Brain Responses of Multiple Colors Based on Regular/Irregular SSVEP Paradigms, Journal of Medical and Bioengineering 2015, 5.2.89-92/2016 Journal of Medical
- Recognition a Multi-pattern in BCI system Based SSVEPs, ERK'2015 conference, IEEE Slovenia section, ERK'2015
- Multiple frequency effects on Human-brain based Steady-state visual evoked potential (SSVEP), 2016 IEEE 6th International Conference on Advanced Computing, 978-1-4673-8286-1/16 $31.00 © 2016 IEEE
- Rapid Computation and Analysis using a Multiple Core to enhance SSVEP based system, notifications (accepted) in IEEE society on 01 Sep. 2016, presented in NGCT-2016 on 15.Oct. 2016
- Duty-cycle beyond Three stimulation frequencies effect based on evoked signal of SSVEP paradigms (accepted) in IEEE on 21.Sep. 2016, presented in ICCES conference at 22.Oct. 2016
- Embedded SSVEP Based on BCI, Poster – locally presented, Institute of Computer Science, Adaptive and Regenerative Software Systems, Universität Rostock, Konrad-Zuse-Haus

CHAPTER 2

BCI SYSTEM CONCEPTS AND PREVIOUS RESEARCH

This chapter is a survey and state of the art of EEG signals based brain-computer interface (BCI) technology. Advances in BCI based brain activity technologies have begun to provide the ability to interface directly with the human brain. Human-computer Interaction (HCI) introduces the idea of a direct communication channel via (electrical-potential) signals, which are produced by the brain's activities. In three decades, BCI based systems have rapidly increased by drawing from many other applications. This chapter discusses various approaches and methodologies that are employed to realise a fully functional based-BCI system. There are different approaches of practical BCI field that submit diverse concepts depending on integrated productivity with new human interactive technology. Furthermore, this chapter introduces the performance metrics that can be used to evaluate BCI systems based on various paradigms.

2.1 Brain-computer Interfaces (BCIs)

Nowadays, advances in technology and signal processing techniques provide BCI researchers with a new view that allows further growth in BCI technology. Understanding of brain functionality enables progress in specific purposes based on BCI techniques that provide greater control in embedded-elec. units, such as artificial limb or motorised wheelchair controller. The BCI can be defined as a communication and control channel that is not dependent on the normal pathway of nerves and muscles [100]. Sending a message and commands through a BCI system is based on brain activity and response signals. Recently, brain-computer interface has been used as a communication system that depends on electroencephalography (EEG) raw encryption signals [102]. The EEG signal acquired from certain brain locations reconstructs hand movements that require different statistical solutions [107]; and EEG rhythms are classified into different frequencies based on brainwave forms [108]. In general, most BCI applications classify and divide accuracy and features by applying certain algorithms that employ a specific purpose [107]. Furthermore, BCI not only supports disabled people, but has also improved use by enabled people in high precision robot control and intelligent-vehicles. By evoking signals based-visual stimulus, the brain generates and activates electric-potential signals that are detectable to control embedded device, such as computer or any other electronics device. A well-known method of spectrum analysis in general converts the biomedical signal to frequency domain or spectral density estimation [101]. However, there are some methods of analysing EEG raw signals that can be applied in the time domain or in both time/frequency domains. The EEG signals contain convenient information about brain activities and responses, but it is very difficult to extract this information directly. Therefore, it is necessary to extract features using signal processing techniques. Most BCI-based systems prefer use recording signals from EEG electrodes, which reflect the potential of brain cortex [100]. Exploring EEG signals based on brain-computer interfaces (BCIs) has involved increasing the signal amplitude [103]. It is important to acquire brain activity signals through amplifiers and filters which decodes and classifies using an algorithm [104]. In practical terms, brain response based activities are a discrete reward response of brain activities. Thus, activities, signals and feedback from consequent brain response, carried-out to control the device, tend to form an essential part of a successful BCI system, which commonly contains sensory stimuli, such as visual [105] or auditory [106] attention, proportionally varying in response to discrete brain activity.

2.1.1 Brain-computer Interface (BCI) Definition

A brain–computer interface (BCI) is sometimes called a brain–machine interface (BMI) [110], mind-machine interface (MMI), synthetic telepathy interface (STI), direct neural interface (DNI) [111], or human-computer interactions (HCI); all these abbreviations can be defined as direct communication routes between the human-brain and the external environment of electronic peripheral devices. In other words, the brain-computer interface (BCI) or any brain-to-machine communication system can interpret and execute intended brain reaction-commands without dependence on normal executive pathways of the human-body, such as neural brain cell, muscle cells or nerves [112].

2.1.2 Importance of Brain-computer interfaces (BCIs)

The brain-computer interface (BCI) is a communication system connecting between the brain and external world that enables brain signals to directly control the specific device by evoking activity based on brain responses using stimulation concept. The target clinical population for BCI treatment is constructed primarily for patients with amyotrophic lateral sclerosis (ALS) and severe central nervous system (CNS) damage, including spinal cord injuries (SCI), with substantial deficits in communication and motor-function [120]. A brain-computer interface (BCI) is technology that allows a human brain to control a computer with focused attention. By evoking visual stimulus brain generates an electric signal called a detection signal of evoked potential or evoked response that correlates to control certain computer/commands. BCI is very useful in neural implants, such as a 'cochlear implant' that supports people who have impaired hearing, by directly transmitting auditory signals into the brain using a visual stimulus. Moreover, cortical brain stimulation and deep brain stimuli are both used to help people who suffer from Parkinson's disease which causes shaking palsy. The future of BCI technology is very effective, since it has demonstrated safe use even with wireless power devices, and the possibility of involving complex stimulation patterns that increase responses. At the European Research and Innovation Exhibition held in Paris in June 2006, the Brunner research group sent a simple message by concentrating on a display that identified a specific letter (alphabet)/character. The Brunner BCI system confirmed a method called the Wadsworth-system [81]. The Wadsworth is a training stimulation technique that adapts an algorithm depending on facilitated visual stimuli-pattern providing a communication channel between humans and machines. This technique was very useful and increasingly efficient with practice training times.

2.1.3 Brain-computer Interface (BCI) Requirement

The electroencephalogram (EEG) is defined as a clinical diagnosis for brain sicknesses. Furthermore, the EEG signal enables the BCI technique in research and application. BCI is an impressive technology that establishes a new communicative pathway. Neural-signals are commonly used through video stimulus or voice stimulus, depending on biofeedback in most measurable EEG signal based BCI practical systems. The main approach of BCI systems was configured with respect to biofeedback therapy, which involves training sessions for volunteers (subjects). This approach allows control and process, based on recording signals using biomedical instruments such as electromyography (EMG), electrodermograph (EDG), electroencephalograph (EEG) and electrocardiogram (ECG) [101]. Some of electrodes, such as EEG channels are placed on Human-scalp of a patient/volunteer (subject) to measure the brain signals. The EEG signals are analysed by a process of decomposing the raw signal into simpler branches by the extraction of quantifier classification according to various actions. These actions can be in the contour of amplitude of power intensity or different phases. The extract command is used for a specific task, such as limb movements. The computers detect and classify these EEGs, using specific algorithms based on different tasks in order to control application.

2.1.4 Brain Activity Rhythms

The human brain tends to follow the different frequencies and harmonious item called brain activities rhythm characteristic that detected based on EEG signals; when listening to a piece of music with a fast tempo, the brainwaves distribution increases and decreases when listening to low/high tempo (music). Furthermore, the periodic flashing spot lights in front of human-eye are stimulates the brain, causing the coordination of brainwaves with respect to a similar frequency of light flashing. The faster flashing increases the rapidity of brainwaves. Billions of neurones are firing together which generate an oscillations and fluctuation presented a different brain activities. This frequency follows the effect of brainwaves, which respond to rhythmic stimulation, as shown in Figure 2.1. The most frequencies are assessing with electroencephalography (EEG) based brain activity.

- Delta, δ: Wave lies between the ranges of 0.5-4Hz that observe the highest amplitude in respect of waveform. It is primarily associated with deep sleep, serious brain disorder and in the waking state [117], [118].

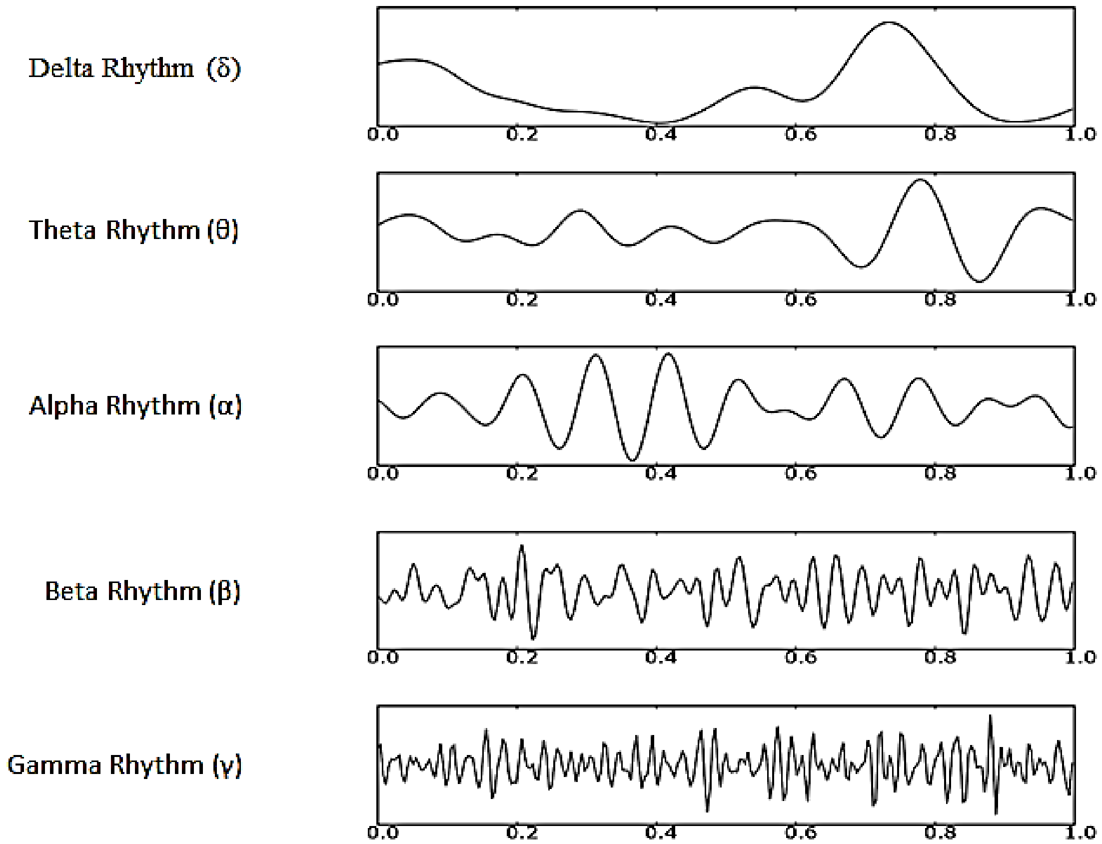


Figure 2.1: Different rhythms descried Delta, Theta, Alpha, Beta, and Gamma [http.wikipedia.org]

- Theta, θ: Wave lies between 4-8 Hz with an amplitude usually greater than 20µv. Theta arises from emotional stress, especially frustration or disappointment and unconscious material, creative inspiration and deep meditation [117], [118].
- Alpha, α: Contains the frequency range from 8-13 Hz, amplitude 30-50µv, mainly appearing in the posterior regions of the occipital lobe (brain region), usually associated with intense mental activity, stress and tension. Alpha activity recorded from sensorimotor areas, is also called mu activity [117], [118].
- Beta, β: Is in the frequency range of 13-30Hz, low amplitude and varying frequencies symmetrically on both sides in the frontal area. Beta waves are characteristics of a strongly engaged mind. Beta wave is usually associate with active things, active attention, and focusing on the outside world or solving concrete problems [117], [118].
- Gamma, γ: Wave lies above 30 Hz, this rhythm is observed on maximal frequencies within 80Hz or 100Hz. The Gamma wave associates with various cognitive and motor functions occurring during sensory processing of sound and sight [117], [118].

2.2 Brain-computer interfaces (BCIs) Types

The fundamental of BCI-system is recognizing by individual stage. These stages are represented in different levels such as stimulation, gathers-data and finally analysis and extraction features. Therefore, the electroencephalography (EEG) is records the electrical-potential activity among the brain cortical that is produced by the firing of neurons which is stimulated under some conditions [90] which present individual levels. Jacques Vidal, a computer scientist who is a researcher at UCLA, described the principles of direct brain-computer interface (BCI) technique [113]. Subsequently technique is extract the result using online BCI implementation within (Four-BCI commands) [114]. Vidal used visual evoked potentials (VEP) that elicited a brief illumination of a checkerboard estimate in order to control a certain moving courser-object in a maze. The signal processing methodology awarded classification module based on acquisition of EEG raw signal. Edmond Dewan [115] described the first accounts in BCI as a communication channel between human-brain and machine. Edmond's experiments extracted the alpha waveforms and converted the brain response to send a control-signal corresponding to the (Morse code). However, the recording technique of EEG signal does not provide a unique EEG pattern, according to different user' intention. Practically, the brainwaves discern the evoked signal of visual stimulations using higher techniques of signal processing approach.

The spontaneous EEG signal refers to the measurement of persistent brainwaves, which include Delta, Theta, Alpha, Beta and Gamma; on the other hand, the evoked signal represents periodic brain potentials as a short-duration reaction corresponding to recorded brain response to specifically evoked stimuli, such as a visual stimulus or auditory effort. In fact, the BCI task based system can be classified into two main categories:

1. The first category (internal support) is specified by a mental state-paradigm based modification of unprompted brain response activity. The mental state BCI paradigms are also defined as Cognitive-Status (CS). Unfortunately, both approaches have a limited task range based design system [92]
2. The second category is an external support, which is modified by normal brain responses based on the function of visible stimulus that provides appropriate brain activities. Evoked stimuli correspond to a selection of concordant attention to choose a certain target which is recognizable through detection by brain response [93], [12], [13], and [28]

Table 2.1: Consequence of internal and external supports summarised based on related work

Refer to feature	Driven by internally/externally
Large Number of Commands	Externally-supported stimulus response
High Reliability of Commands	Externally-supported stimulus response
Short User Tuning Short Training	Externally-supported stimulus response
No Stimulation Equipment Necessary	Internally-supported
No Sensory Engagement Necessary	Internally-supported
Resistant to Mental Fatigue	Externally-supported stimulus response
Switch On/Off	Both Internally/Externally -supported
Resistant to Distraction	Both are Not -supported
Resistant to Neurological Disorders	Both Internally/Externally -supported
Attractive User/Neurofeedback Interface	Both Internally/Externally -supported
Comfortable for User	Internally-supported

The (internal) and (external) supports based on BCI task paradigms are strict controls and imposed using well-known cognitive imagery processes, such as motor imagery; however, external support is a robust phase-lock that is responsive to stimuli-based brain responses that are reliable and detectable from single stimulus/trials, such as SSVEP paradigm. Considering several paradigms of BCI system designs as related work, there are a number of methods that include features driven in both internal and external supports. These are presented in Table 2.1. Parts of BCI systems are dichotomies in two main classification categories, which are dependent on principal brain signal acquisition [29]:

1. Invasive signal recording of neuronal activities these techniques need a medical surgical operation to implant an electrode
2. Non-invasive measurement of reflecting signals; these techniques are highly attractive in large scale of neuronal activations using an external sensory such as EEG, and fMRI

2.2.1 Invasive BCI Technique

Recorded neuronal spike reaction potential-signals were measured using an array of tiny electrodes that are implanted inside brain tissue. Since 1996, Kennedy's group at Neural Signals, Inc. began implanting a special cone-electrode with bowl-shaped tips growth in the neural tissue of the brain [30]. The research group test was conducted with a voluntary (subject) equipped with an invasive BCI based system; the subject could control a computer cursor and spell three letters (alphabet)/minute [31]. Invasive BCI technique studies have demonstrated that it is possible to increase the complexity usage of direct neuronal activity to transfer information, such as the remote control of a TV-set or a computer cursor, which are designed by Donoghue's Brain-Gate device [4]. The entire operation of a robotic gripper arm is controlled by optimizing brain signals from visual feedback [32], [33], and [39]. The procedure of the invasive approach benefits from implementing a local electrode field potential that reflects the activity of definite neurons group to expedite a signal from subdural or epidural regions under the skull to control a computer cursor, for example [99]. Recently, the restriction controlled signal based BCI systems have become complexes that lead to the involvement of a high-level signal processing. Nevertheless, the invasive methodology involves particular clinical risk and technical difficulties. For example, this technique may introduce an infection as a result of contamination from the external environment during a clinical operation, or making damage inside the human-brain; moreover, the region may become inflamed because of a foreign substance. From this point of view, the instruments and requirements are very costly and there is potential danger in conducting a surgical operation in order to implement electrodes for practical BCI systems. Researchers tend to veer away from invasive BCI systems as long as invasive recording techniques remain complicated and require an intricate procedure. Table 2.2 shows a summary of invasive technique based on BCI studies reviewed.

Table 2.2: Summarised invasive technique based BCI system

Approach	Description
Implanted Neurotrophic Electrodes	Control the neural signals on switch on/off fashion [4]
Implanted a micro-electrode Arrays which include the Brain-Gate system	Transfer direct neuronal activity to control computer cursor or TV set [30]
Implemented neural tissue electrode brain	Control a computer cursor and spells 3 letter/minute [31]
Implanted a neurotrophic-electrode base system	Robotic arm controller of visual feedback [32], [33], and [39]

2.2.2 Non-invasive BCI Technique

In recent years, non-invasive research based BCIs have produced impressively successful techniques. This method requires less spectacular procedures due to the influential challenges posed by the recording of largescale synchronized brain activity. The variation in time of encephalographic (EEG) activity is defined by the difference in electric-potential between two electrodes that are placed on the surface of the scalp of a (subject's) head. The gathered signals originate from multiple population cells behind the layers of the cerebrospinal fluid of the skull bone. These signals from EEGs are the summation of weight composed of a large number of neuronal cells in the brain called a cortex. Non-invasive techniques offer a wide range of real-life BCI applications, for both disabled and enabled users. Furthermore, this technique supports accurate controls, which include two-dimensional movement with high reliability compared to reports of invasive techniques in studies of non-muscular monkeys [90].

Table 2.3: Summarised non-invasive techniques based BCI system

Approach	Description
Alpha-wave based BCI	First BCI study based alpha wave is detectable on the scalp on cortical surface. Purpose of this study to convey user wishes to use word processing programs and other software [116]
P300 based oddball paradigm	The P300 speller allows locked in patients to communicate with extremal environment [28]
Slow cortical potentials (SCPs)	The thought-translation device (TTD) is a training device and spelling program for the completely paralyzed [64], [65]
Visual evoked potential (VEP)	Evoked responses or event related potentials in human EEG signals were mostly studied with offline analogy recording and averaging [115]
Steady state somatosensory evoke potential (SSSEP)	Find out brain patterns that are easily detected, one of these detectable patterns present steady-state evoked potential (SSEP) which induced by visual sense [152]
Steady state visual evoke potential (SSVEP)	Applying Discrete Fourier transformation (DFT) and a lock-in analyser system; higher classification accuracy compared to one harmonic and to the standard positions O_1 and O_2 [137]

The non-invasive are very useful techniques in extracting and measuring brain activity in different ways, such as magneto-encephalogram (MEG), functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and positron emission tomography (PET) [41]. Table 2.3 shows a summary of reviewed studies that are covered in this thesis. One of the new technologies in the non-invasive technique field is the near infrared spectroscopy (NIRS), which is defined by functional imaging absorbed with low-energy optical radiation of absorption from brain-tissue; the NIRS technique depends on reflected concentration of deoxyhemoglobin, which activates a trigger by altering neural activity. The disadvantages of non-invasive techniques are associated with providing a lower spatial signal resolution compared with invasive techniques, as they are susceptible to noise, and clinical risk. However, the non-invasive recording process depends on external electrodes that rest on the (subject's) scalp; also, the cost of non-invasive techniques is far less than the invasive method. There are many examples pertaining to non-invasive based BCI-systems.

2.2.3 Slow cortical potentials (SCPs) based BCI

Slow cortical potential (SCP) based BCI control-paradigms have been initiated by the Birbaumer group at the University of Tübingen [64], and [65]. They used SCPs as operant conditioning type according to the BCI paradigm; their implementation is to control a spelling device with two alphabet (character)/minute respects to ITR ratio. This work is called a through-translation device (TTD), whereas the slow cortical potentials (SCPs) sort comprehensive EEG signals that agree with a very low frequency of theta brainwave (BW) bands. Electric-potential is generated by the cerebral cortex, which is observed at a frequency range of 1-2Hz; further, the SCP responses are respectively slow in terms of time elicited after 300milliseconds. This time is correspondingly a long shot response. However, the SCPs technique requires special equipment that measures the overall trend of brain activity collected within an extended period of changes, although it needs to average all of these activities based on many stimuli-trials. Kubler attempted to increase response speed through modulation signals and established a limitation and very short intervals [119]. SCPs require intensive training and it is difficult to obtain accuracy, which tends to be moderate at around 70–85% of control signals [119], [120]. In this paradigm of Kubler, based BCI systems where the subject could facilitate self-learn control using the SCPs technique [119]. SCPs is used to extract visual light stimulation, which affects and changes the electrical-potentials of the brain cortical activities. The brainwaves (BW) consist of a threshold regulation mechanism for local excitatory of negative/positive slow potentials which inhibit cortical networks [120]. The negative waveforms of SCP shift in respect of higher excitability and positive waveforms of SCP reflect concentration of excitability/inhibition [94], [95]. In Figure 2.2, a standard format of EEG raw is shown, which is recorded in the vertex region referred to extract SCP activities by an appropriate filter [121]. Here, a request from the user to provide feedback from a visual computer screen shows two choices at the top and bottom [121]. Users choose between the top/bottom prospects to adopt by decreasing or increasing the measurable voltage level based on an initial voltage level. Within the next two seconds, the voltage appears as the vertical trend of a cursor, which indicates variety between the two choices.

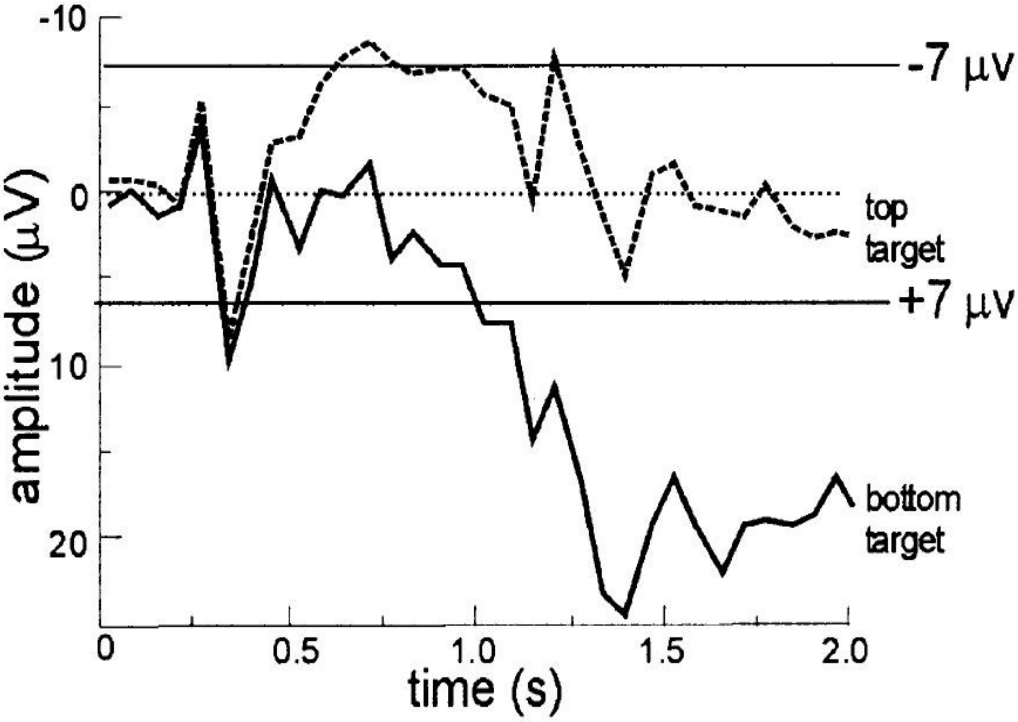


Figure 2.2: Slow cortical potentials (SCP) signal of cortex barin [121]

Although the accuracy of this potential is different among different people, correcting the potential of the context would provide higher efficiency [95]. Multi-channel EEG recording shows the increased responses to SCPs signal size in the centre of the human-scalp; however, a method for feedback is proposed in this experiment [95].

2.2.4 P300 Evoke Potentials based BCI

The P300 evoked potential that is widely studied describes a stable brain response [96], [97] based on event-related potential (ERP) as shown in Figure 2.3. P300 based BCI is involved in eliciting a large difference in ERP waveforms between the targeting and non-targeting of visual stimulus paradigms displayed on a computer screen [58]. Positive ERP potentials are recorded after 300milliseconds in EEG signals. Donchin has developed the first P300 reflected signal based BCI system to select letters from a virtual keyboard [97].

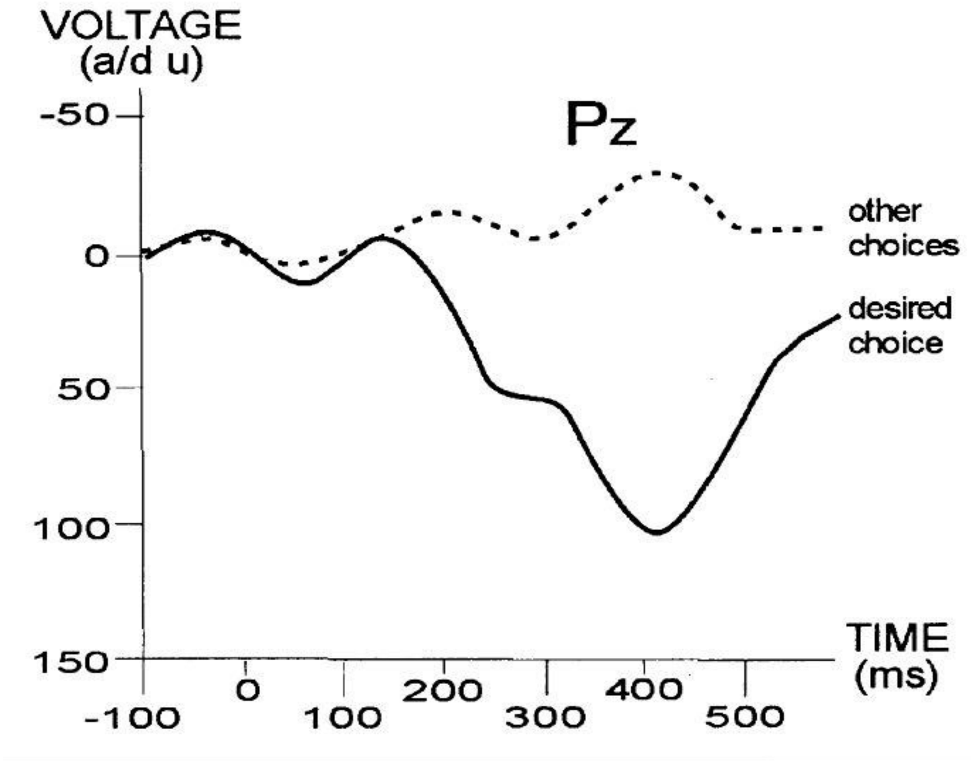


Figure 2.3: P300 waveforms elicit different ERP responses between targeting and non-targeting [121]

In this design, a grid contains a number of alphabet letters within addable flashing functions in each character, while the user focuses all theirs attention on the desired letter [97]. The target flash of P300 waveform signal will indicate a selected letter. This principle of P300 allows high reliability; however, it is necessary to draw-in all multiple trials to achieve the desired letter. A P300 paradigm based BCI system increases attention effort that may cause fatigue faster than other BCI paradigms. The traditional ERP waveforms are averaged synchronously to enhance the evoked signal with respect to brain activity [96]. For example, using step-wise discriminant analysis (SWDA) by Farwell and Donchin [97] followed by peak picking and evaluation of the covariance. Alternatively, the discrete wavelet transform (DWT) could add to the SWDA algorithm to localize efficiently on ERP waveform components in both time and frequency domains [95]. In addition, the independent component analysis (ICA) was used to detect the P300 waveforms [99]. ICA is one of the appropriate approaches used to enhance the ERP waveform that have been employed by Makeig [98], which contributes to analysis and extracts prior knowledge information from ERPs and decides whether a component should be retained or erased. This related-work involves averaging signals using threshold technique and applying matching filter to determine existence of a P300 waveform. ICA corresponds to P300 waveforms after being segmented by selecting a chunk of epoch in the range of -100 to +600 milliseconds, given a virtuous opportunity to detect and easily extract. However, the detection ERPs waveform based on single-trial EEG is favourable, since online processing of the digital signal processing (DSP) can also be performed by providing promptness and greater accuracy (see section 2.5.1 for more detail).

2.3 Steady-state Visual Evoked Potential (SSVEP)

Steady-state Visual Evoked Potential (SSVEP) is a brain activity response that precisely synchronized and modulated in amplitude, which is attractive with visual stimulation under certain condition. Although, the SSVEP signals are periodic waveforms, which are directly affect with different stimuli. In addition, the flashing-lights luminance or flickering-spot patterns on computer-monitor, which are directly effect on amplitude and power of SSVEP signal responses. The SSVEP response is a measurable signal within narrow band frequencies instead of invoking signals of visual stimuli base a certain frequency. However, the SSVEP signal can observed on Alpha band of brain rhythm as well as elicited on Theta band and Gama bands. A standard signal processing method exploits the specific characteristics of SSVEP responses, such as synchronization rhythmicity as illustrated in Figure 2.4. The signal of SSVEP is contents from special spikes that mirror the brain responses; those spikes are substances from stimuli frequency and harmonics. The SSVEP propagated in an EEG signal can extract the power in each frequency being equal to the stimuli or being equal to harmonics based on stimulation frequency [129]. Generally, there are two main different definitions of SSVEPs: firstly, Regan [130] is considered a direct brain response in the primary of the visual cortex; and Silberstein [131] has suggested that SSVEP is an indirect cortical response to certain stimulus via the retina, which contains complex amplitudes and phases. However, current understanding is still far to understood and there is some distance from recognition of the SSVEP responses mechanism signals; in fact, it is possible to induce or evoked such as SSVEP response by different flickers in different frequency bands. As an example, the light-emitting diode (LED) flicker can evoke a clear SSVEP response signals that is constructed by frequency range at 1–90Hz [19]. It has been reported that it is also possible to use a cathode ray tube (CRT-monitor) that can evoke an SSVEP response, taking into account refreshing rate frequency at 60Hz [20].

Table 2.4: Summary of steady-state visual evoked potentials (SSVEP) studies

SSVEP response extracted Approaches	Design Specifications
Frequency Response Bands	▪ Characteristics of average steady-state and transient responses evoked by modulated light [34-38] ▪ SSVEP distributed sources and dynamics wave to flicker frequency [52] ▪ Attentional modulation of SSVEP response depends on tagging of flicker frequency [45] ▪ Human cerebral activation during SSVEP responses [134]
Onset Responses	▪ DFT comparison and lock-in amplifier features optimal electrode positions in SSVEP-based BCI [137] ▪ Relation between psychophysics and electrophysiology based flicker [2]
Time Dynamic Response	▪ Neuromagnetic responses to chromatic flicker: implications for photosensitivity [50] ▪ Steady state visual evoked potential abnormalities [49]
Response on computer screen flicker	▪ Human EEG responses 1–100 Hz flicker resonance phenomena in visual cortex and their potential correlation [19] ▪ Steady-state visual evoked potential to computer monitor flicker [20]
Size Effects	▪ Electroretinographic and visual cortical potentials in response to alternating gratings [158]
Activated Brain Regions	▪ Steady-state VEP Attentional of visual processing cognitive of mind and brain [60] ▪ Cortical sources of components that effect on visual evoked potential [124] ▪ Frequency variation of a pattern-flash visual stimulus during PET activates on brain from striate through frontal cortex [41]
Age and Gender Effect potential (SSVEP)	▪ Interaction between flashing evoke SSVEP and the spontaneous EEG activity in children and adults [48] ▪ Effect of retinal blur on peak latency of pattern evoked [47]

Nonetheless, previous studies have engaged the CRT flicker and utilized the patterns is widely adopt as a visual stimulator [21–25], rather than the LED flicker reported in a few studies [18]. Therefore, the SSVEP techniques have improved to use with brain–computer interfaces (BCIs) based on many of studies [18] and used as application in multiple fields [21–26].

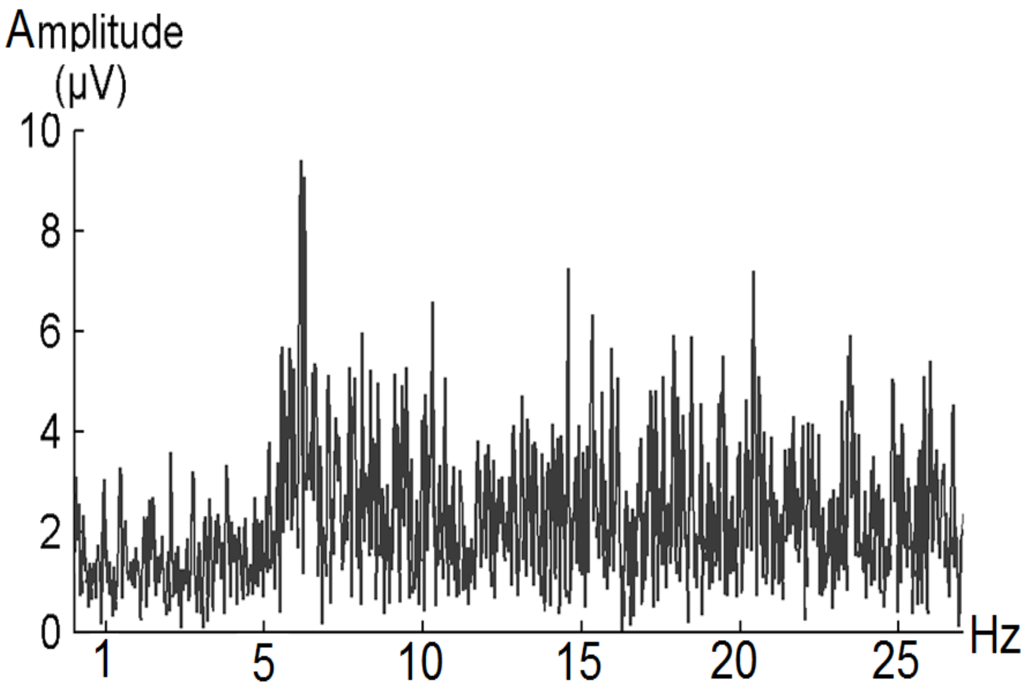


Figure 2.4: SSVEP response signal based-stimuli flashing/light [18]

The SSVEP-BCI based on development and implemented systems have provided more decoding accuracies by improving a most important features and selecting a suitable vital technique as visual stimulator. Table 2.4 presents a summary of studies which have explored and discovered many research based on steady-state visual evoked potentials (SSVEPs) paradigms.

2.3.1 Stimulation Frequencies Responses Based SSVEP

An early researcher, David Regan, has extensively studied several properties of the SSVEP, which affect the adult human-brain. These studies discovered three distinct frequency regions, which are termed low-frequency (LF), medium-frequency (MF) and high-frequency (HF) [37], [40], and [38]. Distinct frequencies are classified respect to brain activities of SSVEP responses paradigm [35]. The response amplitudes on the bands of LF, MF and HF regions provided an inverse relationship in respect of stimuli frequency; however, responses declined at faster light flicker rates [35]. Pastor studied the EEG signals based brain responses applying a flashing (White-strobe light) using 14 frequencies between 5-60Hz [134]. He found a maximal brain response as amplitude at 15Hz in the occipital brain region and at 25Hz in the frontal brain region. However, Pastor has studied a measurable regional of cerebral blood flow (CBF) by employing the positron emission tomography (PET) during flicker stimuli at 5, 10, 15, 25, and 40Hz. PET result showed activation in primary visual cortex at 5 Hz compares with Five-stimulation frequencies. Earlier PET researchers found the strongest response amplitude in the occipital cortex brain region at LF of (7 - 8) Hz using a grid of embedded Red light placed on goggles panel [41]. Furthermore, other researchers used a large (Black/Red) checkerboard [42]. Koch reported a new result based on his experiment using (Red) LED flicker, which indicated a maximum Near-infrared spectroscopy (NIRS) vascular response at (7 – 8) Hz [43]. In the same experiment by Koch, the responses were measured based on EEG signals by flicker stimuli 1 Hz, and (5 - 25) Hz [43]. Many experiments that have compared between EEG and MEG with respect to SSVEP responses demonstrate the disparities in measurements dependent on stimulation frequency using different techniques. However, Thorpe studied the frequency preferences by developing a visual stimulation that reverses larger (Black/White) checkerboard driven frequencies between (2 – 20) Hz [44]. He found the spectral power of SSVEP of amplitude at (15 – 20) Hz. In fact, the EEG studies noted the lower frequencies dominated brain responses for some stimulation types. Furthermore, Krishnan used a higher luminance of flickering LED and he found a near-linear decline in SSVEP peak response with frequency at 4 Hz [46]. However, Srinivasan, Bibi and Nunez showed dense (random dot-pattern) stimuli based on 16 frequencies varied between (3 – 30) Hz, which elicited preferable evoked responses in the occipital brain region [135]. This was an important finding indicating a significant occurrence in the occipital cortex with respect to SSVEP response based frequencies.

2.3.2 Dynamic Time of SSVEP Responses

Recent research based EEG signals exploit short-term SSVEP oscillations, ignoring the envelope changes in time especially at higher stimuli frequencies [46]. The frequency spectrum of time-domain signal is representative of that signal in the frequency-domain. Several decades ago, Van der Tweel offered an examination of SSVEP onset responses corresponding to baseline levels exceeded after ~300 millisecond of visual stimulation applied on a single subject [2]. Subsequent Regan studies showed a long-term SSVEP response at 15.5 Hz depending on a large 14° arc of a stimuli checkboard [34]. The initial onset transient in time coursing on first at 14 seconds of visual stimuli were found to gradually increase and then drop the synchronous activity. In addition, the Regan study presumed the existence of an adaptive neural-mechanism by suppressing stimulation after (12 – 20) seconds [33]. These results illustrated the changes in SSVEP response amplitude according to the subjects observed. However, Regan compared his results using a digital computer in respect of filtering raw-data; he obtained a much larger variability in dynamics SSVEP response at 6 Hz of stimulus frequency [37]. Unfortunately, the Regan studies have dismissed the possibility of time-variable with respect to SSVEP response and the studies suggest implementing a hardware wider pass-band filter (PBF) to compare this result. Use a Fourier analyser was applied on a seven seconds of time segment, so that more noise passed through from adjacent raw-data of EEG signal. Therefore, Regan's result indicates that SSVEP dynamics are also dependent on stimulus feedback-control, such as accommodative focusing.

2.3.3 Effective an Additional parameters on SSVEP response

Different studies have reported the effects of frequencies dominance, which captured the brain responses depending on recording modality. The SSVEP evoked stimulus is also reliant on parameters such as light-luminance, contrast and colour, which likewise play a crucial role [38]. Regan showed in his experiments that checkboard/pattern stimulation in small checks of 0.2° arc exhibit LF preferences response peaks at ~7 Hz. Select patterns were set as larger checks with 0.7° arc to give a HF-stimulus in preference to a similar result to un-patterned flicker stimuli [37], and [38]. In this aspect, visual stimulation prevents the subject from elongated fatigue usage, especially when employing LEDs as stimulator. Surej and John [18] studied the (RGB LEDs) effects with (clear and frosted) glass and tested the performance and qualitative extract signal, taking user comfortability into account. They compared between frosted and clear stimuli in three different colours (Red, Green and Blue) under fickle based frequency of 7, 8, 9 and 10 Hz. The results were extracted using fast Fourier transform (FFT), which showed the stimuli frequency at 7 Hz of (Green-clear LED) the highest SSVEP response [18], although all voluntary subjects indicated that frosted case LED stimulation was more comfortable. Another study showed statistical differences in theta, alpha and beta of brainwave bands instead of SSVEP responses of spectrum power by evoking two colours of blue and red. Yang and Leung developed an SSVEP paradigm to test the differences influencing the effect between blue and red by looking at two-choices of optional colours [27]; the results were classified using a support vector machine (SVM) as classification model; the results showed accuracy between two different colours between 70 – 80 % respectively [27].

2.3.4 Activation Brain-regions During SSVEP Response

Functional magnetic resonance imaging (fMRI) is a technique that demonstrates the SSVEP responses by evoking a band of frequencies. The synchronized striate response at all frequencies affects the lateral geniculate nucleus (LGN), while slower activation occurs in the middle temporal (MT) [41]. The main cortical SSVEP activation occurs in the primary visual cortex, corresponding to the fMRI evidence of circular-stimuli at 6 Hz [123]. Watanabe research also used 10 Hz stimulations and found activation of parieto-occipital of brain region followed by slower occipital responses [50]. Furthermore, Srinivasan, also used fMRI responses at (3 – 14) Hz in occipital cortex and demonstrated activity that was significantly increased [51]. The frontal cortex was instrumental in giving more a dependable response based on frequency, recording maximal response peaks on (3 – 5) Hz [51]. The same study found the occipital cortex region is positively correlated to frontal voxels with respect to fMRI measured units, and the other brain lobe was negatively correlated [52].

2.4 SSVEP based BCI Attitude and Implantation

SSVEP based BCI systems are widely used in different paradigms and digital signal processing techniques, offering many possibilities that provide various applications. Consequently, many research studies have improved and developed the SSVEP response signals; these provide an exact evoked frequency based on stimulation. Table 2.5 illustrates different contributions of SSVEP studies that present the various paradigms and summarises the BCI systems dependent on SSVEP responses. Currently SSVEP approaches provide the fastest and most reliable paradigm to implement a non-invasive BCI system.

2.4.1 Designs SSVEP based BCI Approach

Discrimination in SSVEP response based BCI approach describes the earliest successful online implementation [3]. The first approach modulated the amplitude and phase of SSVEP responses at (13 to 25) Hz flicker frequency; also, neurofeedback training was employed [53], and [66]. The US air force team designed a simple flight-simulator that incremented by 0.5° to the right if the responses of SSVEP amplitude increased, and to the left, if the amplitude was inhibited [66]. Most operators achieved 80 – 95 % information transfer rate (ITR) after 30 minutes of training time. In the second approach, two stimuli flickering at 17.56 Hz and 23.42 Hz were applied as base frequencies to select a command dependent on the feature of spectral amplitudes [54]. The mean result achieved 92% ITR with delay commands between

(1 – 2) seconds [54]. This approach is more efficient to apply the fundamental SSVEP based BCI that synchronizes brain activities to a certain flickering in visual stimulus. Regarding increase in the number of commands, a research group at Tsinghua University presented rise a 12 command based BCI by designing a primitive keyboard-phone. Using (6 – 12) Hz flickering frequencies corresponded with high variability that gives an acceptable result based on Cheng study which detected the FFT outcome [22]. However, the gaming based on BCI system has taken the place of entertainment applications in the SSVEP approaches. In a 3D immersive game called Mind-Balance, an animated character is balanced on a tightrope by a gazing player at two reversed checkerboard patterns [136]. The primary result was dependent on phases of frequency band at (6 – 25) Hz; and offline extraction feature using squared of Welsch power spectral density (WPSD), which estimated and correlated. Moreover, the Müller study concludes with the performance of four classes of SSVEP based BCI system, which depends on three harmonics of each target of frequency analysis. The flickering found based LED stimuli at (6, 7, 8, and 13) Hz as base frequencies that attached to the computer screen, providing a cockpit-design feedback [137]. The system was evaluated in each five second trial, and repeated four times on different days. Online analysis that varied in four conditions gave a variable result range of 35.1 % to 95.8 % improved by mean performance of 74 % [137].

2.4.2 Applied Signal Processing in SSVEP Based BCI

The signal processing technique allows extraction of the SSVEP responses based on EEG raw signals. Fast Fourier transform (FFT) is an important method that elicits spectral power density as preliminary estimated results. The aim of FFT concludes by extracting components of a frequency based frequency domain with the highest spectral power resolution corresponding to the exact SSVEP response according to stimuli frequency [66], [13], [138], and [136]. Consequently, improvement and robustness is contributed to FFT based methods by employing autoregressive spectral analysis [139], and [28] that exhibited better performance than power spectrum for a short chunk of EEG raw. This method requires more training sessions, which build the stability coefficient (SC) model [26]. The SSVEPs are valuable in BCI systems, since the excellent technique of signal-to-noise ratio (SNR) achieves the best performance. Among the different techniques in recent BCI approaches, the independent component analysis (ICA) was used, which is denoted as one of the most successful methods [7]. The ICA has been widely applied to improve SNR task based EEG signal analysis. Furthermore, an efficient method online analysis of SSVEP based BCI approach may be used, such as canonical correlation analysis (CCA), which requires a data window shorter than power spectrum estimation [140].

Table 2.5: Summary of related work using SSVEP based non-invasive BCIs

Number of Reaction-command	Paradigms flicker Style based research study	Specification Design
2	Stimulation large size checkerboard	▪ Video camera mounted on remote-controlled toy truck [153]
2	Normal size checkerboard based SSVEP	▪ Mind-Balance game [28]
2	White squares on computer screen	▪ Covert attention [141], [142], and [143]
2	White-button as unique pattern on computer screen	▪ First comparison of amplitude- and frequency control SSVEP-BCI [66]
4	LED stimulation board based SSVEP	▪ Airplane cockpit design [152]
4	Stimulation Group LED evoked SSVEP	▪ Grid of lights [137]
4	LED stimuli panel using SSVEP	▪ Simulated wheelchair [154]
4	Animation LED based computer screen	▪ Lights mounted under computer screen [155]
6	LED based on multi-frequency to evoke SSVEP	▪ An Sequential Presentation LED Study of methods [156]
8	Stimuli a single LED by (on/off)	▪ LEDs Anti-phase flicker of LED couples [157]
10	LED oddball-style flickering based SSVEP	▪ LEDs Phone number selection [22]
48 Based on only one subject	LED-flicker as groups	▪ LEDs Grid [13]

2.4.3 Artifact Effects on SSVEP based System

The EEG data are sensitive to external electrical noise signals emerging from an external environment. The EEG data that are recorded from brain activity are often influenced by external noise, which creates an artifact. These artifacts must be cleaned-up before continuing with analysis.

The artifact sources are found by electrooculography (EOG) system, which comes from eyes blinking and muscle tissue activity; additionally, the electrocardiographic (ECG) of heartbeat recode system is also defined as artifact in respect of acquisition data. However, electrical devices such as TV, computer, and lights are denoted as primary effect with high noise in EEG gathered signals. It is difficult to remove those artifacts without removing some relevant embedded information from brain activities related to interesting raw data.

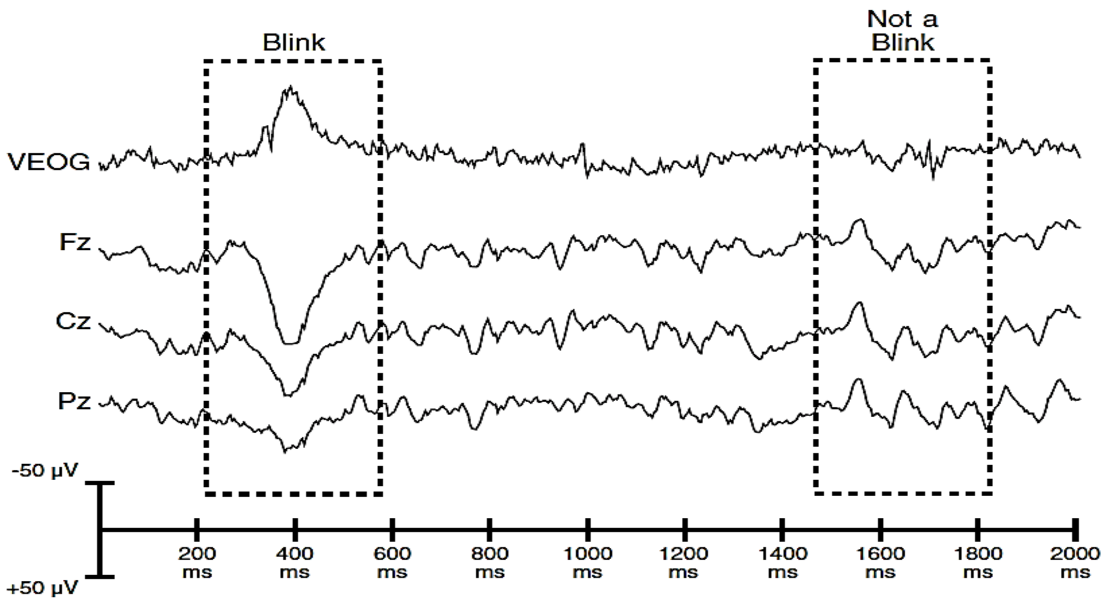


Figure 2.5:Eye blinking artifact is directly effect on EEG signal [69]

Pre-processing steps are defined as a technique that converts regular raw data of signals into a new dataset of signals, which are de-noised and cleaned of any artifacts. In other words, the pre-processing allows an increase in the signal-to-noise-ratio (SNR) with respect to input signals using various methods, such as spatio-spectro-temporal filter (SSTF) [74 - 76]. Figure 2.5 shows the typical artifacts of eye blinking effect on EEG signals, which are measured using an extra electrode placed on a location below the eyes labelled as (VEOG) electrode [69]. Eye-blinking artifacts consist of a monophasic deflection of 50–100mv [53], [62], [73], [56], and [68]. This makes it possible to distinguish between blinking eyes, which would produce an offsite voltage [69]. Some other techniques use the eventual type of feature classification in order to extract and remove eye blink and muscle artifacts [145]. Consequently, these methods have achieved successful results, with reconstructed data and verification to ensure there are no remaining identifiable artifacts.

2.4.4 Eye movements effective on SSVEP BCI

SSVEP based BCI depend on user ability to move his/her eye and gaze, in order to attend and select certain choices by evoking a stimulus. Empirical studies have demonstrated that disabled people with very limited eye movements might have restricted ability to use the SSVEP based BCI systems. Firstly, Kelly discovered in his study that nearby flickers attended visual stimulation as compared to obvious attention; he found 20% drop, as a result of accuracy classification [141]. In addition, two further studies have attempted to quantify limitation effects problems. In the first study, two rectangular stimuli flickers were applied at two different frequencies of 10Hz and 12 Hz; subjects were asked to attend to flickering letters between A to H [141] in a pilot study of visual-spatial attention control. Likewise, realistic BCI systems acquire EEG signal by using two electrodes only [142]. The result achieved 72% based on five trials of a covertly attended flickering target. Kelly, in another report, employed 64 channels of EEG signals during a similar task approach. A linear discriminant analysis (LDA) determined the stimuli in the alpha band at 9.45Hz and 10.63Hz, 14.1Hz and 17.01Hz based spatial attention. The higher frequency flicker gave a success rate by 70.3% with respect to information transfer rate by 2.1 bits/minute [143]. The SSVEP paradigm and alpha brainwave modulation produce higher classification rates. Zhang has developed an SSVEP based BCI in a covert attention using two large rotating set colour dots flicker. The system achieved online accuracy classifiers, which given 72.6% for two commands [144]. Other demonstrations of covert attention used reverse checkboard and line-box stimulations without gaze shifting that enabled a sufficiently strong SSVEP response for BCI control [139]. The checkerboard-pattern flicker at 6 Hz and 15 Hz showed the feasibility based system without gaze shifting, but labelling was suggested by dependent/independent focusing of attention. As a result, checkerboards stimuli elicited much stronger SSVEP responses on line and boxes than checkboard patterns.

2.5 Event-related potentials (ERP)

Event-related potential (ERP) is a common title for electric-potential changes in EEG signals that occur with respect to visual stimulus as a particular event to evoke brain response. The research of Davis was declare unambiguous sensory of ERP recordings [57]. ERP waveform is a measurable signal of the brain response showing the direct result of specific sensors, such as cognitive or motor sensor event, which reflect a stereotyped brain activity to a certain stimulus [58]. Consequently, it is possible to detect the evoked ERP waves by preparing a set of visual stimulation based paradigms. A particular ERP design based BCI is characterised by time-locked-event (TLE) according to the brain response. The TLE is a simultaneous signal occurring within stimulation time that present the neural brain activity in certain locked time [72]. One famous ERP design used a number of alphabet letters arranged as a matrix of visual stimuli [28]. The oddball paradigm is denoted by aperiodic evoked signal. This paradigm is realized by randomly highlighting letters that recognize the brain reaction within a short period of 300 millisecond [58]; ERP is referred to the P300. It mainly relies on a positive/negative of potential-signals [59]. The average process is simplified in multiple trials of ERP waveforms which usually preserve the amplitude and phase with respect to the occurrence of stimulation events [77].

2.5.1 ERP waveform Component

ERPs are used as non-invasive techniques in clinical environments to indicate the brain functionality of human patients. ERP is a voltage change specified to a physical event or mental occurrence which is observed by an EEG signal record [79]. Figure 2.6 shows an ERP signal.

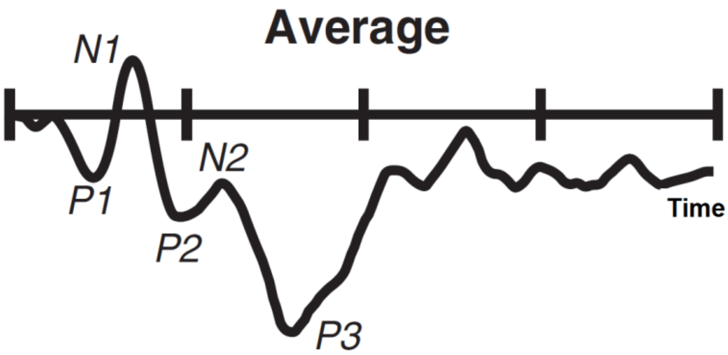


Figure 2.6: ERP components proceed an average the EEG under same condition [58]

The signal shown divided into two major parts, which represent a pre-stimuli section that consists of a baseline with no clear potentials, and post-stimuli section that consists of various potentials. ERP components are usually given with reference to their polarity and position. The first positive potential, called P1, is defined by a downward waveform, followed by a negative potential of N1, defined as an upward waveform, then P2, N2, and so on. The potential latencies are measured from stimulus onset to the maximum peak of potential. Sometimes these peaks are noted by a latency name, (e.g. N1 occurs at latency 40 milliseconds called N40; therefore, a P3 occurring at latency 300milliseconds is called P300), and so forth [69]. The baseline configuration presents the difference in amplitude between the response peak of potential and the mean of stimulus based (virtual Zero-line) [70], [78], and [86]. Furthermore, the shorter chunks of EEG data provide a linked latency to superior cognitive functions [80].

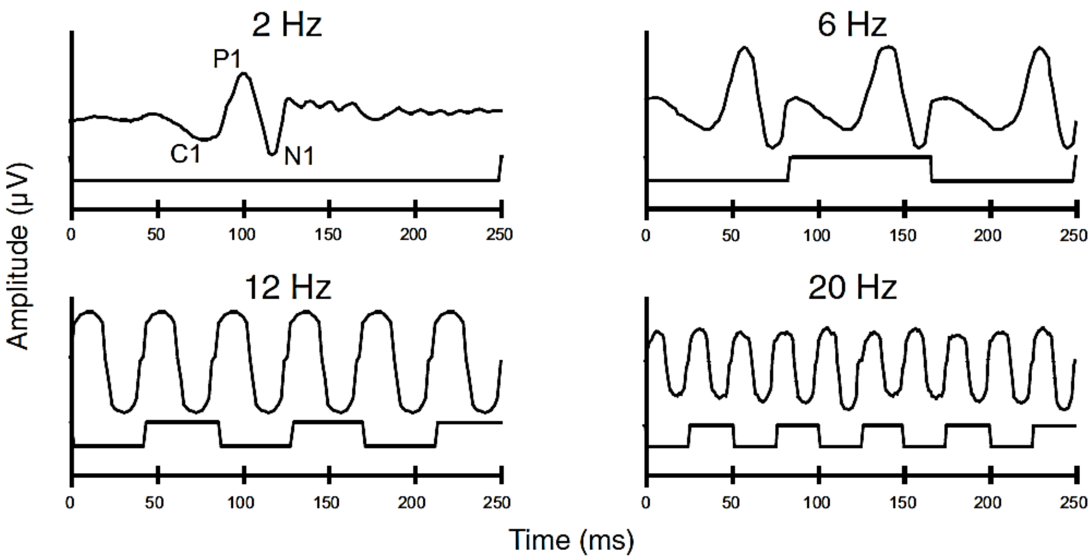


Figure 2.7: Time locked based-ERP result with respect to prior period [69]

This latency can be increased in all accumulated data if the task is more difficult [87], [88]. The P300 potentials commonly occur at latencies between 300–1000millisecond associated with external attention, such as stimulus evaluation [78]. Moreover, the steady-state ERPs recorded a significant shortage response. A large number of studies that investigate the attention of steady-state ERP restrict the transient responses which are evoked by the stimulator. This potential of evoked signals has an asynchronous and low repetition rate [60]. However, the potentials are called transient because there is a slow rate in respect of the stimulation. The transient instance of steady-state ERP waveforms includes three major components of C1 at (60–80) millisecond, and P1 at (80–120) millisecond as shown in Figure 2.7; however, the N1 is at 120–180 millisecond [60]. The rapid stimuli rates of brain response become the same stimulus as sinusoidal. The transient ERP waveform components having a variable phase may also reliably occur in relation to the repeated event [60]. The non-time-lock of ERP waveforms are referred to induce the following occurrence-based stimulus with respect to the period prior to stimulus motor sensory. Because steady-state ERPs have a shortage with high temporal resolution in relation to transient ERPs, they are used only rarely in cognitive studies [69].

2.5.2 ERP based BCI system

The ERP components are contained potentials that are highly reliable in terms of latencies and can be easily detected [28]. ERP waveforms that contain positive and negative potential deflect the EEG signal with respect to occurrences labelled by time-lock after knowing the stimulus paradigm. Fabiani and Luck designed an ERP-based BCI system using oddball paradigm. This design was frequently presented depending on irrelevant stimuli, which were rarely interspersed with relevant target stimuli; this paradigm referred to odd stimulation due to the rarity of occurrence that is locked to time events [146]. However, Zickler research team validated a system dependent on small dots, used as strobe stimuli, which present directly on top of the application. This matrix contains dots, each of which represents one letter and one number, which were exchanged in respect of certain stimulation functions [147]. The system was demonstrated as an assistive technology device for smart environmental control. The control environment connected directly to the internet or email functions when users focused their attention on one of the stimulation dot-buttons present on top of the control panel, such as (send) button to send an email [147]. Münßinger and his colleagues suggested a painting entertainment application. Different painting functions, such as brush size selection or colour change, are also placed in the visual stimulus matrix and can be selected in the same manner, which has been previously described as smart environment applications [148]. The system has been demonstrated with enabled users, as well as severely disabled patients who were able to draw predefined paintings [148]. The ERP-based BCI systems have been suggested as wheelchair controllers, with the users selecting different control options from a visual stimuli display [149 - 151].

CHAPTER 3

PROTOTYPE BCI-SYSTEM: DESIGN AND IMPLEMENTATION

This chapter describes how to set up an SSVEP based-BCI system, which including hardware equipment stuff and software tool; as well accumulative EEG data and schedule EEG signal recording to store individually as template files; in addition, the pre-processing of collective data (templates) are cleaned up from any artifacts. In fact, there are many ways to set up evoked SSVEPs; and many of approaches that are used to extract feature from signals depending on topic research. Therefore, suggestions many empirical studies in this chapter that are provide decent starting point for most stimulation and configuration; also to acquisition EEG raw-data, and removing unwanted signals using filters technique based on digital signal processing (DSP). However, addressing the problem, which is mentioned in (Chapter 1) of reduce the EEG electrodes by inspecting the best responses based on brain-regions. The contribution of this work has been published as interesting results from headline experiments:

- New Paradigms for Brain Computer Interface Based on SSVEP, 2014 World Symposium On Web Applications and Networking, ISBN: 978-0-9940194-1-7

3.1 Stimuli Exhibition and Experimental setup

The BCI system is depending on several techniques to extract the signal feature, such as steady-state visually evoked potential (SSVEP) which demand to use without need training between users and machine. In this conurbations work, a novel style of SSVEP based BCI prototype has been designed that induces many flicker points as (spotlights) based on different frequencies, several duty-cycle, divers colours, regular/irregular and pattern paradigms, which including stimulation attributes. The flicker paradigm was dependent on light emitting diode (LED) with respect to phase-tagged triggers (PTT) or time event-triggers structure to achieve a high transfer information rate (ITR) of data-transformation, and easy feature extraction. The light-emitting diodes (LEDs) present flicker/light sources that give an electroluminescence, rather than incandescence, which provides energy transacted to photons of light that move as wavelengths. These induce flicker light is elicit waveforms of brain activity affect the eye-retina, which tangles SSVEP responses in respect of flicker frequencies attributes. The advantage of using the LEDs is that they provide an over incandescent light sources based on lower energy consumption, longer lifetime, improved robustness, relatively greater durability and reliability. In addition, they are comparatively expensive and require more precise current sources and fabrication compared with traditional light sources. Therefore, they elicit SSVEP response, which is switch-controlled by (On/Off) with respect to LED-flickering. Furthermore, there are supplementary attributes, which provide an all-in-one stimulation unit that content (multiple frequencies, multiple dynamic colours and multiple patterns). Consequently, a low-cost based system is evaluated according to multiple applications that are used in BCI technique. The design of stimuli-panel includes 24-positions. Each position has three (colours: Red, Blue, and White) different LEDs, which imposed a beam of visual induced signals. The users choose one command in respect of (LED positions under certain condition such as diverse frequency) by focusing their attention on repetitive visual stimuli that change periodically based on frequency, different colours, miscellaneous patterns and other characteristics effects on brain responses. These properties are rendered effective on the performance of the base model design in terms of comfort, applicability and safety used as prototype of the BCI platform. The comfort aspect of the design was a deliberate response to a custom questionnaire directly with users. Variability across voluntary subjects was found by exploring the results of evoke-stimuli properties that afford a significant brain influence within the performance and comfort of an SSVEP paradigm based-BCI. Generally, there are substantial differences between each visual stimuli state that are beneficially performance with BCI-system. In order to fulfil all experiment setups within different stimulation based combinations of 24-LEDs (split spots/light positions). Individually controlled on LEDs-flicker with respect to certain frequency and other properties that prompt directly via (C-console) using a personal computer. The multiple visual effect of stimuli panel (shown in Figure 4.13) is prepared to evoke SSVEP response within a close-loop system that connects to a depth board crossing the computer in order to send various stimuli attributes. distinct advantage stimuli characteristics are defined by a couple of configurations provide a respectable concession between each experiment performance, such as choosing-colours, varieties frequency-band, from 1 to 24 LED at different position and diverse patterns module of each stimulus/LED. The flicker in each LED is configured with wide band-frequency based on brain activities response that defines by (0.2 to 38) Hz aspect to multiple stimulation paradigms. Consequences, the EEG/signals recorder system has been set to measure brain activity.

3.1.1 Stimuli Configuration and Structure

Differences in stimulation paradigms based on SSVEP evoked response signals are support to investigate according to the different stimuli types that evoke brain activity corresponding to the extraction features. A pairs of configurations is arranged to provide a compromise model in each stimulus that arrangement to evoke brain with decent responses. The low-cost system based on SSVEP reflects user attention by recording the EEG oscillations, which is present the first stage based on design system; typically the induce light system depending on the lights flicker stimuli at different frequencies and others attributes such as different position LEDs. However, there are requirements, which support to give a decent brain response based on SSVEP paradigm. Therefore, the major requirements are as follows in this contribution work:

- Increment and enhanced the brain response signal which is representing on SSVEP paradigms based-system
- High reliability recognition of SSVEP response signals that are clearly distinguishable using bands of frequencies and other characteristic such as different colours or diverse pattern duty-cycle attributes
- No training is needed or just a few seconds training up which is used as classifier module, and self-paced performance if required

Eight empirical studies have demonstrated using the proposal of low-cost prototype SSVEP based design of multi-stimulus panel. The fabrication of stimulation panel is handmade. Complete hardware design of visual stimulation panel is powered by pure DC of 9V power source to avoid any kind of AC interference component. A maximum error accuracy of flicker frequency was measured, gives less than 0.001% at room temperature corresponding to progress measuring that validates by a digital oscilloscope. There is no common way to present the ideal BCI system, in which connects human-brain to certain machine such as personal computer; in other hand, the BCI-system is always dependent on brain activities, which mirror the responses using the EEG signals. Although, the visual stimulation plays an important role that can represent the flicker LEDs rendering to the main setup argument in prototype designed. The brain waveform of activities provides a primary signal that is amplified and fed into the computer with confident circumstances of visual stimulus. The BCI-prototype was depend is consist of (3 – 12) EEG/channels in addition to the two-main reference electrodes (channels) that connect directly configured according to BioSemi of EEG-amplifier setup. The BioSemi amplifier is also connected to computer that recording EEG raw-signals from the voluntary subjects under confident stimuli test. Therefore, the visual stimulation produces an incentive specific frequency in different pattern according to type of experiment setup. The visual stimulation board (stimuli-panel) is horizontally fixed at the eye level of participants (voluntary subjects), with a distance of approximately 80 Centimetres in between. The stimuli LEDs are separated into different groups by colours that coordinate in the centre and surround as Red group and other two more groups of Blue and White, which are similarly symmetric. Adapted the (Eight-LEDs) in each colour, and distributed on the board, as illustrated in Table 3.1. Most experiments depend on Four-LEDs, which present a one cycle of single visual stimuli to evoke brain activities that are followed by next stimuli-cycle.

Table 3.1: Distribution LEDs according to stimuli position

Position on Board	**Colour groups**		
	Red	**Blue**	**White**
Centre	$R_c^1, R_c^2, R_c^3, R_c^4$	$B_c^1, B_c^2, B_c^3, B_c^4$	$W_c^1, W_c^2, W_c^3, W_c^4$
Surround	$R_s^1, R_s^2, R_s^3, R_s^4$	$B_s^1, B_s^2, B_s^3, B_s^4$	$W_s^1, W_s^2, W_s^3, W_s^4$

The amplitude assessment of light-lumens is significantly large enough to induce the evoked signals of SSVEP response in different paradigms. Such a case study provides many possibilities that deal with inducing electrical-potential waveforms based brain activity that lead to inspecting different stimuli effects of BCI techniques according to flecked LEDs. Evaluating all attendee experiments by estimated the scheduled recording time, relaxing-time (Break) in respect of scene and break-time. Each empirical study has been fixed recording-time intervals toward distinguishing brain response. All experiments are intended to extract the influence of brain responses in respect of prepare scenarios based on stimulation paradigms, which are lead to enhance the outcome result based-research:

- Decrease artifacts that prevent optimization by developing a different approaches (see section 3.2)
- Adjust the suitable evoke frequency based on different brain-lobe stimulation (see section 3.2)
- Multiple frequencies based LF, MF and HF brainwave bands (see section 4.1)
- Three different colours influence based brain responses (see section 4.2)
- Distinguish brain activities dependent on regular/irregular paradigms (see section 4.3)
- Reduce delays of SSVEP signals by minimizing tension and fatigue (see section 4.2)
- Duty-cycle properties inspiration during stimuli (see section 5.1)
- Constructing the brain recognizing based on multiple pattern effects (see section 5.2)

Figure 3.1 demonstrates the procedure of EEG signal recording that began with Relaxation time; here requested from participant to close his/her eye within 20 seconds through recording time of the EEG signal, foreword to use as baseline-data, which covers as comparison based on offline analysis. Toward, three-times recoding issue of EEG signals in every scene shot of a single visual stimulus throughout the schedule procedure of 40 seconds recording time. Conversely, more than three minutes between each session as break-time during experiment.

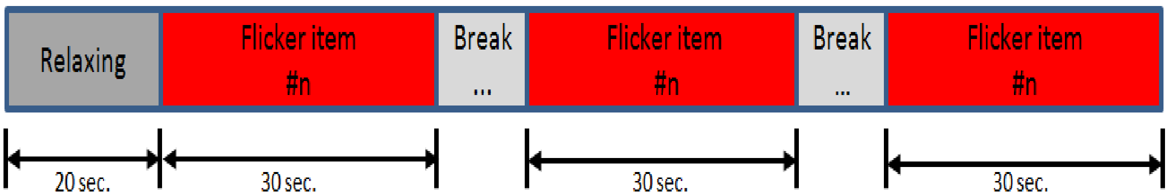


Figure 3.1: Time table of schedule recording EEG signal process according to the experiment setup

The EEG record signals were started on the first flicker light/LEDs, which began after a request from the subject to gaze on flickered LED. Three recording times of (20 – 40) seconds in each session of both control and application studies by gazing at individual flickered groups of LEDs corresponded to experiment format. However, the appropriate of EEG-laboratory is designed with specific conditions of EEG raw recording signals that prevent the interference signal, which effect on the EEG-signal by provides a comfortable environment and good peripheral. Further, the EEG-laboratory is prepared to decrease the power line effect. More than thirty-healthy volunteer subjects participated in a variety experiments based on different empirical studies. All participants had normal or corrected to normal vision. The average age of all participants was between 22 and 39 years. Furthermore, all the voluntary participants agreed to take part as a subject in this thesis, following an approval talk before participating in each experiment test. This ensured participants were fully informed of all procedures in advance, towards a clear understanding of experiment behaviour. Finally, before the experiment began, voluntary subjects were shown a brief stimuli sequence with increasing/decreasing of flickering-LEDs luminance in order to test for photosensitivity in order to increases/decrease the luminance intensity to minimize tension and fatigue.

3.1.2 EEG-Data Acquisition based on BioSemi system

EEG raw-signal was recorded via BioSemi EEG-system with two main sintered Ag/AgCl active electrodes. Active electrodes bias the electronics flow, allowing substantially higher signal-to-noise ratio (SNR) and improved sensitivity to weak brain signals. Two additional electrodes, denoted by driven right leg (DRL) as passive electrode, and active electrode present by common mode sense (CMS) [85]; both located in the posterior of the vertex region that used to enhance the common-mode in respect of the different voltage points. These experimental studies have investigated the SSVEP responses signal characteristics and behaviour that lead to find out a strong response and increase the brain reaction which increase amount of BCI-commands based on archetypes. Employed empirical studies, which are performed with a three-channel EEG-electrodes on a rear-head region of the skull that is configured on the scalp. A highest sampling rate is utilized a 2048 Hz based on BioSemi configure system, and adjusts all electrode impedance less than 3 kΩ. Further, a special electrode Gel is injected between surface skin of the head-scalp and each active electrode points to increase conductivity. The electrodes are placed on the head skin surface of human-scalp, and connect to the AD-Box of BioSemi system through optical-fibre (wires) that to thwart any electrical interference and keep the acquisition of EEG raw-data to clean out from external noises. Offline analysis is exploited on a cumulative EEG data and stored as dataset as individual templets files that used to distinguish between response different with respect to BCI technique. The accumulated dataset reveals SSVEP features in each individual recording stimulus. All EEG-signals are gathered as epochs of collocation EEG signals that subsequent extraction periods in each recoding level of each session based on EEG signals. These signals are collected as templates-file based on individual epochs to analyse offline and compare outcome results referring to brain activity depending on strong SSVEP responses in different amplitudes, magnitudes and phases.

3.1.2.1 ActiveView and Software based EEG-BioSemi

ActiView is a software controller functions regularly used with BioSemi set-system that developed to supervisor EEG signals platform. ActiveViwe provide a new standard of higher resolution measurement based on multi-channel of EEG-electrodes to support the researches and diagnosis. Complementary software of EEG acquisition data is designed to display all EEG-data/multi-channels on a computer screen within external support signals that are used to signify trigger-functions.

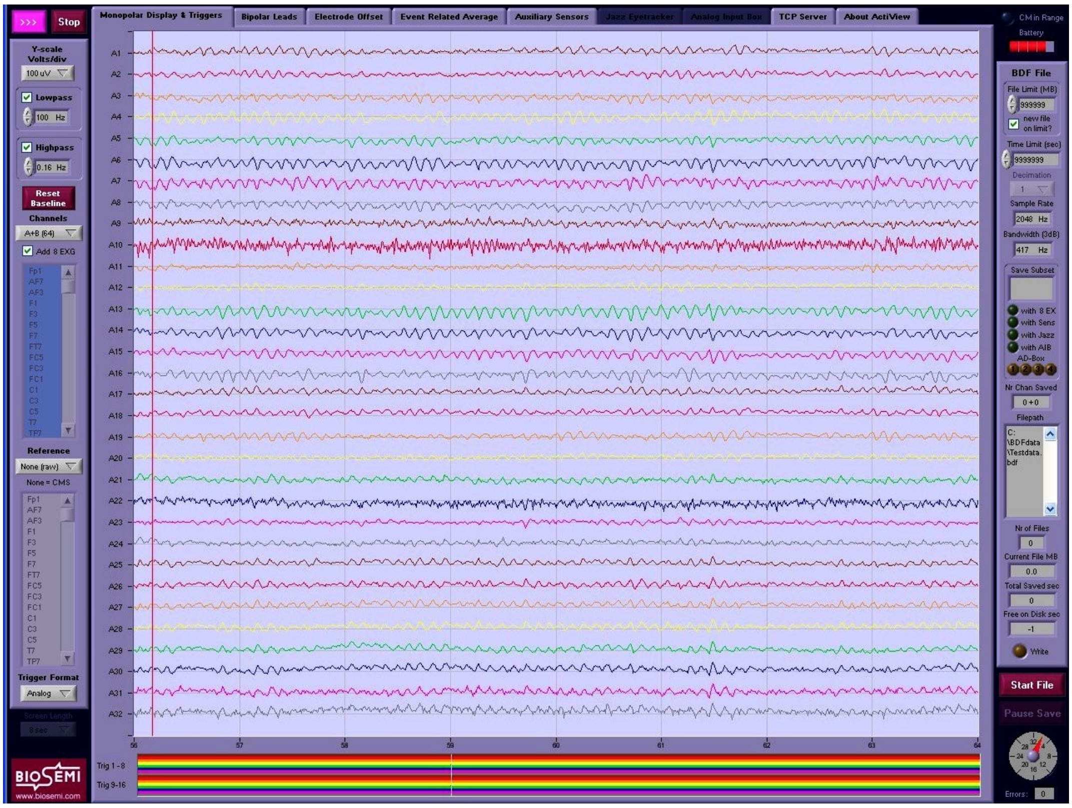


Figure 3.2: BioSemi control-Front panel GUI described 32-EEG channels within 8-triggers

The software saves all EEG raw-data on local computer hard-disk as BioSemi data-format denote as BDF files. Figure 3.2 shows the GUI layout that provides graceful and simple confirmation of data quality. The ActiView is an open source software compatible with LabVIEW platform that makes a particularly versatile tool. This software (ActiView) has been used to convert the acquisition EEG raw-data to digital binary-data. In addition, is support to gather external signal through analogy AD-box; the digital triggers are also connected to the box. Several analogies filter and down sampling are allowed to use corresponded adaptation and enhancement the outcome signals. However, digital buffering single techniques completely construct acquisition of raw-data, which are stable and reliable during multi-tasking experiment. Furthermore, the AD-box adaptor contains circuitry based digital signal conditioning which is connected to the computer via USB port. This system provides many types of setting channel that distributed archetypes by (32, 64 and 128) electrodes/EEG-channels of recording raw signal. In this thesis have reduced the number of EEG-channels and used 12-EEG-channels as maximum amount of electrodes based on active mode including the references.

3.1.2.2 EEG Signal Electrodes Adoption and Localization

Considering common mode rejection (CMR) of amplification module, the EEG signals are compete adapted using the BioSemi system. The difference voltages between active-electrodes and reference-electrodes are achieving potential signal. Advanced technology based-BCI system allow reduce amount of EEG-channel numbers; however, the high accuracy based on digitalized signal resolution; rather than input modulation range that provide a good solution respect with sampling rate and power consumption. In this contribution work utilized a sintered Ag/AgCl type as active electrodes against two reference nodes (CMS and DRL), as mentioned previously in section 3.1.2. Subtractions between electrical-signals presented on active electrodes and reference node, which evidenced potential signals presented by brain responses. Furthermore, the active electrodes are design in smaller-size and less-weight which offering better gathering attributes in terms of noise signal at low and high frequency. Flat active electrodes have used with proportions dimensions of 11mm width, 17mm length, and 4.5 mm height which designed by BioSemi's appropriate with all human body-surface and applications.

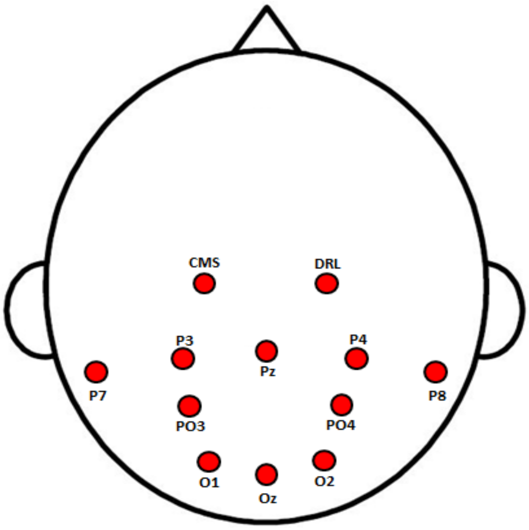


Figure 3.3: Configuration and setting 14-EEG channel including references electrodes

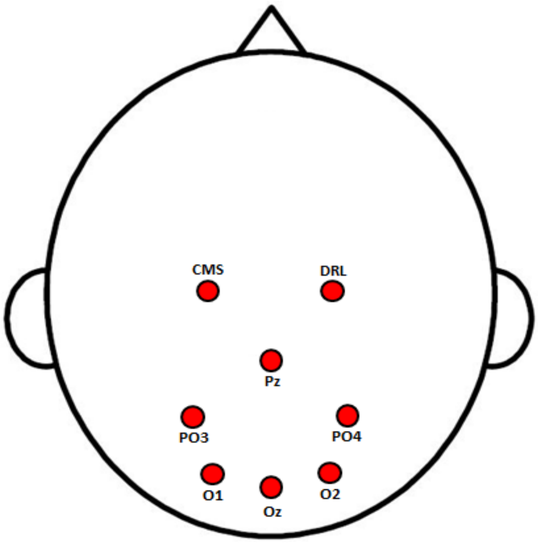


Figure 3.4: Configuration and setting 8-EEG channel including references electrodes

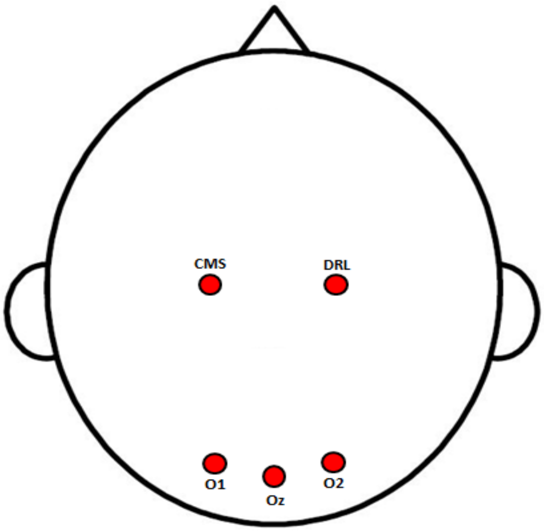


Figure 3.5: Configuration and setting 5-EEG channel including references electrodes

Consequently, low input impedance avoids external environmental noise signals, such as power sources. The common mode rejection (CMR) does not depend only on electrode impedance, is also depend on input amplifier impedance of BioSemi system. The contact impedance between the electrodes and scalp skin was calibrated less than 3 kΩ. In addition, the flat shape of electrodes offer an ideal measure for acquisition of EEG signals. These empirical studies have used maximum (12 flat active/EEG-electrodes) that withdraw a high data rate of measured signal. The Figures 3.3, 3.4 and 3.5 shows three-scheme types that describe the electrode setup and setting configurations based on the BioSemi system arrangement. Therefore, Figure 3.3 illustrates the first scheme, which is used to measure the EEG raw-signal. This scheme used 12-channels are distributed on brain lobes and placed cover the parietal lobe at PO_3, PO_4, PO_7, PO_8 and P_z, and occipital lobe at O_1, O_2, and O_z; a further two-addition reference electrode of CMS, DRL is fixed on posterior vertex region in standard position. The second scheme in Figure 3.4 demonstrates partly of the parietal lobe at PO_3, PO_4, and P_z, and conceals most of the occipital lobe at same points of previous scheme. Finally the ultimate scheme presented in Figure 3.5 show the three main O's electrodes, which are configured on the occipital region because this brain region provide the strongest response amplitude respected to LF and MF frequency band in forwarding results.

3.1.2.3 EEG Cleaning-up and Artifacts Rejection

The discussion in Chapter 2 reviewed the state of the art and background of cleaning process for EEG raw-signal (sections 2.4.3 and 2.4.4). This process leads to discover many approaches that remove artifacts, which are basis contamination through recording the EEG signals. These contaminant signals (artifacts) such as eye movement, eye blinking and muscle activity are rooted with EEG raw-signals. A large comprehensive EEG raw-signals are present a great noises when, therefore, the independent component analysis (ICA) over average process is support to remove some affected artifacts. In other hands, comparative strategies such as systematic artifacts occur between certain conditions than others. It is possible to reduce the contaminant signals using digital signal processing (DSP) techniques [86] by employing a high precision filtering process or other filtering techniques. However, increasing stimulus to evoke trial numbers is not effective on EEG data but reduce the contaminant noise signals by averaging chunks of EEG raw-epochs. Furthermore, the most concluding results are considered the average process techniques. The average process used primary dataset, then moving on to reject artifacts using the procedures accumulating based on point to point then formulate a new-datasets.

The averaged approaches of EEG-chunks based on individual trials produce residual noise that content signal-to-noise-ration (SNR) which progressively permits the artifacts affected. In these studies, have been handled three trials recording EEG raw-signal that conserved in each session under the same circumstances (see section 3.1.1) to overcome the problem of contaminant noise by average the entries trials. This procedure presents the initial process of averaging technique that is proved a succeeded eliminating of contaminant noise component in every experiment setup [90]. The primary extract results have been achieved ~30 percent of reducing unwanted signals based on average approach, which depends on time-locking events according to phase-tagged trigger (PTT) of stimulus that provide a least loose signals. In fact, increasing the number of trials is a reasonable solution, which reduces contaminant noise signal in such a case of eliminating artifacts. However, the long time span of the experiment causes fatigue for participants (voluntary subjects), thereby increasing contamination. Therefore, independent components analysis (ICA) has been vindicated mathematically in recent studies, since the ICA technique can be used to remove a blinking and eye movement artifacts that mixture with electrical noise signals [86].

The artifact rejection based on ICA can involve problematic progress in averaging procedure, because accumulated EEG raw-signal based on targets-event/(brain response) in which the ICA is applied to remove eye blinking and other tissue activities such as movement muscle. Essentially, the ICA is presented by an input array of x as linear superposition of component vectors s, which is substantiated by the assumption model:

$$x(k) = A\,.\,s(k) \qquad 3.1$$

where the linear $x(k) = \left[x_1(k), x_2(k)\ \ldots\ x_q(k)\right]^T$ represents the q observed sensor at time point k, and source vector of $x(k) = [s_1(k), s_2(k)\ \ldots\ s_n(k)]^T$ are unknown by (n) which presents components with respect to sensor space. Non-singular matrix (A) contains unknown mixture signal sized by $q \times n$ Jung group, who originally developed the ICA technique [86], which conducted in this study (see Appendix A.1). In particular, this approach provided convincing results that depends on the assumption model in respect of time course artifacts according to PTT technique.

3.1.2.4 Alpha Brainwaves based SSVEP responses

Alpha-brainwaves are kind of oscillatory EEG/signals that divert between 8-13Hz which is stimulated using simple light flickers. The largest amplitude of alpha waveform is located in posterior brain-lobe and occipital brain-lobe regions, also occurs frequently when subjects respond to evoked visual stimuli (see section 2.1.4). These types of brain-signals are mostly used and appointed based on contribution empirical studies of this thesis. A strong rhythmicity of EEG/signal is affected by the visual cortex, which achieved high responses by applying flashing-lights directly on eyes-levels, which is apparent a sudden rise in alpha amplitudes brainwave. In particular, the alpha-brainwave provides the best rhythm and harmony based SSVEP response signals, which is realized by the averaging process. The significance of alpha waveforms provides a promising result, theoretical have been proved the BCI control system based on foundation and experimental experience that controlled more complex devices such as (personal computer). The stimulus flickers that induce the brain response which is detecting alpha brainwave based-EEG of non-linearity singles. The alpha brainwave is locked into narrow band frequency [90]. Because of alpha brainwaves can be considerable as self-organized oscillations through the interactions of a massive number of brain-cell activities [82]. Underlying, the mechanism of alpha brainwave is modelled by a coupled of non-linear oscillator system [83]. Dependence alpha waveform on brain response properties that are affect directly with stimuli frequency, light intensity and stimulus colour to provide powerful transformation information [84]. Underlying the mechanism of the alpha brainwave is spatiotemporal characteristics [84]. Furthermore, observe the temporal EEG signal properties based alpha brainwave through empirical studies, which identify a non-linear oscillation of brain signals and conducted to stimulation frequency (see sections 4.1.4 and 4.2.2). The EEG signals under certain flicker stimuli is strongly include a steady-state visual evoked potential (SSVEP); as well as, the transient signals that are termed by alpha brainwaves providing decent evoked brain potentials which have the same base-frequency of stimulus flicker.

3.2 Extract SSVEP Response base Time-locked events

The SSVEP signal is a periodic response reflects the repetitive visual stimulus modulated at a fixed or multiple–frequency. This response is embrace within comprehensive of EEG raw-signals. Most recent studies depend on some sorting of averaging process that extract feature signal and reduces contamination noises (artifacts); correspondingly, the average procedure is typically accompanied by a procedure that removes the artifacts effect. This approach is relatively simple, and Figure 3.6 shows the traditional method of averaged signal technique [58]. The brain responses are labelled using an external marker (trigger-events) signals. This method is depending on trigger on occur event with respect to evoke stimulus of brain response. The locked-response-events or stimulus tagged-trigger are used with average process to accumulate response signals and correct the position at assured time point [58]. These markers are aligned with EEG recording in respect to time-locked-event (TLE) which depends on cycle mode-trigger and flicker mode-trigger paradigms. These triggers are present on each onset-stimulation to indicate event occurring through recording procedure and bounded by marker signals. These triggers simplify the averaged process, which allowed gathering the dissimilar EEG-chunks aspect of extracting epochs between boundaries markers, in manner of point-to-point tagged-triggers-events in every schedule recording time. There is an assumption of bounded epochs/EEG-chunks that select a trial consisting of SSVEP response with a high mixture of signal to noise ratio (SNR). The gathering approach of individual trials of EEG based on average process is applied simultaneously on equivalent stimuli conditions.

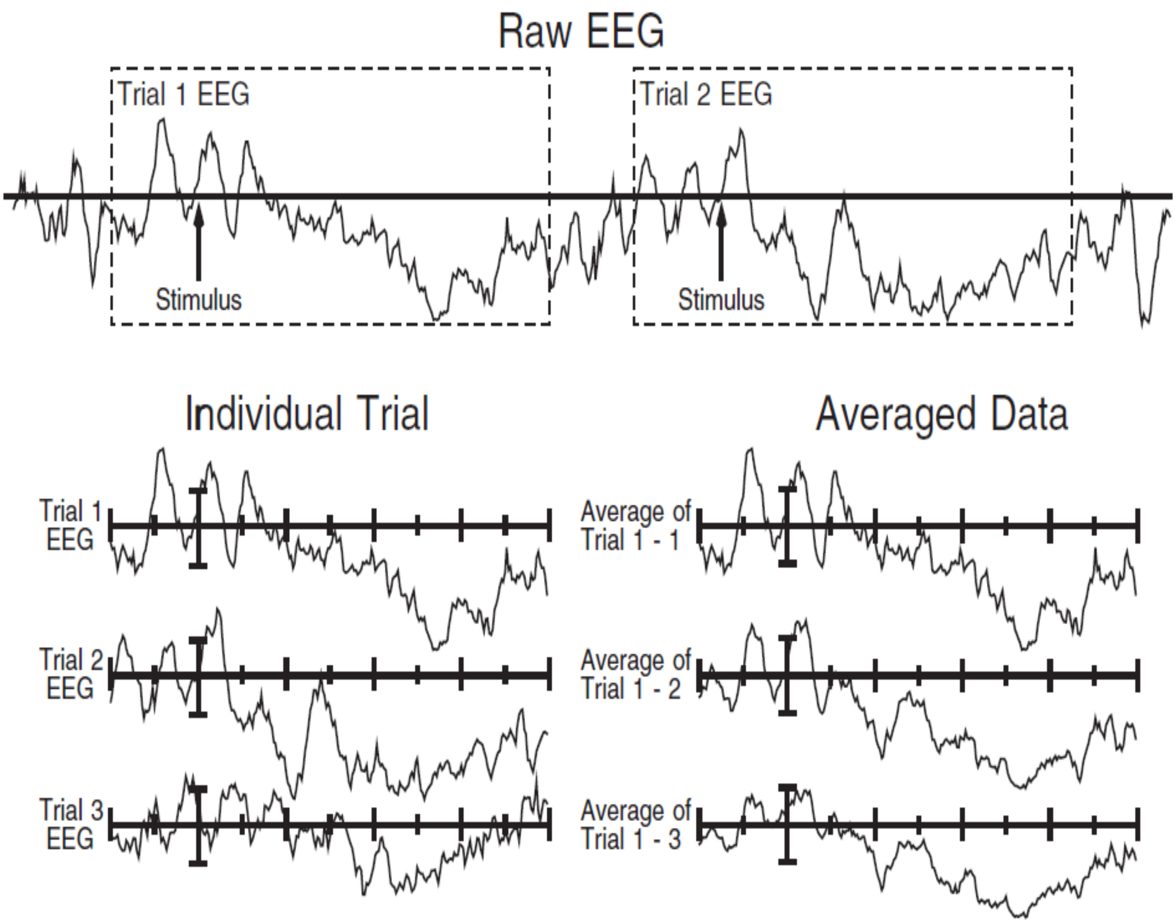


Figure 3.6: EEG raw-signals of individual trails are gathering into dataset respect to average process [58]

The SSVEP responses are present in a different time, which match each stimulus trial with respect to response waveform. Extract these waveforms based-SSVEP responses from a single or multiple trials. The tagged-trigger has been used to detect and determine exact firing time-point in each onset-stimulus with respect to trial, and extract the feature based on time-locked-response then stored in datasets. Extracted features of brain response from stored dataset that is contained an SSVEP response signals within random contaminant signals. Mathematically, the number of trials (N) presents the stimulated EEG signal that contains a noise range of signal ratio (R) average process of (N) trials is equal to $\left(1/\sqrt{\mathrm{N}}\right)$ R. The average process is a function of the square root applied to multiple stimulus trials. In order to decrease the contaminated of artifacts signal and increase SSVEP respond based on the square root function, since cumulative data of EEG signals are reduce the effect of contamination signals using average process using the square root role methods (see section 4.1.2.1). However, the accumulate signal-to-noise-ratio (SNR) is increase to collect the respond functionality of SSVEP. In other words, the relationship between the number of trials and averaged SNR achieves a significant acquired signal based on a repetitive number of trials, which improve the quality of accumulative data by increasing the number of trials to decrease noise effects as mentioned before.

3.2.1 Frequency Domain Procedure based SSVEP response

Decomposed of any signals into a set of (sine- /cosine-waves) indicatives a various frequencies, harmonics, amplitudes and phases; these signals can be easily reconstructed again based on effort domains with respect to time-domain or frequency-domain. The filtering techniques, in terms of decomposing signal provide the ability that increasing induced characteristic and suppress other based on configuration and filter types. These induce characteristic and feature properties are extracted using filters, which expressed usually by transferred function based exertion domain. The transfer functions are extract the incoming signals that rendered into components. The responses are specified by filtering approach, which observed the changing in amplitudes of each frequency and different phases with respect of response functions of each incidence brain stimulation. The principle of transformation signals between frequency-domain and time-domain is exact gives a (sine-/cosine) waves-set that represented by different frequencies and different phases. Mathematical, the procedure apply the fast Fourier transform (FFT) (see Appendix A.3), which adapt any signal into frequency-domain; in such a case providing power spectrum, which is computed to extract both amplitudes and phases. However, it is possible to inverse the out-come result using inverse fast Fourier transform (IFFT) to convert again to the original signal. In fact, the frequency responses can be constructed by setting many of scale-factor, which configured to suppress and restrain the signal. Attenuate some frequency by a specific amount corresponding to scale-factor. To complete suppression and an inter-mediate value for undesired frequencies will be partially attenuated based-filters design. The structured filter design is setup values, which are allowed to (passed or un-passed) band of frequencies by zero or one; these values can pass certain frequencies without unaffected by designed filter; and completely suppress undesired frequencies which are partially or completed attenuated. In other word, the frequency response function is a convolution between two signals in the frequency domain or time domain. The essential filters are amplified and digitalized the non-stationary of EEG signal. Therefore, it is necessary to setup filters, which are suppressions and attenuate unwanted signals, such as AC power-line noise. All empirical studies that contributed in this thesis have used the sampling rate of 2K Hz. This sample-rate allow to use a high precision filters and provides the highest accuracy base Nyquist frequency (NF). In addition, it is necessary to suppress very low frequencies of artifacts, such as eye-blinking or eye-movements; by setting a high pass filter (HPF) with (low cut-off freq. at 2 Hz) to remove such is eye-movement artifacts. However, all experiment strategies were depending to eliminate the effects of power AC electrical line noise, which are as described before (see section 3.1.2.3). On the other hands, it is possible to reduce all effective of power-line noises sufficiently. A more specific way by implemented a low pass filter as half amplitude, within high cut-off freq. at 35 Hz that direct effectively on noise without misrepresenting the EEG raw-data as much as the notch filters design.

3.2.1.1 Selective Brain region-based Spectra Analysis (First study)

Open source tool of EEGLAB provides a graphic user interface (GUI) that is consecutively under the MATLAB platform environment, which processes multiple functions applied on accumulative EEG raw-signals such as average procedure based on point-to-point under multiple trails with same conditions. Built-in functions of EEGLAB such as the Fourier transform that decompose and interpret signal into frequency-domain. However, there are other many functions, which depend on triggers to interpret signals in time-domain, can be applied on individual channels. The EEGLAB functions are structured as stand-alone processing unit to process filtering raw-signals, artifacts rejection and average-process.

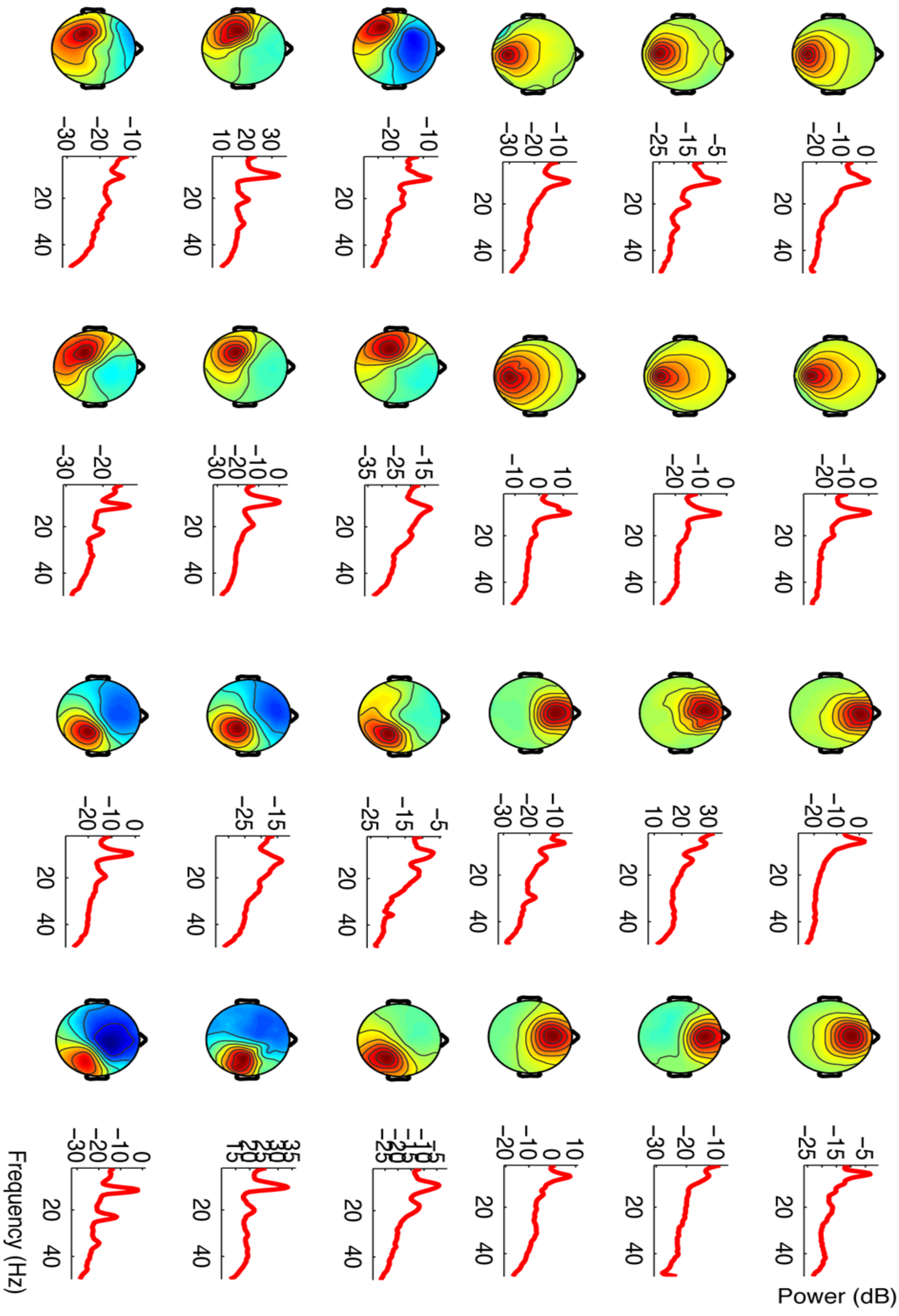


Figure 3.7:Power spectrum result present 32-EEG channels respect to brain lobes analysis

Independent component analysis (ICA) technique, which extracts the consistency component of each electrode supported by bootstrap statistical methods based on data resampling, has been considered to extract statistical results. A preliminary assessment is used all 32 channels of EEG-electrodes, which decompose the EEG raw-signal to inspect the stronger stimuli based on distribution of spectrum power on scalp maps in respect of topographical result. This approach is estimate to find out stronger power spectrum that appear on different brain lobe areas; however, it is possible to measure diverse effects based on event-related potential (ERP) on specific located points. Cleaning the EEG signals and stored, as dataset is one important function done it with EEGLAB. The gathered of EEG/epochs are passed through a high pass filter (HPF) at (1 – 20) Hz to remove drift signal and low pass filter (LPF) at 38 Hz to remove power-line contaminate noise. However, removal of all artifacts that are associated with eye-artifacts blinking and movement using ICA in each EEG epoch. The spectrum analysis has been applied on a cleaned dataset, which is gathered based on multi-trials recording procedure to extract features of brainwave under same conditioner of visual stimulus. Figure 3.7 illustrates four brain-regions, whereas the occipital lobe react the activity with alpha frequency band near to ~10 Hz, however the frontal lobe activity with theta frequency near to ~5 Hz, also theta band, and the partial left/right-temporal lobes demonstrate the activities on region near to ~3 Hz and ~20 Hz. The power spectrum based on brain activity in this experiment was calculated in order to analyse the effect of stimulation on brain regions with respect to different stimulus-frequency bands. The topographical result of spectrum analysis showed significant alpha and theta band frequencies which lead to major effects in the frontal and occipital lobes region. Furthermore, it was discovered that a narrow-band frequency associated with alpha brain waveform has more effect on occipital lobes, which is recording a maximum spectrum. Therefore, it was determined that different levels on amplitude in cerebral areas and give higher alpha band frequency (10 – 13) Hz as the strongest response. The activate brain region is examined with respect to stimuli events by determining the model and setting the log-transform base on normalize distribution in each EEG-channel. However, a range of frequencies (10 – 13) Hz presents the alpha band that are selected to estimate in other experiment based-spectral power analysis. Different effects of spectral power are presented on the single electrode, which are located on EEG-channel No.31; this channel is representing occipital centre lobe that denoted by (O_z) as shown in Figure 3.8.

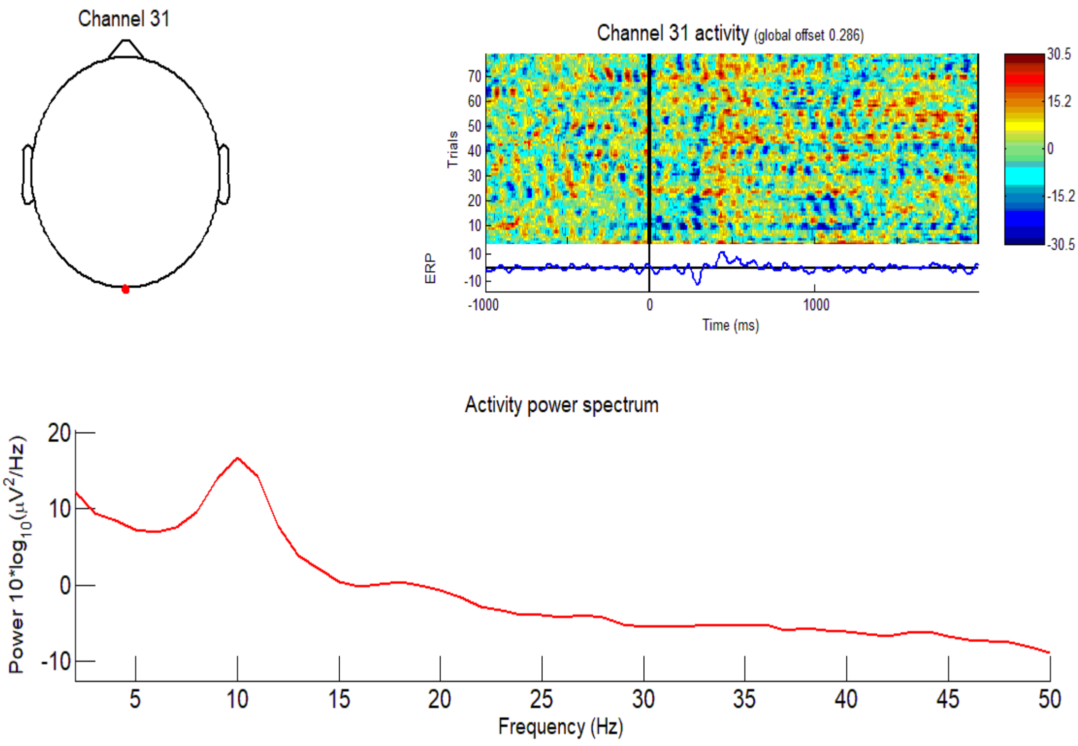


Figure 3.8:Power-estimation on Oz present brain activity at centre of occipital brain region

The illustrated results are separated into two main categories: the first presents result that extract the event-related-potential (ERP) in blue-curve and the second, estimation power spectrum of red-curve. The results are confined to a single electrode at O_Z, which provides significant differences in the frequency band based-power estimation of induced potential signals. However, the feature of ERPs is given a vital response based on SSVEP evoked signal that is growth affected on alpha band.

3.2.2 Time Domain Procedure based SSVEP

Time-domain procedure is described by setting a filter-type, which is considered a common approach of epitomizes the suppression process of high noises signal effects. Attenuate the high noises and other effects using the average-voltage process (AVP) which is utilized as time-point accumulator with respect to presenting the pick-voltage. Adjustment the time-point dependent on (time tagged-triggers) accumulated responses. In fact, this design is accumulative filter that computes time-point (n) based on unfiltered data points of (n – 1) and (n + 1) with respect to cover all data points. Consequently, the fundamental of inverse-Fourier transform (IFT) allow presenting the SSVEP response signals in time-domain, according to time-points voltage average process in terms of time-series-point. This designed filter is eliminating the responses based-brain waveform activities. This procedure on accumulate averaged response can be formalised based on SSVEP responses by:

$$f_{SSVEP_i} = \sum_{j=-n}^{n} W_{SSVEP_{i+j}} \qquad 3.2$$

Since, $f_{\mathrm{SSVEP_i}}$ present a time-domain signals, which are gathering responses of SSVEP waveform at time of i-time at each point (n). However, compute the averaged-voltages and summation the weight of each (n) with respect to recording series-time data. Therefore, the weight summation is modulating one-side at certain time-point respect to current value $W = 1/(2n+1)$. This technique is called the averaging (post-points) aspect to current points of (+n), whereas the (next-point) presented on (2n+1). This filter type is providing a straightforward to attenuate and remove the higher noise signals. By gathers unfiltered raw EEG signal with respect to incident of brain response using triggers, in which is equal to sum of high/low components based time domain.

The impulse response function is equal to weight-function process. Wherein, the desired signal is symmetrical shape waveform that respect to baseline assumption. Since, the visual stimulus iterates periodically and subsequently the brain-evoked responded are echoed the periodic-stimulation. However, the concept of digital filter that is implemented based on impulse response function to extract responded signals at certain time-point of waveform instead to the weight function is formalised as:

$$f_{SSVEP_i} = \sum_{j=-n}^{n} IR_j \, W_{SSVEP_{i-j}} \qquad 3.3$$

The same procedure of filtering operation is performed as described in equation 3.2 by substituting and adopting argument of IR_j, which presents the coefficient values of impulse response function at the desired time j. The combination of impulse response function and weighting signal according to responses, which are convoluted together based-DSP technique. Therefore, improved the question 3.3 regard to convolution signals based on state of impulse response function and unfiltered waveforms; a new formal of combination filter can be written as:

$$f_{SSVEP} = IR * SSVEP \qquad 3.4$$

Impulse response functions and brain waveforms manner are convolved together and typically symbolized by $(*)$ in equations that indicate convolution operator. In fact, the sub-set of filters in equation 3.4 and called impulse response filters. This filter does not need a feedback signal; however, it is easily designed and implementation using MATLAB/script or tools.

3.2.2.1 Relationship between Time and Frequency Domains

Digital signal processing (DSP) allows to design filters that achieve both frequency-domain and time-domain based techniques. The time/frequency domains are two different methods used to examine the incoming signals. However, the analysis domains are commonly used in many applications such as (electronics, acoustics signals and others). The time domain analyses is convert the raw-signal over chunk period that measured the variability against time function, (e.g. electronic signal are mainly analysed based on voltage-time plotted). Rather, the frequency domain is a technique that used to convert time function signal to frequency and different phases. Furthermore, the frequency domain analysis is mostly used to detect power spectrum with respect to periodic or non-periodic signals.

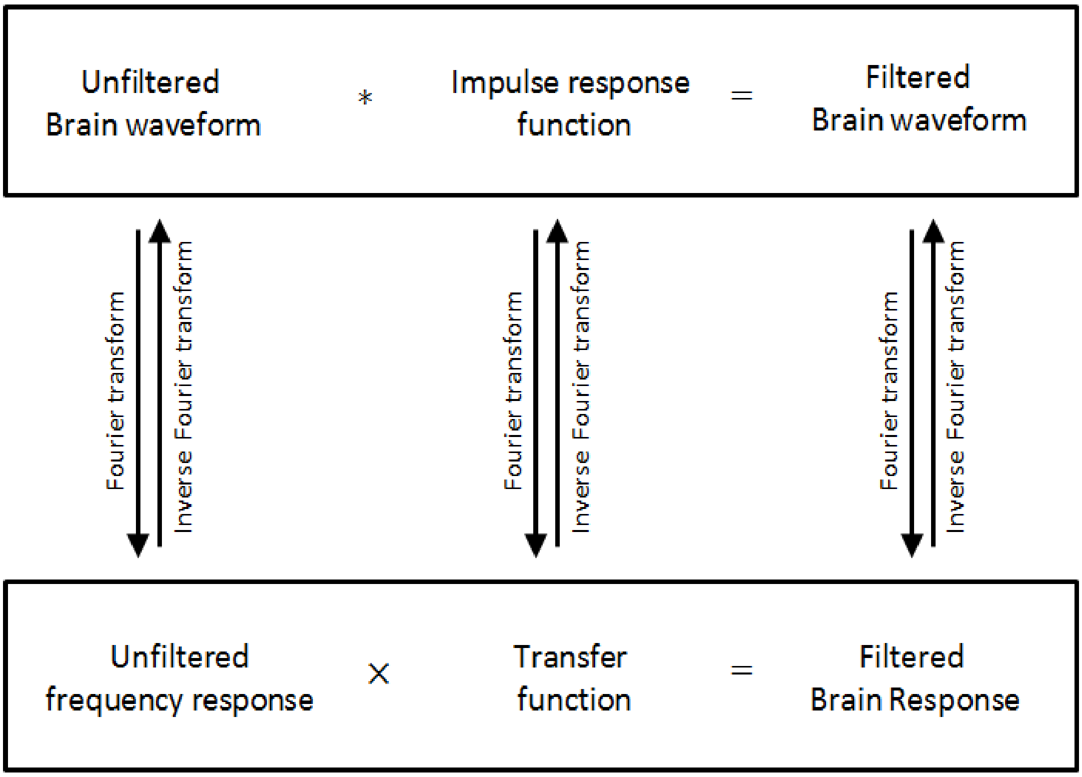


Figure 3.9:Relationship between time and frequency domains that convolved and multiplied [58]

However, it is possible to analyse raw-signal, such as non-stationary in frequency-domain. There are many different mathematical algorithms that can used to evaluate and analysis the signals, which are referred in both of time/frequency-domains. Indeed, the design filter is a straightforward signal conversion among the responses based on convolution or multiplication; the domains are dependent on transfer function, which determines by convolved or multiply functions respect to domain. The multiplication constructed in the frequency-domain, which is equivalent to convolution in the time domain, is fulfilled to establish a relationship between time domain and frequency domain. Often the convolution operation is denoted by '*' and multiplication operation is'×'; in order to classify between them. Therefore, it is possible to determine a filter-type that transforms response function into frequency-domain. However, inverse Fourier transform (IFT) types of function can used to recover any time function, which convolved with Fourier transform. In fact, impulse response function is equal to Fourier transform based-filter design. The impulse response function is obtain the desired transferring function conversely simply transformations function into time domain, as illustrated in Figure 3.9 [58]. Constructing filters technique is usually recommended to obtain of extraction features from time series functions. The function could convolve or multiply to extract features based on contribution domain.

3.2.2.2 Extract Feature using Time/Frequency Domains

The filtering technique in EEGLAB gives the advantage of linear filtering that implemented with the signal processing toolbox of MATLAB platform. The time/frequency decomposition in EEGLAB is a separate tool that includes morelet wavelets to use in different manners. As mentioned before the EEGLAB is an open source tool that contributes to implement time/frequency analysis. The new approach integrates the ICA technique regarding to time/frequency analysis. The changes of induced potential signals on evoked brainwaves based-stimuli events are measured in dynamic-power spectrums, although event-related potential (ERP) is nearly complementary to explain these changes in electrical-potentials signal according to certain stimulus respect to brain responses. This approach of time/frequency analysis takes place to attractive the gathered of EEG raw-signals, which are stimulated under same conditions process to cover all 32-EEG-channels instantaneously. The EEG-channels are individual indicated which referring to stand-alone electrodes denoted by EEG-channel name.

The anticipated epoch of EEG-raw signal is filtered using the finite impulse response (FIR) with low frequency at 38 Hz and high frequency at 2 Hz that remove the AC power line effects; however, reject the artifacts of eyes and other muscle movements using ICA technique; correspondingly averaging process have been take place on selective EEG/epochs. Here, the data of EEG-recording signals order to provide the best stimulate frequency based on different brain regions. The brain activities are realised the different cortical areas that are concurrently responded. Consequently, each EEG recording channel has own weight mixture-signal that signifies different in cortical neuron sources based-activities respect to strong responses. A single spick or basin waveforms in event-related-potential (ERP) might present an index that combines brain response. Figure 3.10 shows (two-dimensional) results of evoke ERPs dynamic signal in respect to time domain analysis consistency across a multi-trial based on time-lock-events trigger technique that contributed in this experimental work. The measured activity regarding to ERP represent independent component sources, which are occurrence on positive and negative waveforms.

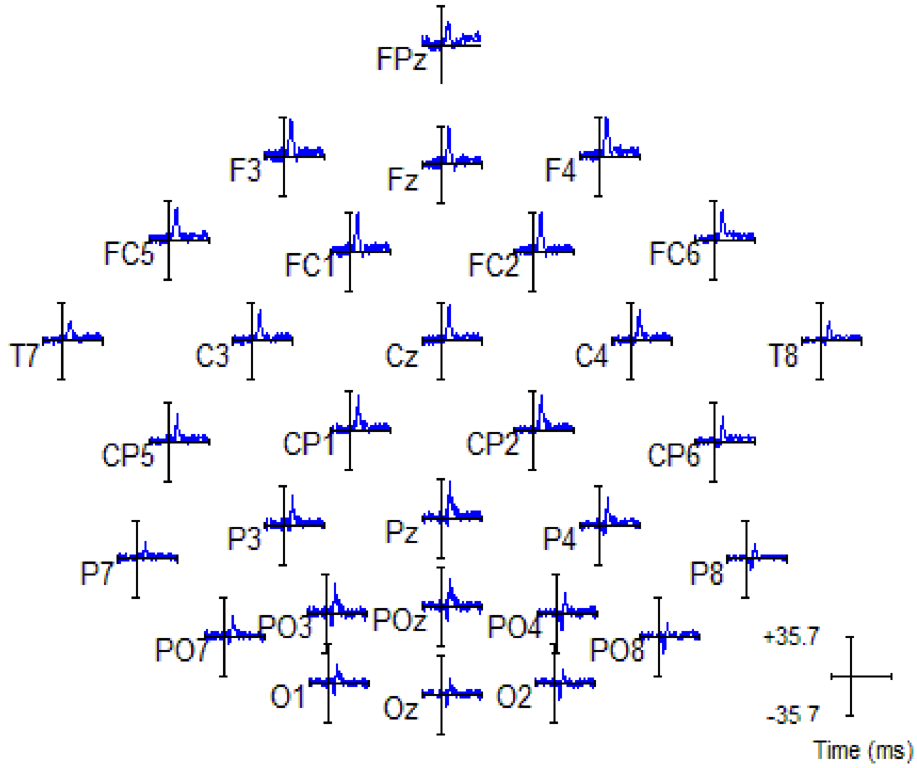


Figure 3.10:Primery result based on ERP waveform respect to overall brain regions

From the point of view, the time-domain analysis that exposes ERPs results according to the time-locking events are emerge several interesting argument from deduction in each channel. Averaged process of ERP is provide the alpha band stimulation effect at frontal region at F_3, F_4, Fz, FPz, central region C_3, C_4, Cz and FC_1, FC_2, FC_5, FC_6, temporal T_7, T_8, parietal P_3, P_4, P_7, P_8, P_z, cerebral region at CP_1, CP_2, CP_5, CP_6; and occipital O_1, O_2, O_z. The stimulation effect on results were exploited overall EEG-channels that placed on helmet on scalp, and provide significant differences in alpha band frequency based-evoked potentials. The features of power spectrum and ERPs results provide a substantial SSVEP responses affect.

3.3 Conclude of Initial Experiment based-Configuration

Brain-computer interface (BCI) based-system has been implemented as a low-cost prototype to induce the brain activities and responses based on steady state visually evoked potential (SSVEP) paradigms. Light-emitting diode (LED) that is used to stimuli the subject-brains. Set up LED flickers with fixed flickers represented by (spotlights) with respect to time-locked events. Intended essential amplified and digitalized of non-stationary EEG signal. All un-necessary signals have been suppression and attenuate using different filters type, which are remove the artifacts from EEG-raw signal. In this chapter, the experimental study is prepared to observe different brain-region based on band diverse band of stimulation frequency. The comprehensive EEG signals are sorting to process averaged technique that maximized the feature extractions. The averaged approach has taken place to extract responses and support to removal must of the artifacts effect. Open source of EEGLAB based-graphic user interface (GUI), consecutively used under MATLAB platform environment are processes an accumulative amount of comprehensive EEG-raw signals. A 12-EEG channels are place on scalp to cover the parietal lobe at PO_3, PO_4, PO_7, PO_8 P_z, and occipital lobe at O_1, O_2, and O_z, and two-addition reference electrode of (CMS, DRL) that used to gather the raw-signals. Utilize different scheme that configure EEG-channels to improve the best responses power based-four differ brain region. Reducing amount of EEG-channels number that are configured in different schemes. Topographical results represent the spectrum analysis of brain responses behaviour under different stimuli frequency. The spectral-power illustrate the responses in four different brain-regions and different frequency, at occipital lobe with alpha frequency band near to ~10 Hz high activity, frontal lobe with theta frequency near to ~5 Hz high activity, and theta band in left/right-temporal region near to ~3 Hz to ~30 Hz high activity. The result of spectrum analysis shows significant alpha and theta band frequencies which lead to major effects in the frontal and occipital regions. However, different effects of estimate spectral powers are present a single electrode, which is located on centre of occipital lobe no. channel 31 denoted by (O_z). However, a stimuli range of frequencies at (10 – 13) Hz of alpha band present a decent power. Time-domains procedure is considered the event related potentials (ERPs) according to the time-locked event technique, which provide several interesting points from deduction in each channel effort based on potential signals. This technique is extracted directly depending on average-voltage process (AVP) beads on time-point-series and event tagged-triggers to accumulate responses. The outcome result of ERP is illustrate different responses between brain region, which allowed to select the occipital region and frontal because are provide the SSVEP responses, and neglect the partial of left/right brain region-

CHAPTER 4

SSVEP BASED ON FREQUENCY, COLOUR, AND TWO DIFFERENT STIMULUS-PARADIGM

The visual cortex-brain is highly adaptive with effective visual stimulus. Different responses can be evoked through stimuli flicker, which contains different characteristic based on brain activity. Steady-state visual evoked potential (SSVEP) paradigm is echo of brain activity responses that elicited by iterate brain-stimulus at appropriate medium, such as spotlights flicker based certain frequency. The flicker is depending on range of frequencies bands of LF, MF and HF based on SSVEP paradigms. This chapter discusses the effective frequency band that gives a stronger brain activity response. Beyond stimulus frequency band debated a three dynamic colours that influence the brain activities and directly effect on SSVEP response. Furthermore, two stimuli-types of regular/irregular paradigm are found out the oddball effort based on SSVEP responses. The criteria of frequency, colour, and oddball paradigm are applied in different experiments to discover and discriminate the contiguous range of parameters that yield optimal strong and largest level base-SSVEP response. These contribution works have been published results as follows:

- Multiple frequency effects on Human-brain based Steady-state visual evoked potential (SSVEP), 2016 IEEE 6th International Conference on Advanced Computing, 978-1-4673-8286-1/16 © IEEE
- Beyond Pure Frequency and Phases Exploiting: Color Influence in SSVEP Based on BCI, Computer Technology and Application 5 (2014)
- Discriminate the Brain Responses of Multiple Colors Based on Regular/Irregular SSVEP Paradigms, Journal of Medical and Bioengineering 2015, 5.2.89-92/2016
- Exploiting a Short-Terms Adaptation: In Brain Computer Interface Based on Steady State Visual Evoked Potential, 2014 NNGT: International Journal of Information Systems, ISSN Online: 2356-5888

4.1 Stimulation using Multiple Frequencies

The visual cortex provides robust brain activities dependent on light flicker; high responses can be defined at most stimulation frequency bands of LF, MF, and HF. In order to expose specific band frequencies that depend on the relationship of flicker stimuli based SSVEP paradigms, this section, presents a low cost prototype BCI based on multiple flickering frequencies of visual stimulus, as shown in Figure 4.1. However, the phase-tagged (PT) technique has been used with all conceivable of stimuli flickering that directly indicated with SSVEP response signals, which are revealed certain brain activity. The design model is prepared as a closed-loop and ready to extract features of an offline /online analysis based system. The stimuli-frequency responses are extract features from EEG raw-signals that decoded from brain activities regarding the voluntary subjects to intention on desired flicker. The differences between several bands of frequencies that are demonstrated based on flickering LED light to distinguish the responses in amplitude of spectral power recorded from EEG signals using three electrodes. This study has explored the frequency bands to discover the optimal frequency that provides a reasonable response quality of SSVEP signals. Consequently, the stimulus flicker frequency confined in low frequency (LF) and medium frequency (MF) bands, which are covered at (2 - 25) Hz, can evoke the largest SSVEP responses amplitude compared to the high frequency (HF) band. Using transection phase information based on phase-tagged trigger (PTT) in analysis, which supports the encoding of the SSVEP approach. However, a classified the accuracy dependent on the primary influence strength response based system. Using the signal-to-noise-ratio (SNR) property to extract features of brain wave activity based stimuli-frequency, which restricts SSVEP response signals. The stimulation paradigm of multiple frequency sequence is set up on a stimuli panel, which responds via an embedded microcontroller crossing a computer in order to change the individual frequency in each position of light emitted diode (LED). Visual stimulators play an important role by presenting a flicker within multiple frequencies using a single LED. Taking into account the effect of stimulation parameters relying on stimuli frequency, the methodology of FFT was employed as the (offline) technique to recognize the different responses regarding (power-spectrum) analysis. However, wavelet was used to decompose the EEG signal into a series of frequencies depending on three band levels of LF, MF and HF, which included many impulsive components based on evoked component of brain waves. The spontaneous nature of SSVEP components is influenced by the potential evoked based frequency, so that the differences between amplitude according to analysis signals are uneven.

4.1.1 Accumulation EEG Signals based Multiple Frequency

The configuration system of the current experiment is illustrated below in Figure 4.1. The system of a multi-stimuli panel was configured with programmable LEDs using depth embedded system board. The EEG signals were recordings of brain activity that are fed to an "Estimator prototype". The prototype consists of an EEG analytic module to (analyse brainwave), where the instruction of the visual-stimulation changes, along with decoded command that connected to controller to updates the evoked of stimulus LED, and SSVEP generator mixer utilises ordering to change a new stimulus based frequencies.

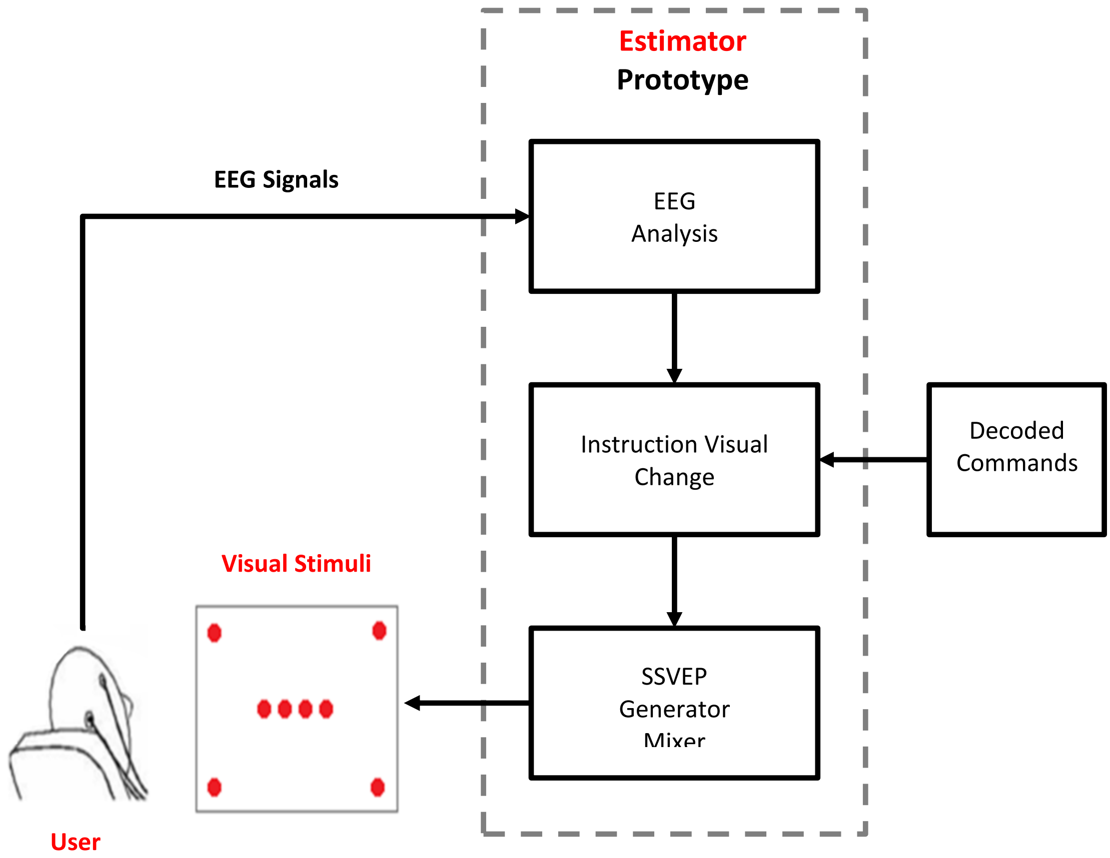


Figure 4.1: Proposed prototype that used a unique-colour LEDs based on stimulus evoke signals

The flickering/LED base-frequency was set into diverse frequencies at (2, 4, 6, 8, 10, 12, 14, and 16) Hz. The panel contained (Eight-visual stimulus positions) distributed in the centre (R_c^1, R_c^2, R_c^3, R_c^4), and surrounding (R_s^1, R_s^2, R_s^3, R_s^4) according to (Table 3.1), which is presented a fashion of patterns. The stimuli patterns were considered to exploit the multiple frequency effects on brain activities; in addition, the duty-cycle stimulation effect (see section 5.1) was employed to explain in other experiment that discriminate the influence of brain responses based on new paradigm. In order to produce the experimental conditions corresponding to an SSVEP responses paradigm based BCI system, all LEDs are set to attract with a flicker simultaneously (in same time of evoke stimulation), and each stimulus/flicker corresponded to a different frequency. The active Ag/AgCl based on EEG recordings were timed at 20 seconds duration for each stimulation onset in each session (see section 3.1.1). The voluntary participants (subjects) were instructed to pay attention to the single LED, driven by computer a permanent-command that switched a definite LED attend with specific frequency. Taking into account main verbal instructions which guided the subject to focusing on the desired LED in the centre and surrounding manner corresponding to a given frequency by (f). Due to the completion time of the experiment, it was divided into eight sessions of 60 seconds, which were recorded complete three session times. Analysis of the EEG raw-signals was distributed into individual EEG/epochs in split of set-files (templates), which are substantial to arrangement as dataset of experiment contribution.

4.1.2 Process analysis and Result of Multiple Frequency

The voluntary participants were seated at a constant distance of ~0.9 meters from LED stimulus panel. Each LED had a diameter of eight millimetres with light intensity of 1450 mcd. The stimulation LEDs were controlled using a microcontroller that connected to the computer via a serial-data bus. The accuracy of the generated stimulus frequency was checked for validity using a digital oscilloscope. The flicker patterns were previously stored in the memory of the microcontroller that implemented with FPGA using a depth board that controlled by computer of permit-command. A variety of band frequencies based on phase-shift of flicker frequencies had been sorted with respect to patterns, which were used to evoke the SSVEP signal. A maximum error of stimuli-frequency was measured within less than 0.0015 Hz, which provides a high accuracy flickering under normal operating conditions and room temperature. Considering individual LED as a evoke-signal presenter stimulator, the variation in frequency with regard to phase-shift was constrained also in phase-tagged triggers (PTT) technique, which depends on a marker boundary among evoked brain (response-signals in time-consuming) based on segmenting epochs of EEG signal recordings. The stimuli sequence was recoded into 20 seconds that were marked with cycle trigger and onset firing trigger, which indicated when LED state-on. Flickering LED in all stimuli frequencies depended on 25% of duty cycle. A multiple frequency empirical study had been protocoled based on variable flicker frequencies of (2, 4, 6, 8, 10, 12, 14 and 16) Hz to induce evoked SSVEP signals. These frequencies were used to ensure the best flickering frequency for stimulation; subsequently, offline analysis occurred of induced SSVEPs effect based on EEG recordings of brain activity. Furthermore, in this experiment consider single trial, which used to measure the SSVEP response strength. The EEG signal was pre-processed by extracting and cleaning the dataset from artifacts, which included the eye-blinks and AC-powerline interaction (see section 3.1.2.3).

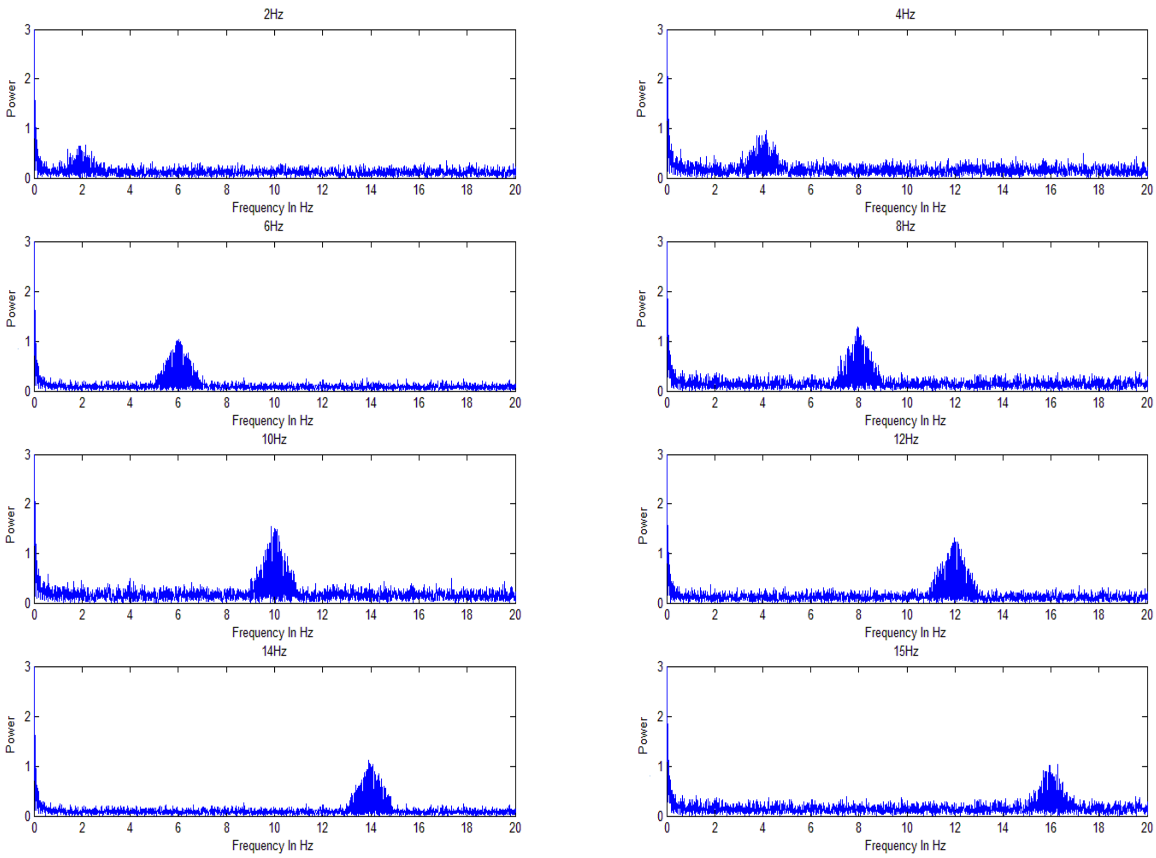


Figure 4.2 : Different stimuli flicker based frequencies which impart diverse levels of spectrum power

The power-spectrum of different stimulation frequencies imparted as primary result that is illustrated in Figure 4.2. The result of this study identified optimal range frequencies that are restricted on LF and MF bands frequency at (2 – 16) Hz based-induced evoke SSVEP responses. These results were extracted using filters of high-pass (HPF) and low-pass (LPF) which were implemented using MATLAB within offline analysis. The preliminary analysis helps to select the best stimuli frequency based-evoked SSVEP response signals, which are employed as the main stimulation flicker to use afterward in further experiments.

Excerption results provide evidence, since 2 Hz and 4 Hz stimuli-frequencies give a similarly low power spectrum at 14 Hz and 16 Hz. In other words, the power spectrum at stimuli frequency at (8, 10, and 12) Hz with respect to response is sufficiently large. The induced SSVEP signal was carried out at a fixed frequency within a regular interval (periodic pattern), as illustrated in Figure 4.2. The LED flicker depended directly on cycle was trigger using phase tagged (PT) according to various frequencies, as mentioned before. Each LED has a certain phase based individual flicker sequence of base stimulus frequency that presents in ith LED and delay time ti corresponding to Equations 4.5, and 4.5. All stimuli flicker are generated within a constant regular interval based on various frequencies. The demonstrated result presents the primary consequences of different frequencies that influence brain activities based on SSVEP paradigms.

4.1.2.1 Signal to noise ratio (SNR) based on Multiple Frequency

The EEG raw-signal was acquired using unipolar optical-fibre of EEG/channels with three electrodes and two more of reference electrodes are fixed on a scalp-helmet, and connected to the bio-signals recorder of BioSemi-EEG system. More than (Twenty) voluntary healthy subjects, aged between 23 and 39, participated in this study. Each participant was asked to focus their attention by eye-gazing at individual flickering LEDs (see section 3.1.1). The EEG raw-data was recorded under control setup conditions and actual modes of experiment study. This experiment was set to discover the optimal effect frequency and reduce amount number of recording channels-EEG. The stimuli frequency and EEG-channel amounts number played a role in design of a practical BCI-system in real time applications. The steady-state visual evoked potentials (SSVEPs) are defined from a visual cortex of the brain region, in terms of a natural accumulation of EEG signals by placing EEG-electrodes over the occipital brain region. In this model, the bio-signals measured at main occipital of (O_1, O_2 and O_z) as illustrate in Figure 3.5 (as shown in previous chapter 3), in compliance with the BioSemi EEG system (see section 3.1.2.2). In this experimental work have realistic electrode locations were obtained by preliminary measurements. However, acquiring a (wet gel) to reduce impedance between the scalp and contact electrode to obtain a high signal quality that assisted in exploiting and extracting. SSVEP response was investigated using Signal to noise ratio (SNR) based on three electrodes. The highest SNR value are located in the occipital brain region, as proved in this experiment. The filtering technique has been widely used in EEG signal analysis; and pre-processing is conducted to improve the SNR values based on EEG signal inquiry. In practice, the synchronize interaction of EEG signals are used with setup filters to compute a linear combination of EEG signals based on all electrodes (as shown previous chapter 3). Therefore, the EEG signals have been sampled at 2 KHz, subsequently setting a band pass filtered (BPF) in frequency range at (0.5 - 35) Hz, which prevents the artifacts. The measurement of electric-potential based on neuronal interactions is conducted to validate the SNR value. Improve the SNR technique by selecting a three recoding electrodes, which is computed dependent on the SNR ratio between power intensity that is given by base frequency of (stimuli) and neighbouring frequency of induced SSVEP response. To generalize equation that compute the SNR in desired design system is as follows in Equation 4.1:

$$SNR_m(f_n) = \frac{P_m(f_n)}{\frac{1}{x}\sum_{q-x}^{x} P_m(f_{n+q})} \qquad q \neq 0 \qquad 4.1$$

Since, the $P_m(f_n)$ presenting the Fourier of spectrum power at anticipated frequency at f_n in channel (m); however, the (x) represent the neighbouring frequencies, which distributed by upper and lower bounds. Hence, the reference signal is defined f, which presents the exact of stimulating frequency. In the case of the study only three-channel have been used, produced the SNR based on evoked SSVEP responses were calculated using the EEG channels projection analysis mode. The SNR signals of three EEG channels were estimated the values in defined mode, which is selected a combinations of two electrodes that including the reference electrodes (channels). Furthermore, feature extraction of SNR value is averaged structured to demonstrate the compression between two flicker frequencies. This procedure was applied on all stimulation frequency terms of this experiment. Anywise allocated area of EEG-channels consumed the highest SNR signal, which was selected to compare between responses.

4.1.2.2 Fast Fourier Transform (FFT) based on Multiple Frequency

This analysis is described by detecting variable parameters such as amplitudes and phases based on flickering-light /LEDs of stimulation frequency that is distributed into various frequency bands. Firstly, the stimulus-frequency is provoked the strongest SSVEP response which are extract from multiple stimuli frequencies using Fourier Transform (FT), followed by filtering signal to clean-up from any artifacts and find the spectacle power of induced evoke-signal based-desired flicker/LED of stimuli-frequency. Essential analysis is implemented by a digital signal processing (DSP) technique called fast Fourier transform (FFT) given by Equation 4.2; the aim of Fourier analysis is decompose any periodic signal-type in terms of amplitude, frequency and phase which is expressed as sufficient result in frequency-domain. This facilitate is support to extract the spectrum-power of multiple frequency bands in different terms results, more mathematically detail (see appendix 7.A.3).

$$F(f) = \int_{-\infty}^{\infty} x(t).e^{-j2\pi ft}\,dt \qquad 4.2$$

The applicant of signal $x(t)$ is present in the time-domain where signals are transformed into frequency-domain signal by $F(f)$. Each frequency is integrated with respect to conjugating over 2 π periodicity in one cycle. Theoretically, the terms of the signal processing based FFT can be extract decent features corresponding to Equation 4.2 that obtained on sufficient length of waveform.

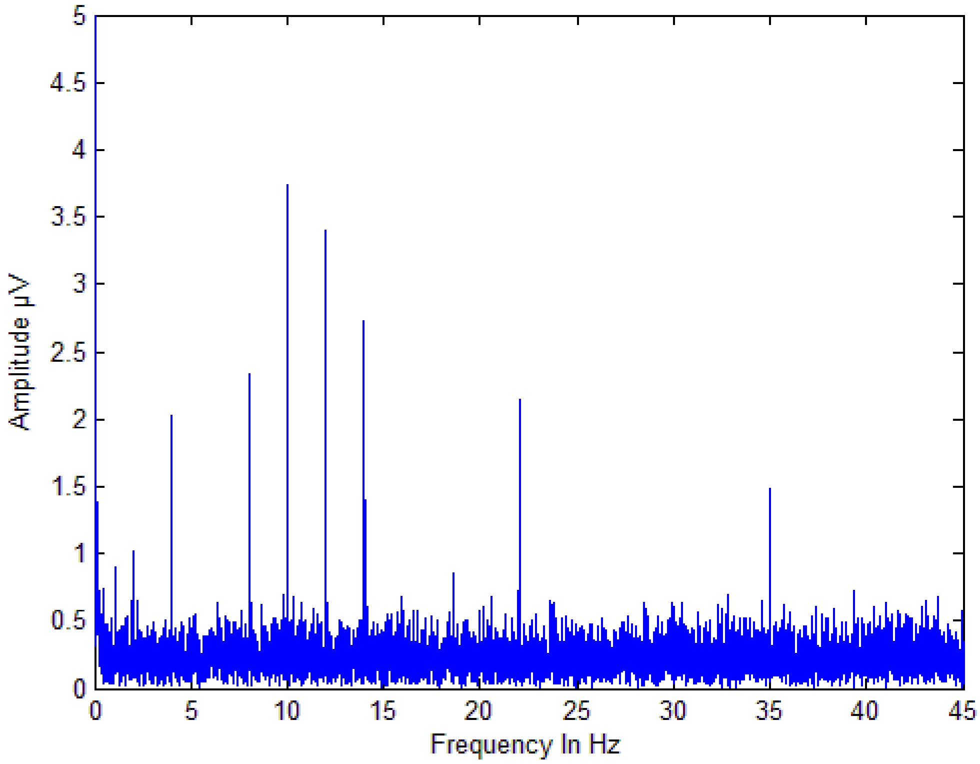


Figure 4.3 Multiple flickering observed the 10Hz stimulus strongest response of SSVEP

The first target was isolating desired stimulation frequencies depending on responses that are presented in brainwaves. The purpose of FFT is to distinguish a difference between stimulation frequencies, as shown in Figure 4.3. The spectral power have been plotted based on different visualized flickers, which are instructed with each individual stimulus-frequency. Robust evidence is discriminated 10 Hz stimulus-frequency of induced signal, which provides the strongest evoke SSVEP responses. As well as that is proved in previous chapter (see section 3.2.1.1). Digital signal processing (DSP) support to utilize precise-filters, such as finite impulse response (FIR), which proceed to extract features based on FFT approach. The biological signals of EEG raw are contaminated with 50 Hz power-line frequency interference. Therefore, it is necessary to extract pure features and cleared from unusual contaminants signals. However, the reason for choosing FIR is that it is inherently stable, having a linear phase and being flexible in magnitude responses and easier implementations using MATLAB tools. A common transfer function implemented as filter design corresponds to Equation 4.3:

$$H(z) = \frac{Y(z)}{X(z)} = \frac{\sum_{k=0}^{M} b_k z^{-k}}{1 + \sum_{k=0}^{N} a_k z^{-k}} \qquad 4.3$$

The linear filter is adapted to enhance the response based SSVEP paradigms have been used in this approach. The linear filter is presented by $H(z)$ aspect to 4.3, which produces an output that dependent on components b_k and a_k. Anywise, the objective to use a linear filter that enhanced the extraction feature of response based-SSVEP signal, however this filter-type is adjustment tolerate to change filter-coefficient regarding to anticipated stimulus frequency. The adaptive filter is involves minimizing a cost design by determining the filter-coefficients with each flicker frequency. Since the EEG is a non-stationary and non-linear; therefore, the desired design of filter is allowed to change any coefficients in respect of time according to achieve optimum response signal. The analysis result leads to decent evidence of a reliable design that customizes by coefficient-filters, which isolate the sturdiest evoke SSVEP signal based on recording of brainwave activities. From Equation 4.3, can be substitute $N = 0$, and non-feedback FIR filter of linear time invariant (LTI) system that optimize filter performance. This design methodology is denoted as a non-recursive filter of the Equiripple-filter. The Equiripple filter is a uniform tolerance that limits each band of stimuli frequency, thereby minimizing noises and optimize ratio in each band frequency corresponding to the Equation 4.4:

$$\epsilon = max_w \, |E(w)| \qquad 4.4$$

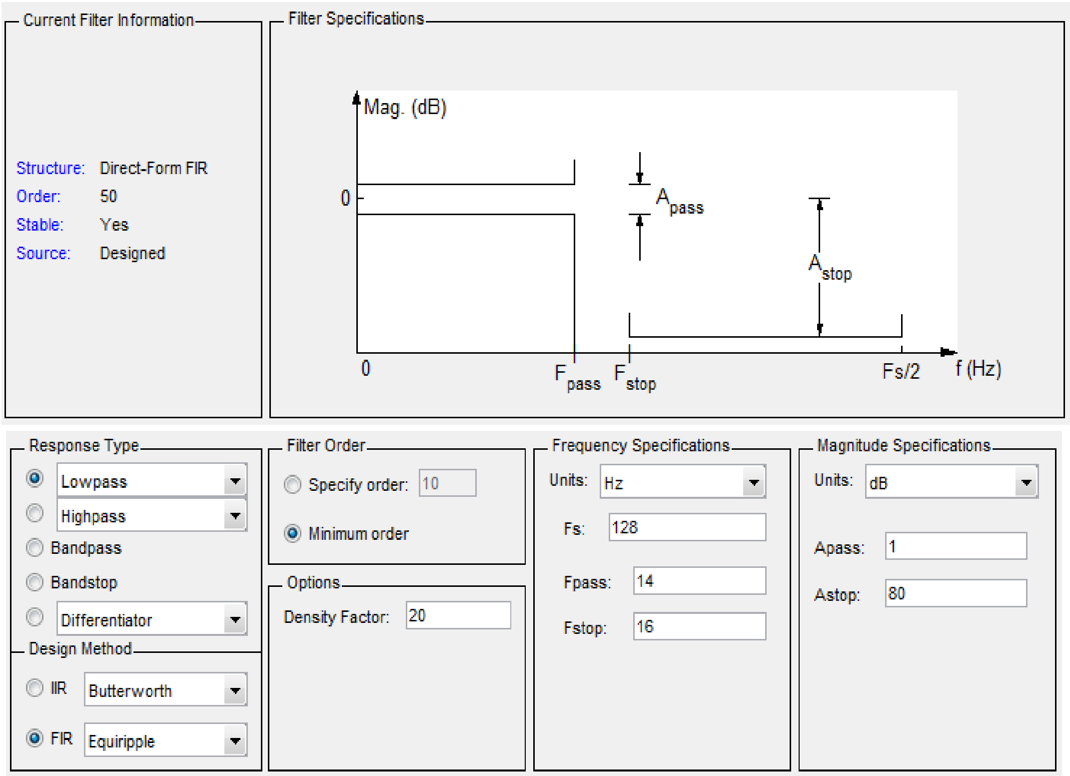


Figure 4.4 : A low-pass based FIR Filter design and implantation

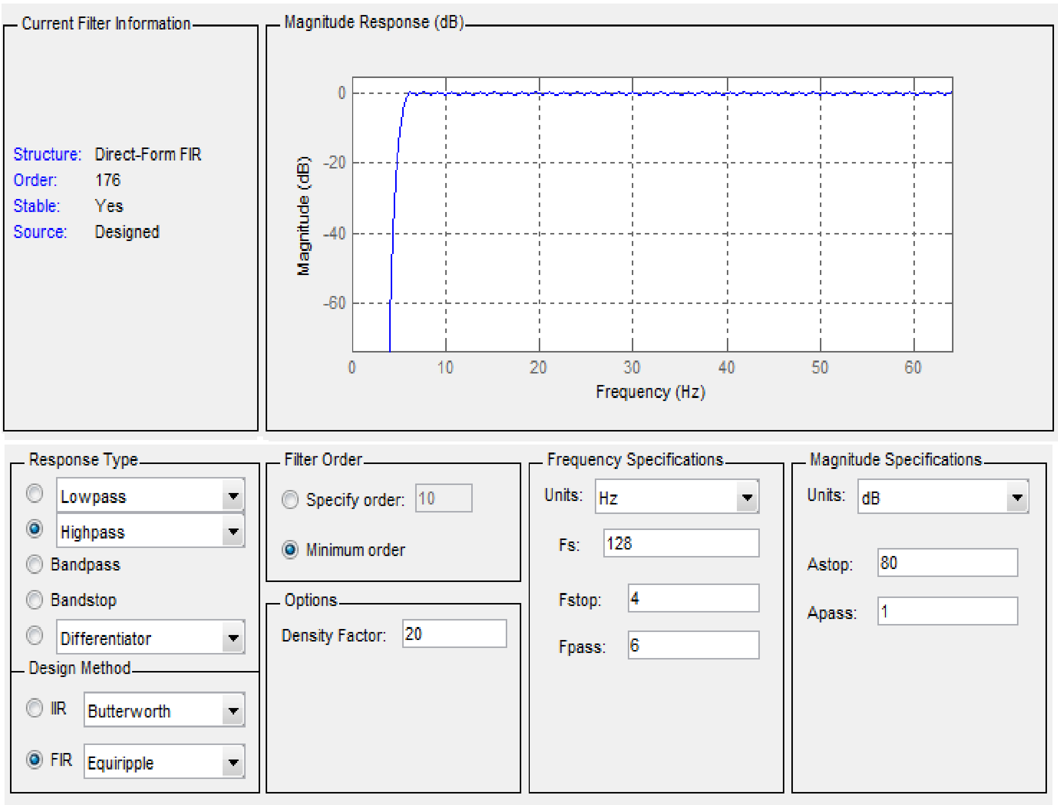


Figure 4.5: A high-pass based FIR Filter technique design and implantation

Designed FIR filter of low pass filter (LPF) and high pass filter (HPF) have been utilized the parameters, as illustrated in Figure 4.4 and Figure 4.5. The purpose design is contribute with different stimulation frequencies that are used in this empirical study, and provide decent results based on brainwave influence responses with respect to evoked SSVEP signals, which are plotted as spectral amplitude power on frequency-domain. The extant result present individual of each flickering frequency that is extracted from bands of evoked stimulus. Figure 4.6 shows a multiple frequency spectrum based on the source of LED light/stimuli-frequency, that isolated in each flicker sessions.

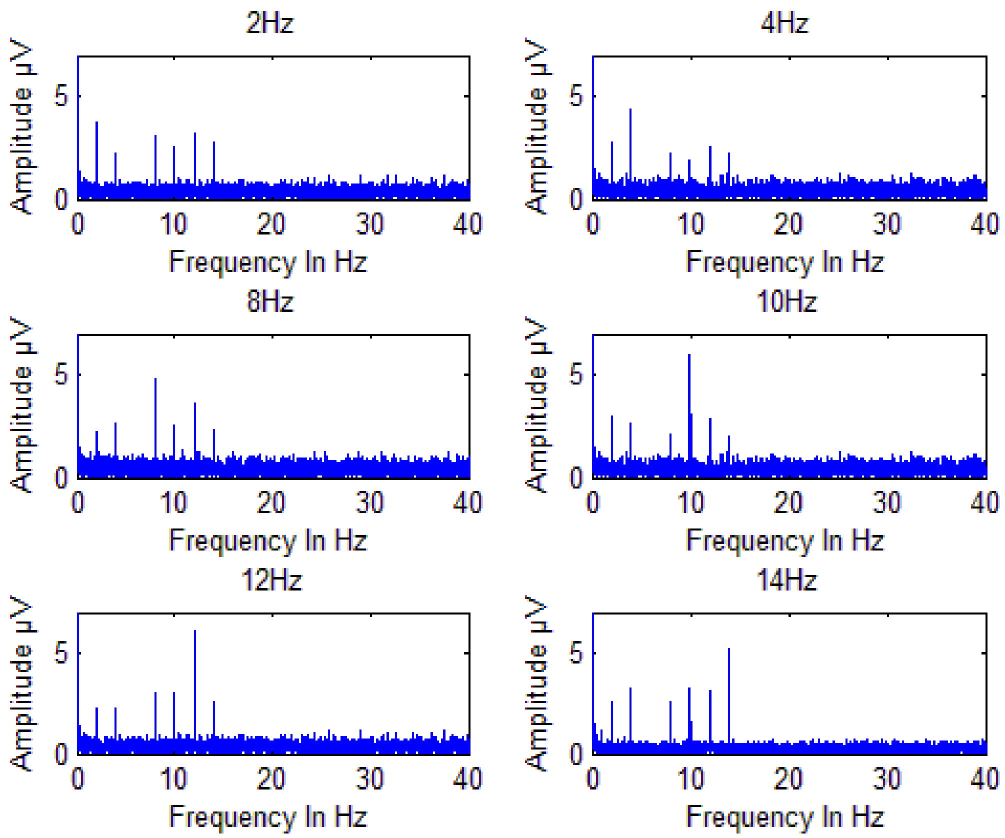
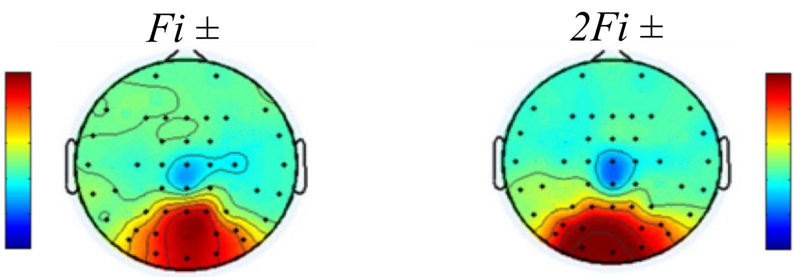


Figure 4.6 : Comparison spectrum based-multiple frequencies stimulations of evoked SSVEP response

In this experiment, the participant subjects were asked to direct pay their attention at a particular frequency (e.g., 2 Hz flickering on LED No. 2), while other stimuli/frequencies were flickering on other LEDs simultaneously. The idea was to access the effect of attention bias on induced SSVEP responses, if the subject chooses to pay attention to one flickering frequency while other frequencies are also flickering.

As shown in Figure 4.6 the stimulus frequency at 10 Hz provides the strongest induced responses in terms of imparted amplitude of spectral-power ~5μv, consequently, computing the neighbourhood effects of stimulus-frequency at 10 Hz that indicates decent response based on SSVEP signal corresponding to the SNR topography.

By quantizing the spectrum analyses aspect of Equation 4.3 at 10 Hz with other neighbour frequencies with respect to SNR value, this argument makes more sense concrete discussions between neighbourhood frequencies and stimulus-frequency effects. The average results of SNR topography demonstrated in Figure 4.7 illustrates the target of base-frequency at 10 Hz to substitute in comparing formal of $Fi,\ Fi \pm fj$; however, the other frequency substituted in $2Fi, and\ 2Fi \pm fj$. Both frequencies present the visual flicker, which are observed simultaneously.



Target 10Hz

Figure 4.7 : A comparison between desired target and other stimulation frequency respect to SNR

The topographically result demonstrate the effect between the target of base stimulus-frequency at 10 Hz and the neighbourhood frequency at diverse stimulations. The quantitative values of SNR ratio provide compression between desired target frequency (i.e., 10Hz) on Fi and other stimuli of eight neighbouring frequencies. Substitute the eight neighbouring frequencies on $Fi \pm fj$ to become new set of stimuli frequency at (2, 4, 6, 8, 12, 14, 16 and 18) Hz. However, gathered target frequency that presented by *2Fi* with a double of eight-neighbouring stimuli frequencies by substituting on *2Fi, 2Fi±fj* at (6, 12, 16, 18, 22, 24, 26 and 28) Hz respectively corresponding to desired stimulus. By substituting in Equation 4.1 to compute the effect on target frequency in respect of other different stimuli frequencies based SNR topography, which is achieved by setting anticipated of stimulus-frequency and one neighbourhood of frequency.

By substituted veritable freq.: $$SNR_i(f_j) = \frac{P_i(f_j)}{\frac{1}{8}\sum_{q-x}^{4} P_m(f_{i+q})} \qquad q \neq 0 \qquad 4.1$$

Figure 4.8, presents a bar chart of SNR comparison ratio that computes all involved subjects after the averaged procedure, wherein, each bar indicates to average SNR value respect to different stimuli-frequency and neighbourhood. As illustrated in the chart of Figure 4.8, the target stimulus-frequency successfully indicates differences evoked respect to SSVEP response by comparing with other eight-stimulus-frequency. Additionally, the induced effect of SSVEP is robust to stimulation in neighbouring frequency spectra. Therefore, average processes have taken place in SNR technique over participant subjects in this experiment, and showing effects that are consistent over the statically test.

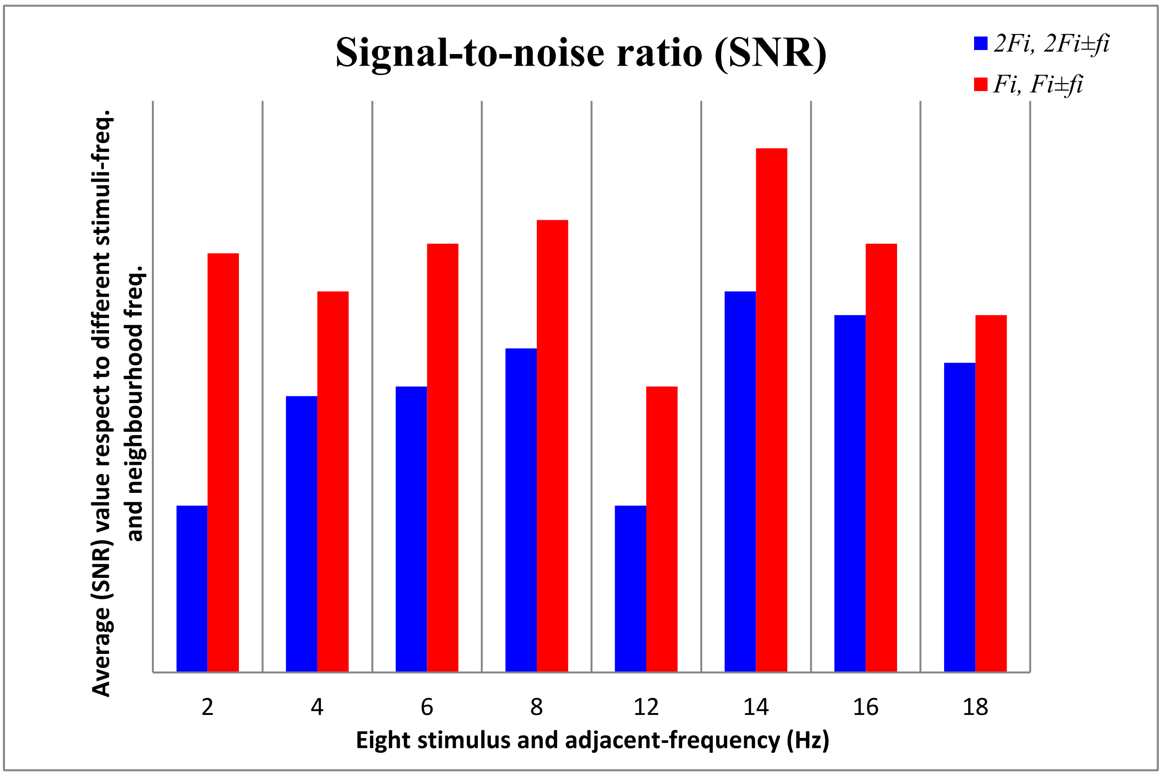


Figure 4.8: Average SNR of desired target frequency at 10Hz with neighbouring frequencies

However, the chart shows individual SNR result, which are averaged together with respect to the SNR in both target frequency by Fi and neighbour frequency, which is substituted on $2Fi$. Consequently, the FFT results, which are reported in Figure 4.3, demonstrated all stimuli-frequency. Therefore, the stimulation frequency is strong near to all neighbouring frequency and interference based on the outcome result of average SNRs. A powerful analytical technique depends on signal processing approach, which utilises the independent component analysis (ICA) (see appendix A.1 more theoretical details). The independent components ICA analysis a multi-dimensional data (MDD) that depend on multi-variate sources (MVS), which are separated between the linearity components of mixture signals.

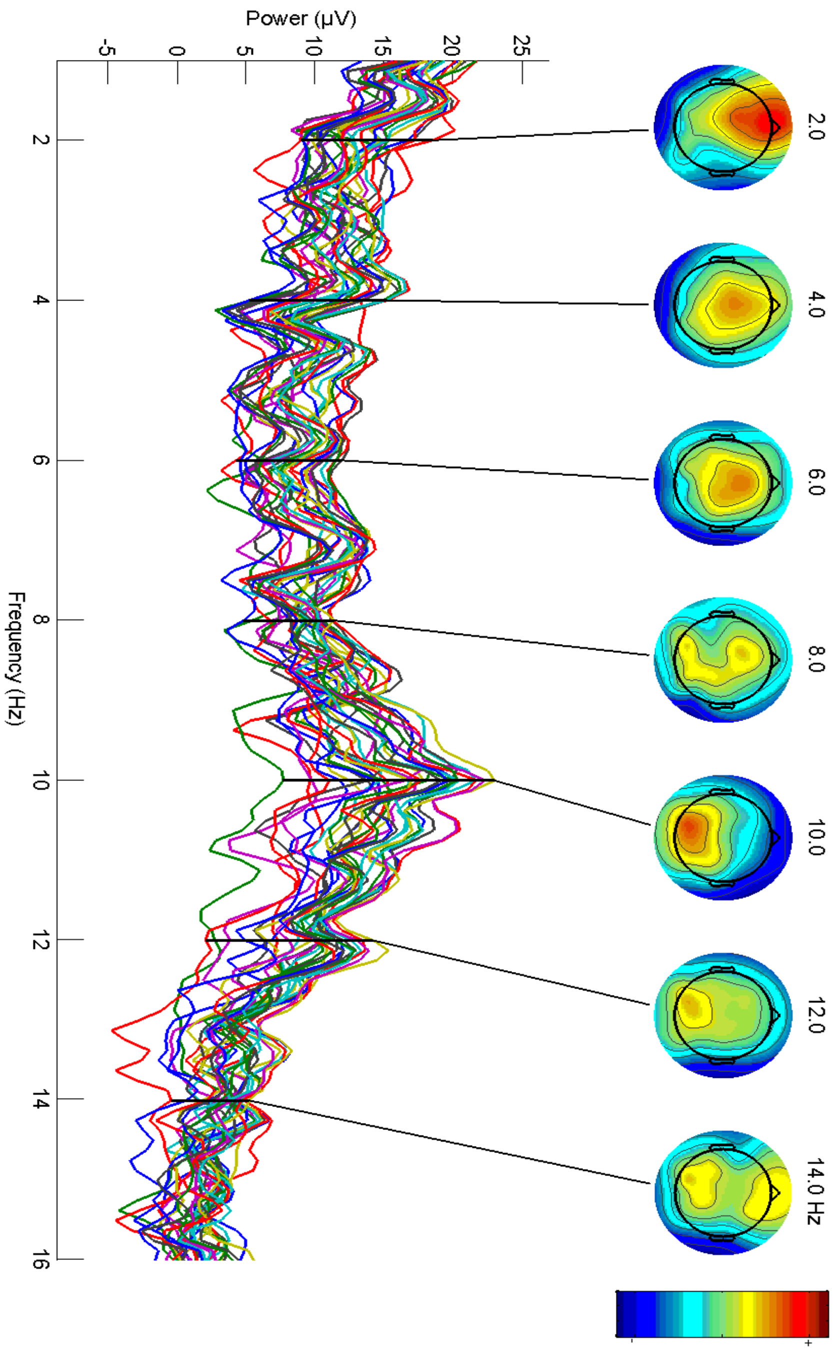


Figure 4.9: Reflected multi-channel depend on SSVEP paradigm by decomposed EEG based-ICA

The signal processing based on ICA implies discover the target signal that has a minimal correlation with other additive components (signals). The designed model sorts a separation components by assuming multiple variant-sources which are non-Gaussian in nature and statistically independent. The EEG raw-signal that co-operative from first study presented by 32-configuration channels transformed a simultaneously the brain responses under stimuli condition (see section 3.2.1.1). Therefore, accumulating the EEG signals from different positions of the brain depend on multi-channels. The ICA and BSS were performed using a multidimensional-data projection (MDDP) onto un-mixed matrix in time-domain, since the (un-mixed matrix) is composed of weighted and linear combination based on fundamental frequencies. Subsequently, the experiment of multiple frequency analysis offline , to found out the possibility of observe spectra frequency that corresponding to induced power based on linear independent of evoked response signals of ICA technique. As demonstrated in Figure 4.9 hue colours to present the dark-red region of maximal SSVEP responses and the gradually diminished in yellow-region; however, the green and blue–regions respectively plotted a decreasing the evoked response. The accumulated signals of the multi-source of mixture signals is decomposed into linear-independent frequency components of each frequency by awarding band of brainwaves which are denoted onto delta: (1 – 3) Hz, theta: (4 – 8) Hz, and alpha: (9 – 14) Hz. Furthermore, Figure 4.9 shows the separated independent source result, which provides a relatively strong reflection of response among each stimulus frequency of inducing SSVEP response signals, whereas the stimuli frequency at 10 Hz presents the strongest induced response. However, the electrode at O_z that placed on centre occipital lobe of brain region provides sturdy power with respect to stimulus-frequency (as show in Figure 4.9) and previously proved in chapter 3.

4.1.2.3 Extract a Brain wave in Wavelet Approach respect to SSVEP

The EEG biological raw-signals are gathered from the surface of the scalp by placing pairs of electrodes, which transfer the stream potentials of firing neural cells as non-stationary and noisy signal in both amplitude and phases. The frequency-domain based on EEG analysis is complicated because analytic signals are dependent on amplitude and instantaneous phase on signals. In other words, the time-domain methodology supports understanding of signal behavioural-based time interpretation. Therefore, the wavelet transform (WT) methodology is particularly presents an influential tool that analyse EEG signals within a time and frequency interprets. In this methodology, the quantitative of time-frequency parameters have been extracted from EEG signals during time discrimination of flicker based on stimulation row of regular pattern, which are illustrated in Table 4.2. Compute a wavelet topography correspondent to the origin EEG signal in respect of time series of $x(t)$, which convolved with a certain scale and converted to the new form based-wavelet function as illustrate of Equation 4.5:

$$W_x^{\psi} = A_{\psi} \,.\int \psi^* \left(\frac{t-b}{a}\right) .x(t)\, dt \qquad 4.5$$

The convolution technique on incoming signals cooperate with coefficients; since ψ denote as a complex number that represent the conjugate function; both b and a represent wavelet scale parameters; also A_{ψ} is presents a normalized parameter [161]. This function is a contemporary of continuous complex wavelets [161]. Here the continuous function contains complex exponential by which it modulates the signals depending on restriction values of a, and b. The tuneable parameter is related to the (time and frequency) resolutions that are determined by the standard deviations of (σt and σf), respectively [7]. In this contribution work, the tuneable parameter was fixed as ad-hoc constraint coefficients in each of three considerable rhythms at 5 Hz, 10 Hz and 25 Hz are setting up based-experiment stimuli-frequencies. However, those stimuli-frequencies are applied using only single LED_1. This approach has been implemented in order to improve the evoked SSVEP response resolution based on time and frequency analysis. The electrodes that are placed on occipital lobe presented by O_1, O_2, and O_z have been utilized to reflect the activity of brainwaves, which are analysed based on wavelet approach. In particular, the values of σt are expressed in milliseconds and σf is expressed in Hertz (Hz) at real-signals, which provide a suitable result that is describe the temporal spectral change related to external stimuli based-flicker LED_1. The results are presented respectively the brain activity responses in frequencies of (theta-band) at at σf = 5 Hz, however the response of (alpha-band) presented by σf = 10 Hz, and (beta-band) at σf = 25 Hz with respect to wavelet analyses of EEG brainwave rhythms as demonstrate in figure 4.10. Several variation signals in EEG rhythm activities were found close to stimulus-flicker, which offset signals by shifting the target of stimulus-frequency. To extract the feature based on average technique depends on marker-indexes (triggers) of quantitative values of EEG epochs with respect to phase tagged of three base-frequency and different time intervals. Besides the results of wavelet amplitude oscillation were demonstrated to begin at zero point and increase time variants until decreasing back to zero, which typically exhibits the visualizing flicker in different frequencies, which are convolved with a wavelet form frequency; however, the frequencies of the wavelet can be specified by the number of data points in the time series. Wavelet technique is used the topography result that divides the continuous time signal into different scales with respect to time invariant component; however, there are used three different frequency range of each time invariant component can be assigned, according to varying of EEG rhythms. Oscillatory changes in frequency are fact to distinguish three different rhythm theta, alpha and beta of brainwave bands. Figures 4.10 shows the total average change of incoming signals based on wavelet analytic perspective of activations signal W_x, which present three stimuli fashion levels. While Figure 4.10 illustrates the first band level of (theta) brainwave, and demonstrates the (alpha) brainwave level; however, the (beta-wave) band showed in same figure.

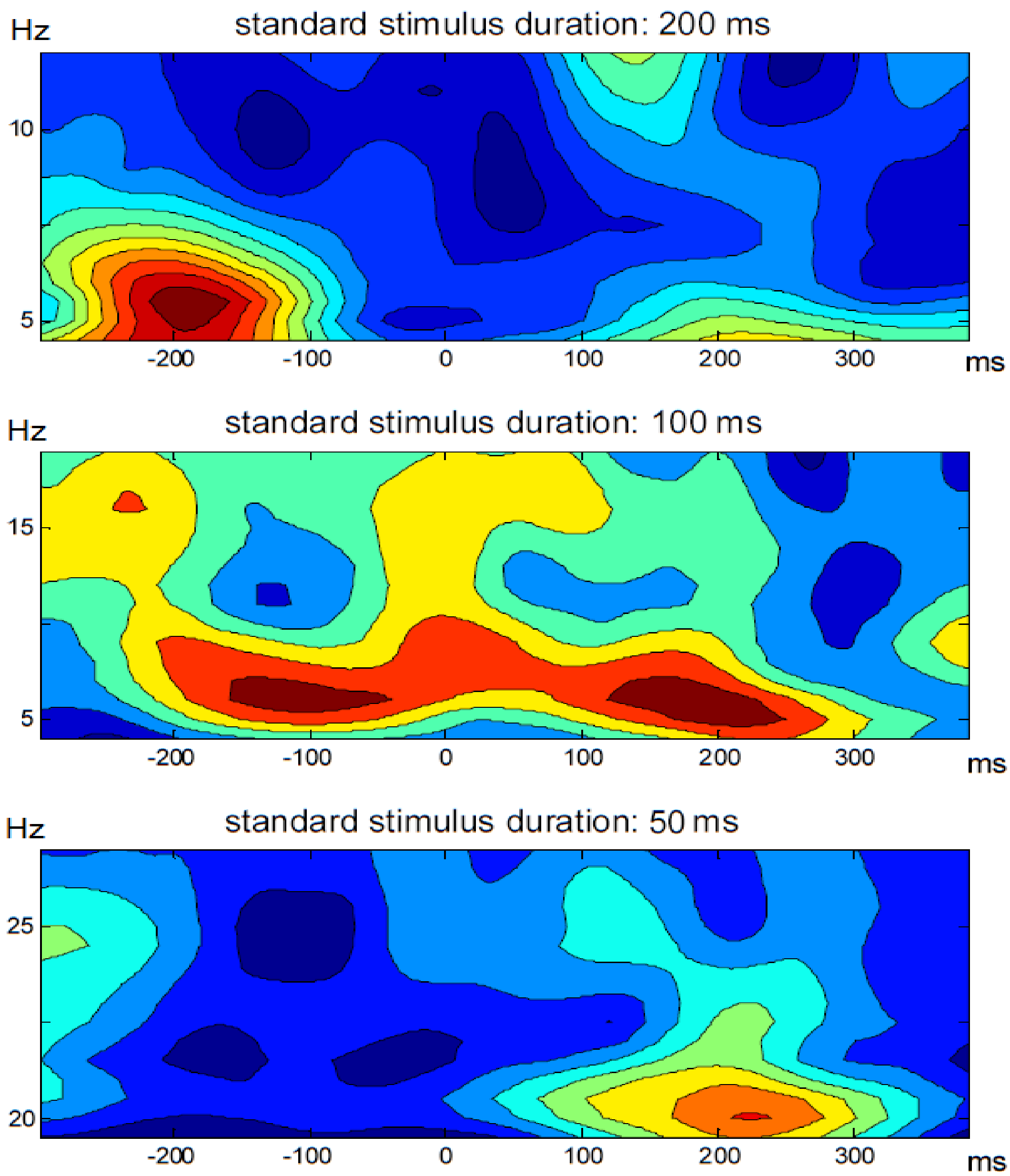


Figure 4.10: Reflected SSVEP paradigm by decomposed EEG based-wavelet analysis

The dark red colour region indicates the increase in brain activity in respect of response compared with the other two stimuli, and the dark blue colour region indicates non-activity regions in respect of brain responses; however, the orange, yellow and light-blue regions present the gradation response with respect to stronger evoked signals of SSVEP paradigms. The extracted results based on three bands of brainwaves of brain activity levels. The analysis method dependent on time-invariant to distinguishes between different responses of brain activities. Discrimination results occupied corresponding to time intervals segmented to produce three brainwave bands of (theta, alpha and beta) respectively of stander stimulus duration represented as (50, 100 and 200 ms). The gathered, occupied segments are analysed by considering the wavelet coefficients and obtaining the evoked potential through conventional average in all involved participant subjects. Generally, the results are deliberately given a specific property, depending on signal processing, to combine the extracted alpha brain waves band activity at different points on three levels, which indicates more activations related to the occipital-brain lobe. Alpha brainwave is interesting and reliable, according to stimulus flicker.

4.1.3 Multiple Frequencies Conclusion

These three empirical studies implement SNR, FFT and wavelet, which are demonstrate the multiple frequencies effects using a low-cost prototype of BCI based on SSVEP paradigm. A visual stimuli-panel has been designed with electronic circuit, which includes buffers, shift-registers, ordinary LEDs and some other electronics components. The stimulation LEDs contain two main groups: The first group placed in the centre; and the second group placed in the surrounding area. Each group contains four LEDs in different positions. Software controls all LEDs by permitting in C-program that regulates the flickers and distributes the frequencies on individual LEDs, according to close-loop system with respect to experiment setup configuration. Voluntary participant subjects were asked to gaze on one stimulus-LED, which is flicker with respect to a certain frequency. The experiment was performed successfully to induce SSVEP responses with all voluntary participants. Three major frequency bands of theta-θ, alpha-α, and beta-β were considered, which determine the brainwaves of activity levels. An offline analysis was concluded using FFT and wavelet transform (WT) to realize the behaviour of brain activity base frequencies band of SSVEP paradigms. Firstly, the FFT extraction detects the spectrum power analysis of maximum and minimum spectrum-power in each band frequency. There are three bands based brain activities were exploited by implementing simple filters; however, the extracting result based on frequencies band improved by ICA to remove unwanted signals; and FIR technique to restrict frequency band. The FFT result provides all stimuli frequencies of (2, 4, 6, 8, 10, 12, 14 and 16) Hz. The stimuli frequency at 10 Hz proves to be decent stimulus/flicker, which provides a greatest power with respect to SSVEP responses. The second step use SNR to measure the EEG signals at main electrodes of (O1, O2 and Oz). These realistic electrode locations are obtained in the preliminary experiment setup. Investigation by SNR based on SSVEP response depends deference categorize acquisition of the brain response, which is concluded in previous Chapter 3. The highest SNR was discovered to be located on the occipital brain region compared with other brain lobe locations, according to multi-trials in terms of the number of voluntary subjects by applying eight stimuli-frequencies sessions. However, the ICA technique beside SNR proves to determine the evoked brain region based SSVEP responses. Furthermore, it was found that stimuli frequency at 10 Hz presents the most robust induced SSVEP at electrode Oz occupying the occipital brain region, which affords the strongest power with respect stimulus frequency. The filters technique was utilised, together with the wavelet function, to determine the ad-hoc results according to multiple frequencies which concerned the EEG rhythms at 5 Hz, 10 Hz, and 25 Hz, in order to improve SSVEP responses resolution based on (time and frequency) domains, which are proved the alpha band as decent stimuli frequency. A different influence on SSVEP response was discovered with respect to brainwave activities, which indicates the stimuli at 10 Hz is more appropriate within occipital brain region. Interesting results were published in:

- Multiple frequency effects on Human-brain based Steady-state visual evoked potential (SSVEP), 2016 IEEE 6th International Conference on Advanced Computing, 978-1-4673-8286-1/16 $31.00 © 2016 IEEE

4.2 Stimulation using Multiple Colours

This section describes the efficient parameters that directly effect on BCI-system. Stimulation of evoked signals that depend on visual different colour flickers within a fixed (stimulus-frequency) to observe brain influence, which provides difference in SSVEP responses based on EEG activities in respect of different colours of visual stimuli. In this section, addressing the problem, which consider fatigue and exhausting when engaging the SSVEP paradigms that mean uncomfortable users to stare at a flickering stimuli procedure, causing tiredness and lack of attention. This experimental study investigates how the different colour simulations directly influence on brain activities based on SSVEP paradigms, which analyse to extract the different result based on frequency and phase (latency). The colour flickering simulations that are applied and utilise a regular intervals paradigm to excerpt SSVEP affect. Three different colours have been employed, dependant on two (base-frequencies). However, the phase-tagged triggers (PTT) presented in the visualize stimulus were used to indicate the flickering events of each LED and terminus cycle event. A new prototype as closed-loop BCI system has been realized to gathered EEG raw (datasets) and analyse the extract epoch offline . The analyses methodology is used detecting SSVEP response depending on stimuli-periodic manner. Nevertheless, in this study three types of analyses have been performed: using fast Fourier transform (FFT); event related potential (ERP); and one way analysis of variance (ANOVA), which support the conclusions.

4.2.1 Multiple Colour Flickers Technique

The dynamic brain responses effectiveness and influence by SSVEP paradigm based on BCI techniques were demonstrated, utilizing (three-LED colour) to flicker onto 24 positions. Figure 4.13 shows the configurations and positions of each colour LED on the stimuli panel with regard to designing a porotype proposed as a BCI system. The designed and implemented module inspects the brain response influence based on a closed-loop BCI system using two fixed flickering frequencies at 6 Hz and 13 Hz, which are present the boundary of alpha band of brainwaves (see section 3.1.2.4). The stimulation board is fixed at eyelevel on the participant subjects. The multi-function panel connects via FPGA depth board through computer to control on each LED in respect of the experiment setup. The control signal is received from the personal computer to change the colours and positions (i.e., red LED (R_c^1) blink at centre of first position; whereas the other LEDs are blinking in different colour and frequency at other positions (surround or centre), which is controlled by a promote command signals. The complete multi-function panel powered by 9V battery, to avoid any kind of AC interference.

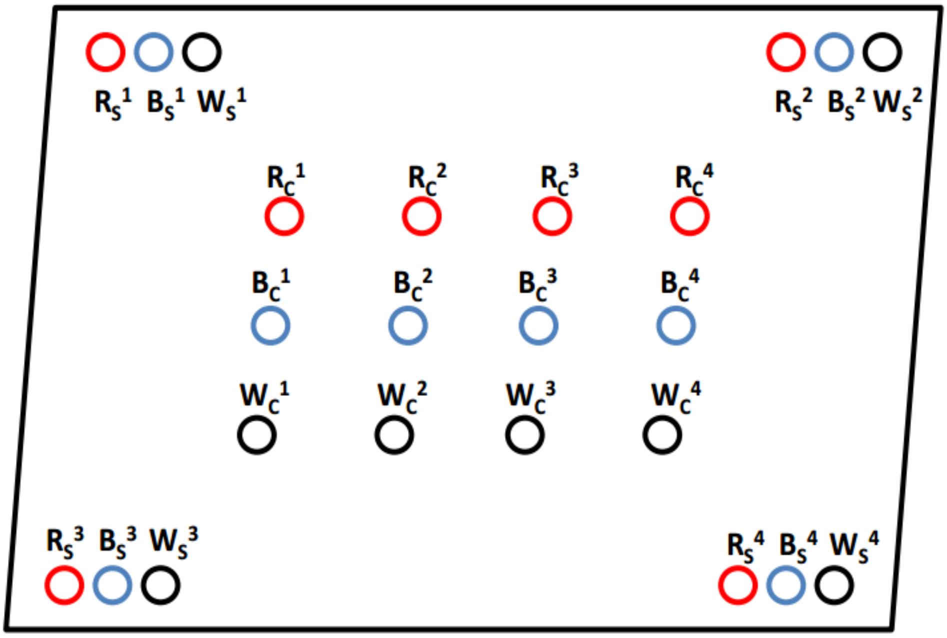


Figure 4.11: Multi-function panel LED based stimulation of BCI-prototype

The flicker on each LED depends on a single pattern previously stored in the local memory of the depth board. As shown in Figure 4.13, there are three colour LED categories based on the experiment setup configuration, which are distributed on the stimuli panel by Red, Blue and White, which presented with the (black colour in Figure 4.13 for illustrative purposes). Each colour contains eight LEDs to represent a certain group in rows at centre positions and sporadic in surrounding fashion. There are 24 LEDs in total spread onto the multi-function of the stimuli panel, which provides different phase-tagged signals (e.g. 0°, 90°, 180°, and 270°) that indicted within EEG raw-signal through AD-Box of BioSemi system (see section 3.1.2) with respect to flicker frequency at 6 Hz and 13 Hz. A stimulus-LEDs group is labelled as shown in Table 4.1, divided into different clusters to represent individual colours coordinated in respect of the centre and surrounding manner of the stimulation paradigm. Each group has an ID, LED colour and position (respectively), similarly symmetric to the LED names. All groups LED-cluster are arranged correspondingly to three colours of Red, Blue and White LEDs respectively. The advantages of this technique are produces a confident evoked flicker to stimulate brain activity to reduce the fatigue BCI users; however, the designed model prevents the shifting of participants' eyes during the stimulation procedure of the experiment.

Table 4.1: Stimulus LED shows different positions and colours of each, fixed on stimulation panel

Colour Flickered LEDs setup				
Group ID	**Total LED**	**LED Colour**	**LED Location**	**LED Names and Position**
1	4	RED	Centre	$R_c^1, R_c^2, R_c^3, R_c^4$
2	4	RED	Surround	$R_s^1, R_s^2, R_s^3, R_s^4$
3	4	BLUE	Centre	$B_c^1, B_c^2, B_c^3, B_c^4$
4	4	BLUE	Surround	$B_s^1, B_s^2, B_s^3, B_s^4$
5	4	WHITE	Centre	$W_c^1, W_c^2, W_c^3, W_c^4$
6	4	WHITE	Surround	$W_s^1, W_s^2, W_s^3, W_s^4$

The EEG signal recorded from three electrodes of O_1, O_2, and O_z locations on the occipital scalp region, as shown in Figure 3.5 (see section 3.1.2.2). The common mode sense (CMS) activates electrodes and drives right leg (DRL) passive electrode drive (average potential with respect to BioSemi EEG recoding system, see section 3.1.2).

4.2.2 Variable Flickers Approach

The aim of this study is exploit the SSVEP paradigm properties and characteristic based BCI system using two-fixed frequency corresponding to the variable colour flickers. In this empirical study, all possibility and conditions are conserved to induce the evoked SSVEP response signals based on configuration setup. Stimulus of the brain activities was obtained (side-by-side) with accumulated evoked signal according to the phase-tagged triggered (PTT) technique which possibility each colour group of stimulation, and EEG raw-signals recording from brain activity which are gathered completely dependent on the combinations of (three EEG-channels), in addition to the two reference electrodes. The generated stimulation pattern is divided into four-cycles of multi-colour rhymester stimuli, based on focus a single LED in each session, as shown in Figure 4.14. Rhymester stimulation style corresponds to the time difference between each stimuli LED, depending in each cycle of base-stimulation frequency. The flickered patterns are considered a phase-tagged triggering (PTT) generated by Equation 4.5:

$$\theta_i = (i-1) * 90^\circ; \; where\ is\ incremented\ \ i = 1, 2, \dots, N \qquad 4.5$$

Since, flicker's LED_i is shifted respect to phases, which distributed into (phase-angle) over full cycle by 360° incremented by ($N = 1, 2, 3, 4$ and 5), however can be compute the delay for each trigger regarding to Equation 4.6:

$$t_i = \frac{\theta_i}{360°} * T \qquad 4.6$$

Here θ_i is present the phase delay of each flicker sequence of LED_{ith} and t_i is conformed the delay time, which is request according $T = 1/f$. In addition, the period T is presents the flicker cycle duration, where the f presents the flicker of stimuli base-frequency. Setting a fixed flicker base-frequency at 6 Hz and 13 Hz, which are characterized the bounded alpha band brainwave. Although the other stimulus LED_{ith} is used same evoke pattern but in diverse of phase shifting as illustrate in Table 4.2 of regular stimulation.

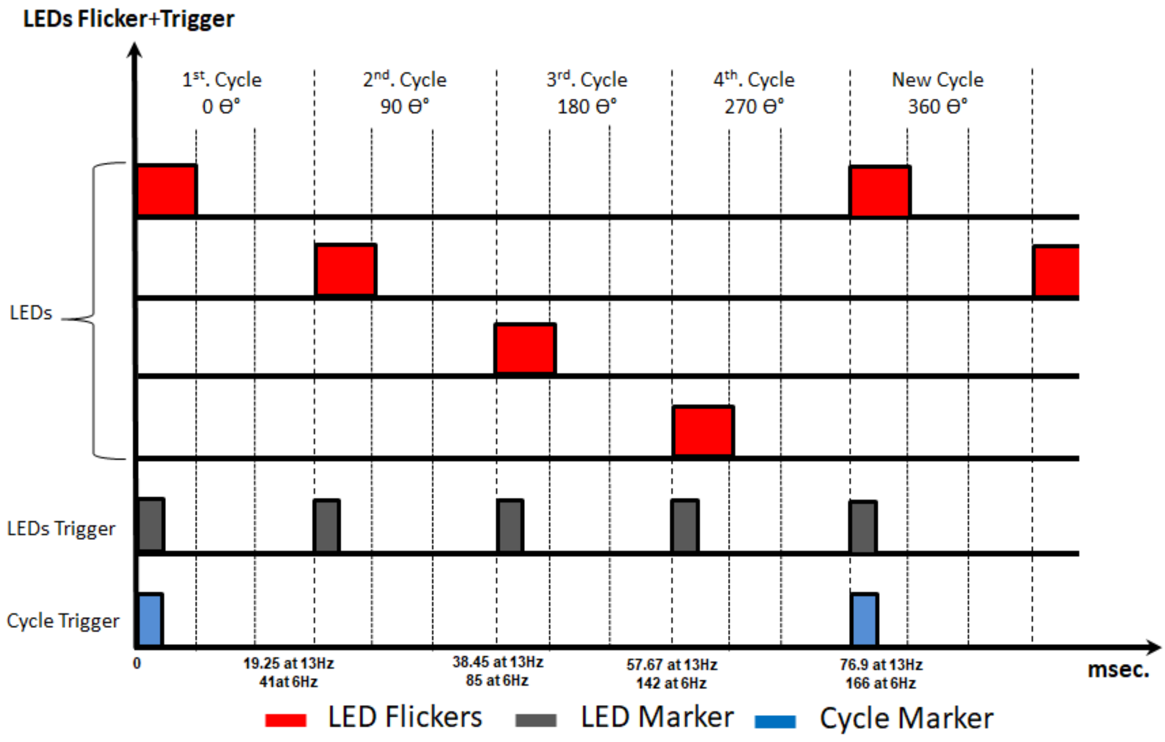


Figure 4.12: Regular pattern flicker with 25% duty-cycle as sequence based on 4-LED in one-cycles

The regular pattern is generated based on (Four LEDs) within equivalent time intervals, in five cycles of two-stimulus rhymester as demonstrate in Table 4.2. The time difference of flicker sequence is divided into (0, 19.225, 38.45, and 57.75) milliseconds as illustrated in above Figure 4.14 which is demonstrate 13 Hz as base-frequency based on 4-LED of 25% duty cycle. Single row group stimulations have phase delay that presented by θ_i in respect of $LED_{i=1}$, gives a onset of certain angles by (0°, 360°, 720°, 1080°, and 1440°) respectively. Two trigger events were invoked in each cycle. The first trigger was present at the onset of each time pulse-on of individual LEDs while the second trigger indicated every new cycle. The complete stimulus cycle had a period T, contained in T_{on} and T_{off} demarcation. The onset flicker contains on-time stimulus presented in red blocks, and LED off-time presented in white spaces; however, the blue blocks indicate cycle trigger, also the grey indicate when the LED is on-state as shown in Figure 4.14. A 25% duty-cycle flickering has typically been used, which provides comfortable viewing to subjects (user). Contrast in the experiment setup was effected by setting the flickering frequency to high/low according to desired base both frequencies at 6Hz and 13Hz.

4.2.3 Extract Colours Effects based on ERP, FFT, and ANOVA

Firstly, the features are extracted from accumulated EEG epoch of raw-signals as primitive (dataset) from all participant subjects based on three analyses methods that are presented by event related potential (ERP), fast Fourier transform (FFT) and one-way variance analysis of ANOVA respectively. Therefore, the amplitudes and phases are extracted with regard to two-fixed stimuli frequencies at 6 Hz, which presents a low-stimuli level and 13Hz to presents a high-stimuli levels. However, the gathered signals of EEG are sub-divided into two groups of datasets corresponding to two stimuli frequencies. These analysis methods depend on segmenting the EEG epoch/trials according to onset-flicker of LEDs based on PTT pulses in each colour of recording session (see section 3.1.2).

4.2.3.1 Event related potentials (ERP) Analysis Results

Event related potential (ERP) process detects the phase difference and the latencies in each colour with regard to two fixed stimuli frequencies of 6 Hz and 13 Hz of low and high stimulation fashions. In this analysis technique, the EEG raw-signals converts into datasets were segmented into epoch/trial according to the firing onset of flickering stimuli with respect to PTT pulses. However, the signals were divided into groups, corresponding to two stimuli frequencies. The pre-processing signals by passing through a low pass filter (LPF) with cut-off frequency at 16 Hz and high pass filter (HPF) of cut-off frequency at 2 Hz. These filters removed unwanted signals of AC-line noise, and DC component from any other artifacts apart of eye blinks or movements, which were using the (Cartool) software that depending on ICA/BSS technique. However, a threshold voltage by 100μV was set to remove the muscle artifacts, which are not allowed above any threshold potentials. Each trail/epoch was reliant on time-line trigger-window respect a baseline (BL) setup. The time-window was configured by selecting 250 milliseconds as Pre-frame duration prior to trigger, and Post-frame 500 milliseconds after the next trigger.

ERP is a technique that provides quantified brain activities response to sensory stimulation (see section 2.5). The ERP is a method of non-invasive mythology, which demonstrates the stereotypical brain signals as different latencies based on responses. Practical the EEG record-signals reflect the brain activity in respect of evoked response over brain reaction that consummates from the scalp-area. The electric-potential component background is mixed with ERP waveform, which increases to distinguish between noisy signal and actual ERP waves. Multiple trials are conducted to solve this problem over the same stimulation conditions to average together of accumulated responses signals that indicate on the same stimulus. However, the signal-to-noise-ratio (SNR) provides another solution that increases diminished background components of noise signal based ERP waveform analysis to distinct and clarity. Conversely, there is an important assumption, which restricts the recording EEG trials by adding an event, such as PTT, to store locked onset-events. These PTT locked event signals are aligned beside the EEG signals, properly averaged is reduce the background noise signals. Using correlated inter-trial of recording EEG signals can be accounted based ERPs according to Equation 4.7:

$$y(t,n) = s(t) + k(t,n) \qquad 4.7$$

Where $s(t)$ presenting the desired signal and $k(t,n)$ is noise signal. The averaging of M trials can be mathematically formulated using Equation 4.8:

$$\overline{y}(t) = \frac{1}{M}\sum_{n=1}^{M} y(t,n) = s(t) + \frac{1}{M}\sum_{n=1}^{M} k(t,n) \qquad 4.8$$

However, the quotient's area is conserved by ERP waveforms and provides an expected the average value of signals $\overline{y}(t)$ in respect of time, wherein the estimation value $E[\overline{y}(t)]$ equals $s(t)$. Subsequently, the variance can be computed based on the following Equation 4.9:

$$\begin{aligned} Var\,[\,\overline{y}(t)] &= E[(\overline{y}(t) - E[\,\overline{y}(t)])^2] \\ &= \tfrac{1}{M^2}\; E\,[\,(\textstyle\sum_{n=1}^{M} k(t,n))^2] \\ &= \tfrac{1}{M^2}\; E\,[\,k(t,n)^2\,] \\ &= \tfrac{\sigma^2}{M^2} \end{aligned} \qquad 4.9$$

A de-coding is attempted of ERP event waveforms that occur in brain activities, depending on the signal of evoked SSVEP responses based on locked-event of stimulation, which is invoked by external stimuli-signals of the multi-colours. ERP waveforms are extracted in different potentials of amplitude signals. The gathered signals are averaged the extracted brain response waveforms with respect to the same stimuli conditions and circumstances based on baseline (BL) manner and phase-tagged triggers (PTT) techniques, which restrict a particular time-locked event. Figure 4.15 shows the ERP waveform extracted form of brain responses. The average process of ERP waveforms was obtained by accumulating the trials/EEG epochs in respect of relevant flicker frequency at 6 Hz. These results present three mean brain waveforms of evoked SSVEP signal, which are affected by individual three-colours of flickering LEDs. These waveforms are pre-defined in terms of standard nomenclature of ERP signal, which is denoted by the traditional number of negative N peaks and positive P peaks. Three curves in red, blue, and black correspond to the three stimuli of LED colours by (red, blue, and white) respectively. The nomenclature curves present a maximum peak in white LED stimulation results with respect to a positive peak at P1; however, the blue LED stimulation results at P1 peak, and red LED stimulation results at P1 peak.

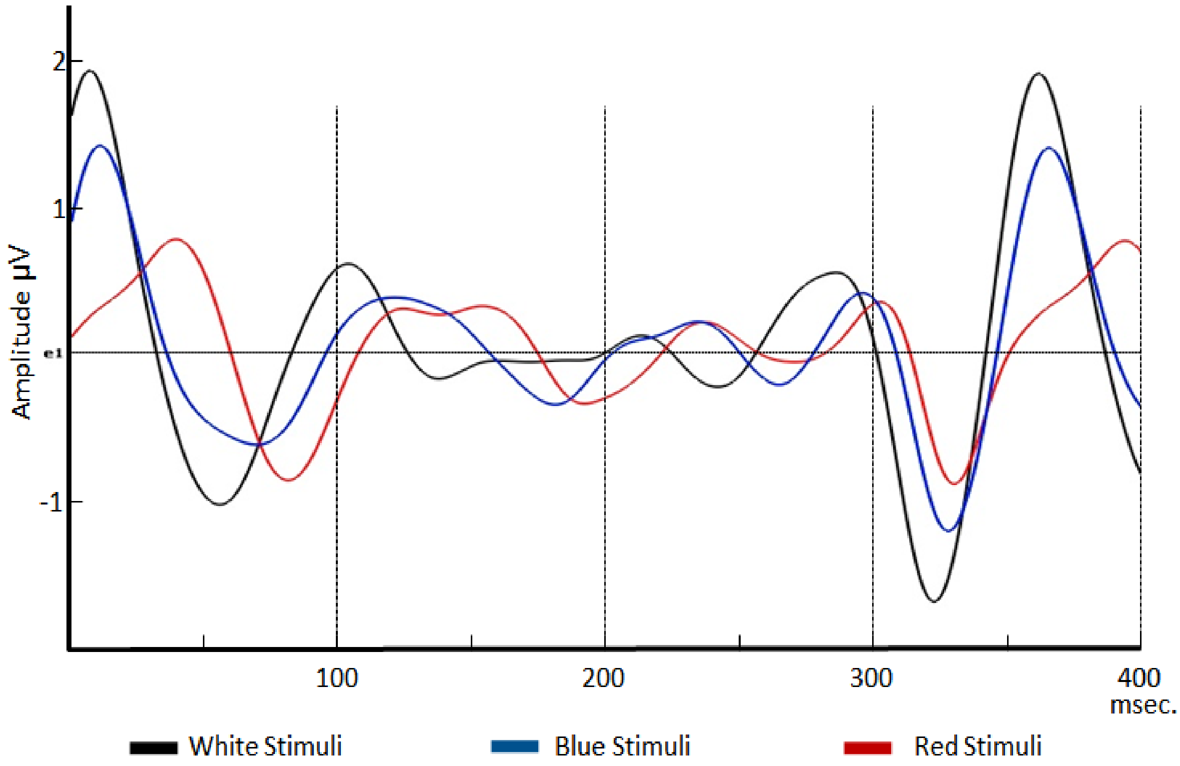


Figure 4.13: ERP result at 6 Hz that appeared three different colours white, red and blue

These nomenclature curves indicate the white LED stimuli flicker presents the highest potential corresponding to stimulation by blue LED and red LED flickers. Furthermore, significant differences are observed in the phase between three stimuli signals in respect of one stimulation cycle based on 400 milliseconds. The white stimuli LED demonstrate at 53 milliseconds, and red stimuli LED appear on 87 milliseconds; however, the blue stimuli LED arrival on 65 millisecond is estimated to the SSVEP response. Therefore, the red and blue stimuli LED have lagged latencies behind the white stimuli LED, with the differences in phases being apparent for both positive P and negative N cycles. Moreover, the differences in amplitude of ERP waveforms presented on the white stimuli colour LED invoked the highest SSVEP response by 2μv, corresponding to a comparison between the red stimuli LED 0.5μv and blue stimuli LED 1.3μv.

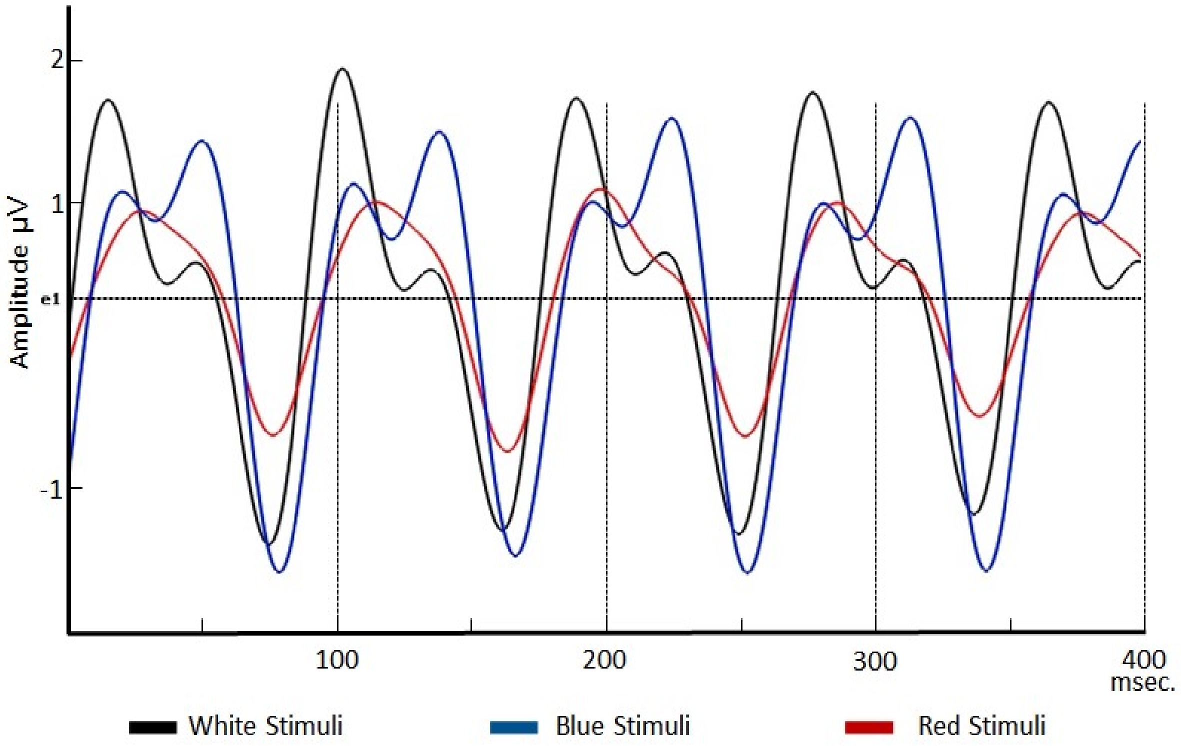


Figure 4.14: ERP result at 13Hz that appeared three different colours white, red and blue

Similarly, with a high flicker stimulus frequency at 13 Hz, a different SSVEP response is observed, as shown in Figure 4.16, by following the standard ERP nomenclature, as discussed earlier, in the white LED stimulation; however, the red LED stimulation and blue LED stimulation result in positive P peaks. The amplitudes analysis of ERP waveforms shows that on the positive part, where the white LED stimulation results provide saturation to a higher potential than blue and red LED stimulation, these are consistent at 6 Hz stimulation results. In addition, the red LED stimulation is more smoothing to induce SSVEP responses; on the other hand, the blue and white stimulations have a considerably smaller rise potential. Conversely, for negative peaks the blue LED stimulation lags (latencies), followed at the same time by white LED and red LED stimulation. These results indicate differences in induced SSVEP responses are dependent upon the flickering frequency of the stimulus. In phase analysis, there are differences between positive peaks N that are relatively larger at 50 milliseconds compared with 6 Hz stimuli frequency. However, the negative peaks are observed as tiny differences in between and can be called all waves are synchronous. This indicates minimum contingent negative variation of induced SSVEP responses.

4.2.3.2 Frequency Domain Results

The EEG signals are pre-processed by involving a similar step, which is described in the previous sections (see section 4.1.1) of removing the artifacts effects using ICA technique and filtering the gathered of raw-signals from multi-trials (see sections 4.1.2). Induced evoked SSVEP signals based on frequency-domain components of response are analysed after modifying the signals with fast Fourier transformer (FFT) methodology. The frequency analysis of SSVEP responses based on onset of measuring approach is supported by gathered SSVEP signal strength, according to multi-trial of the colour stimulation. FFT was used to extract the SSVEP response at 6 Hz, which is presents a (low stimulus frequency), and at 13 Hz to presents a (high stimulus frequency) based on spectrum power extractions. The Fourier analysis fundamental provides analytical spectrum power exploration by extracting the amplitude and phases which have been given in Equation 4.2 (more details see appendix A.3). The objective to use a Fourier analysis that is decomposes any type of periodic signals. In this study utilised a regular stimuli of periodic flicker based on different colours. The brain influences that are affected by the three colours-stimuli of red, blue and white based on low/high frequencies of alpha brainwave range. The SSVEP responses of the primary result are discriminated between induce responses, which are captured via EEG signal. The non-stationary signals, such as EEG signals, include the coefficients that are changed with respect to time according to the variation of brainwave activities. The DSP is utilised to establish a precise filter such as FIR, which proceeds to extract features based on FFT-based approach. The reason for used FIR is that it provides inherent stability on flexible magnitude responses; however, this is easy to implement, as mentioned in the previous section (see 4.1.2.2). The transforming function of FFT in Equation 4.2, and implementation of the FIR by Equation 4.3 enhance the responses based SSVEP paradigms. The FIR filter design of low pass filter (LPF) and high pass filter (HPF) has employed parameters that are discrete to a certain brainwave of alpha (α), as shown in previous Figures 4.4, and Figure 4.5. The above analysis was followed to relay the strongest induced SSVEP response in recording brain activities.

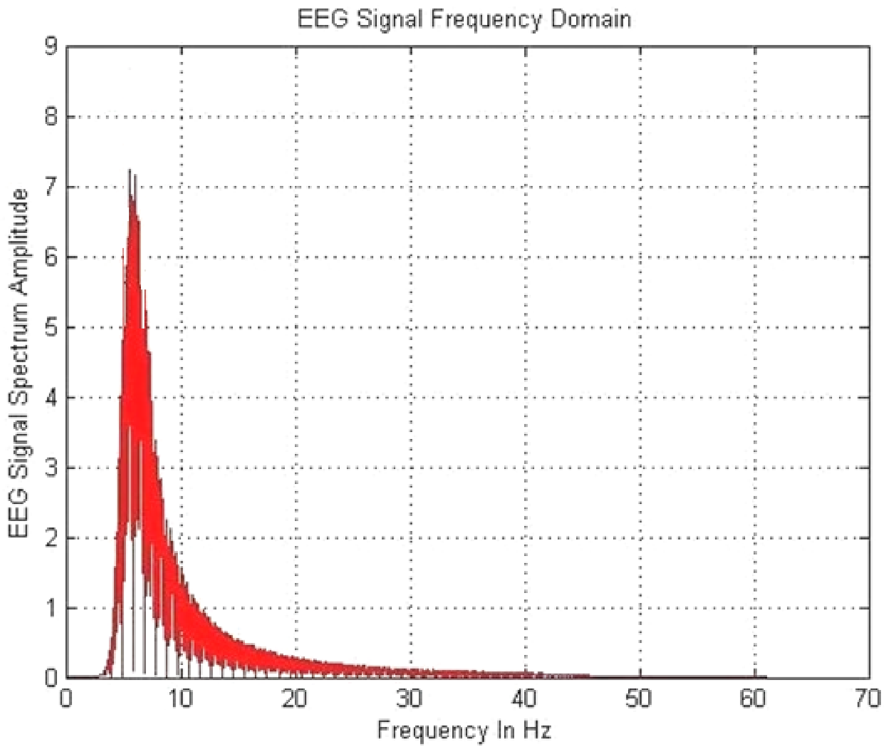


Figure 4.15: SSVEP response record 7.2µv for red LED stimulus flicker at 6Hz

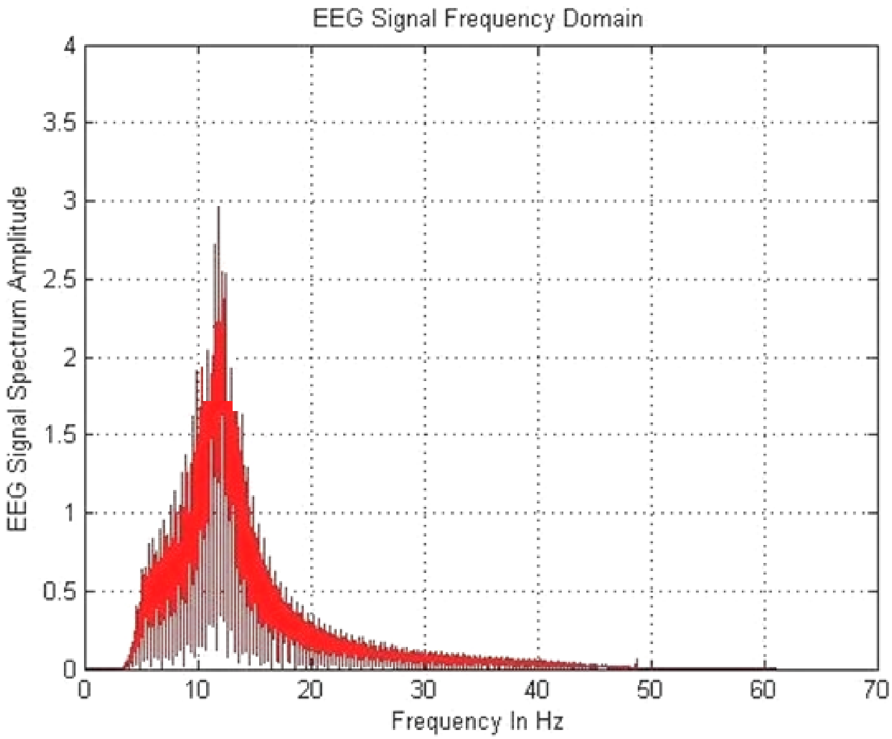


Figure 4.16: SSVEP response record 2.9µv for red LED stimulus flicker at 12Hz

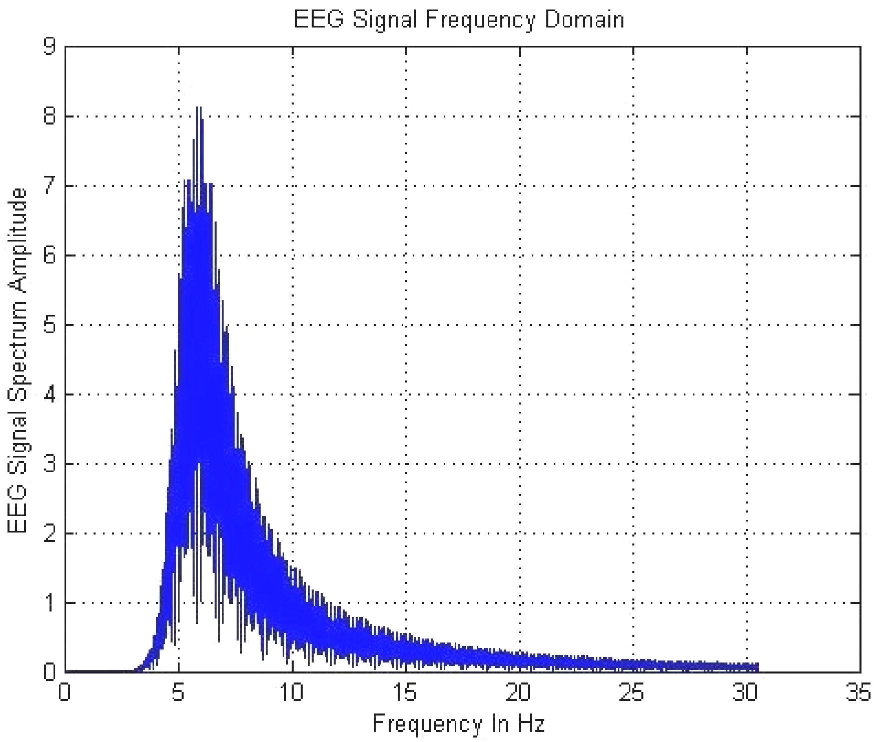


Figure 4.17: SSVEP response record 8.2µv for blue LED stimulus flicker at 6 Hz

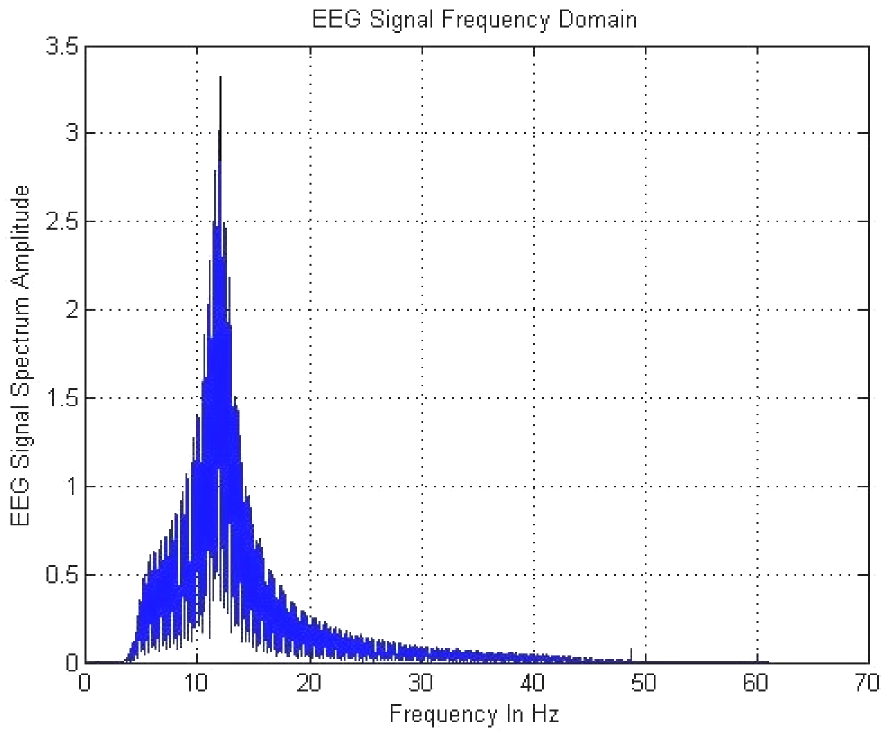


Figure 4.18: SSVEP response record 3.3µv for blue LED stimulus flicker at 13 Hz

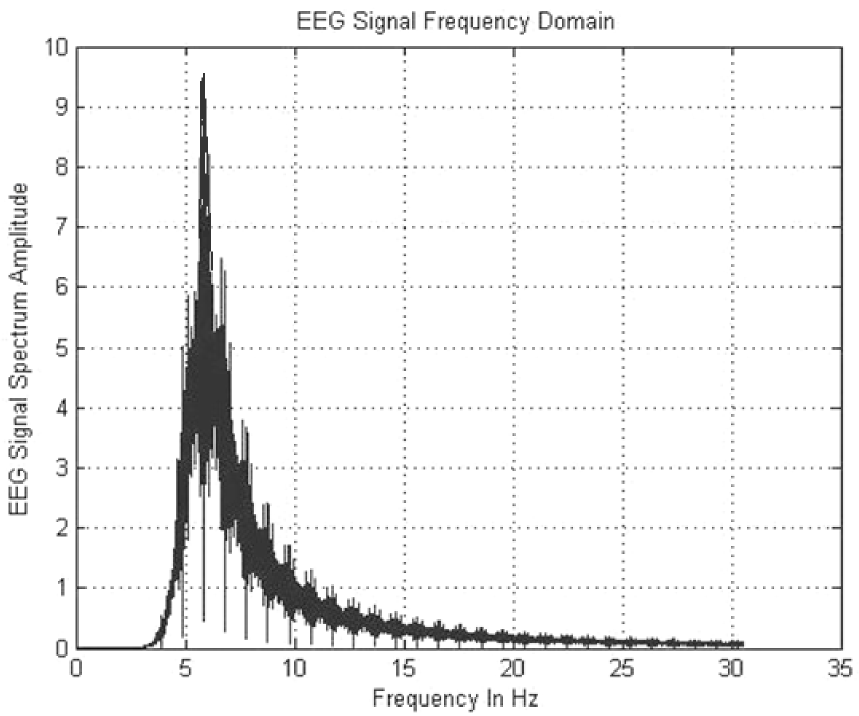


Figure 4.19: SSVEP response record 9.6µv for white LED stimulus flicker at 6 Hz

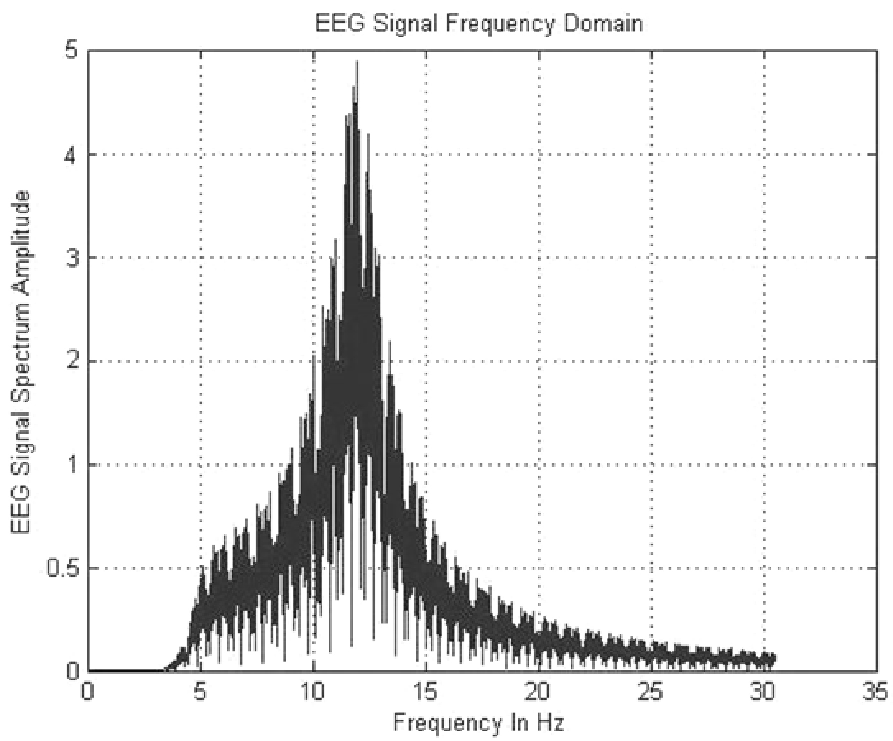


Figure 4.20: SSVEP response record 4.9µv for white LED stimulus flicker at 13 Hz

Figures 4.17, 4.18, 4.19, 4.20, 4.21, and 4.22 demonstrate the spectral power dependent on induced SSVEP responses; the flicker frequencies are based at 6 Hz and 13 Hz of stimuli in three types of flickers onto colour-LEDs of red, blue, and white respectively. The reported results illustrate that the red stimuli LED has induced a stronger SSVEP response at 6 Hz by recording a 7.2μv compared with the red stimuli LED at 13 Hz recording a 2.9μv. In consequence, the blue stimuli LED has recorded the strongest response on 8.2μv at a lower frequency of 6Hz and on 3.3μv at a higher stimuli frequency at 13Hz. Therefore, the white stimuli flicker LED is the induced evoked SSVEP response, which records 9.6μv at 6Hz and 4.9μv at 13Hz. In exploring the results, there are induced potentials differences between the low/high frequencies, which restrict the brainwaves of each stimuli colour, since the white stimuli gives a robust power response of evoked SSVEP paradigms, according to spectral analysis. However, the slower flicker provides a powerful response compared with the higher flicker with respect to amplitude of power spectrum analysis. The low and high frequency corresponding to 6Hz and 13Hz present a superior SSVEP response in all stimulation colours. Furthermore, the white LED stimulation results induce a much sturdier power based SSVEP response compared with red and blue stimuli LEDs; in addition, the blue stimulations provide satisfactory power compared with red stimulation.

4.2.3.3 One way analysis of variance (ANOVA) Results

The exploration of extracting the spectral powers is followed by boosting powerful statistical analyses used to discern effect of each stimulus colour based on evoked of SSVEP response. One-way analysis of variance ANOVA procedure assumes that the EEG datasets are normally distributed, in addition to those variances of different conditions also being identical based analysis. One-way ANOVA a comparison process establishes a significant hypothesis for the different entire groups. This approach enables determination of whether the mean of any group member is significantly different from others.

A null hypothesis H_0 is assumed, which establishes (all-entry groups) are equal to mean values that determine whether any entry group is significantly different from others, as illustrated in 4.10:

$$H_0\colon \mu_1 = \mu_2 = \mu_3 \dots = \mu_k \qquad 4.10$$

Correspondingly, the invalid null-hypotheses are established by considering the alternative hypothesis of H_1, which represents an unequal entry group in respect of the mean values of a significantly different hypothesis according to 4.11:

$$H_1\colon\ \mu_1\ \neq\ \mu_2 \neq \mu_3 \ldots\ \neq\ \mu_k \qquad 4.11$$

The different strictures of statical-analysis results of the ANOVA test are computed likewise; the mean square within groups by (MS_{within}) based on mean square between groups of ($MS_{between}$), which are the summation of squares within groups in (SS_{within}), according to 4.12:

$$SS_{\text{within}} = \sum_{j=1}^{n_i} (\,Y_{ij} - \overline{Y_i}\,)^2, \quad df_{\text{within}} = n_i - 1 \qquad 4.12$$

The square is substituted between groups ($SS_{between}$), since the individual group is represented by observing the value on Y_{ij} of pattern j of each group; however, the $\overline{Y_i}$ represents the sample mean for group i.

Correspondingly, in 4.13 the estimate mean square is computed within group values:

$$\text{MS}_{\text{within}} = SS_{\text{within}}/df_{\text{within}} \qquad 4.13$$

Estimated from the summation of the square between groups, the distinction of j within group is computed as follows in 4.14:

$$SS_{between} = \sum_{i=1}^{k} n_i\,(\,\overline{Y_i}\ -\ \overline{\overline{Y_i}}\,)^2\,, \quad df_{Between} = k - 1 \qquad 4.14$$

Here $\overline{\overline{Y_i}}$ represents the grand mean, since the k is a unique deviation based on degrees of freedom df with respect to $k-1$. Similarly, the mean square is estimated between groups, which employed the formula on 4.15:

$$MS_{between} =\ SS_{between}\,/df_{between} \qquad 4.15$$

Following a summary of one-way analysis of variance (ANOVA), Figures 4.23 and 4.24 show the analysis between entry groups that have provided three stimuli colours of (blue, red, and white) corresponding to (1, 2, and 3) respectively on the illustrated scheme. Firstly, remediation of pure EEG (raw data) is considered by removing the eye-blink artifacts using threshold technique then occupying as a (new dataset), which does not apply any kind of filter on gathering of raw-data.

Figure 4.23 illustrates a low colour stimulus at 6 Hz to the analysis between groups, which demonstrates white and blue are tightly packed and much closer to each other by inducing the responses based on evoked SSVEP paradigms.

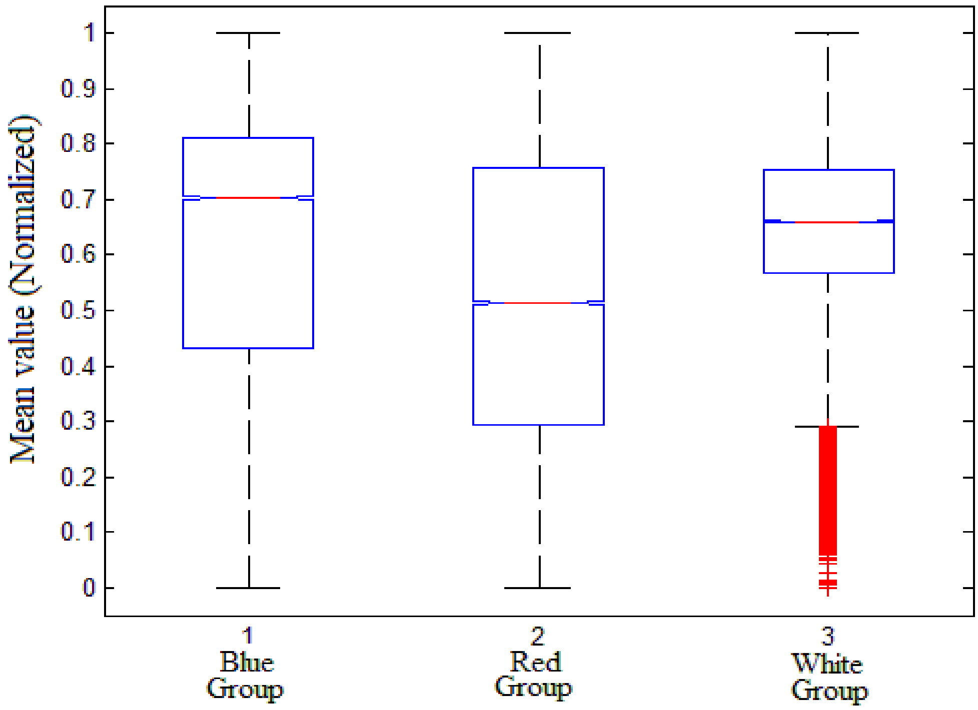


Figure 4.21: Stimuli LED flicker at 6 Hz in three different groups

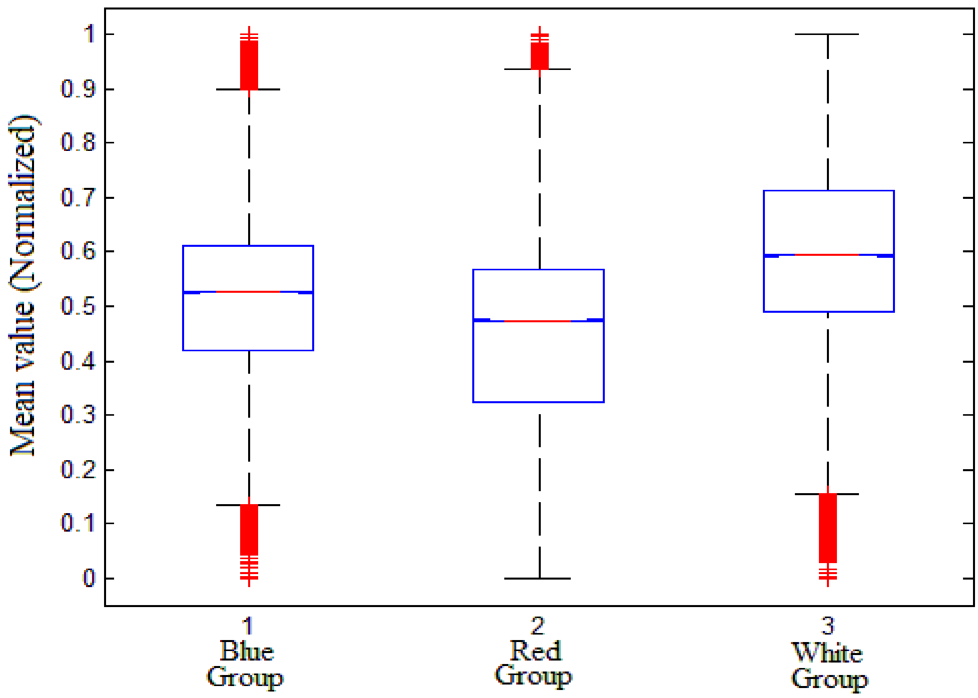


Figure 4.22: Stimuli LED flicker at 13 Hz in three different groups

However, the red stimuli flicker is loosely packed. Furthermore, Figure 4.24 shows the different schemes between the three stimuli based on colour present a high level with respect to the alpha band of brainwave at 13 Hz. Here, the white stimuli LED records a strong response compared with other two stimuli of red and blue. On other hand, the high-level stimuli based frequency provides a compatible result, which is explored previously. From the fundamental of ANOVA analysis, it was discovered that the induced response of SSVEP effect is much stronger than red and blue LEDs at 13 Hz. The ANOVA test on 6 Hz stimuli frequency shows a stronger effect for all three conditions in respect of the value of rejection area [$F (2, 12) = 927$], and the probability equal to [$p < 0.005$]. A multiple comparison shows a significant effect of white stimuli LED by $M = 0.6$, and $SD = 0.18$ compared to red stimuli LED on $M = 0.46$, and $SD = 0.23$, also the blue stimuli LED is provide $M = 0.53$, and $SD = 0.18$. Correspondingly, the induced SSVEP response at 13 Hz, of the blue and white stimuli LEDs induces much stronger effect than red stimuli. The test result shows stronger effect for all three conditions with respect to rejection area [$F (2, 12) = 603$], and the probability equal to [$p = 0.001$]. A post-hoc multiple comparison shows significant effect of (white stimuli LED) by $M = 0.67$, and $SD = 0.12$ compared to red stimuli LED in $M = 0.52$, and $SD = 0.31$ and blue stimuli LED in $M = 0.7$, and $SD = 0.27$.

4.2.4 Multiple Colour Conclusion

The contribution of this work successfully demonstrates as low-cost prototype BCI system based on SSVEP paradigms using three colours of white, blue and red LEDs. Visual stimulation board was powered by a 9V battery source to avoid any AC-line interferences. Each colour has established with eight-stimuli-LEDs starred in the centre and surrounding area on a stimuli board. Throughout the experiment, a regular flicker paradigm was preferred to evoke the brain activities respect to SSVEP responses. The flicker of periodic sequence of each LED was regularized according to a mathematical formula with respect to individual groups of variable flicker approach. The flicker was set with constant base frequency at (6 and 13) Hz that were present on stimulation LEDs for each recording session. The experiment results were obtained on three analyses methods; using the event related potential (ERP), which revealed the phase shifted behaviour in each colour stimulus, and the FFT to detect the maximum amplitude power in each colour. However, the one-way ANOVA was employed to realize the behaviour of brain activities with respect to colour stimulus by extracting the EEG raw-signal to detect the maximum effect.

These results present three main brain waveforms of SSVEP response affected by individual colours of flickering LED. ERP results have demonstrated the phase different waveforms, which possessed average trails accumulate technique with respect to relevant flickers of high and low based alpha band. These waveforms are defined in terms of the standard nomenclature of ERP signals, which are denoted by negative upward N-peak and positive downward P-peak. Nomenclature curves of ERP analysis present by N and P peaks as maximum and minimum values. The white LED-stimulus at positive peak P1 recorded a higher evoked SSVEP responses of potential 2μv. Correspond, to red stimuli-LED, that records 0.5μv, also blue stimuli-LED on 1.3μv. A significant difference between observed phases of three stimuli signals according to latencies, since the white and blue colours are leading red at 6 Hz of stimuli frequency according to ERP waveform results. On other hand, the white colour is leading from blue, and red LEDs is lagging from blue at 13 Hz of stimuli frequency. However, the colours appear in phase in P downward at both stimuli of 13 Hz and 6 Hz. This indicates a minimum contingent of negative variation of induced SSVEP responses. The results of FFT indicate that colour stimuli based flickering induces strong responses. However, it was discovered that the white stimuli LED induced a much stronger SSVEP effect based on analysis; also, the red and blue stimuli LEDs induced SSVEP irrespective of flicker frequency. Indeed, base frequencies were found to be much stronger at 6 Hz stimuli frequency effect than 13 Hz stimuli on all stimuli session. ANOVA explores the results of different induced potentials between (low and high frequency) which are restrict alpha brainwaves based-stimuli colour, since tightly packed on white and blue are much closer to each other by inducing the responses based SSVEP paradigms. However, the red stimuli flicker provides a loosely packed flicker stimulus at 6 Hz. From the fundamental of ANOVA, analysis discovered the induced evoked response is a much stronger SSVEP effect than red and blue LEDs at 13 Hz, although the different schemes between three stimuli based on colours are present at high-level responses with respect to alpha band of brainwave at 13 Hz. Therefore, the experiment is adapted to configure as online BCI application based SSVEP. Multi-colours could be helpful in new applications to support disabled people for a more attractive external environment. This will make a more objective comparison among BCI systems with single and multiple colours. A multi-colours paradigm will introduce a different protocol for different applications. Finally, this provides advantages to exploit this method as a future application work in SSVEP based on BCI system fields since it is adapted, optimized, and configured with the support of FPGA as future online experiments. The interesting results were published in:

- Beyond Pure Frequency and Phases Exploiting: Color Influence in SSVEP Based on BCI, Computer Technology and Application 5 (2014)
- Discriminate the Brain Responses of Multiple Colors Based on Regular/Irregular SSVEP Paradigms, Journal of Medical and Bioengineering 2015, 5.2.89-92/2016 Journal of Medical

4.3 Short Terms Adaptation based SSVEP paradigm

Brain-computer interfaces (BCI) have successfully emerged to assist disabled people by introducing a new technique which provide possibilities to use based on brain technology. The increased amount of BCI-command control number offer higher possibilities for BCI users, and leading to decrease classification algorithm effort and increase accuracy. This empirical study explores a prospect by employing irregular versus regular-stimulations to increase the number of target of reaction BCI-commands. Dynamic brain activities, which are extracted from evoked signals of SSVEP response, are dependent on non-symmetrical paradigms in order to increase the commands hypothesis. The Flickering stimulus, found by Phase-tagged (PT) with respect to EEG signals, which is facilitated to extract the induced SSVEP responses from brain activity. Moreover, the SSVEPs can be automatically detected by engaging a series of signal processing steps that include pre-processing by filter that prevent artifacts, and extract features using spectral content at stimulation frequencies. Visual stimulator presents two main pattern based flickers of regular and irregular on a single LED based constant frequency. The average of stimuli effects that are recommended are combined using fast Fourier transform (FFT) to find spectral different and event related potential (ERP) to explore phases and latency of brain responses. As offline analyses based on accumulative brainwave of EEG raw-signal, which extracted to distinguish the brain activities in terms of evoked SSVEP paradigms. The decent results between regular versus irregular are found by high different on amplitude with respect to a conjunction of stimuli-flickers based fixed-frequency according to two-patterns.

4.3.1 Exploit a Short Terms by Regular/Irregular Paradigms

The steady-state visual evoked potential (SSVEP) is a brain response type evoked by invoked light/flicker of visual stimulus based on a frequency range from (1 to 90) Hz [19]. A virtuous response is normally acquired on (5 to 15) Hz, which has been proved previously (see section 4.1). These two stimuli paradigms of regular/irregular based SSVEP supplement augmentation of brain activity. The preliminary experiment results of short term explores the ability of the human brain to distinguish between regular/irregular based SSVEP paradigms, where the different SSVEP evoked elicit the difference between amplitude and phases of brain waves response. Pre-progressing towards a concept requires an understanding of the extent of brain activity, which enables excitations to specific tasks. The inspired of this study is increases the amount of brain commands based-BCI system depending on stimulus sequence. By compare the regular with irregular stimulus to recognize the influence of brainwave based-stimulation paradigms. In general, the multi-stimulus panel can offer four-stimulation LEDs to evoke SSVEP response. Both paradigms of stimuli flicker LEDs are induced the evoked brain responses with respect to PTT that used to decide the different phases in each mould paradigms regarding to unique frequency. The LEDs are configured with base frequency at (12 Hz of 4-LED × 2 Paradigms).

Table 4.2: Regula paradigms present 4LEDs onset respect to four different phases

Stimuli LEDs Position Number	**LED Pattern**	**Different Phases θ^o**
LED1	1000, 1000, 1000, 1000	0^0, 180^0, 360^0, 540^0
LED2	0100, 0100, 0100, 0100	45^0, 225^0, 405^0, 650^0
LED3	0010, 0010, 0010, 0010	90^0, 270^0, 450^0, 630^0
LED4	0001, 0001, 0001, 0001	135^0, 315^0, 495^0, 675^0

Table 4.3: Irregular paradigms present 4LEDs onset respect to four different phases

Stimuli LEDs Position Number	**LED Pattern**	**Different Phases θ^o**
LED1	1000, 0100, 1000, 0100	0^0, 225^0, 360^0, 585^0
LED2	0100, 0010, 0100, 0010	45^0, 270^0, 405^0, 650^0
LED3	0001, 0001, 0010, 0001	90^0, 315^0, 540^0, 670^0
LED4	1001, 0000, 1001, 0000	0^0, 135^0, 360^0, 495^0

The SSVEP evoked by stimuli are separated into two different groups to demonstrate as symmetry regular paradigm and likewise for a non-symmetry irregular paradigm. The rhymester on Four-LED includes calculation with White stimulus-LEDs because the white stimulation provides a stronger evoked response as proved before (see section 4.1.2.2) based on onset stimulation of flicker with respect to main shift phases, while is change base phase incremented by 45^0 respectively, according to the configuration of Equation 4.16:

$$\theta_i = (i-1) * 45^{\circ}; \quad where\ i = 1, 2, \dots, N \qquad 4.16$$

In spite of stimuli configuration, Table 4.2, and Table 4.3 illustrate the different phases on θ^o with respect to Regular/Irregular paradigms; furthermore, the stimuli flickers are always displaced with (45^0) among Four-LEDs, into one cycle of one rhymester stimulation. The time difference between each stimuli LED based-one cycle is discriminated according to single frequency. Two additional signals provided in each cycle decelerated events of onset LED-trigger and the other is cycle began, confined by periods of T_{on} and T_{off}. The EEG signals were measured by three-electrodes placed on (O_1, O_2, and O_z) of occipital lobe of (brain region); while, the CMS activates electrode and DRL passive electrode drives the average potential accord to references electrodes of BioSemi EEG system.

4.3.2 Extract Feature based Onset of Regular/Irregular

The technique of flicker was identified by fixed stimulation frequency, which elicits as the strongest evoked SSVEP response that is proved in (section 4.1.2.2). The based frequency was isolated using independent component analysis (ICA) followed by filtering signal procedure by digital signal processing (DSP) to clear induced effects of brain activities, then implementing a basic analysis of Fourier analysis fundamental 4.2:

$$F(f) = \int_{-\infty}^{\infty} x(t).\, e^{-j2\pi f t}\, dt \qquad 4.2$$

The purpose of the Fourier analysis is to decompose any periodic signal-type within a sufficient length based on the foundation of transformation analysis [144]. The rhymester on Four-LEDs includes onset-stimulation flicker with respect to phase shifts in 45^0 among each LED into one cycle. This work realizes the difference between two paradigms based on change in phase and amplitude onto brainwave activities. Therefore, the work relies on two types of analysis methods to distinguish the brain responses, which are gathered EEG raw-signal then sorted as individual group of EEG/epochs (template) according to each recording session. Thereafter, analyses the template file separately according to methods of frequency and times –domains. The FFT is utilised to present the spectral-power in the frequency-domain; while the ERP analyser is utilised as time domain to distinguish the phase shift in each paradigm. The hypothesis of irregular paradigm of random LED flicker provides high amplitude responses based on brain activities. Therefore, it is easy to distinguish between paradigms in respect of diverse stimuli patterns, which are evoked potentials signals of produced SSVEP responses; furthermore, irregular paradigm leads to increasing the control commands based BCI system compared to multi-frequency flicker.

4.3.2.1 Frequency-domain Analysis of Regular/Irregular paradigms

Firstly, the FFT is utilised to achieve the power spectral in each paradigm corresponding to the entrance stimulus-frequency, which is proved previously in (section 4.1.2.2). The frequency-domain analysis approach is applied after gathered EEG/epochs have been pre-processed by setting filters of low-pass filtered (LPF) that contain cut-off frequency at 35Hz to release power line interference artifacts. Notably, the signal processing is performed to deduct unwarranted signals by automatic artifacts rejection using MATLAB tools, based on ICA technique to remove the eye-blink and muscle movement artifacts (see Appendix A.1). The candidate signals x(t), according to the Equation 4.2, represent the time domain signal that is transformed into frequency domain signal F(*f*) by integrating each constituent frequency. The term signal has infinite bound but in practice, it can be integrated over sufficient length to obtain a good approximation. Therefore, conjugates over a period of 2 π periodicity. The first target of the extraction approach is of stimuli frequency at 12 Hz, in order to compute the amplitude by withdrawing the power spectral depending on certain frequency from inward EEG/epochs as offline analysis.

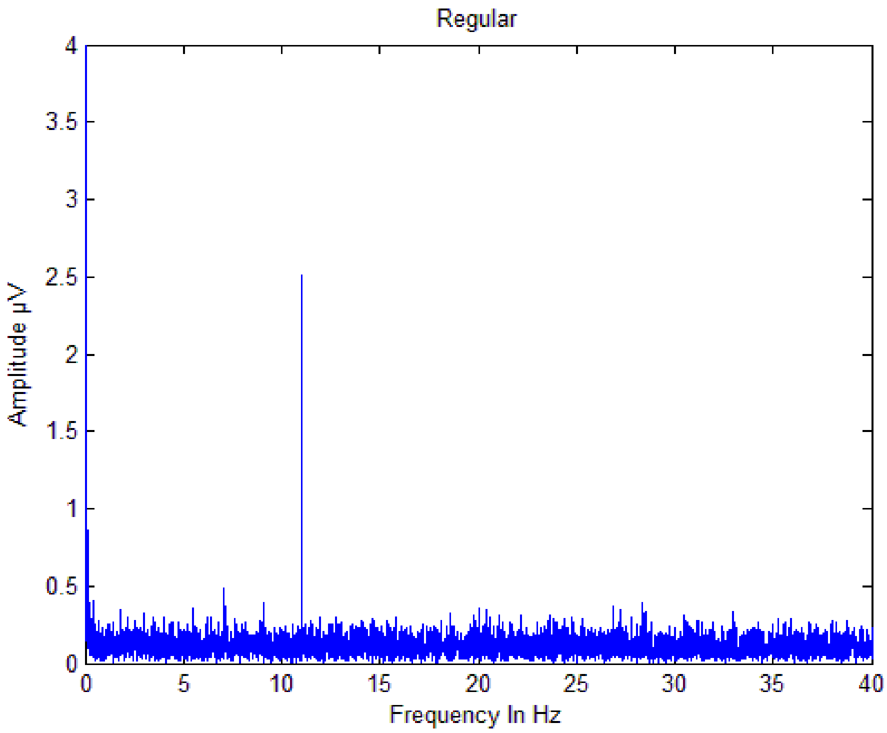


Figure 4.23: Primarily result demonstrate regular paradigm response based single stimulus white-LED

The FFT is applied onto different stimulation ranges of regular and irregular of both paradigms, as illustrated in Figure 4.25, and Figure 4.26, which illustrate the plotting resu7lt of spectral in each visualize stimuli frequency. The EEG signals are non-stationary, and spectrum will change with respect to frequency domain is not given an exact result; or can be approximated piecewise from non-stationary signals. Therefore, questing a short chunk from EEG/epochs, according to trial-windows (see section 5.3.2.1) that proved to given an sequence of independent stationary segments which conclude a good result. All individual/trials are gathered from voluntary (subjects) participant to average and extract based on evoked SSVEP signals in each paradigm. The trial-windows are normalized among ~5 seconds before applying FFT algorithm as baseline (BL) of threshold value. Subsequently, the FFT is performed, which depicts a spectral frequency of SSVEP response.

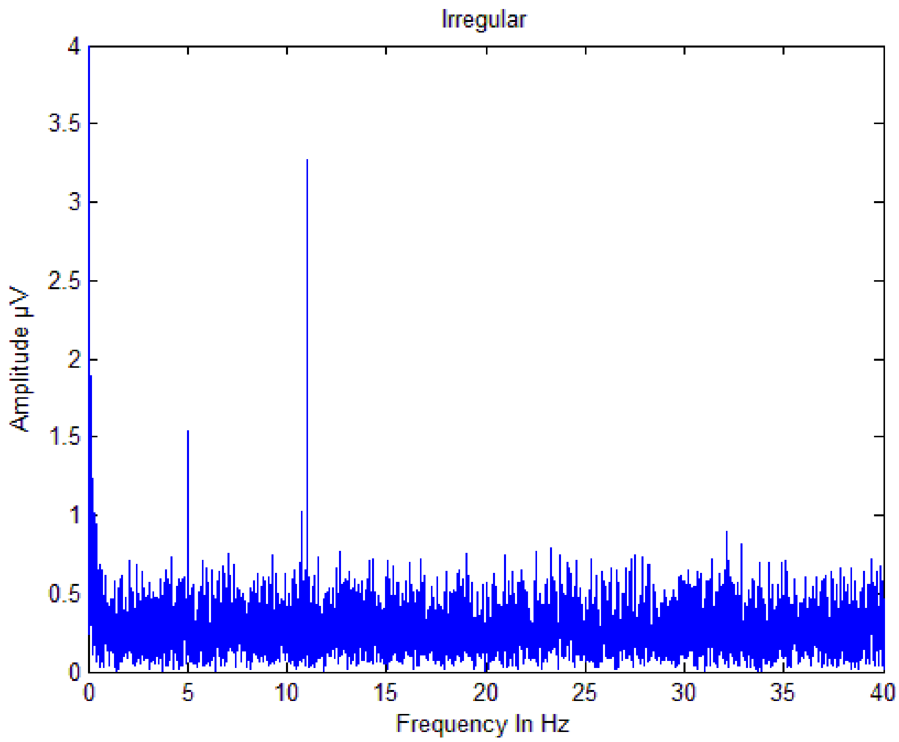


Figure 4.24: Primarily result determine irregular paradigm response based single stimulus white-LED

In addition, consider removing the second and third harmonics with respect to base stimulus-frequency, which are effects on extracted responses. The concept of the alpha brainwave band contributes significantly to a sharp peak of spectral distribution amid at 12 Hz flicker stimuli, which is described in the previous section (see 4.1.2). Therefore, extracted amplitude on alpha band is fetched under the same condition of the stimulus frequency from gathered epochs that provide a similar response flicker stimuli frequency.

In fact, the spectra analyses under invoked signals of stimuli conditions are similar in each paradigms; however, there are two amplitude peak appear in most stimulus in both paradigms of regular/irregular stimulations, which are illustrate the SSVEP response effect according of two-pattern (as shown in Figures 4.25 and 4.26). Observed clearly amplitude signal (spikes), which defined differs paradigms as primary results based on this study. In particular, the amplitude of the spectral demonstrates a second harmonics is comparable with flicker frequency and smaller than SSVEP response signals in term of fundamental of frequency domain, referred to in (section 4.1.2).

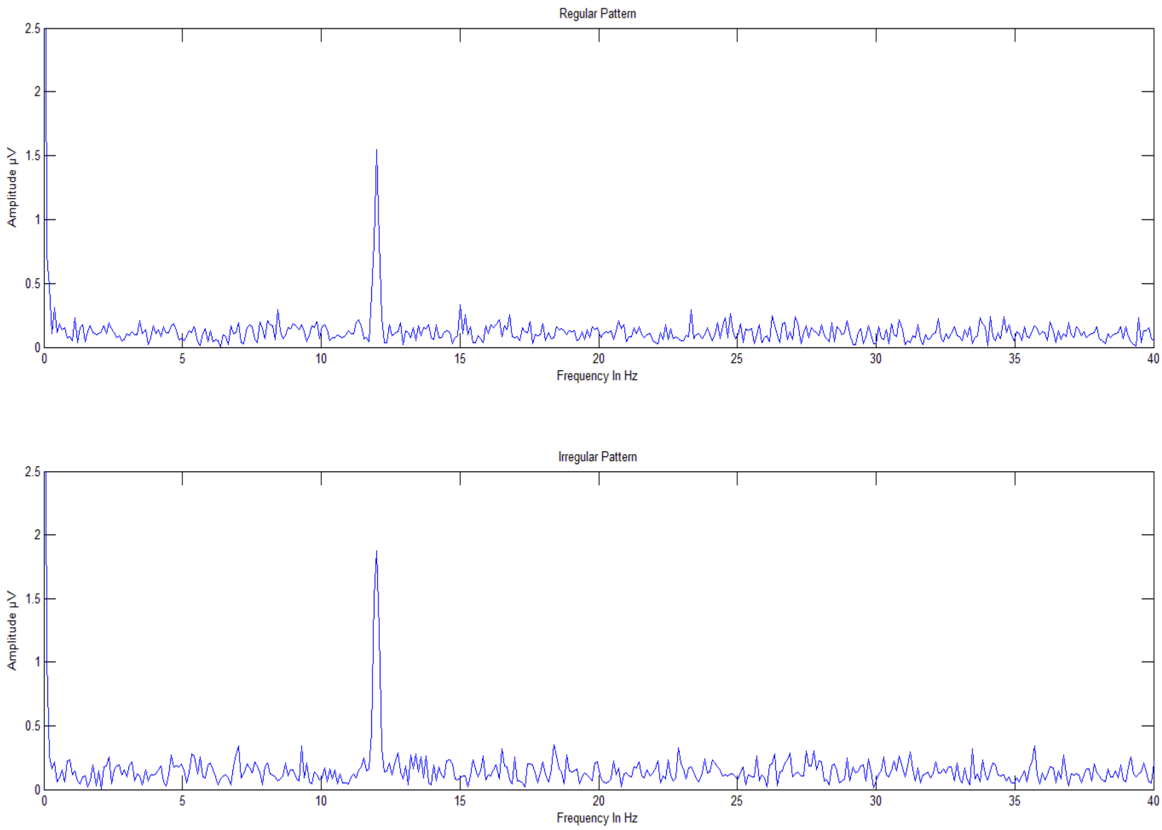


Figure 4.25: Discernment amplitudes that demonstrate the regular/irregular paradigms response

In other word, Figure 4.27 shows the feature of amplitude that evoked from SSVEP signal in medium frequency (MF) range of alpha waveform band (see section 2.1.4), which are extracted from flicker stimuli using a fundamental of FFT after applying the FIR on the clean-dataset which are gathered from raw EEG/epochs. The results of irregular paradigm over equivalent circumstances recognize the maximum spectral by ~1.9µv compared to the spectral efficiency in regular paradigm as ~1.5µv.

4.3.2.2 Dynamic Time-domain Analysis of Regular/Irregular paradigms

The second analysis approach considers the advantage of ERP techniques to detect the phase difference in each paradigm with respect to phase-tagged PTT structure according to stimulation configuration. The fundamental concept of amplitude and phases of de-coding EEG signals by average process to extract epochs identifies based on target across the reference of phases using ERP technique. In this work the offline analysis based occur event of ERPs that referred to baseline (BL) and threshold (voltage). Reveals reasonable evoked SSVEP responses are extricating associated with brain activity of evoked stimuli signals that provides a clearly distinguishing between two stimuli paradigms. Usually the ERP waveforms presents by latencies of responses, which content from amplitude and phases. The ERP waveforms are measured depending on averaging process of gathered evoked response signals. An effective approach has been dependent on reflecting brainwaves correspondingly to accumulate of multiple-trials of EEG/epoch. ERP waveform processing is reflect an external events of stimuli light/flicker specifically at LF and MF, which are concentrated around the occipital and central brain regions based recording EEG/epochs (see section 3.2.2). The visual flickers are elicits by brain response based on ERP event occur. Extracted epochs from EEG raw-signals were accumulated from each participant and gathering individually according to stimuli-based two paradigms. The phase-locked events (PLE) have been obtained by PTT in terms of (timing windows technique), which accumulating process a 1536 epoch in each template file to present one evoke-paradigm session. Each recording file (templet) represents onset stimulus-paradigm accrual by adding the external triggering signals to indicate flickers onset-trigger and a complete take place of one cycle-trigger. The constraint ERP waveforms is compute based on SSVEP responses for each epoch, dependant on time interval of elicited evoke signal based-triggered in each trial-window and baseline (BL), which are determined by pre-frame duration and post-frame duration. These windows are averaged together according to restrict PTT pulses which associated with brain activity property of SSVEP response signals. This method detected induced SSVEP signals, which have averaged onto epoch amount according same stimulation conditions, particularly for each paradigm group regarding regular/irregular patterns. In order to compare the result between frequency-domain base (FFT) and dynamic time-domain base (ERP) with respect to essential components of ERPs which are systematically extracting regarding to time-locked windowing techniques corresponding to phase-trigger PTT that illustrate the different between latencies of amplitudes and phases.

Figure 4.28 shows the phases in regular paradigm stimulation, which gathered after being averaged from individual voluntary subjects under stable conditions, based on fixed stimuli frequency at 12 Hz. The brainwaves represent the SSVEP responses as extracted into ERP waveform; correspond to positive P peaks in one cycle as (0, 88, 177, 266 and 355) milliseconds respectively and different phases in θ^{o} with respect to single flicker/LED that is presented by (0^{o}, 180^{o}, 360^{o}, 540^{o}, and 720^{o}) respectively attuned to Table 4.2. The time shifting of SSVEP responses are demonstrated onto an extracted curve in one stimulation cycle that is directly affected on ERPs waveform with latency responses based on brain activities.

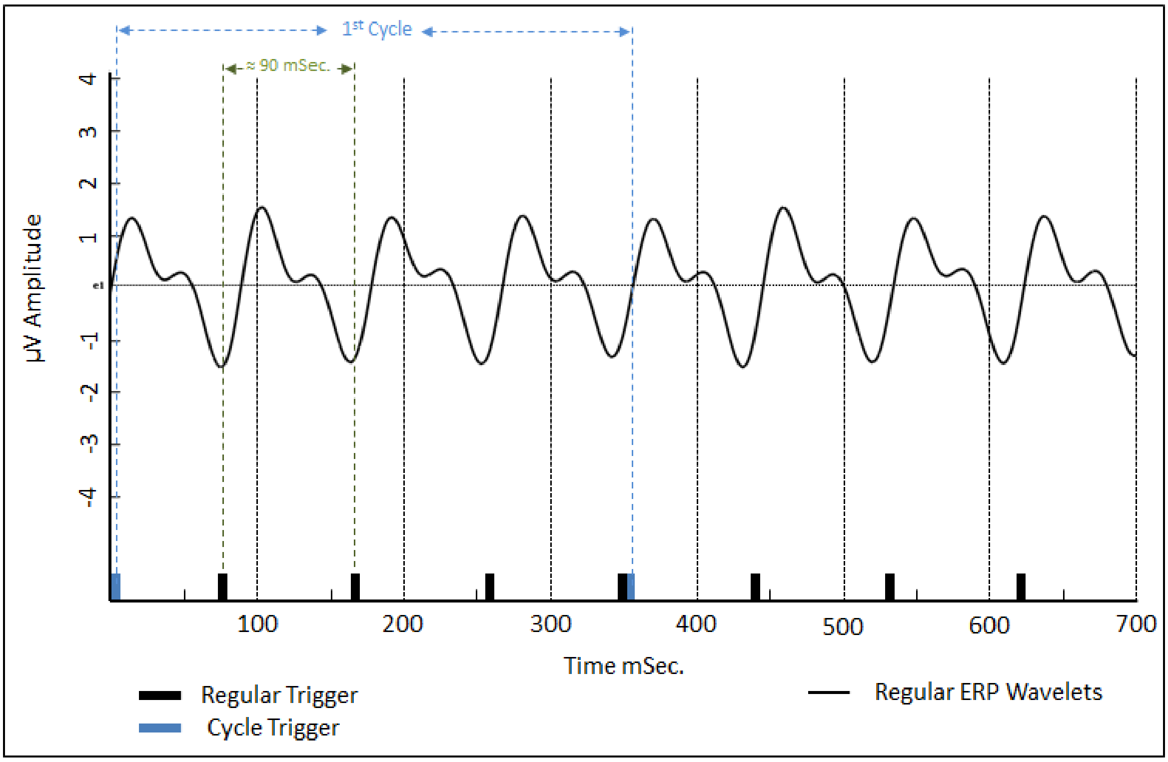


Figure 4.26: ERP waveform of regular paradigm with PTT pulses in each onset-LED and cycle

The vertical Black Boxes show the onset-event occurs with respect to triggers which illicit the responses corresponding to latency in each evoke-event. However, the Blue Boxes present a complete stimulation cycle. This paradigm has been adapted as a result of sensory responses which provides a positive downward at (N30) followed by negative upward on (P70) of brain waveform based-ERP, which means the response on the negative part has been delayed ~30 milliseconds; however, the positive part has been delayed by ~70 milliseconds. The focusing attenuation plays a role by provides the identical stimuli indices based on the visual cortex storing strength of the inhibitory pathway of human-neural system. The downward of positive waveform aspects on P70's are present the absolute amplitude of difference proceeding through and the negative upward on N30. Both P70 and N30 can elicit a steady-state signal of SSVEP paradigm (responses). The entire sequence in one cycle covers 355 milliseconds that include the whole onset-LED based on a single stimulation paradigm. The effect of random-contour with respect to irregular paradigm, shown in Figure 4.29, that demonstrates the brainwave response based ERP result.

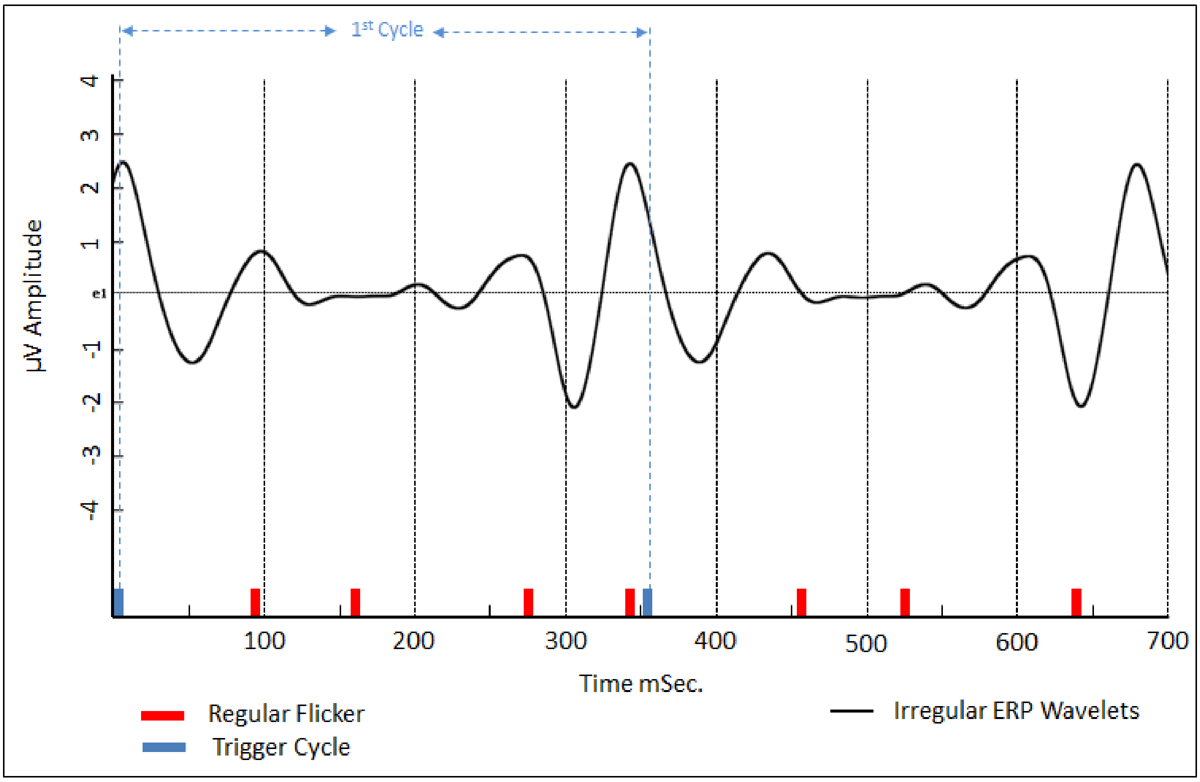


Figure 4.27: ERP waveform of irregular paradigm respect to PTT in each onset-LED and cycle

The positive peak appears on ~P40 followed by N10, which means the positive downward peak occurs after 40 milliseconds and the negative occurs after 10 milliseconds in respect of latency of ERP components. However, a clear onset based-stimuli two-pattern can be observed according to the ERP of latency components. Nevertheless, it is difficult to determine the other component because there is a temporal (event-position) extension without a sharp peak. In other words, the hypothetical of stimuli pattern shows all the expected spikes in the reserved time window that can be measured on one complete cycle, which includes negative N and positive P peaks. The design pattern of irregular related to evoke brainwave that obtains ERP component to compute the different sites based on SSVEP responses. The brainwave activities in one cycle are represented by (50, 120, 225, 305 and 280) milliseconds respectively, according to positive downward P on different phases at θ^{0} of stimulus flicker

(0^0, 225^0, 360^0, 585^0, and 720^0) respectively, (see section 4.3.1), as mentioned in Table 4.3. Generally, different latencies are recommended by combining ERP result in both paradigms. Since the optimal parameters appear in 30% - 50% increasing area based on latencies, with a slightly negative boundary by N components and with a slightly at positive boundary for P components.

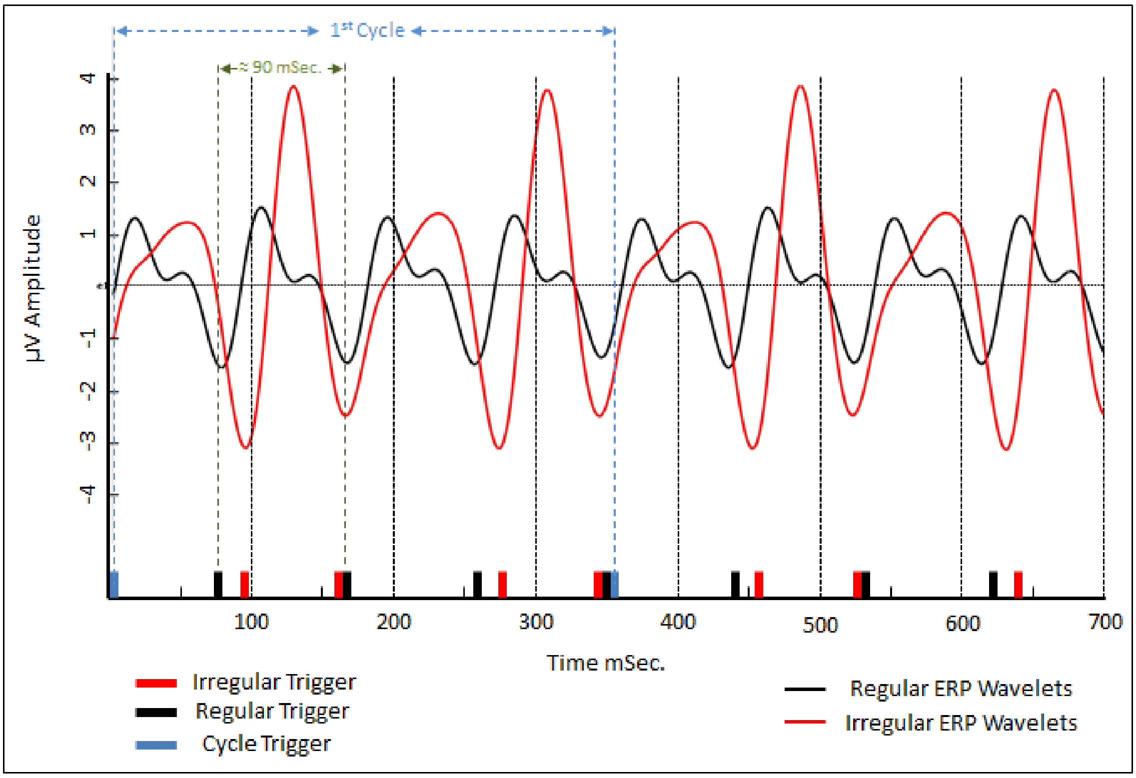


Figure 4.28: ERP waveform of regular/irregular paradigms indicates different phases and amplitudes

Theoretical, the ERP waveform present stimuli patterns, which reveal two curve based SSVEP response with respect to the same timing windows as analogous to construction of (black and red curves), as shown in Figure 4.30. The properties of stimuli are affected in terms of short flickering with respect to different paradigms. Illustrated curves in above Figure 4.30 are shifted along the time axis, since the N components occur later than in the control condition within 50 milliseconds. In this case, the peak of downward positive and upward negative latency difference reflects the actual shift with respect to origin stimulus. A uniform black curve implies smoothness across brainwave responses, which have been evoked as a regular paradigm, but it is not as much amplitude value compared to the red curve, which presents an irregular paradigm, having approximate amplitude values 4μv in agreement to the base frequency. In other words, both involved the same base frequency at 12 Hz.

4.3.3 Short Terms Paradigms Conclusion

A low-cost prototype SSVEP based BCI system was constructed to demonstrate brainwave utilization Four-LED stimulation that evoked SSVEP signals. Voluntary participants (subject) gazed at LED flickers depicting two paradigms types, according to phase-tagged production of PTT that was obtained to recognize the target-LED. Two approaches have been used and combined the results. Conventional technique of offline analysis SSVEP response is used to extract feature. Firstly, FFT methodology used to distinguish between extracted spectral-power based on frequency-domain; second, ERP technique was used to discriminate between evoked stimuli phases and different in latencies. The stimulation of two paradigms based SSVEPs revealed standard procedure to evaluate a latency effect, which estimates the differences between phases of satisfactory paradigms depended on PTT technique. The analysis results were consistent in tendency under effect of invoked stimuli flicker; spectra EEG/epochs were considerable difference brain activity with respect to SSVEP responses. Discovering difference responses between two paradigms based on regular/irregular. The most important features of this study were stability and reliability in respect of desirable methods. Wherein, the regular paradigm drives limitation view based-BCI design system, in fact restricts a single frequency with one or more patterns dependent on number of LEDs that used in stimulation procedure. On the other hand, irregular paradigm authorizing to introduce many stimuli-patterns that used regarding unique frequency based-single or multiple-LEDs of visual attention. The analyses methods are obtaining robust spectral results to observe stronger power on irregular compared with regular paradigms. However, the amplitude of ERP result indicates regular paradigms, which provide less amplitude than irregular. Furthermore, ERP result spreads phases between stimulation paradigms, which indicate shift in time of both paradigms based-onset of stimulation. Moreover, ERP results found out positive downward P and negative upward N components are similar with regular paradigm; on other hand, the same components were non-similar with irregular, despite the advantages of irregular paradigms that expand number of stimuli commands by increasing oddball patterns. This empirical study is optimized SSVEP. The interesting results were published in:

- New Paradigms for Brain Computer Interface Based on SSVEP, 2014 WSWAN, ISBN: 978-0-9940194-1-7
- Exploiting a Short-Terms Adaptation: In Brain Computer Interface Based on Steady State Visual Evoked Potential, 2014 NNGT: ISSN: 2356-5888

CHAPTER 5

EXTRACT SSVEP BY DUTY-CYCLE AND MULTIPLE PATTERNS

The steady-state visual evoked potentials (SSVEP) in brain–computer interface technique (BCI) progressively increased in recent years. This chapter inspects three empirical studies that discuss brain influences based on BCI technology by induced duty-cycle effect on the evoked signal of brain activities and invoked multiple patterns to extract the SSVEP responses. The duty-cycle study explored with three intensity flicker types that discuss the attractive of brainwaves effect. The Hilbert transform (HT) based analysis technique was utilised to distinguish between patterns by detecting the phases of each stimuli. High performance computing (HPC) has been used to reduce exaction time based-system. The multiple patterns technique with high performance computing is new challenge paradigm that extracts a specific signal from a massive EEG dataset. This new prototype design presents an effective solution to improve rapidly process dependent on multi-core using open source library of OpenMP. The approaches and result of this contribution works have published in the following compact journal and conference papers:

- Recognition a Multi-pattern in BCI system Based SSVEPs, ERK'2015 conference, IEEE Slovenia section, ERK'2015
- Rapid Computation and Analysis using a Multiple Core to enhance SSVEP based system, notifications (accepted) in IEEE society on 01 Sep. 2016 well presented in NGCT-2016 on 15.Oct. 2016
- Duty-cycle beyond Three stimulation frequencies effect based on evoked signal of SSVEP paradigms (accepted) in IEEE on 21.Sep. 2016 well presented in ICCES conference at 22.Oct. 2016

5.1 Duty-cycle effects beyond SSVEP response

Evoked SSVEP signals of a non-invasive technique that are detected using the electroencephalogram (EEG) are efficient paradigms based on BCIs. One important issue in SSVEP paradigms is converting the influence of brainwaves stimulated through duty-cycle effect of stimuli/flicker. These sections discuss and develop an SSVEP based-BCI system engaging a duty-cycle flicker that affects alpha and beta band frequencies with respect to brain activity changes. The duty-cycle effect is evaluated using impact flicker-LED stimuli with a constant luminance at 0.25cd/m^2 to evoke the SSVEP signal of brain responses. Three types of stimulation paradigms are proposed depending on single of white-LED that exploits different behaviour of brainwaves based on duty-cycle influences using visual stimulation technique, which is provides a decent brain responses as described in the previous section 4.1.1. However, the accumulated approach of EEG raw-signal was used again to compare between extract epochs in respect of each stimulus, according to time-locked events (TLE). Typically, the SSVEP response evoked signals were leveraged by flickering under certain frequencies directly on the amplitude signal by selecting stimuli frequencies lower than 20 Hz to achieve a high SNR; thus, taking into account critical frequency based flicker, which often make subjects feel uncomfortable which proved in (Chapter 3). The proposed design employed a single flicker LED based on three frequencies at 5 Hz, 12 Hz and 24 Hz driven by consistent sequences of repetitive stimulus cycles with fixed duration of three types duty-cycle on 25%, 50% and 75% based-onset of powered stimuli-LEDs. Each stimulus cycle included two flexible states duration represented by T_{ON} and T_{OFF}; the duty-cycle is defined by $T = T_{ON} + T_{OFF}$, which were extracted from the ratio by T_{ON}/T based on approach of time-locked event (TLE). The stimulus flicker also depended on white colour LED that proved strongest power effect (as explored in section 4.2). Consequently, the SSVEP responses were induced in three different duty-cycles using LED flickers by adopting the phase-tagged techniques of PTT based on time locked events manner of TLE, as mentioned previously in (section 4.2.2); however, the setup and configuration of this experiment were conducted in the same routine as previous studies that are described in (section 3.1.1). The EEG signals were prominent in the cortex of the occipital brain region. Classified results, using offline analysis, were obtained to extract epochs by employing a time-series-analysed based on DSP of special-filter type. The amplitude of regular paradigm stimuli fashion is considered. The relationship between amplitude and the higher harmonic based on duty-cycle takes the place from the fundamental frequency.

5.1.1 Difference SSVEP by Configure Duty-cycle Approach

The amplitude and phase are define brain response depending on focal parameters, which are described by frequencies, intensity of lights flickering and structure of visual patterns; all these arrangements are directly effect on SSVEP paradigms. This research point has used an ordinary stimulus generator by light-emitting diode (LED) of flicker/-light using the multi-stimulation panel (see section 4.2.1). The stimulus panel was horizontally fixed at eye-level. Repetitive stimulus approach was considered in three constant base frequencies and unique colour of (white LED). The SSVEP responses recorded the EEG signals by accumulating the (raw-data) from the human-scalp. The accumulated signals were almost too sinusoidal in waveform, which gives the same fundamental frequency as driving from a stimulus flicker, often including higher harmonics. These sinusoidal signals or pulse structure signals contain the amplitude attributes of SSVEP response depending on upon of the stimulus flicker frequency of intensity and duty-cycle. Using single LED as a spot flicker/-LED light allows selection of a suitable duty-cycle, in order to obtain a larger of measurable SSVEP response amplitude based stimuli. Three base frequencies were selected at (5, 12, and 24) Hz as pulses LED to drive brainwave evoked signals, and the duty-cycle was set up by 25%, 50%, and 75% based on three paradigms that were tested with oscilloscope. Each paradigm corresponds to a different duty-cycle effect, which is considered to change in each base frequency. Table 5.1 illustrates the stimuli signal that is structured into three paradigms in respect of base frequencies. Identical protocol in each paradigm was applied with voluntary subjects, who were requested to gaze at a particular white-LED of EEG time recoding. The task is organised to record the EEG epoch/multi-trials equalized within each subject; all the trials were divided into two time periods of EEG recording blocks. Each block has three trials, and each trial consists of a continuous 20-second recording time, which demonstrates the three flicker scenario of different frequencies and different duty-cycles. However, a break-time of five minutes as rest was inserted between each recording block, with this scenario being repeated in the same manner with all subjects (see section 3.1.1). From previous studies, the spectrum power of SSVEP responses was extracted using the main fundamental frequency of FFT technique. In this study, a spatial filter (SF) technique is used and statical calculation made to classify between the extracted results based EEG epochs/trails analyses. The relation between the duty-cycles and SSVEP responses led to creating a new BCI paradigm approach, since each evoked based stimulus can provide a new command relating to, for example, selecting reliable symbols based on duty-cycle. Corresponding paradigms teste a different duty-cycle;

the first paradigm had been set to provide the duration of total T = T_{ON} + T_{OFF}, since total T is equal T = 25% in respect of the whole cycle of 100% which is repetition based on visual stimulation in white LED. Therefore, the second paradigm was set as T = 50%; however, the final duration is given period by T = 75%, which represents a structure paradigm for each base frequency of $T = 1/f$.

Table 5.1: Setup three base frequencies based on three type of duty-cycle stimuli

Duty-cycle Flickered LED		
Paradigm Group ID	**Frequency (Hz)**	**Duty-cycle**
A	5 5 5	25% 50% 75%
B	12 12 12	25% 50% 75%
C	24 24 24	25% 50% 75%

The regular pattern has been generated depending on five-cycles of stimuli rhymester. This pattern of flickered LED was packed with phase-tagged triggering (PTT) by 5.1:

$$\theta_i = (i-1) * 45^{\circ}; \; i = 1, 2, \ldots, N \qquad 5.1$$

Where flickering LEDi is shifted respect to phase angle distribution over the full phase series of five segment cycle of 360° incremented by N. Delayed trigger signals are computed based on $t_i = (\theta_i/360°).T$, since θ_i presents the delay in phase of each flicker sequence based t_i of time.

5.1.2 Assessment of the duty-cycle approach

Duty-cycle influence on brain activities based evoked SSVEP signals can traced the dependence of stimulus-frequency based on frequency-domain as mentioned in previous sections (see section 4.1.2.2). In real BCI application, there are several categories that have a direct effect on SSVEP responses and can be taken into account such as duty-cycle properties. However, other categories of SSVEPs correspond to specific frequencies or phases, which are discussed in previous sections on (4.1, 4.2 and 4.3). The stimulation process based on a single LED flicker is set according to three base frequencies at (5, 12 and 24) Hz, to achieve varied duty-cycles onto invoked signals by 25%, 50% and 75% within a maximum constant of luminance by emitting LED light. In this assessment, a spatial filter (SF) and statical analyses technique have been used to compute the gathered EEG/epochs as a multiple predefined classes that are extracted from the clean dataset. Since N_f classes are considered for each group of A, B, and C as illustrated in Table 5.1, they correspond to SSVEP response. A visual stimulation of flicker frequency at *f* Hz is applied through the SF filter by the following signal of $y_i(t)$ which presents the potential of input voltage between electrode N<u>o</u>. i, and reference electrodes (CMS and DRL) at time *t*:

$$\mathrm{y_i(t)} = \sum_{\mathrm{k=1}}^{\mathrm{N_h}} \mathrm{a_{i,k}} \sin(2\pi \mathrm{kft} + \emptyset_{\mathrm{i,k}}) + \mathrm{B_{i,t}} \quad 5.2$$

The gathered signals of EEG are decomposed and the extracted responses of SSVEP signals correspond to the evoked stimulus, prior to clean-up by removing the DC offset components and unwanted artifacts. Firstly, the evoked SSVEP responses signal, which are estimated from the number of harmonics frequencies related to the base stimulus frequency, are considered, with the number of harmonics represented by N_h. Therefore, the amplitude sinusoid signals are defined by $a_{i,k}$ and phase $\emptyset_{i,k}$, according to 5.2, since the second part of harmonic presents the noise signals dedicated on $B_{i,t}$. Detection of SSVEP signals based on this technique requires time segmentation of each epoch according to the recording time and sampling. Here, a segment time is considered by *N* numbers of harmonic, with respect to sampling frequency of Fs = 2048Hz.

$$y_i = x_{ai} + B_i \quad 5.3$$

Since $y_i = [y_i(1), y_i(2), \dots, y_i(N_t)]^T$ contain evaluated EEG/epoch which represents an individual electrode by i in respect of time segmented. The responses of SSVEPs information appear in matrix the X within the size of $N_t \times 2N_h$. Therefore, N_y represents all desired electrodes and is substituted in 5.4:

$$Y = XA + B \quad 5.4$$

Consequently, the matrix $Y = [y_1, y_2, \dots, y_{N_t}]^T$ represents all EEG sampled signals which have been accumulated from the three electrodes that are placed on the occipital brain region Figure 3.5. Improved combination between the three different electrodes is made by 5.4 to discriminate the extracted features from incoming signals based on the desired channel. The signals that are accumulated from individual electrodes are converted into the weight vector of EEG-channel's, which are substituted in 5.4. The extracted evoked SSVEP signals include a time-lock events (TLE) technique, which retrieves the results in the time-domain with respect to phase. Each recording session is triggered by one trap-event that allows the amplitudes of stimuli frequency and harmonic component to be averaged. Furthermore, a robust statistical analysis is used, which extracts the amplitude of each individual response signal of SSVEP (response-curve) to analyse the variance test by the one-way ANOVA. Comparison is made between significant hypotheses for the entire group, which is able to determine whether the mean of any group member is significantly different from others. By assumption, the null hypothesis on H_0 is established as being all means are equal.

$$H_0:\ \mu_1\ =\ \mu_2 = \mu_3 \dots\ =\ \mu_k \qquad 5.5$$

Similarly, invalid hypothesis establishes all mean are not equal by the alternative hypothesis of H_1 represents the entire group with a significant difference.

$$H_1:\ \mu_1\ \neq\ \mu_2 \neq \mu_3 \dots\ \neq\ \mu_k \qquad 5.6$$

This method assumes each frequency provides correctly detected evoked SSVEP signals. However, it is necessary to remove the artifacts from considering hypotheses. Therefore, the relationships of hypotheses are observed from three expected waveforms base frequencies. This allows the combination of a fixed number of electrodes, which minimises the noise signals. The obtained channel can extract features from base frequencies and their harmonics, which are calculated from two other channels. Nonetheless, each base-frequency evaluates an SSVEP response. Finally, the epochs are prepared based on accumulated data of (Onset flickering) to discriminate and compare the difference in duty-cycle.

5.1.2.1 Duty-cycle Result based Approaches

Before analysing the in-row EEG dataset, average approaches have been referenced between three-groups of (A, B, and C) from stimuli sessions Table 5.1. Relative in-sensitivity of evoked signal of SSVEPs, which are contaminated by common artifacts, permits rejection by setting the criteria of threshold value at 100μv. Furthermore, the averaged the in-row data depend on the baseline (BL) technique that refers to time-locked events, which are adopted based on trigger events that occur in each cycle of signal stimulation. Therefore, there are differences in amplitudes and phases, which illustrate the three types of duty-cycle.

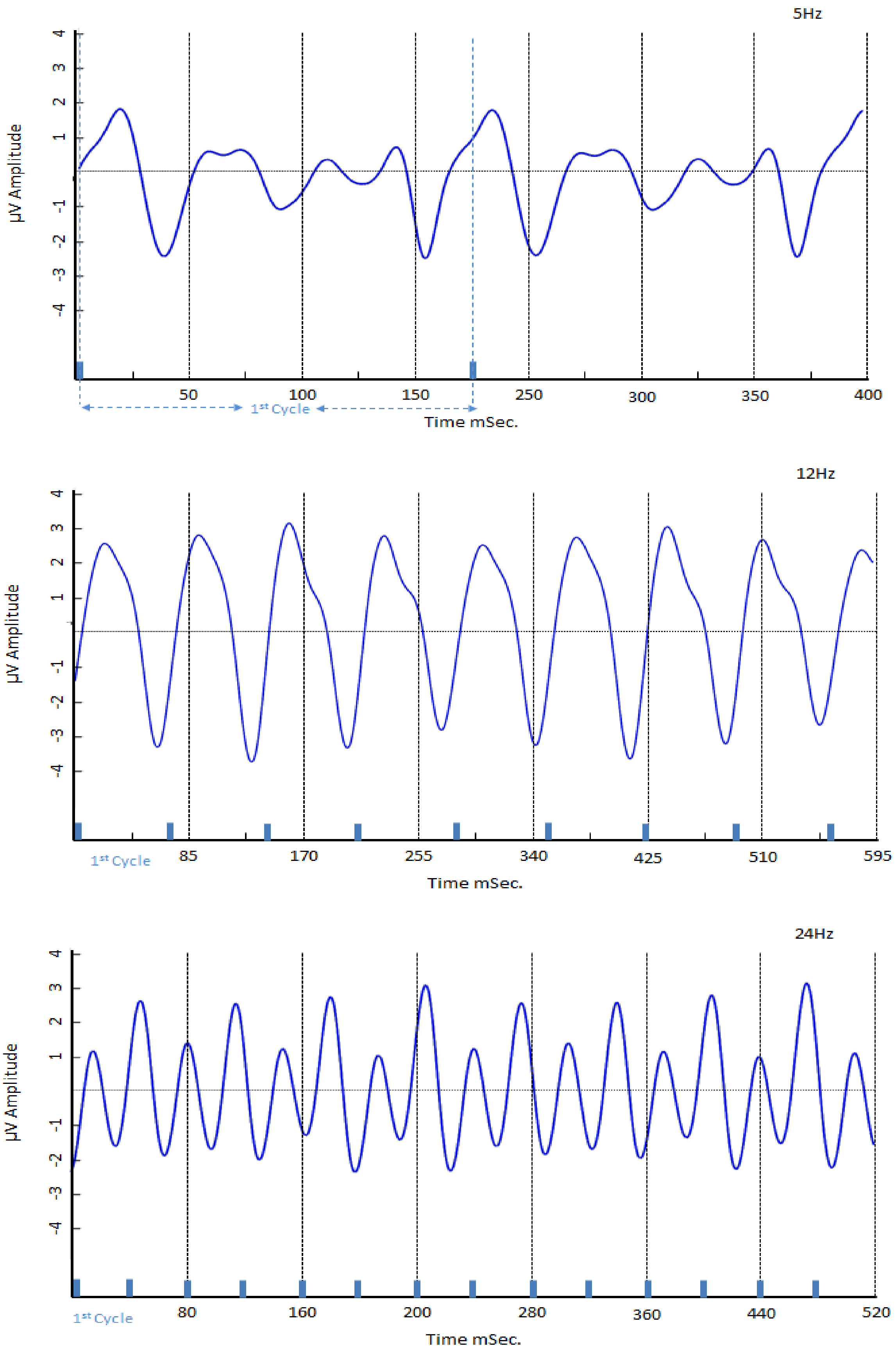


Figure 5.1: Evoked SSVEP signals in time-domain with respect to three frequencies that are extracted

The distribution of phases between the three different paradigms is also detectable based on proposed BCI prototype. The time segment based trigger is considered dependable in the signal processing of the accumulated parameter of simulate conditions. Consequently, the Figure 5.1, show the average process at 5 Hz that provides ±2μv; on the other hand, the 12 Hz and 24 Hz are given approximately ±3μv, which provides more power based analysis. Table 5.2 presents the detailed result based on three paradigms by execution of the SSVEP signals. The signals from the gathered dataset in each frequency have been averaged according to different paradigms, which are exposed as standard deviation (S.D.) and the accuracy (Acc.) based on statical analysis. Observing results from paradigms A, B, and C represents the classical setup for SSVEP experiments, whereas the duty-cycle is set up as previously described in Table 5.1. The total result of average values based on all three paradigms of A, B, and C have been processed with respect to paradigm A, which provides an average accuracy of 92.66% and SD value of 7.47. Furthermore, in paradigm B, the average accuracy is 90.73% with an average power of SD equal to 5.94, and in paradigm C the average accuracy is 84.38% and, similar to B, decreases within accuracy have clearly dropped total average accuracy at 84.83%.

Table 5.2: statistical computational results based on three base-frequencies

	Frequency 5Hz			Frequency 12Hz			Frequency 24Hz			Total		
Paradigm Group ID	Mean	S.D.	Acc. %	Mean	S.D.	Acc. %	Mean	S.D.	Acc. %	Mean	S.D.	Acc. %
A	7.32	2.04	95.57	7.03	1.77	99.68	6.07	1.55	87.74	**7.47**	1.37	**92.66**
B	5.66	1.30	93.62	6.21	1.17	97.75	5.97	1.42	88.82	**5.94**	0.97	**90.73**
C	4.87	1.06	86.93	5.88	1.14	94.90	4.57	1.13	77.31	**4.96**	0.83	**84.38**

However, the dataset shows an intake in the different duty-cycles on three stimuli levels that are plotted as shown in Figure 5.2. This figure illustrates the classes of A, B and C based on statistical analysis. Normalisation is used to balance the size of datasets of individual cleaned epochs, with each combination level of the experiment having taken the same number of observations of the brain responses. The plot demonstrates all entry affected means and interaction terms were not significant, as they probably represent only the means for main effects. The means are extracted from the epoch, which takes a few extra steps base analysis. Each of the three-classes of A, B and C corresponds to three different supplemental stimuli-frequencies.

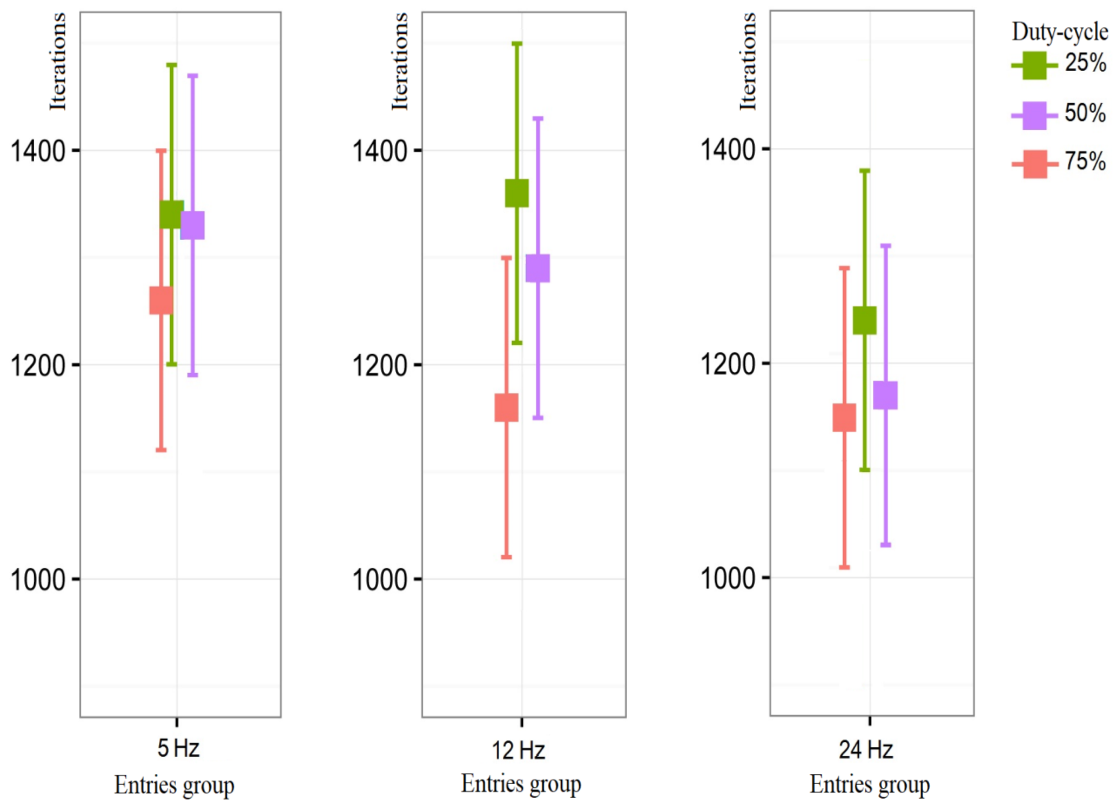


Figure 5.2:Statistically analysis of three different frequencies with three duty-cycle stimuli

The spatial filter (SF) technique and statistical calculation are both classified in between to plot results based on EEG epochs/trials. The relation between duty-cycles and SSVEP responses led to significant differences between the entry groups. Correspondence to evoked paradigms was tested at different duty-cycles. The setting of the first paradigm of 25% provided a respectable result based on the three levels of stimulation frequency. However, the second paradigm set at 50% provided a sufficient result corresponding to three levels, and finally the 75% gradually decreases when the stimuli frequency increased.

5.1.3 Conclusion of Duty-cycle influence

The effect of the duty-cycles evoked the SSVEP signals using a visual stimulus of regular periodic evoked signal. During the tasks of this experiment, the activity of the brain influenced based SSVEP responses are sensitively impact with respect to different duty-cycle. By contrast, SSVEP simply applies an epoch/average process corresponding to the phase-tagged technique. The fundamental frequency was improved by extracting the feature of signals using a spatial filter based time-domain analysis method. The classification accuracies depended on the average process of SSVEP response to all stimuli at each level based on three sessions. Three types of duty-cycles and three base-flicker frequencies were recommended for testing voluntary subjects. Offline analysis was utilized to classify the evoked response signals that successfully achieved with time segment based triggers approach. Fixed stimulus frequencies with assured duty-cycle evoked influences in brain responses based SSVEP paradigm, which invoked the largest SSVEP responses. The waveform distributions of fundamental frequency within harmonics in SSVEP signals are elicited vicissitudes, especially at duty-cycle of 5 Hz, which demonstrated in the time-domain analysis. There close effect with harmonics had non-clear effect in other stimuli. The prominent features of the proposed system included duty-cycle at 12 Hz waveform energy based fundamental frequency increases and provided more powerful evoked SSVEP signal. This variability also exists for duty-cycle effect as some clear performance drops and some stable situations were noted that gave a less comfortable achievement by high duty-cycle on 75%. Hence, the analysis depended on statistical correspondence to evoke paradigms that tested a different duty-cycle, whereas setting the first paradigm at 25% provided a respectable result based on three levels of stimulation frequency. However, the second paradigm was set at 50%, providing a sufficient result into three-level. Future studies could conduct further research towards understanding and measuring the visual fatigue in relation to the duty-cycle. Interesting result that contributed in this work have been published as follows:

- Duty-cycle beyond Three stimulation frequencies effect based on evoked signal of SSVEP paradigms (accepted) in IEEE on 21.Sep. 2016 presented in ICCES conference on 22.Oct. 2016

5.2 Stimulation using Multiple Patterns

Brain–computer interface (BCI) systems using SSVEP paradigm allow disabled people to communicate with a certain machine. A multi-pattern of visual stimulus based on SSVEP is practically helpful to extract the observing of multiple patterns by distinct advantage differences between multi stimuli-patterns, which are alerted by dynamics brainwave that are presented from brain activity states. In this section, a novel SSVEP based BCI is demonstrated using multiple pattern flickers that included different types of variation in phase sequencing; furthermore, the technique that provides a practical BCI system is evaluated by designed new prototype. The multiple patterns evaluation is a sufficient hypothesis of the BCI control system, which evokes patterns to use with multiple commands. The brainwave dynamics expose a noisy signal, non-stationary, and non-linear based EEG raw. Therefore, three methods are utilized to extract features of stimuli responses based on two agreements of (i.e., phases and amplitude): ANOVA; modifying the quadrature amplitude demodulation (QAD); and Hilbert Transform (HT) to analyse based offline approaches. The human-brain has the capability of distinguishing between patterns that are dependent on regular/irregular stimulations, as mentioned in the previous section 4.3. The evoked brain signals of flicker LEDs from visual stimulation based SSVEP foundation exploited this ability. Analysis of Variance (ANOVA) based on QAD is used to explore the preliminary result. Furthermore, the Hilbert transform is followed to recognize the difference between patterns with respect to amplitude and phase shifting in SSVEP response. Six patterns were proposed in this contribution work that were verified by a series of experimental tests, corresponding to different responses in each pattern, which accompanied the effects on feature extraction.

5.2.1 New Structural Prototype based BCI

A multiple pattern flickered paradigm is realized in Figure 5.3, which illustrate the new prototype design. This model is structured on a stimulation board with unique colour LEDs that flickered at a sufficiently high amplitude of luminance to invoke the brain responses that controlled via a personal computer. A live EEG recording of the human subject’s brain activity resulted in recording signals using BioSemi device. Closed-loop system was designed to analyse the activity of the brain, as well as controlling the stimuli on the stimulation panel. LEDs on the stimulation board flickered at a fixed frequency rate of 11.8 Hz. The stimulation panel was fixed at eye-level and subjects were seated at a constant distance of 0.8 meters from the panel. A differential pattern flickering system was categorized as:

- **Regular pattern flickering at fixed frequency**
- **Irregular pattern flickering at fixed frequency**

Each invoked stimuli of regular/irregular presents three patterns; together with respect of phase-tagged triggered (PTT). As mentioned in the previous section 4.3.1, the (White LED) stimulation induced a stronger SSVEP in comparison to other colours, as proven in section 4.2. The LEDs were soldered on a stimulation board in Matrix-fashion of (3 × 4), distributor centred on the board at (1 × 4) positions, taking into account the surrounding locations on the board in four-positions. Each LED of the Matrix produced six flickering patterns that are indicated in Table 5.3.

Table 5.3: Six flickering sequences divided into regular and irregular patterns, for single LED

Stimuli LEDs Number Position	Pattern Number	LED Colour	LEDs Pattern	Different Phases θ^{o}	Pattern Type
LED1 Center/Surround	1	White	1000,0000,0000,0000	0^0	Regular
LED1 Center/Surround	2	White	1000,1000,1000,1000	0^0 360^0 720^0	Regular
LED1 Center/Surround	3	White	1110,1110,1110,1110	0^0 360^0 720^0	Regular/Duty-cycle
LED1 Center/Surround	4	White	1000,0100,1000,0010	0^0 450^0 720^0 1260^0	Irregular
LED1 Center/Surround	5	White	1000,0100,1000,0100	0^0 450^0 720^0 1170^0	Irregular
LED1 Center/Surround	6	White	1100,0110,1110,0110	0^0 450^0 720^0 1170^0	Irregular/Duty-cycle

In order to exploit the human-brain behaviour and effectuation of activities based on all desired patterns, the stimuli cycle is divided into five segments of rhymester on LED as onset of stimulation. The SSVEP paradigm is provoked, depending on flickers beside the phase-shift for each cycle according $\theta_i = (i-1).90^{\circ}$ by increasing of $i = 1, 2, \dots, N$, as mentioned in the previous Chapter 4; when the flickering LED_i shifts in respect of the phase angle distributed over full-phase 360°, $N = 5$ is incremented by 90°. The stimulus of each LED flicker is considered a pulse trigger at the same time as the onset event. In each cycle, a control delay signal is implicit, which anticipates phase delay by θ_i that is evaluated by t_i to indicate event occurrence with respect to time trigger event.

$$t_i = \theta_i / 360^{\circ} \qquad 5.7$$

Table 5.3 illustrates different patterns, which are considered in terms of (Regular and Irregular) stimulation paradigms with respect to different phases. Generated patterns depend on θ° in each stimulus as functional of the onset flicker. The pattern numbers 2, 3, 5, and 6 are the same phases, but provide a high/low duty-cycle. In fact, to discern the brain activity when the effects increase, refer to the same stimulus patterns that are proven in section 5.1. Nonetheless, in this experiment a four-LED sequence in each pattern and consider a single flicker LED to evoke and extract the SSVEP response. The flicker frequency at 11.8 Hz is presented in sequence on four-LEDs that are controlled based system; in other words, t_i is given the iteration time request compacting with $T = 1/f$, since T is flicker cycle duration, and f represents flicker frequency, setting one stimulus frequency, which is surrounded by an alpha brain response range of (8–13) Hz [15].

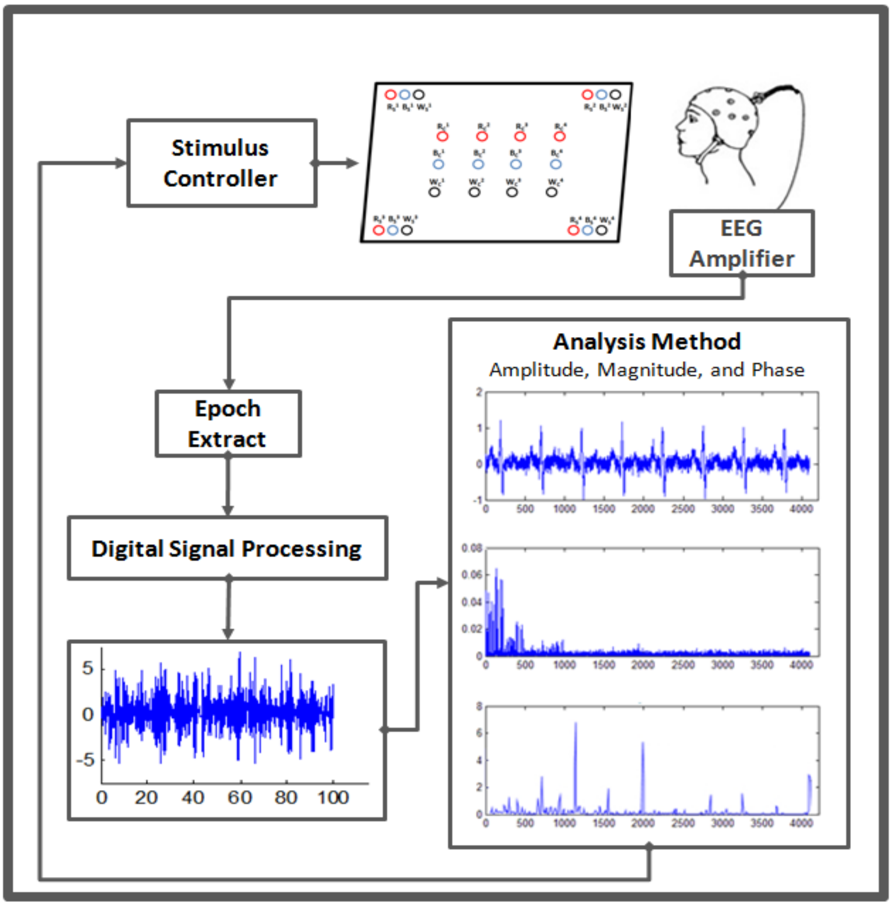


Figure 5.3: New Structural prototype based-BCI

Time-locked events (TLEs) are used to mark the LED pulse-on event onset flicker and mark a new cycle that is indicated in every new stimuli-segment. This approach of phase-tagged segments each trial and take intra-trail epoch/averages for each stimulation based analysis.

5.2.2 Analysis SSVEP Response Approach

The effectiveness of the induced SSVEP in brain activities is estimated with regard to regular and irregular based multiple pattern flickers, which employ an offline analysis. Therefore, use of a common practical example is recommended, where it is assumed that non-linearity and non-stationarity of dynamics brainwave of gathered EEG/signals; their sources in brain waveforms, and these signals are decomposed using two approaches. Figure 5.4 shows the reliable approaches that have been used to extract the features from different patterns based on improve traditional techniques.

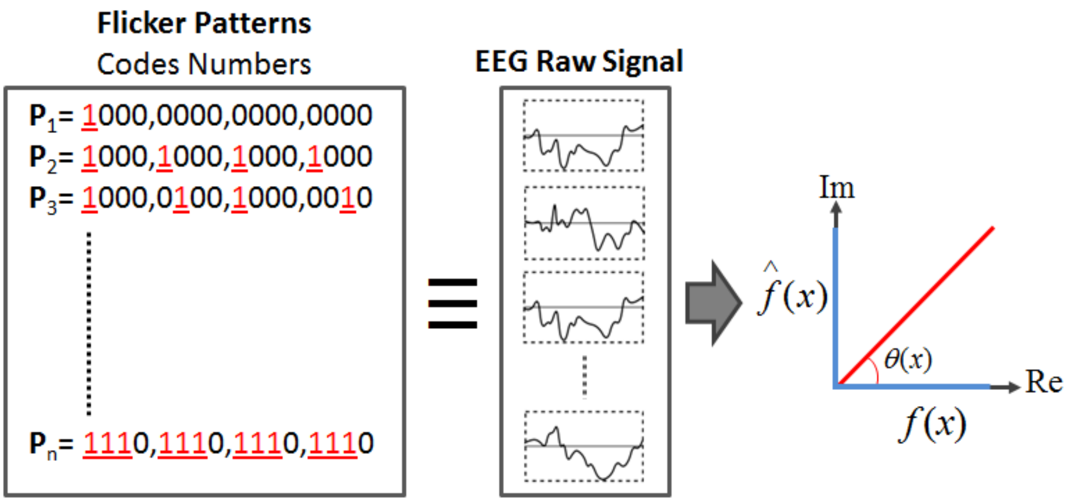


Figure 5.4: Analysis approach based on amplitude and phase

Offline analysis is adopted, after EEG raw-data have been accumulated into separate epochs according to LTE technique of time-shift signals requested by onset of the stimuli flicker sequence in each extracted epoch group. The difference between phases and amplitudes into the brainwaves of stimuli/patterns is obtained by dynamics time extraction based on ordinary technique of one way ANOVA in terms of adopting a quadrature amplitude demodulation (QAD) presented in the first approach. However, the Hilbert transform is approved to identify the difference between patterns based on diversity phases.

5.2.2.1 Primarily Analysis based on Variance of ANOVA

This study investigates the different influences between stimuli/patterns with respect to flickers on (Four-white LED), which motivates the change in brain activity based on SSVEP paradigms. Firstly, the Analysis of Variance of (ANOVA) technique is utilised to discriminate brain influence in respect of different patterns with stimuli frequency. It is also concerned with the extraction of EEG/epochs in each recoded time-level of EEG-data/signals, which are accumulated as templates to analyse and compare a significant hypothesis-based statistical exploration. ANOVA calibrates by the F-tests, which examine the pre-specified set of standard effects, (e.g. ‘main effects’ and ‘interactions’), as described in statistical principles in the experimental design [15], depending on six stimulus patterns, which are supported to determine the change in brain activity corresponding to the evoked SSVEP response signals to present the primary result. The raw signals of EEG data are processed with respect to the experiment setup and configuration by involving a similar stimulation approach to that described in previously chapters. The artifacts are removed using ICA techniques, which include to removal the AC-Line interference of noise at 50 Hz, in addition removing the baseline of (reset-period) which corresponding to linear de-trending of any DC components. However, remove any artifacts that exist due to eye blink; furthermore, attempts a single-trial based SSVEP onset response have been obtained especially in this empirical study with respect to dynamics-time extraction.

The synchronous of SSVEP response oscillations observed into embrace envelope which employed by demodulation procedure applied after gathered EEG-data/epochs [137]. The demodulation has been used productively generate a certain envelope that includes the oscillating of SSVEPs based on modified quadrature amplitude demodulation (QAD) method of EEG/signals. Further, the QAD method is utilized to recover the amplitudes and phase-shift based on Y_1 and Y_2 with respect to modulated carrier signal correspond to (SSVEP response signals):

$$Y_1 = X\ \cos 2\pi f t, \qquad and \qquad Y_2 = X\ \sin 2\pi f t \tag{5.8}$$

Both of Y_1 and Y_2 are used to reconstruct the modulating signal using the following equation:

$$Z = \left|H^f(Y_1)\right| + \left|H^f(Y_2)\right| \tag{5.9}$$

Since f represents the count-phases modulation frequency, and H^f represents a Butterworth low-pass filter (BLPF). Here the QAD model provides an output by Z, which represents the envelope covered of single-trial SSVEP response, as shown in Figure 5.5. The envelope curves (green lines) in Figure 5.5 surrounded the desired signals (blue line), which demonstrate the mean values (red line), normalising the quadrature amplitude demodulation (QAD) by enveloping onset with respect to SSVEP responses.

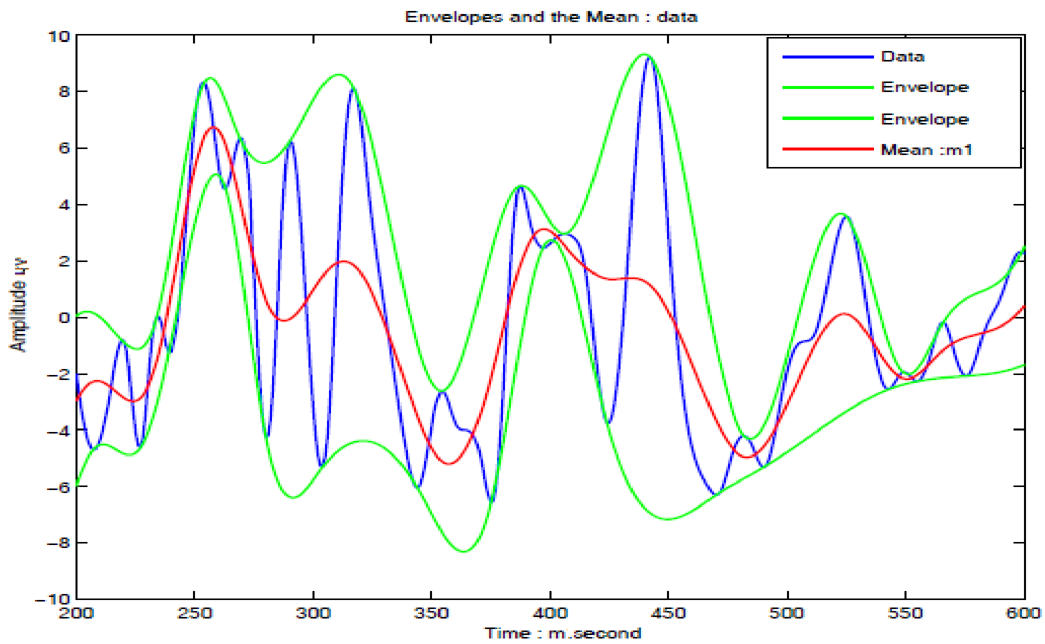


Figure 5.5: Normalize QAD envelope based onset to present the effective SSVEP response signals

The mean-values are accumulated from brain responses corresponding to patterns that demould the influences of each stimuli pattern. Comparisons between independent groups using the ANOVA approach, that determine whether any of those groups are significantly different from the others. The test assumed a null hypothesis H_0 against alternative hypothesis H_1. The H_0 assumed all entry groups are equal based statical analysis of all stimulus-test conditions in each pattern and are equal without restricted common value. However, it is assumed the alternative hypothesis H_1 signifies not equal, which is significantly different.

$$H_0\colon\ \mu\, Pattern_1\ =\ \mu\, Pattern_2\ \ldots\ =\ \mu\, Pattern_k \qquad 5.10$$

$$H_1\colon\ \mu\, Pattern_1\ \neq\ \mu\, Pattern_2\ \ldots\ \neq\ \mu\, Pattern_k \qquad 5.11$$

The groups have individual and different values of Mean Squares, which are observed individually from each pattern in respect of the estimated value with respect to 5.12 [11].

$$SS_{\text{within}} = \sum_{j=1}^{n_i} (\, Y_{ij} - \overline{Y_i}\,)^2, \qquad df_{\text{within}} = n_i - 1 \qquad 5.12$$

Hence, the (n_i = 6) in each group, which represents individual LEDs within different patterns. Therefore, it is important to estimate the sum of square differences by SS_{within} for each flicker session pattern. However, the *df* represents a degree of freedom, in this case representing the number of trials per subject [6].

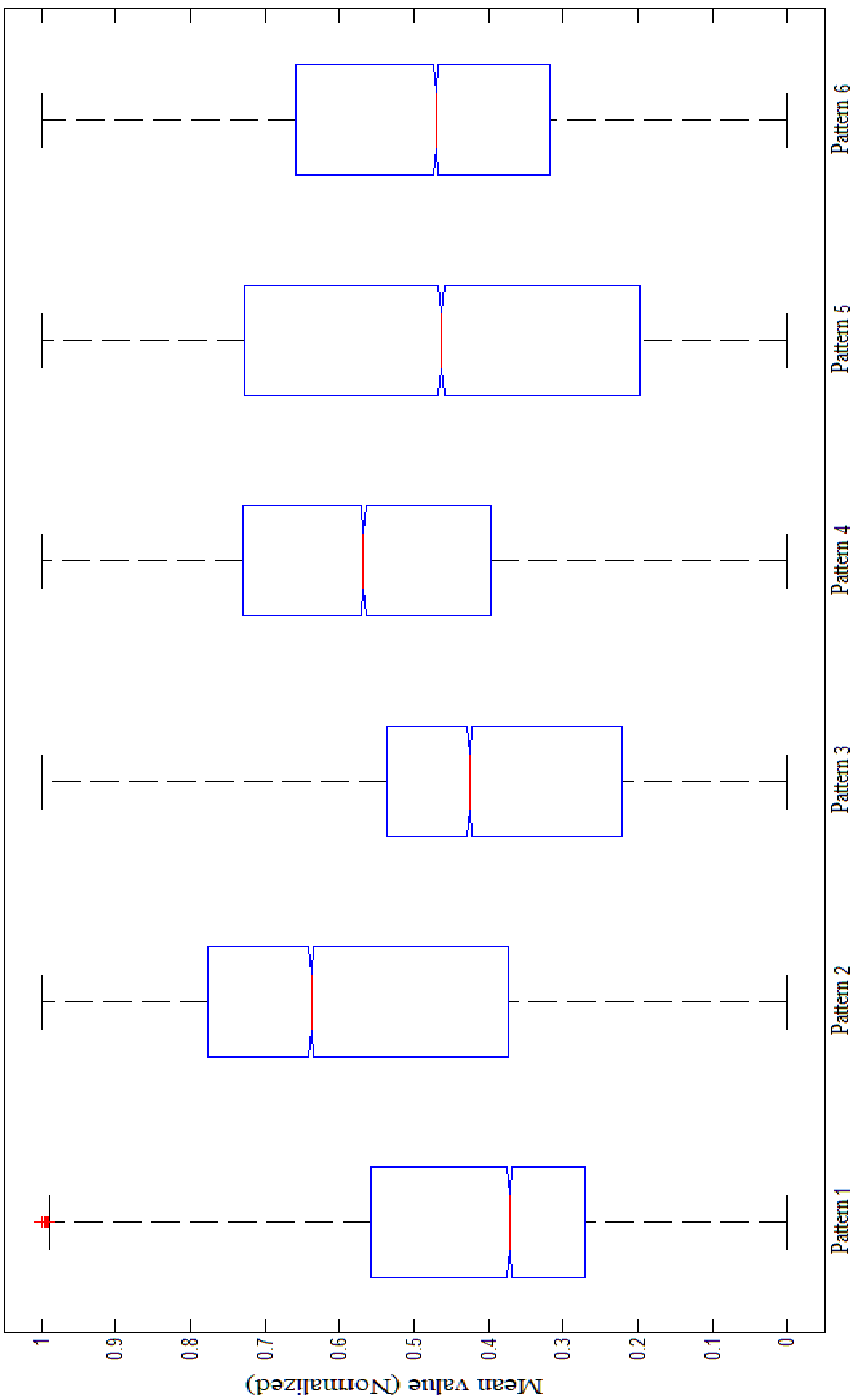


Figure 5.6: Illustrate significant difference between entry groups respect of six-stimuli pattern

ANOVA comparison results detect each stimuli output. Figure 5.6 shows six patterns of brain activity influences, which provide a significant difference between stimulation patterns. The alternative hypothesis condition of Mean values is factual, which indicates that the interties groups are not equal. However, the white stimulator LED is successful in inducing SSVEP effects across six pattern conditions. Table 5.4 presents the result under six pattern conditions that provide a statistical summary for each stimuli pattern. Therefore, the condition means are significantly different with respect to $p < 0.05$ for all six patterns [F (5; 350) = 255.8; p = 0:002].

Table 5.4: Analysis of variance of (ANOVA) result

Source of Variation	SS	MS	F	P-value < 0.05
Between Groups	668.72	133.743	255.8	0.002
Within Groups	484.88			
Total	10084			

5.2.2.2 Hilbert Transform (HT) technique based extraction features

The Hilbert transform analysis was performed aligned to single-trial-approach based on evoked SSVEP response signals. The EEG/signal in Hilbert Space (HS) is decomposed, which gives a relative variable state for each frequency band, according to stimuli/frequency that proved previously (see section 4.3). The EEG/signals were analysed to determine an increased output of reaction brain command based BCI that is dedicated by demodulated SSVEP signals. Detecting reaction command signal by observed the phases of EEG signals were calculated using a normal process based on Hilbert transform (HT) method. The EEG/signals were accumulated from the occipital surface of the brain region at O_z, O_1, and O_3 (EEG channels), followed by down sampling that applied by bandpass FIR filter. The raw-data were processed and the prior signal set with FIR to remove any unknown and undesired noise signals. EEG also reveals the dynamic of brain activity signals, which is denoted as noisy, non-stationary and non-linear. Therefore, prominent results among previous sections 4.1, 4.2, and 4.3 have used the traditional technique of Fourier transform (FFT), which decomposes the EEG raw signal into familiar state variables.

Typically, the Hilbert Transform (HT) provides a high spectral resolution of arbitrary frequencies. Furthermore, it is useful for rendering EEG decomposition into components corresponding to the diversity phases and spectrums, according to disparity of stimuli patterns. On the other hand, Hilbert transform offers a high temporal resolution and rapid analytical solutions to extract the frequencies, phases and amplitude of non-stationary EEG signals. Therefore, the Hilbert transform (HT) is very useful for handling and analysing non-linear signals by expressed frequency as a rate of change based on phases, unlike the FFT topography, which pursues a linear type of periodic signal. Nevertheless, in Hilbert space (HS), the signals are decomposed into main two parts that present as real part of $\mathrm{v(t)}$ and imaginary parts of $\mathrm{u_i(t)}$, as presented in 5.13.

$$V(t) = v(t) + u_i(t) \qquad 5.13$$

Here, the real part $\mathrm{v(t)}$ represents the amplitudes signal, as in FFT topography analysis [7-9], which is demonstrated in Figure 5.7; the imaginary part $\mathrm{u_i(t)}$ depicts a phase difference according to the following equation 5.14.

$$u_i(t) = \frac{1}{\pi}\ PV \int_{-\infty}^{\infty} V_i(\acute{t}) \,/\, (\, t - \acute{t})\ \acute{d}t \qquad 5.14$$

The PV is the constant multiplier of (Cauchy Principal Value) [72]. The independent variable will not affect the resultant transformation $u_i(t)$; therefore, the output is dependent on the input function in the time domain. Similarly, the original function of *V(t)* presents the harmonic conjugation in Hilbert Space. However, the arctangent angles in polar coordinates depict the state variable of phases in each flickered pattern based on equation 5.15; more details are explained in Appendix A.2.

$$P(t) = \tan^{-1}\frac{u_i(t)}{v(t)} \qquad 5.15$$

In order to track phases that are presented on $P(t)$ over arbitrary values of $u_i(t)$ and $v(t)$, the large time intervals disjointed phase sequences are aligned to signals by adding [±π] to the desired of extraction epoch respect to EEG/signals. The sequences of digitized values provide a trajectory vector, which is rotated in the complex plane according to elapsed time. However, the EEG/epochs are accumulating by separated templates that are gathered from revealed SSVEP signals in each stimulus pattern by extracting the Hilbert approach in each epoch group.

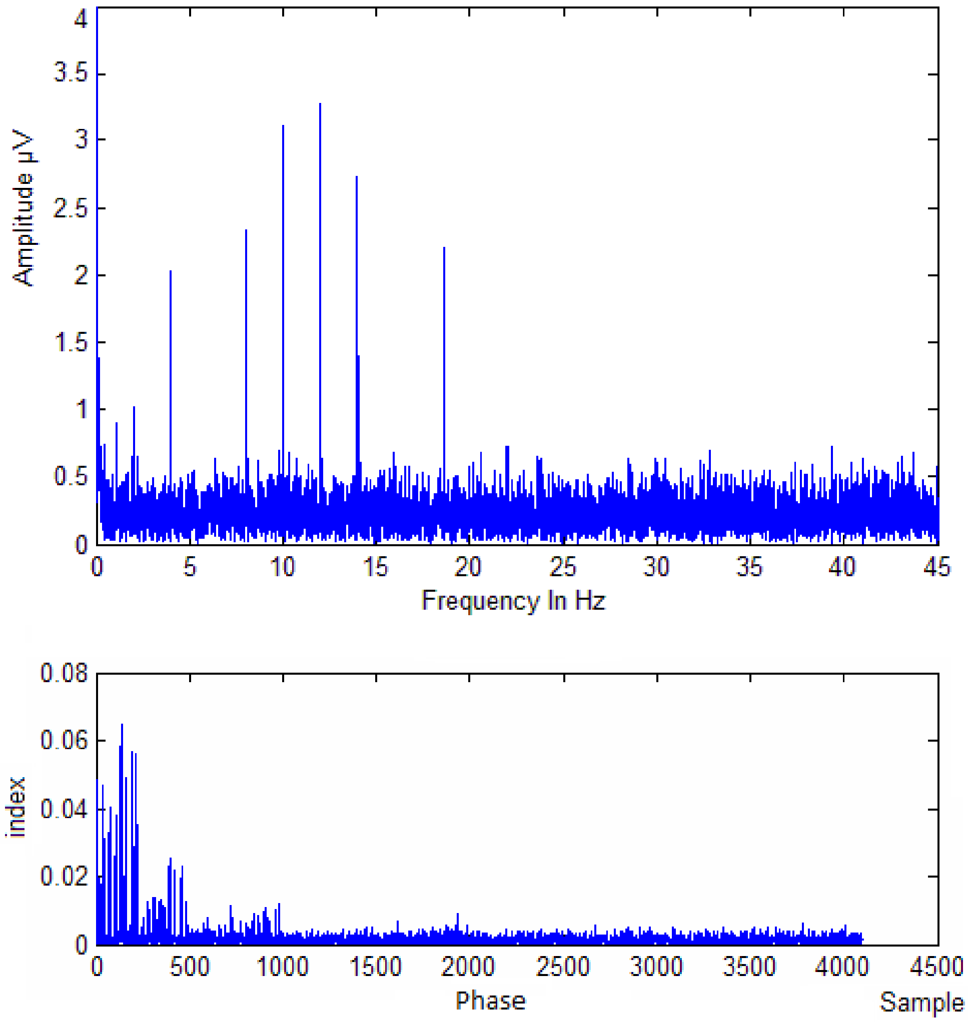


Figure 5.7: Instantaneous result of amplitude and phase based-Hilbert space (HS)

The results of HT presented a complex structure function based on the space value of $V(t)$ of Equation 5.13, corresponding to the component of amplitude and phase functions. Furthermore, the superior of Hilbert space functions in Figure 5.7 illustrates the frequency function of $u_i(t)$ and instantaneous phase function $v(t)$. Those components are outcomes of exploitation and provide a clear understanding in the event of incoming signals being non-linear but stationary based on extracted features from EEG raw. Therefore, it is difficult to explain the behaviour of firing the brain-cells, which generates the activities that give the brain-waveforms in a classical sense of the main concept, because the EEG-signals are a mixture of signals and incorporated in long sequence event moments; nevertheless, it is possible to describe by means of amplitudes and phases.

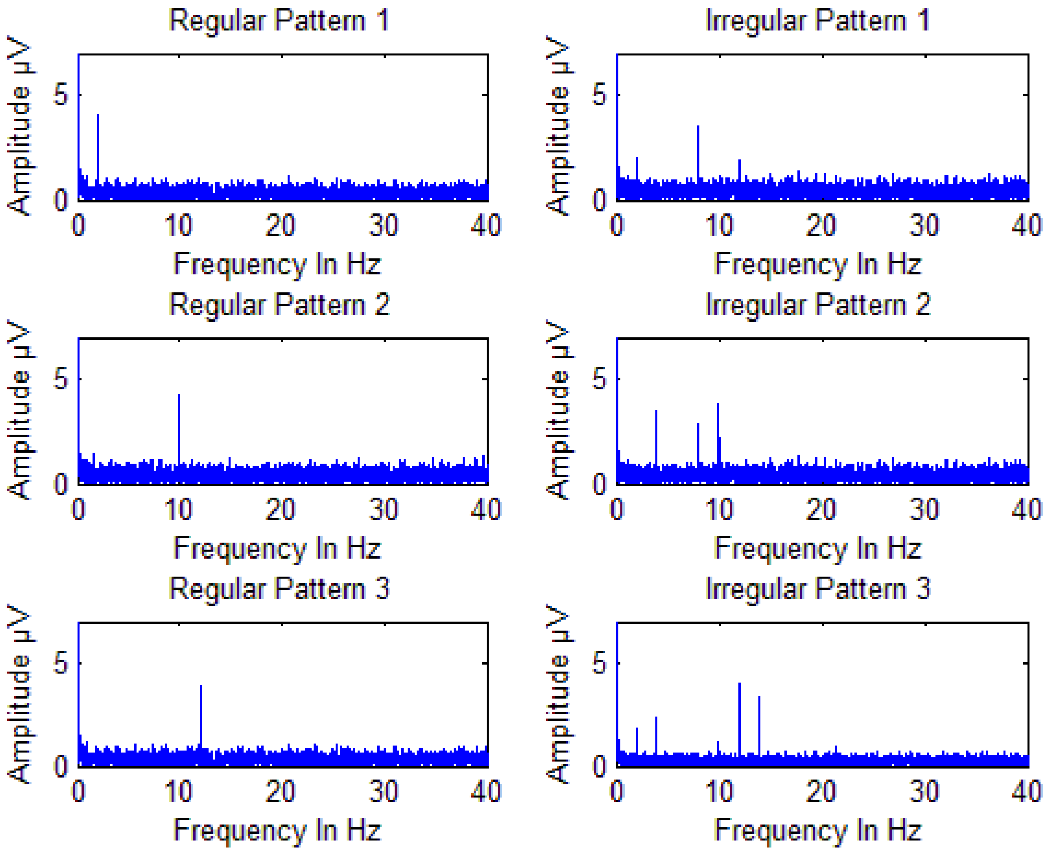


Figure 5.8: Spectral analysis observing diversity spectral power of multiple patterns stimulation

The approach based on Hilbert analytic, is intuitive and directly adapted by decomposing signals and providing intrinsic models of various oscillations. Therefore, the amplitudes are explored from the real part $u_i(t)$ depending on Hilbert Space (HS), which detects the maximum spectral expected, based on six paradigms of regular/irregular stimuli patterns. These spectra demonstrate different frequency components in the brain response (Figure 5.8). The subplot of Figure 5.8 exploring the result of frequency components has been elicited by different spectral power at (5, 8, 10, 12, and 14) Hz corresponding to evoked stimuli patterns. A straight power is observable for each instantaneous frequency component, as expected from a theoretical perspective. However, there is a short deformation onto the signals, because of the short length of gathered signals and the sampling rates effects. In specific terms, the flickers of multiple stimuli/patterns present a variable amplitude and phase according to the certain frequency of time function. The second type of analysis was efficient in extracting the phase information from a single dimensional.

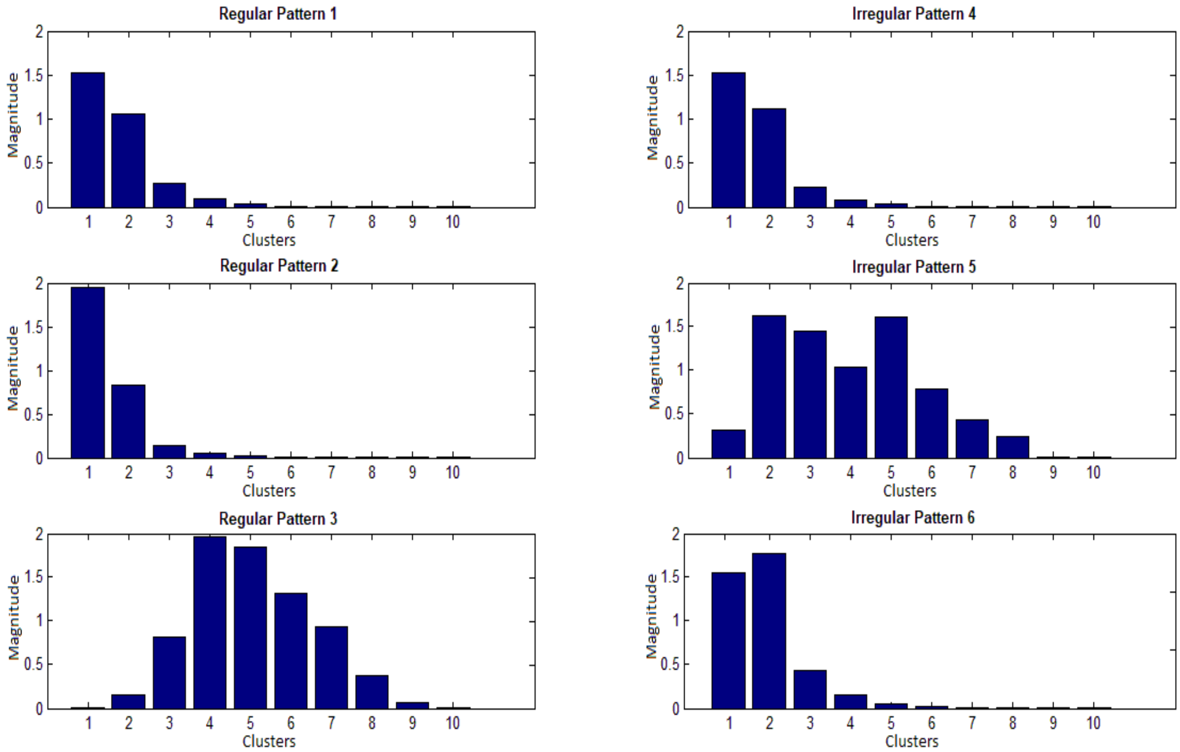


Figure 5.9: Influences of six patterns that observed different base-instantaneous phase

The decomposition method of HT provided a posteriori definition derived from the incoming signals. Inherent mode has been dependent on the expanded intervals in [-π, +π] that overcome the time-lag correlation on phase θ distributed in the range of stimulation events corresponding to cycle and onset triggers. These intervals cover a trough-to-trough event, which is considered a time-locked event (TLE) using PTT technique. The instantaneous phases were extracted to discover the phase value based on equations 5.14 and 5.15. Figure 5.9 shows the quantified response of induced SSVEP signals. Brain activity based responses are observed in (Three regular and Three irregular) pattern sequences, as mentioned in Table 5.3; since, the HT shows discrimination statistics of phases on evoked SSVEP signals. The features extracted are associated with a stimuli flicker phase for every peak of one stimuli cycle, which illustrates six different patterns according to regular/irregular paradigms stimulus procedure, as previously explained. According to the experiment setup, this phase's θ have been accumulated in respect of each individual pattern, which discriminates the differences between patterns.

5.2.3 Conclude a Multiple Patterns

This study has successfully demonstrated the aspect of inquiry offline analysis of evoked SSVEP signals. The results presented general outlined assessment of multi-patterns, which are defined by visual stimulus depends on SSVEP response paradigms. The structure of regular and irregular stimuli flickers at different patterns of stimuli according to the experiment setup configuration. Through the preferred experiment, different flicker paradigms observed different brain response which given an enhancement and improvement to increase reaction brain command based BCI. In fact, two approaches were concluded as analysis: firstly, analysis of variance (ANOVA) based on quadrature amplitude demodulation (QAD) using envelope technique, which realized behavioural brain responses with respect to a multi-pattern stimulus by assumptions hypotheses condition of mean values; secondly, Hilbert transform (HT) to recognize different patterns in respect of phase shifting waves. A summary of the pattern recognition study of multi-patterns sequence found a different brain activities response between six patterns with regard to Regular/Irregular stimulus paradigm. Multi-pattern paradigms presented a number of available choices commands reaching to 24, depending on each pattern slot, which prepared a different phase in each pattern. This experiment performed six patterns only, which were in pursuance of 64 theoretical commands. The results of ANOVA, which detects distinguishing patterns, and Hilbert transform, which discriminates amplitudes and phases were compared to discover there are varieties of brain responding activity levels in each pattern. Consequently, increased numbers of control signal command based-SSVEP paradigm, which provide stability and reliability in distinguishing detection in phase based stimuli patterns. This, in turn, leads to creation of new applications based-BCI system by increasing control commands depending on amount numbers of patterns. Although, this prototype based-brain technology is more attractive to external world environments with respect to several stimuli patterns, a multi-pattern paradigm would introduce a different protocol for different applications. Finally, this research study provides the advantages to exploit this method as a future applications work in SSVEP based BCI system fields since it has been adapted, optimised, and configured with the support of real time experiments. The interesting result was published in:

- Recognition a Multi-pattern in BCI system Based SSVEPs, ERK'2015 conference, IEEE Slovenia section, ERK'2015

5.3 Efficiency of multi-core on BCI based SSVEP

EEG-signal based brain-computer interfaces (BCI) face a significant challenge in online applications. Successful application of advanced techniques depend on miniature EEG electrodes and a distributed computing system to offer a promising result and to overcome existing gaps. Therefore, the obstacle in developing a BCI is ensuring reliable capability to take decisions in real time or predict an inclination in real-life application-based BCI systems. Brain-computer interface (BCI) technology is a communication system relying on a pathway to explore brain activities to the external world. The BCI technique makes it possible to monitor certain physical processes that occur within brain activity that correspond to certain forms of flickering through stimuli. A thousand brain activities are observed to be firing instantaneously, allowing a BCI system to clearly state one or more signals for control by computer command or dominance of any other devices. Furthermore, the speed of processors and clocks in the last decade has been developed based on modern computer techniques. Consequently, the neural methodology approaches realised by digital signal processing (DSP) can process a huge amount of EEG raw-data, which are sorted into short time periods as EEG/epochs. In other words, parallel computing systems are processing an analysis and comparing the gathered EEG/signals that have been collected in order to detect certain brain activity based paradigms. The parallelism performances precede an executed program under multi-processing paradigm or multi-core progression based on systems that decrease the consumed execution time. However, multi-core performance systems are available within an affordable price range. Previous studies employed a single CPU system that revealed a reasonable performance for smaller EEG/datasets, but open multi-processing, such as OpenMP platform, provide higher performance computing with more accuracy within large EEG/epochs (datasets). The main concept of parallel programming is that it can separate the tasks individually, which allows a parallelised process and analyses to extract features. In this section, two approaches have been utilized: firstly, high parallel performance computing to realize faster recognition based on evoked patterns detection by exploring the Hilbert transform (HT) depending on patterns detection; and secondly, classified feature based frequencies, employed after extracting the FFT within multiple window functions.

5.3.1 High-performance Computing (HPC) Perception

Multi-core processing operates within a single computing component unit based on two or more independent processor-cores, which are read/write and execute program instructions [6]. Nowadays, a multi-core is widely used beyond many application domains that include a general-purpose, such as (DSP) and other scientific appliances that allow execution of instantaneous multiple task functions. The architect of multi-core shares same part of memory chunks that leads to increase overall speed and execute programs amenable to parallel computing. Therefore, a single core presents a particular part of the processor that can execute instructions one by one. The single core processor is an ordinary CPU, processing instructions, such as addition, subtraction, move, jump function and other conventional instructions based on 32/64 Bit-address, which fixes the length-variable of data. In comparison, a multi-core can also run multiple task instructions instantaneously that increase global speed of execution time. Rapid processing within smooth flow operation sequences based on read/write data is reasonably accountable with respect to multi-core in high performance based systems. Brain-computer interfaces (BCI) have largely been development based real-time analysis and extraction that depended on computational speed. Parallel processing is a fact that reduces the executed time and increases computational factors, leading to reduction in the complexity of design and cooperating with the largest algorithms that drive improvement of BCI based systems. Typically, this methodology is dependent on a particular algorithm that computes intensively using highly customised hardware architectures based on signal processing of DSP. Several of application-programming interfaces (API) support a shared memory and multiprocessing performance. Open Multi-processing (OpenMp) platform is one of the application-programming interfaces (API) that consists of a compiler of directives and environment variables that support influence to run-time behaviour programs. OpenMP is a scientific parallel computing application that allows progression of a huge dataset within high performance that achieves 100 times greater function compared to a standard unique-CPU [159]. Furthermore, OpenMP is reliable in parallel programming models that are supported by different programming languages, such as C/C++, under different platforms and operating systems. Any BCI system is comprised of several elements that amplify and digitise acquired EEG neural signals to produce an appropriate control signal by processing several levels to drive an output as indication signals. The signal processing levels depend on certain applications, such as control of a computer cursor or spelling system [64].

A high quality estimation of power spectrum and phase difference are recognise in fast Fourier transformation (FFT) and Hilbert Transform (HT) instead of steady-state visual evoked potentials (SSVEP) based BCI system. In this study, easement experiment datasets of multiple frequencies (see section 4.1.2) and multiple patterns (see section 5.2.3) are applied in two different approaches based on high-performance computing (HPC). The aim of this study is to increase the computational performance based parallelisation approach by addressing the power estimation algorithm and Hilbert technique to evaluate the use of a new prototype of parallel implementation. The parallel processing has been executed under single-core CPU and multi-core based on OpenMP platform. As mentioned previously in section 5.2.1 on the new prototype structure, which compares between evoked brain activities by multi-stimuli patterns. The different patterns and different frequencies of visual stimuli were predefined EEG/datasets and stored as individual templates. These templates have been prepared as new-dataset of EEG/files that were cleaned and free from any kind of artifacts.

5.3.2 Extraction and Detection by using HPC

Signal processing is the first step that relies on filtering signals and analyses to extract a certain signal using parallelising process to detect specific action regarding multiple patterns experiment as HPC approach.

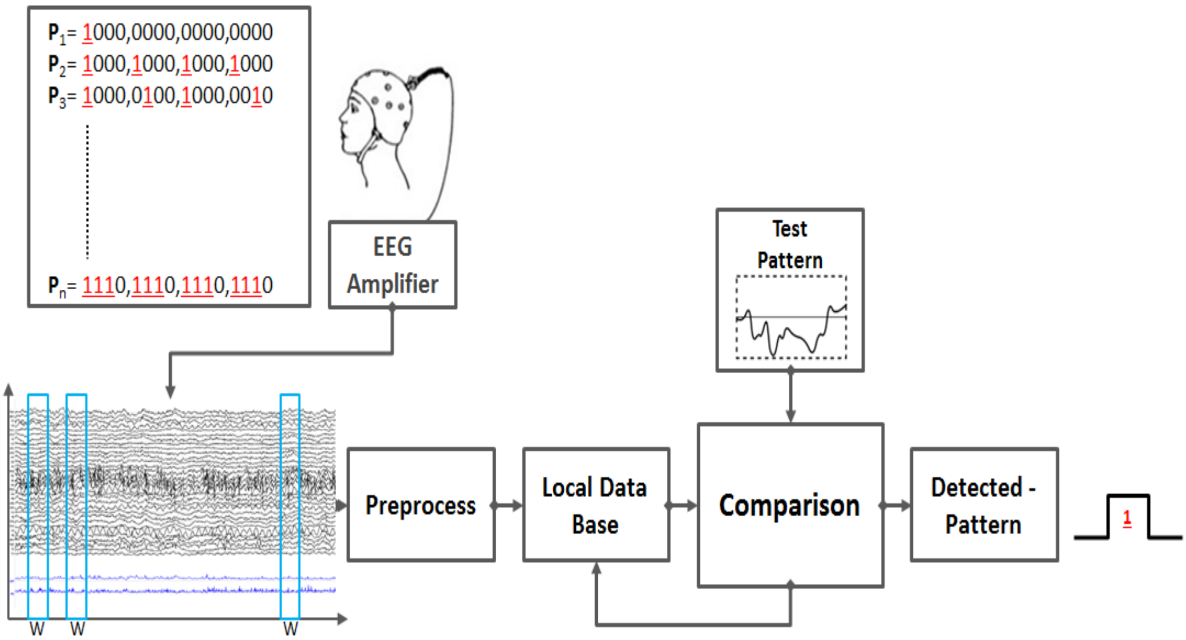


Figure 5.10: HPC design with OpenMP platform to detect an active-control signal based SSVEP

The parallelisation provides an output signal; this (detection signal) is independent of other action signals and it is possible to calculate each action signal in any order with minute synchronization referred to (embarrassingly parallel) problem [159]. BCI based real time systems are still far from high-accuracy also is low-speed detection. This study contributes to implementing an algorithm specifically to evoke SSVEP brain responses using multiple patterns and intensively computational offline analysis, which addresses the issue of increments in the reaction command based BCI system. The computational approach extracted the power spectral estimation and classification with multiple filter-types. The signal features were explored to extract the instantaneous phases with respect to multi-patterns that select an action signal to control an output. Figure 5.10 shows a new design prototype which includes the processing unit, local store unit (memory blocks), and comparison unit. Two approaches are used: firstly, the windowing technique extracts an estimate in the power of various frequencies at (8, 10, 12, 14, and 16) Hz based on single and multi-core processors. Secondly, a comparison between templets (patterns detection) tested the equipped, stored patterns with strolling stream input filtered of EEG epochs, according to the preparation procedure of the previous sections 4.1, and 5.2.

5.3.2.1 EEG based Windowing Function Analysis and Result

As shown in Figure 5.10, the experiment setup of flickering LED corresponding to (Five base-frequencies). The configuration of this experiment was repeated in section 4.1.4, but the analysis method is in a different methodology. The experiment consists of five recording sessions distributed into 60 seconds per-session. Each recording/session appeared on one frequency based on LED-flicker fashion dependent on a single stimuli pattern that would change sequentially every 10 seconds. The voluntary subjects were asked to gaze at the LED corresponding to flickering based on multiple frequencies experiment. The EEG/signals were gathered based on only three active electrodes placed in the occipital cortex region. After cleaning from artifacts and filtering the EEG/dataset, the length was deducted from a complete chunk of each stimulus epoch in respect of time. The SSVEPs are continuous signals, which reflect the brain activities affected by repetitive stimulus. Therefore, the reasonable power density estimation based on certain frequency components achieved by the short time approach is important in SSVEP based BCI. In most SSVEP based BCIs, the Fourier-transforms are widely used to extract the power density estimation [45].

This contribution work also estimates the power density at a definite frequency on ω with respect to time t; using short-time fourier transform (STFT) technique to determine the amplitude and phases both are distribute in EEG/epochs into small sections (segmenting process), which change over time. In continuous time of STFT written as 5.16:

$$STFT_x(t, w) = \int_{-\infty}^{\infty} x(\tau)\, w(\tau, t)\, e^{-j2\pi w\tau}\, d\tau \qquad 5.16$$

Since the x represents the input signals, and $w(s, t)$ presents the window time function, where the time (s) approaches from [t − L/2, t + L/2]; therefore, L represents the size of window, where the power density estimation of frequency by ω at time t is according to 5.17:

$$P_w(\mathrm{t}) = \frac{1}{L}\, |STFT_x(t, w)|^2 \qquad 5.17$$

The truncation signal in STFT provides a leakage problem as disadvantage when extracting the estimate energy. Subsequently the windowing functions are represented by Four-type filters as (Rectangle, Hamming, Hann and Triangle), which are used to reduce the leakage problem and increase the evoked SSVEP response signal. The spectral characteristics demonstrate the power density based on time-frequency properties in respect of $P\omega(t)$ function of stimulation frequencies at (8, 10, 12, 14 and 16) Hz; after applying a high pass filter (HPF) which is setting to clean dataset within cut-off frequency at 2 Hz that is allowed to pass all desired stimuli-frequencies. The windowing approach has been used a window setup with respect to size-time by (L = 5) seconds of time segmenting based [0.5, 5.5] seconds. Therefore, the power density of $P\omega(t)$ have been extracting using the rectangle window function as first result which is illustrated in Figure 5.11. All desired stimulation frequencies were used to extract the primary result using a (Rectangle-function). Wherein, Figure 5.11 (a) presents the observing power density of five-stimulus frequency components. Since the stimulus-frequency at 16 Hz provides faster oscillation than the stimuli frequencies at (8 Hz and 10 Hz) with clearly slower oscillation. However, applying the conventional FFT to fetch the $P\omega(t)$ function; consequence of primary result illustrate in Figure 5.12 (b) that shows the power spectrum density (PSD) of $P\omega(t)$. Furthermore, it is very clear oscillation in $P\omega(t)$ which declared an relationship between the amplitude of frequency domain at ω based on PSD. The amplitude of oscillation decreases when there is growth on ω base stimulus frequency.

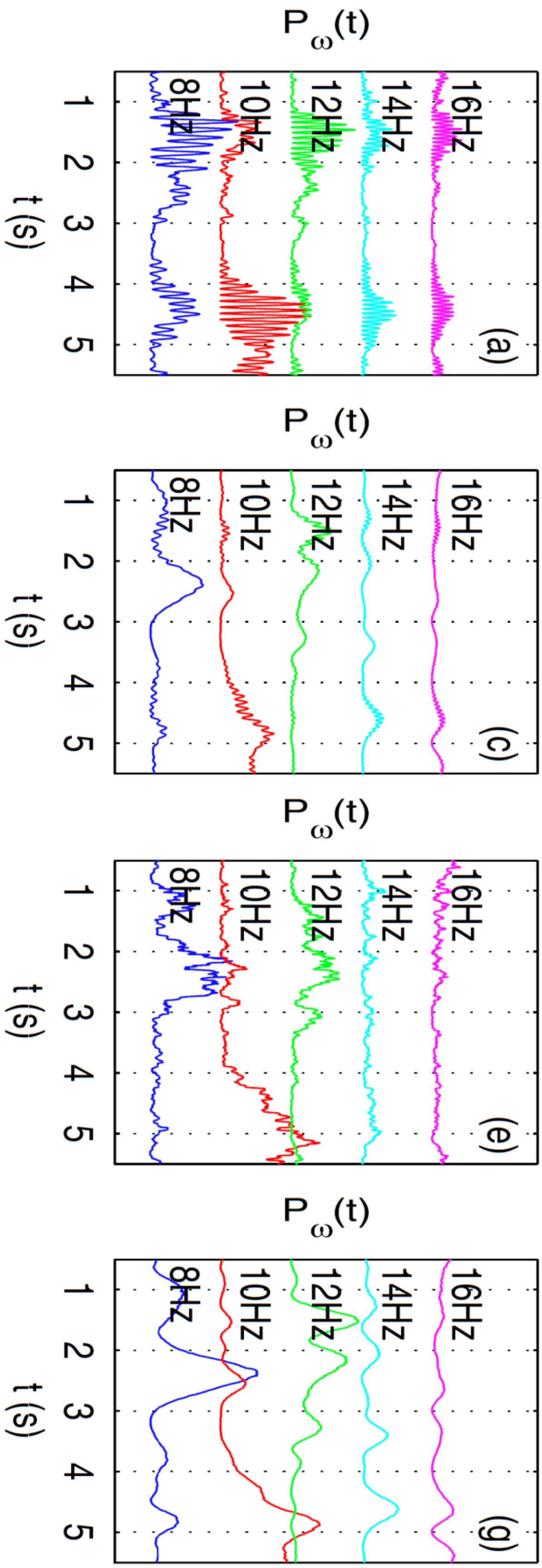


Figure 5.11: Power density of STFT based on time-frequency analysis

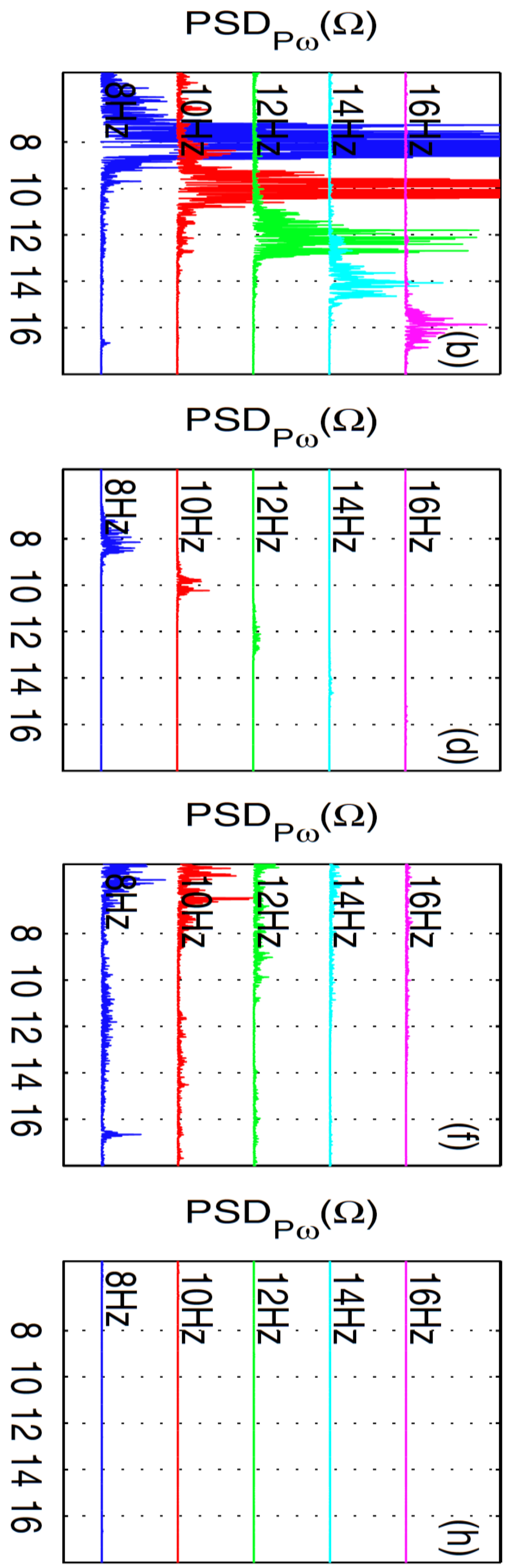


Figure 5.12: Spectral power of STFT based on frequency analysis

The consequences results demonstrating in Figure 5.12 the spectrum analysis of frequency component in respect to estimation power in brainwave band of LF components. It is also declare to be much higher and making a larger oscillation than further stimulus frequencies, which indicate the SSVEP response signals on LF of the brain band are more powerful that gives more shore as mentioned in chapter 4. The procedure of STFT technique based (Rectangle-windows) function does not cover all evoked SSVEP point signals, which are stored in a new-dataset; indeed, the spectral leaked problem of power density estimation affects on extracted result. Nonetheless, high energy on LF is a revealing result that presents a spectral leakage problem. On the other hand, some other window functions can be used to reduce the leakage problem. By improving, the extracting results based on the leakage problem Figures 5.11 (c) and Figure 5.12 (d) shows the (Hamming-window) function, which reduces the oscillation but does not reduce the effect of LF component. Although, the High-pass FIR (HP FIR) technique approach overcomes the leakage problem, as illustrated in Figures 5.11 (e) and Figure 5.12 (f), that demonstrate the extracted result of power density estimated. The output from HP FIR is not smooth but provides an exact oscillation on ω, while the other frequencies still exist. Finally, Figures 5.11 (g) and 5.12 (h) are combinations between HPF and (Hamming-function) window, which provides smooth curves of power estimation. The second approach applied high performance computing (HPC) to compare between the windowing functions result after application of the four filter type functions to extract the power estimations from stored datasets. Assessment spectral powers were enjoined with windows filter functions in the second step of analysis. This step utilized different window function of four types which were applied on cleaned datasets, and then with the power spectral again using HPCs to compare between the extracted results before and after windowing with respect to the activities of SSVEP signals. In this approach, two copies of cleaned-datasets have been created and stored into local memory blocks, and then applied the HPF on the first copy of the dataset, before applying the multiple windows functions on both datasets. Table 5.5 shows the existential results of accuracy rate in respect to multiple frequencies and four type window functions of Rectangle, Hamming, Hann, and Triangle. The results are classified between filtered and non-filtered dataset within HPF respect to brain activities, which demonstrated as comparison between applied filters. The best classification among result based on Four-windows functions are marked in bold. The Hamming, Hann and Triangle windows approach produce similar results, but the Rectangle window result is interesting because achieves better results after the filtration process.

Hence, the greatest accuracies of most subjects come from the rectangular window. The test was extended to different window sizes with respect to the time window by (L = 0.5, 1, 1.5 and 5) seconds, extracting the accuracies before and after correspondingly applying HPF technique.

Table 5.5: Four types' windows functions accuracy rate within filtered and non-filtered datasets

Subject	Clean Dataset with HPF				Clean Dataset without HPF			
	Rectangle	Hamming	Hann	Triangle	Rectangle	Hamming	Hann	Triangle
Sub.1	71.78	**80.00**	**80.00**	**80.00**	**95.57**	**80.37**	79.70	**80.00**
Sub.2	**86.59**	75.74	77.37	79.11	**92.44**	**81.89**	77.22	**80.23**
Sub.3	77.19	78.52	77.70	79.99	**90.56**	**80.89**	**88.81**	77.70
Sub.4	**89.80**	78.021	68.99	73.99	**93.00**	70.03	**89.80**	79.70
Sub.5	78.90	71.80	78.88	76.90	79.89	78.82	72.90	67.88
Sub.6	**84.90**	68.90	69.90	78.00	**88.71**	**82.90**	76.89	73.90
Mean	**81.52**	75.49	74.36	77.99	**90.02**	79.15	78.22	76.56

Offline analysis using MATLAB tools has implemented a linear discriminant analysis (LDA) that categorizes between the window filter functions. Figure 5.13 presents (blue stars and red circles), which indicate filtering and no filtering data-points. Explore the recognition accuracy rates in all four windows by growing the size in respect to increase the time-window. Found out greatest accuracy when decreases of time-window width that indicated to effectively suppress. However, the accuracies are greatly improved after applying HPF. Furthermore, the increase in main width time-window of sorted frequency domain resolution gives a weakened, which leads to a decrease in accuracy. However, the result of HPC of comparison process is described in next section 5.3.2.2.

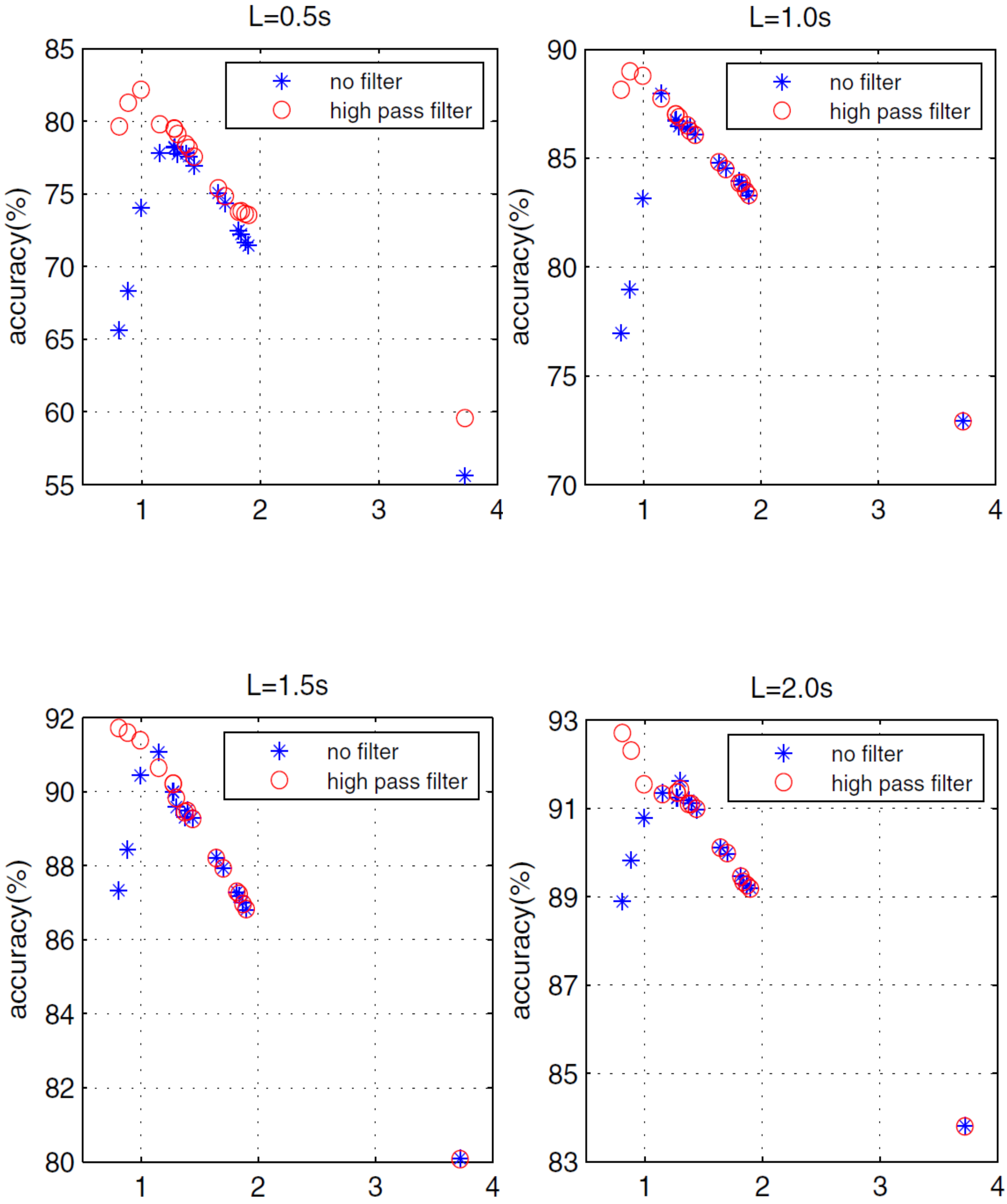


Figure 5.13: LDA classification between Filter and Non-filtered based-HPF

5.3.2.2 HPC based windows functions and patterns detection

In this section, a new way to extract the features has been proposed, using multi-core processing based on the HPC technique. Parallel computing allows exhaustive computations and accelerates demand that leads to increased BCI commands, due to the high energy of LF components that extract the features based on FFT, HT, and STFT or other further techniques. In this work, two approaches have been used that efficiently implement basic HPC parallel processing programs with openMP platform based API. Firstly, the sliding-window procedure is utilized, which compares between the spectral power estimation coefficients of each stimulus according to iterated stimuli/patterns that are stored in memory blocks as individual templet clean EEG/epoch files. However, used patterns comparison as the second approach to indicate a match estimated coefficients. Both approaches are used an offline analysis and allow the development of an online analysis for future work. Several co-dependent values are calculated based on a simple process for serial processing within a single thread that compared with multiple threads based on the sharing memory technique of openMP platform. Subsequently the spectral power, does not present a perfect as parallel solution, because the processing contains numerous sequential steps; however, some of these steps depend on previous values. Therefore, the spectrum analysis process is a complicated when Thousand-threads running at the same time that requires a several independent synchronization points based analysis technique. The CPU (processor) based a multi-threading algorithm is identical to that found in BCI2000 [xxx160]. Additionally, the thread-processing model plays a crucial role based on memory management in computational efficiency. Three memory space levels must be available with the threading process. The lowest level is reserved as local-memory for each thread and is not accessible out of threads. The next level is denoted by shared memory, which is visible to all threads in one-block. Consequently, the OpenMP allows many threads to work on the same memory blocks simultaneously. The highest level of global memory is visible for all threads to access certain block. In general, it is necessary to copy the desired segment of dataset (extracted clean EEG/epochs) into the global memory and further perform the computation of stored templet/files (certain EEG/segment indicted an response based on time locked event approach), which are shared between the global and shared memory. Figure 5.13 shows the first accession of the parallel computing based windowing function technique. This approach averaged the extract signals and normalised the gathering responses with respect to the desired SSVEP signal, which is defined as a continuous brain activities that are evoked by a repetitive of visual stimulus frequency. The visual stimulus depends on different frequencies that are consecutively presented to the subject, as described in section 5.3.2.1. The estimation of spectrum power requires the greatest amount of computational resources, in terms of sharing-memory and processing time. In this step, extracted spectral features are stored in certain memory chunks to slide over the pre-processing stream of stored EEG data as offline , which compares the performance efficiency base on single-core, dual-core, and quad-cores. Wherein, the x-axis represents the number of repetition with respect to the execution time depend on CPU-cores. Initially the elements (normalized SSVEP responses) are calculated over the sliding loop based separate thread. It is important to consider the available number of CPU cores, which require 120 threads to the 120 overhead samples; each thread contributes significantly to the total computational time. A multi-thread CPU implementation outperforms an assessment using the single-thread implementation when the number of electrode channels is equal to, or greater than three. However, the sampling rate is 1200, 600, which is recommended by 125 Bit/Sec.

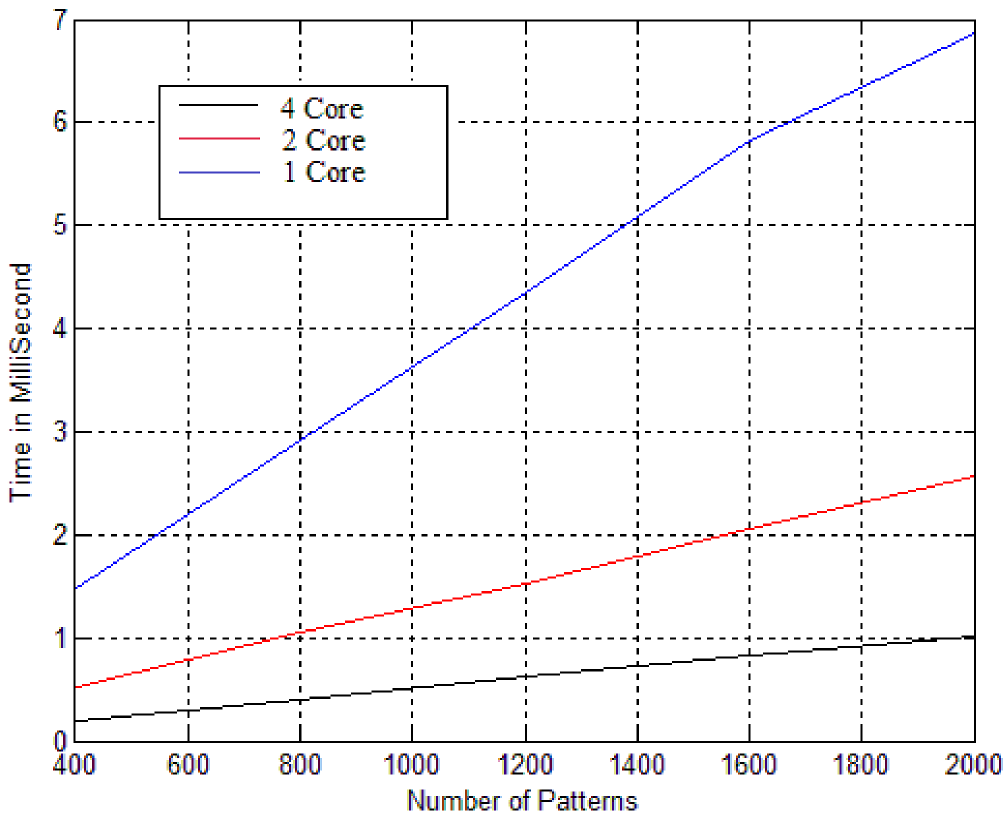


Figure 5.14: Comparison between single-, dual- and quad-cores based-sliding window approach

The blue line in Figure 5.14 illustrates the speed of execution time processing for single-thread, and the multithread based dual core and quad core processing that illustrates the black and red lines respectively. The second approach based on HPC technique is compares the independent pattern based detection of active stimulus signal. The acquired EEG data is gathered and cleaned-up of artifacts then placed on new datasets as templets (files). These new datasets are stored and sorted into main globule memory blocks; these files are segmented based on six different pattern stimulus based many trials see section 5.2. Each pattern stimuli have been iterated more than three times in respect to experiment configuration, as mentioned previously section 5.2.1.

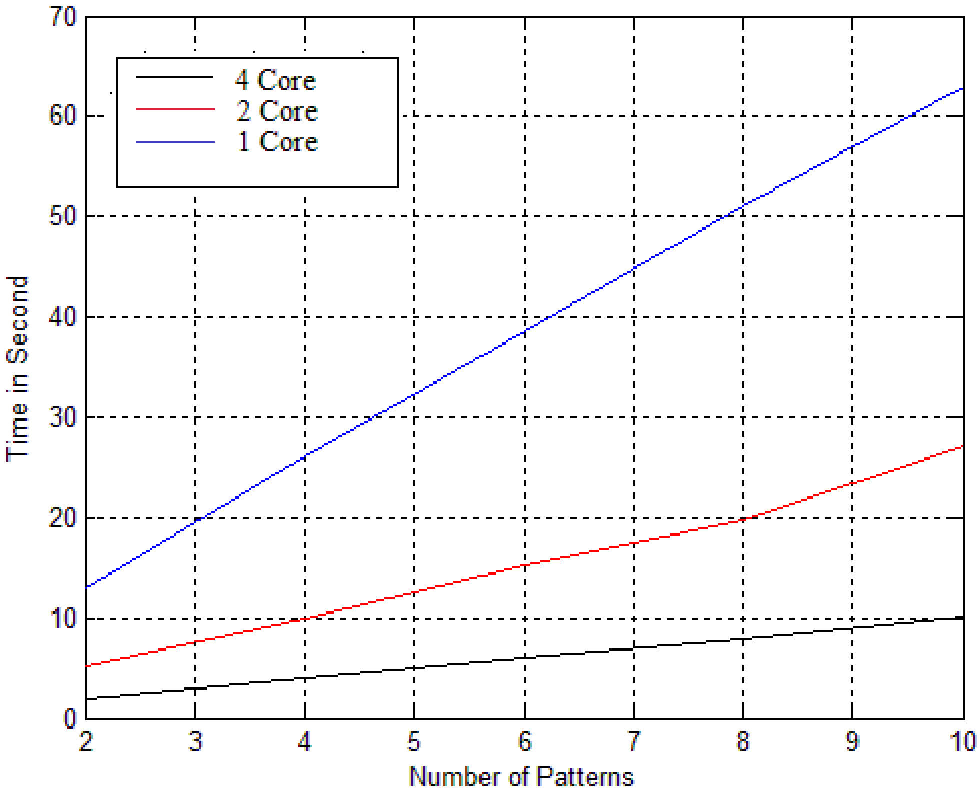


Figure 5.15: Comparison between single-, dual- and quad-cores based-template/pattern approach

The estimating phase procedure is divided into distinct steps. The HT model is evaluated by extracting the coefficients of Imaginary part (*Im*) Figure 5.4, then finding out as resultant of statically crucial of different phases that extracted based on separated Six-pattern . The theory behind this algorithm is beyond the scope of this paper, but can be found in (Recognition a Multi-pattern in BCI system Based SSVEPs) [166] that discuss how to extract the brain responses based HT algorithm. The general concept is parallelization, which implements the algorithm depending on the openMP platform. Wherein, the Hilbert transform (HT) was involved, which parallelised the computing process to compare all accumulated epochs in each pattern, in order to detect a specific brain activity performed by multiprocessing based openMP. Figure 5.15 shows the efficiency rate based on single-core, dual-core, and quad-cores, which compare a single template with multiple patterns. Therefore, the x-axis represents the number of repetition patterns that respect to the execution time depend on CPU-cores.

5.3.3 Windowing filters and detection patterns based HPC Conclusions

This work depended on two experiment datasets which employed an offline analysis to discover the effect beyond Four-windowing function based on Five-multiple frequencies and Six-multiple patterns. A four-type diverse window function was classified, which compared between them in respect to spectral power; however, detection patterns were used based on steady-state visual evoked potentials (SSVEPs) responses both of these studies have used a high performance computing (HPC) technique. Five different stimuli-frequencies were adopted to extract the power spectrum using short-time Fourier transform (STFT) results. The consequences results were exploited, leading to a high power response on low-frequency (LF) based on brainwave response regions. Four different timing windows based on Four-type filters were used to extract the accuracies before and after correspondingly applying a high-pass finite impulse response filter (HP FIR). Consequently, the offline analysis has used the MATLAB (tools) to implement a linear discriminant analysis (LDA) to distinguish between window function accuracy of filtering and non-filtering based EEG raw-data. The outcome results indicate recognition accuracy rates into four window types by increasing the size in respect to time of size L, which cover all evoked points in the stored new dataset. In fact, the spectral leaked problem of power density estimation affects the extracted result since the high energy on low-frequency (LF) reveals the effect; however the spectral leakage problem has been detected which affect directly on responses. The extract results based on leaked problem were improved using (Hamming-function) window which reduces the oscillation but does not reduce the low-frequency component. In addition, the normal high pass filters (HPF) were used, which also overcame the leakage problem. The output form HPF is not smooth but provides the exact oscillation on ω, while the other frequencies still exist. Nonetheless, there was a combination between HPF and Hamming window function, which provide smooth curves of power estimation. Furthermore, most accuracy results were similar and decrease when reduced by time-window width, which indicates effective suppression. Rectangle window-function achieved more accuracy with respect to frequency-domain resolution analysis. Since the EEG data analysis using a single processor, based on the designed system, reveals a decent performance for a smaller dataset, in other hand the multi-processing has exposed enhanced performance and accuracy in a large scale of dataset. The multi-processing with OpenMP platform based application-programming interface (API) modifies a new structure model which employs the parallelization programming code. The constructed model was implemented using C language based on OpenMP of high performance computing (HPC) system, because it is an open sources library and the most suitable model for BCI application. Furthermore, the OpenMp depends on a shared memory approach and is easily installed on many platforms, compared with CUDA or OpenCl which face many restrictive problems, such as specific hardware support requirements to the essential graphical processing unit (GPU) and high accuracy routing. However, the message passing interface (MPI) models require a computer cluster and significant installation restrictions to support a high accuracy networking and maintenance environment. Therefore, a parallel computing based windowing function technique has been used after accumulating the averaged responses and normalising the gathered responses. A spectral power has been obtained from extraction signal features that are sorted and stored in a separate memory block; further a slide-window was passed over a stream of EEG data which is previously prepared to compare offline the performance efficiency based on 1, 2, and 4 CPU-cores. It has been discovered that the multi-cores base multiple threads give the best result with respect to exaction time. The second approach is comparison of independent patterns base detection, after gathering acquired EEG data and cleaning to store as a new templet of datasets. This templet is sorted into main globule memory blocks, to compare all trial segments based on pattern. The final step of analysis used phase detection procedure based HPC. This analysis technique inspired from HT model, which extracts the different phase depending on imaginary part, then award of statically crucial of individual pattern phases. The computing process is parallelized to compare all accumulated epochs in each pattern in order to detect a specific brain activity performed by multiprocessing based OpenMP.

Rapid Computation and Analysis using a Multiple Core to enhance SSVEP based system, NGCT 2016, IEEE 2016

CHAPTER 6

CONCLUSION AND OUTLOOK

The research work was dependent on multipurpose empirical studies, which are described in this thesis; those studies are discusses to enhance essentially performance of brain-computer interfaces (BCI) based-SSVEP paradigm. Generally, eight of EEG experiments were performed to obtain necessary information that extracted from brain waveforms. This contribution (thesis) has successfully proven signal processing techniques and neurophysiological recoding experiment. The following conclusion is contributed with diverse studies; also discussed open problems and future work based on research.

Chapter 2: In chapter 2, surveyed background details based-research of brain-computer interface (BCI) system, including perception and disparate concept approaches that inform practical paradigm. Furthermore, the chapter has included the materials that can be used to evaluate BCI systems based on diverse affected paradigms in different facilities of feature extraction methodologies and types of brain reaction responses. However, realize different types of brain waveforms and understand the EEG signals, which allowed observing the brain activities under a certain circumstances using an individual stimulation models.

Chapter 3: This chapter has explored the main configurations and experiment setup, that including requirements of hardware/software equipment. In addition, the chapter has described accumulated EEG raw-signals by schedule time recording and provided a reasonable starting point for most essential stimulations. In addition, attainment biological EEG-raw signals using hardware of BioSemi system. Gathered all signals and divided as EEG/epochs to produce a clean datasets. Pre-processing based on digital signal processing (DSP) techniques have been exploring that including filtering on gathered EEG/epochs to render a new datasets which is free from any artifacts. This chapter has addressed the problem of extraction feature and classification using streaming scheme of acquisition EEG signals that is restrict results, especially when increasing BCI reaction commands based brain activities. Consequently, the feature extraction and classification signals optimising number of EEG-channels with respect to located electrodes on the scalp by reducing the acquisition electrode numbers (EEG-channels). This takes into account the averaging procedure, which is expounded based on onset of stimuli flickering that referred to phase-tagged triggers (PTT) of time locked events in both of time and frequency domains to be exploited and easy extracted. The brainwave activities indicate SSVEP responses signals by referring to the brain location in respect of frequencies that are uncover a primary result based-offline analyses. Through the headmost experiments that are holds in this chapter, a regular flicker paradigm has been preferred to evoke sequencing flicker/lights within individual LEDs that were randomised on locations according to the positions of stimulation panel. Mathematically formulate the flickering/lights in respect of individual groups into variable approaches. Each experiment explored the influences of brain (sensory-lobes) location based on measurable SSVEP response signal quality at Four-lobe brain regions located on the occipital region, left/right-temporal region and frontal region respectively that allowed designation of the best brain lobe region according to the powerful responses of SSVEP signals.

These brain region locations offered a measureable signals using non-invasive paradigms of evoked SSVEP response, which indicated more effect on the occipital lobe with LF of alpha band at ~13 Hz in respect to brain activity waveform. Furthermore, the frontal lobe was affected by theta band that near to the stimulus frequency at ~5 Hz based brain activity; although the theta band indicates on the left/right-temporal regions at ~3 Hz in respect to brain waveform. However, found out that occipital brain lobe is inclined to provide the highest SSVEP response regarding alpha band-frequency, with weaker quality signals in other brain-cortex locations in respect of the same stimulus frequency band based on empirical study. Similarly, realize the stimuli frequency at 10 Hz presented the strongest evoked SSVEP signal based offline analysis. Nevertheless, at a specific location that indicated by the electrode denotes by $O_{Z,}$ which occupied on occipital brain lobe region, strong power in terms of 10 Hz of stimulus frequency was recorded.

Chapter 4: This chapter proposed three empirical studies, which addressed sufficient recognition of brain response that provide desirable brain activities to increase reaction command numbers based-BCI technique by exploiting human-brain capabilities using SSVEP paradigms. The chapter also addressed the problem of ceaseless attention producing fatigue after few work-hours operation that lead to minimal distractions; a low signal-to-noise-ratios (SNRs) is discussed whereas intent onset recognition essentially requires substantial time. Different responses can be evoked through improved paradigms of stimuli light/flicker, which consists of different characteristics that provide diverse responses based on brain activity. In fact, the steady-state visual evoked potentials (SSVEPs) present an echo that reflecting signals of brain activity responses elicited by existing iterate stimulus at an appropriately medium level, such as flicker LEDs light based definite frequency. The flicker stimulus is dependent on a wide range of frequency bands at LF, MF and HF based on SSVEP paradigms. This chapter discusses the effective frequency band that provides stronger brain activity response. Thereby, adding innovative attributes and new characteristics, which essence providing a high modification and adaptability with respect to efficient visual stimulus system. The multiple stimulation units equip different stimuli frequencies, multiple colours stimulate LEDs and short-term irregular paradigms to prove a reasonable evoking signal instated to SSVEP responses. Therefore, a low-cost BCI prototype based-system has been designed and implemented stimulation panel.

The stimuli panel included (24-LEDs) spread uniformly in different positions within altered colours. Each position contained three colours of (Red, Blue and White LEDs) to stimulate SSVEP paradigms.

– **Section 4.1**: the first empirical study of multiple stimuli frequency considered three major frequencies of brain waveform band of theta (θ), alpha (α) and beta (β), which determined more actively responses of brain band levels. In this work, an offline analysis was concluded using FFT and wavelet transform (WT) to realise the behaviour of brain activities with frequencies level bands in respect to SSVEP paradigms. Primary results were extracted from FFT spectrum power analysis, which discussed maximum and minimum spectral in each band level. A three band levels based brain activities were exploited by implementing digital filters which extracting results based on various frequencies in term different band was improved using ICA to remove unwanted signals of noises signal; furthermore, FIR technique was used to restrict frequency band based on digital signal processing. The FFT result delivered all stimuli frequencies of (2, 4, 6, 8, 10, 12, 14 and 16) Hz. It was substantiated that stimuli frequency of 10 Hz furnished greatest power in respect of SSVEP responses of alpha band level. Further steps used SNR topography, which measured the EEG-signals at the three main electrodes of EEG-channels on (O_1, O_2 and O_z). This step realistically used EEG-electrodes, which were contained in preliminary experiment setup. The SNR results assimilated from electrodes were categorised and investigated based on SSVEP response. The highest SNR was discovered to be located on occipital brain region, compared with other brain lobe locations, according to multi-trials in respect of all stimuli frequency sessions that applied on multiple voluntary (subjects). The ICA technique, as well as SNR, provided evidence that determined crucial evoked brain region based SSVEP responses. Furthermore, it was discovered that the stimuli frequency at 10 Hz presented the most robust induced response signal of SSVEP at electrode O_z which occupying on occipital lobe of brain region and given a strongest power with respect of 10 Hz stimulus frequency. Digital filters technique was utilised by adding a wavelet function to determine results according different bands in respect to multiple frequencies, which considered the EEG rhythms at 5 Hz, 10 Hz and 25 Hz; in order to improve SSVEP responses signal resolution based time-frequency analysis in terms to found the affect brain band level. In this study, different influence based-SSVEP response was discovered with respect to brainwave activities, which indicated the stimuli at alpha level more certain on occipital brain region.

– **Section 4.2**: Beyond the stimuli frequency at different band levels and three different colours stimulation that present second empirical study to illustrate effect and influences on brain activities based on colours/stimulation of SSVEP paradigms. Flickers/stimuli were set with two-constant base-frequencies at 6 Hz and 13 Hz, which proved to be low/high on alpha band waveforms and verified stronger responses. The evoked stimulus was obtained based on three different colours of red, blue and white. Recording EEG individual session depended on dynamic stimuli signal by markers based on time-locked events (TLE) techniques. The results concluded offline analyses of event related potential (ERP), which revealed the phase shifted behaviour in each colour stimulus, together with the FFT to detect the maximum amplitude of spectral power in each colour. Outcome of ERP results demonstrated brain waveforms in each colour/stimulation in respect of average EEG/epochs after cleaning the gathered signals. These results were defined in terms of standard nomenclature of ERP waveform. The nomenclature curves presented a maximum peak of white stimulation on a positive peak at P1 to record highest evoked signal response by 2μv, corresponding to red stimulation that recorded 0.5μv and blue stimulation on 1.3μv at stimulus frequency of 6 Hz. In other hands, stimuli frequency at 13 Hz gives amplitudes as long as (1.8, 1.6 and 0.9) μv respectively in each stimulation colour. Significant differences were observed in phase between three colours/stimulations, since white and blue colour led on red stimulation at 6 Hz. Although the white colour led blue stimulation and red was lagging blue at 13 Hz. The flickers apparently in phase in P downward (waveform) at both stimuli of 13 Hz and 6 Hz, which indicated the minimum contingent of negative variation of SSVEP responses. Furthermore, the results of FFTs indicated strong response in respect of colour stimulation based-spectral power. Outcome result specified on white/stimulation that induced considerable power regarding SSVEP. However, red and blue stimuli LEDs induced SSVEP, irrespective of satisfactory response based frequencies of flicker finding a 6 Hz stimuli frequency effect much stronger than 13 Hz stimuli on all sessions. Finally, ANOVA explored is give consequences of difference induced potentials between low and high frequencies which restricted brainwaves of each stimuli colour, since white and blue are more tightly packed and much closer to each other as result of inducing responses based-SSVEP; however, red stimuli provided loosely packed flicker stimuli at 6 Hz. From the fundamental of ANOVA analysis that discovered the induced evoked response was much stronger from SSVEP response effects than red and blue LEDs at 13 Hz. Difference outcome schemes between the three stimuli based on colours presented high-level responses with respect to the alpha band of brainwaves at 13 Hz.

– **Section 4.3**: the short-term paradigm based on regular/irregular stimuli were extracted to distinguish between two prompting archetypes. The contention between two stimuli paradigm-types of regular and irregular paradigms was oddball (aperiodic) effect on SSVEP signals. The offline analyses with FFT and ERP techniques were used to discriminate between evoked stimuli that referred to phases and amplitudes. The outcome result explored brain activity in respect of SSVEP responses, which specifically differed between the two paradigms. The analyses methods used were consequently very proficient and discriminated the contiguous range based addable parameters that yielded the largest and most optimally strong activity levels based on SSVEP response. This study extracted a robust spectral result that observed a stronger power on irregular compared with regular paradigms. However, the amplitude in ERP waveform result indicated the regular paradigms provided less amplitude than irregular. Furthermore, the ERP result spread the phases between stimulation paradigms, which indicated a shift in time in both paradigms with respect to onset of stimulation. Additionally, ERP results found the positive-downward and negative-upward of P and N components were of similar value in regular paradigms stimuli; on the other hand, the components were non-similar in respect of irregular stimuli paradigms. The advantages of irregular paradigms were that they expanded the number of stimuli commands by increasing the irregular in respect to the number patterns. Consequently, these three experiments can be adapted by configure three type stimulation which address the problem of enhancement and increase numbers application of BCI commands based SSVEP.

Chapter 5: Three additional studies were inspected and discussed brain influences based on BCI technology by inducing differ duty-cycle effect on brain activities, and evoking multiple patterns to extract the SSVEP responses. In addition, high performance computing (HPC) was used based on BCI, which is improve speed of processing regrading to large amount number of EEG (datasets) dependent on multi-core process and multiple threads with open source library of openMP platform. These empirical studies address optimised problems that are adapted to configure as offline experiment using SSVEP of BCI application.

– **Section 5.1**: BCI system must be convenient for all users and simple to use and adapts as new communication channel. The BCI systems require a special external stimulus evoked signal, which provides the quality to increase the BCI command numbers. The stimulation process must be reliable and free of any kind of inconvenience, such as visual fatigue or other exertion problems. Consequently, there is possibility to obtain different responses that are related to diverse frequencies, as proved in previous studies, regardless of whether a duty-cycle is increasing or decreasing the brain activities based on SSVEP responses signal, which has been presented in this chapter as first study. One important issue in SSVEP paradigm is converting influence of brainwaves that are stimulated through duty-cycle effect of stimuli-flicker based fixed-frequency. The effect of duty-cycle on SSVEP signals using a visual stimulus using regular of (periodic stimuli signals). The activity of brain influenced by SSVEP responses insensitively that improved based-fundamental frequency to extract features of signals using a spatial filter. Three types of duty-cycles and three base-flickers/frequencies were recommended for testing and overcoming this problem. The contribution of this experimental study has been to focus on evoked SSVEP signals that compared with three stimuli/frequencies and three levels of duty-cycle based-BCI. Evoked SSVEP signals were detected based on non-invasive technique using efficient paradigms in BCIs. Typically, SSVEP response observes amplitude signal, by selecting stimulation frequencies lower than 20 Hz to achieve a high SNR. Consequently, a prototype has been proposed to flicker a single LED with three frequencies at 5 Hz, 12 Hz and 24 Hz, which are driven by consistent sequences of repetitive stimulus cycles (periodic/regular) with fixed duration of duty-cycle on 25%, 50% and 75% to conclude the extracted result. Classification accuracies depended on averaging process of SSVEP response of all stimuli at each level based on three individual sessions. Three types of duty-cycles and three base-flicker-frequencies are recommended for tests with voluntary subjects. Offline analysis has been utilized to classify evoked response signals that were successfully achieved with time segment based triggers techniques. Fixed stimulus frequencies with assured duty-cycles evoked an influence on brain responses based SSVEP paradigm, which can invoke largest SSVEP responses. Outcome results extracted SSVEP signals, which elicited vicissitudes, especially at duty-cycle 12 Hz, and demonstrated in time domain analysis. The prominent features of proposed system include the duty-cycle at 12 Hz waveform energy based on fundamental frequency rises, and provision of more powerful evoked SSVEP signals. This variability also exists for duty-cycle effects as some clear performance drops were noticed and some stable situations gave less comfort achieved by high duty-cycle on 75%. Hence, the analytic method was depended on statistical computational correspond to evoked paradigms at different duty-cycle; since setting a first paradigm by 25% provided a respectable result based on three levels of stimulation frequency. However, the second paradigm was set at 50%, providing a sufficient result at three-levels.

– **Section 5.2**: multi-pattern evoked stimulus signals based on SSVEP were extracted practically by observing distinct differences between stimuli patterns, which alerted dynamic brainwaves that were presented by brain activity states. This experimental study presented the second research point in this chapter where a novel SSVEP based BCI was proved using multiple pattern flickers that included different types of flicker/light variations based on phase in each pattern sequence that address increasing reaction commands number problem based-BCI. The multiple patterns evaluation sufficient hypothesis for a BCI control system, which evoked patterns to use in respect of evoking multiple commands based-system. Moreover, the dynamic-brainwaves exposed a noisy signal, non-stationary and non-linear based EEG raw-signals. Therefore, three analyses methods were utilised, namely: ANOVA, Modified quadrature amplitude demodulation (QAD) and Hilbert Transform (HT). Extracting the features of stimulation responses was dependent on two agreements of (phases and amplitude). The analysis of variance based on QAD represented a preliminary result in this study. The Hilbert technique was used to recognise the difference between patterns with respect to amplitude and phase-shift of SSVEP response signals by proposing six-patterns. In this contribution verified a series of experimental tests corresponding to different patters responses in each stimulus session. A live EEG recording was conducted with voluntary subjects turning on to record signals using a BioSemi of biological signal-device. The LEDs on the stimulation board flickered at a fixed frequency rate of 11.8 Hz based on all stimulation/patterns. Each invoked stimuli-pattern of regular/irregular paradigms presented a three evoked patterns also utilized the phase-tagged trigger (PTT) technique to restrict the desired SSVEP response signals. The regular and irregular stimulation paradigms generated patterns depending on phases by θ° in each stimulus as a function of onset light/flickering. The inherent mode depended on expanding the intervals in $[-\pi, +\pi]$, which overcame the time-lag correlation on phase θ distributed in a range of stimulation events corresponding to cycle and onset triggers. These intervals covered a trough-to-trough event, considered by time-locked events (TLE). Furthermore, extracted EEG/epochs in each recoding time-level of EEG raw-signals were accumulated as templates to analyse and compare a significant hypothesis based statistical exploration. The primary result of the QAD model provided an output value, which was obtainable as a mean value that included trials of SSVEP responses. Mean values were gathered from brain responses corresponding to the same stimulus of each pattern that demoulding the influences individually.

The comparisons between independent groups using the ANOVA approach determined whether any of these groups were significantly different from each other. The test assumed a null hypothesis H_0 against alternative hypothesis H_1. Since the H_0 assumed all entry groups were equal based on statistical analysis of all stimulus-tests, conditions in each pattern were equal without restricting common value. However, assuming alternative hypothesis H_1 signified not equal, there were significant differences. The outcome result from the ANOVA analysis detected a different output in each pattern, which provided a significant difference between them. However, white stimulator LED successfully induced SSVEP effects crossing six-pattern conditions. Therefore, the means were significantly different with respect to $p < 0.05$ for all six patterns by [F (5; 350) = 255.8; p = 0.002] respectively according to test. The second approach in this study used the Hilbert transform analysis by performing aligned single-trial based on individual dataset of raw-data. The EEG/epochs in Hilbert Space (HS) were decomposed provided relatively variable state in each frequency band according to stimuli/frequency that observed diverse phases; however, the bandpass FIR filter was applied after down-sampling to remove any unknown and undesired signal. Furthermore, it was worthwhile to decompose EEG into components, corresponding to diversity phases and spectra analysis, according to disparity of stimuli patterns. Consequently, amplitudes were explored from the real part $u_i(t)$ of Hilbert Space (HS), which detected the maximum spectral expected based on six-paradigms of regular/irregular stimuli patterns. These spectral responses demonstrated different frequency components in brain activities, which explored the result of frequency components by eliciting different spectral power at (5, 8, 10, 12, and 14) Hz, corresponding to evoked patterns. The decomposition method provided a posteriori definition derived from the incoming signals. Subsequently, led to increased amount number of control signal commands based on SSVEP paradigms, which had the stability and reliability to distinguish phase based stimuli patterns. In fact creating new aggregate applications based on BCI systems by increasing control commands depending on several patterns. Although this type of prototype based on brain-technology provides more attractive prospect with external world environments with regard to several stimuli patterns to introduce different protocol for different applications. Finally, this study give an advantage to exploit employ method as future applications work in SSVEP based BCI system fields, since it can be adapted, optimised and configured with support as real time experiments.

– **Section 5.3**: successful advanced techniques have been used based on massive EEG raw-signal to extract features with distributed computing systems, which offer to solve the problem of decreases in computer processing time. The promising result is overcome problem of waked reactions and consumption time in computational analysis and extraction. Previous studies utilized single CPU system, which reveals a reasonable performance for a smaller (EEG dataset); on the other hand, the open multi-processing (OpenMP) platform give high performance computing with greater accuracy and supplemental precise outcome within large datasets. The main concept of parallelized computing is separated amount of dataset individually, which allows parallelization process to be used based on multiple CPUs. In this contribution include two approaches utilize high performance computing (HPC) to realize faster analysis reaction in respect to analysis brain activities and recognition based on evoked SSVEP signals by exploring the Hilbert transform (HT) and quadrature amplitude demodulation (QAD) techniques. However, five frequencies have been employed to extract features using a short-term Fourier transform (STFT) based on four types filters with windowing function. Both approaches were adapted into HPC technique to discriminate extraction and execution time. Consequently, neural methodology approaches realized by DSP that processed a vast amount of EEG raw as individual datasets by sorted into short-term periods. In other words, the parallel computing systems process an analysis and compare the gathered EEG signals in order to detect certain brain activity. However, the parallel computing performance defines by executed program under multiple processing paradigm or multi-core (CPUs) based systems, which decrease the execution time. Nonetheless, a multi-core performance system now a day is available within a sensible price range. This study has contributed to the implementation of an algorithm that is specific to evoked SSVEP brain responses using multiple stimuli patterns and intensively computational offline analysis. The computation in the first approach extracted the spectral estimation and classification, as well as exploring the features to extract instantaneous phases in respect multi-patterns that select an action signal to control an output already used in previous sections. This work depended on two types of experiment datasets that were analysed offline to discover the effect beyond multiple frequencies based multiple patterns. Four types of diverse window functions were classified in order to make a comparison between them in respect of spectral power; however, detection patterns were used based on SSVEPs responses by HPC. Five different stimuli-frequencies were adopted (8, 10, 12, 14, and 16) Hz to extract the estimation spectrum utilising STFT technique.

Four-different timing windows were extended based on Four-types of filters presented by (Rectangle, Hamming, Hann and Triangle), which were used to extract the accuracy features based on (Before and After) hypotheses by correspondingly applying high-pass of (HP FIR). Consequently, the offline analysis implemented a linear discriminant analysis (LDA) to categorise between window functions as to the accuracy of (Filtering and Non-filtering) based on clean EEG raw-data. Outcome resultant indicated recognition accuracy rates in four-window types by increasing size with respect to time of window-size on L, which covered all evoked points in the new stored dataset. In fact, the spectral leakage problem of power density was estimate and appeared affected on high energy of low-frequency (LF). The extraction results based on the leakage problem were improved using (Hamming-function window) which reduced the oscillation without reducing response amplitude level in low-frequency (LF) components. In other hand, the high pass filters (HPF) used to overcome leakage problem and indicating greater accuracy. The output from HPF was not smooth but provided exact oscillations on ω, while the other frequencies remained. Nonetheless, the combination between HPF and Hamming window functions provided smooth curves of power estimation. Furthermore, most accuracy results were similar and decreased when there was a reduction in time-window width, which indicated effective suppression. Rectangle window-function achieved reasonable accuracy in respect of frequency-domain resolution result; since the EEG signal analysis using a single processor based on the designed system revealed performance for the smaller dataset. Therefore, steps over was used a multi-processing that exposed and enhanced the accuracy of performance in the large dataset. The multi-processing with OpenMP platform based application-programming interface (API) modified a new structure model that employed the parallelisation programming code. The constructed model was implemented using C language based on OpenMP of high performance computing (HPC) system, because it is an open sources library and the most suitable model for BCI application with simply impanation. Furthermore, the OpenMp depended on a shared memory approach and was easily installed on many platforms by comparison with CUDA or OpenCL, which face many restriction problems, such as specific hardware support, requisite essential graphical processing unit (GPU) ,and high accuracy routing. However, the message passing interface (MPI) models require a computer cluster and considerable installation restrictions that support a high accuracy networking and maintenance environment. Therefore, parallel computing based windowing function techniques were utilized after accumulating averaged responses and normalising the gathered epochs of EEG data.

A spectral power was extracted to obtain signal features, which are stored in separate template-files in memory block. The slide-window was passed over a stream of template-files to compare efficiency performance based on (1, 2 and 4) CPU-cores. The multi-cores base multiple threads were discovered the best results with respect to exaction time. The second approach compared independent patterns base detection. After the acquired EEG data had been gathered and cleaned to store as a new templet of datasets, the templet was sorted into main globule memory blocks, to compare all trial segments based on pattern. Phase detection procedure that used HT model exploited and extracted the imaginary part, then determined the statistically crucial phases based method. The computing process was parallelized by multiprocessing based OpenMP to compare all accumulated epochs in each pattern in order to detect specific brain activity.

Open Case Problems based study:

This contributory work based on research of empirical study has exposed several unsolved problems. Some of these problems are described as fundamental-problems, since they require a new theory or new research level towards understanding the relevant brain mechanisms. Therefore, undoubtedly the efforts of many research groups will address solutions that are not yet evident.

– The SSVEP response based frequency curves, stimulus shapes and colours:

The brain activities that incite the SSVEP based stimulation are very reliant on various stimulus parameters; subsequently, the visual-brain system is highly sensitive to all circumstances of the visual scene. By estimating the SSVEP paradigms based on frequency curves, there is no distinguish-active-signal as to its profile. The particular importance of the stimulation procedure depends on frequency stimulus, shape, colour and composition pattern. As an example, SSVEPs stimulation using White stimuli provides a more reasonable response than SSVEP with other colour or natural content of stimulation patterns provide a good brain reaction. It is imperative that researchers should understand the objective of this stimulation dependency in the visual cortical area, so that conclusive result can be made in SSVEP applications without the need for complicated measurements in each stimulus form. From the research archive, knowing the SSVEP responses signals based frequency can contribute substantial results, which are improved by comparison between various studies, leading to the development of other, similar knowledge of mapping efforts [93].

– The time-dynamics problems by inherent SSVEP of non-stationarities signals:

Although the subject can clearly perceive un-interrupted training based on evoked signal of SSVEP flickers, repeated recording of EEG brain activities is highly uneven (unequal) and changes over time-length into several milliseconds. Therefore, the stimulation paradigms are probably imperfect in respect of recording equipment; however, continuous interference between concurrent brain response processes in generating EEG-raw provides unstable output signal based SSVEP stimulation-bands. Consequently, it is very useful to create a new path of recording issues based on stationary evoked SSVEP signals within clear onsets and synchronised evoked signals.

– Methods and techniques for extraction of features:

The gathering of signals from extraction of SSVEP response is dependent on research requirements. Therefore, the creation of systematic paradigms based on an SSVEP extraction algorithm is required that provides strength and sufficiently active-signals to allow and enabl researchers to make better comparisons between studies based on SSVEPs.

- The SSVEP based BCI command delays; the time-dynamics limitation causes a postponement because of the inherent nature of brain activities. The incoming result in the phase-locking-events approach as offline is more sensitive and a promising alternative to the classic FFT based estimation methods. However, a more complicated approach is needed as an online signal processing extraction method that can reliably detect signals without extensive delay to the based onset, even with weak SSVEP signals
- The SSVEP based BCI sensor (electrodes) problems, mainly use the conventional recording way of electroencephalography (EEG) for data-acquisition because of the compact size and high price of these kind devices. An essential problem related to record-mode that prevents the wide use BCI in daily applications. Here, the EEG-electrodes (sensors) normally involve use of a conductive (gel) that provides acceptable SNR signals for the acquisition of brain activities. This gel might dry-out within a few hours and needs to be washed away at the end of each experiment. This kind of problem is recognised by Blankertz [104], who has developed a new type of (dry) electrodes without the need for a conductive (gel). Again, the primary experiments in Chapter 3 have explicitly investigated the feasibility of using such brain locations according to SSVEP based BCI, and found acceptable results, albeit with declined performance. However, this problem still remains with new signal processing techniques in achieving the weakness of non-stationary signals based SSVEP responses from brain-lobe locations

Future Work based on these contributions:

Brain technology such as BCI has the strongest potential to serve within a social environment. In addition, it is possible to pursue future work directions regarding SSVEP based BCI designs systems as follows:

- Strong brain activities based on a hybrid BCI system by integrating three or more independent system-types, such as SSVEP-BCI, motor-imagery BCI and P300-BCI. Accessibility in switching between them assists the user who has difficulties with a particular BCI-type; this leads to enhancing more command based BCI-types that are used simultaneously
- The strength of the SSVEP based BCI system is that uses more than 24 independent reaction commands to work reliably in most home environments, which leads to implementing a new online algorithm based on this contribution work
- The non-invasive nature of BCI technology allows the design of a remote control used in intelligent e-homes. SSVEP BCI system of e-homes might provide a novel feature with smart environments, such as TV or smart phones that correspond to BCI based system.
- A standalone BCI system allow disabled people to control a wheelchair reliably depending on SSVEP, which provides high responses using FPGA with multiple processing based-HPC units that increase reaction commands; however, the algorithm of this study can be improved to use as individual processor-units that perform using a FPGA based embedded of hardware/software co-design system
- Performed data Fusion-techniques in BCI systems of gathering EEG signals in term of precision and accuracy to extract features [162]; new concept of gathering operators called ordered weighted averaging (OWA) [163]; this operator is different than a classical weighted average which is not associated directly with particular attribute but rather to ordered position [163]; introduce a new operator for accumulation EEG signal called ordered weighted aggregation (OWA) operator allow combining of spirit criteria under supervision of a quantifier [163]; most of criteria is satisfied correspond to one of OWA operators [164], that lead to enhance more command based BCI-types that are used simultaneously

APPENDIX

A.1 Independent Component Analysis (ICA)

In this appendix, describe the details of Independent Component Analysis (ICA) theoretical method in more general case.

A.1.1 Introduction

The objective of ICA procedure is separates a multiple channels that include an input stationary signal of raw-data as source components. The un-mixing process based ICA performed without any prior knowledge of properties of input signals like EEG-signals. The estimation independent sources would afford low-complexity and best linearity predicted. The Independent Component Analysis (ICA) represents the subset depend on the blind source separation (BSS) approach, which include criteria of statistical independence components of datasets. Therefore, the ICA based BSS performance depend on several features such as (number of channels, data length and interface level of 'noise-signals'). The essential problem in ICA techniques restricted by pre-processing the EEG-raw data based on DSPs, which present a challenge that select benefit component from mixture environment [5]. As well as, this technique will depend on a multi-trial structure by accumulating amount of datasets based raw-data [4].

A.1.2 Independent Component Analysis (ICA) algorithm

The ICA is processing that can extracts from exploratory of observed data, which presented by the m-dimensional of vector x(t), where t = 1,2,…,N. New set of statistic independent components are presented by n-dimensional vector. The weight W matrix presents the activity of individual independent component, since multiply matrix of x present the active component of input-channels respect to time:

$$y(t) = \mathrm{W}\mathrm{x}(t) \qquad \text{a. 1.1}$$

The estimated component correspond a hidden or latent variable in dataset, which called sources. The ICA process is assumes that time series of x(t) has embedded mixture, can written as:

$$x(t) = \mathrm{A}\mathrm{s}(t) \qquad \text{a. 1.2}$$

Here the A is denote as unknown mixture-matrix and s(t) is a vector which presenting unknown-hidden or (latent) variables. However, the ICA approach allowed de-mixing or decomposition that able to recover the original sources respect to time domain:

$$y(t) = \hat{s}(t) \qquad \text{a. 1.3}$$

Hence, two or more of random variables are un-correlated and not imply. This fact is involved to use other methods such as Principal Component Analysis (PCA). This approach is seeks to find such independent directions through maximization of suitable cost function called 'contrast function' respect to statistical independence. Such as this function can be maximize or minimize to optimize extracted features. Therefore, can be considered a new extension of principal component analysis (PCA) method. Since, the input-data of PCA presented by *x(t)* which is de-correlated and the components are maximally un-correlated according to SOS topography. The principal components analysis (PCA) is one of suitable algorithm that concluded to solve the problem; by assuming available of data-set which multivariate respect to time series of $\{x_i(t)\}$, where t=1,2,…,m. This time series is also corresponding to individual EEG-signals, which accumulated from multiple electrodes; the consequences result of unknown mixture process is defined by the follow relationship:

$$x_i(t) = \sum_{j=1}^{n} a_{ij}\, s_j(t), \qquad where\ i = 1, 2, 3, .., m \qquad a. 1.4$$

That's lead to similarly compact of matrix form $x(t) = \mathrm{A}s(t)$ as mentioned in (a.2) respect to the time variant in (t=1, 2, .., N); since the A presenting the unknown mixture matrix sized by (m by n), and hidden (latent) components presenting by $\mathrm{s(t) = [s1(t), s2(t), \dots, sn(t)]^T}$ of individual sources. Hence, the observed data by vector in $\mathrm{s_j(t)}$ presented on $\mathrm{x(t) = [x1(t), x2(t), \dots, xm(t)]^T}$. Find-out the de-mixture matrix by extracting the weight matrix W from $y(t) = \mathrm{W}x(t)$ which is separate the hidden independent components. It is possible to assume the number of sources of hidden components by same number of time series, which are observed by inputs n, when the matrix A is a square (n by n).

$$W = A^{-1} \qquad a. 1.5$$

Then we can perfect separation between y(t) = s(t). Optimization in y which is permutated and scaled version of s, since it possible to find W such that WA = PD, where P is also permutation matrix, furthermore the D is a diagonal scaling matrix. In general, the ICA of certain random vector of x(t) is obtained by (n by m), taken in account m ≥ n.

A.2 Hilbert Transform (HT)

In this appendix section, have been describe the theoretical details of Hilbert Transform (HT) topography in more general case.

A.2.1 Introduction

Feature extraction from recording EEG-raw signal is further use in the field of brain-computer interfaces (BCI). Congregated a lot of attention in recent years subsequently a large range of possibilities to choose among of features and diversity drives such as a methods to extract. Therefore, the Hilbert Transform (HT) is one of important technique that used to extract the instantaneous phase and magnitude over chunks of EEG-raw in time quantification by means of various statistical dependence parameters. In generally, the Hilbert Transform (HT) supports an inverse technique that related to real and imaginary fragments of complex function which defending by a $\pm$ ib. The relationship between real and imaginary parts gives the easily way that derived an application based on BCI. The definition equation can be seen the imaginary part of analytic function providing a component of phases θ and amplitudes A according to the time function series. In other word, it seems a natural inspissation of inverse Fast Fourier Transform (FFT).

A.2.2 Properties of HT Algorithm

The traditional analysis methods based on linear and stationary hypotheses is distinguished features referring to incoming datasets. The Hilbert Transform (HT) is an experimentally data analysis method which expansion and adaptation techniques. Therefore it can produce the physically magnitudes that extract raw-data based non-linear and non-stationary approach. The real time function of x(t) of Hilbert transform (HT) is defined as [8, 9]:

$$\hat{x}(t) = H[x(t)] = \frac{1}{\pi} \int_{-\infty}^{\infty} x(\tau) \frac{1}{1-\tau} \, d\tau \qquad a.2.1$$

Realize from (a.2.1) an independent variable with non-change as consequence result of transformation approach, therefore the output of $\hat{x}(t)$ present the time dependent function. Furthermore, the $\hat{x}(t)$ present an linear function by x(t) that obtained to convolve with $(\pi t)^{-1}$ as exposed in the following relationship:

$$\hat{x}(t) = \frac{1}{\pi t} * x(t) \qquad a.2.2$$

The traditional Fast Fourier Transform (FFT) provides a convolution after rewrite equation (a.2.2):

$$F\{\hat{x}(t)\} = \frac{1}{\pi} F\left\{\frac{1}{t}\right\} F\{x(t)\} \qquad a.2.3$$

Where $F\left\{\frac{1}{t}\right\} = \int_{-\infty}^{\infty} \frac{1}{x} e^{-j2\pi f x} dx = -j\pi \, sgn \, f$, Since sgn of $f = \begin{cases} +1 \; where \; f > 0 \\ 0 \quad where \; f = 0 \\ -1 \; where \; f < 0 \end{cases}$

Therefore, the Fourier transform of Hilbert transform in x(t) is substituted in (a.2.3) which given:

$$F\{(\hat{x})\} = -j \; sgn \, f \, F\{x(t)\} \qquad a.2.4$$

Consequently, obtained the frequency domain by multiplying the spectrums in $j\,(\frac{\pi}{2})$ for negative part and $-j\,(\frac{-\pi}{2})$ and positive part to overcome a result in time domain. However, performed an inverse Fourier transform that give a real signal x(t) [10], which described by the expression as:

$$y(t) = x(t) + j\hat{x}^2(t) \qquad \text{a.} 2.5$$

Hence, the envelope of Z(t) is defined by $\sqrt{\mathrm{x}^2(\mathrm{t}) + \hat{\mathrm{x}}^2(\mathrm{t})}$ which allowed to extract the instantaneous phase θ in complex plane defined by:

$$\theta(\mathrm{t}) = \tan^{-1}\left(\frac{\hat{\mathrm{x}}(\mathrm{t})}{\mathrm{x}(\mathrm{t})}\right) \qquad \text{a.} 2.6$$

The common tangent respect to same value at a certain point of x̂(t)is determined by Z(t), since the slope and magnitude of original signal in x(t) at local maxima is consequently seen on Z(t) which is always a positive function.

A.3 Fast Fourier Transform (FFT)

In this appendix, describe the Fast Fourier Transform (FFT) technique in more general case.

A.3.1 Introduction

Generally, the FFT is presenting the spectrum of various frequencies by plotting frequency carves of incoming signals. The EEG-signal is describe by amount of many individual frequency components and harmonics. Many of analysis approaches utilized the fast Fourier transform (FFT) of spectral analysis of EEG signals in frequency domain. Moreover, the Fourier transform is formulated and suitable for linear, periodic and stationary signals respect to the time domain based a certain frequency bands, which unchanging frequency components. The higher characteristic frequency elicited respect to responses, which allowed to implementation the BCI system using simple signal processing techniques. Therefore, the Fast Fourier Transform (FFT) has been utilizing to extraction the feature and classification. On the other hand, the FFT technique is restricted to detect frequencies which is maximized a half of sampling frequency called (Nyquist) frequency. The advanced signal processing is necessary to differentiate between classes which be forced a complicated in system design.

A.3.2 Spectrum Frequency using FFT approach

The basic approached that to analyses an acquisition EEG-signal, which proper desired information by applying the Fast Fourier transform (FFT) method. One of important condition that acquisitions signal is reversibility when applied method by converted satisfied signal based on one by one of frequency [3]. The Fourier based topography is assumed that the time series repeated as periodic waveform in case is implicit. This assumption leads to extract the spectral estimates. The spectral analysis based Fourier of acquisitions signal into frequency domain of signal is involved to decomposition, in other words the original signal can be separated into components which can observe the slim spikes that represent intentional frequency within harmonics. The spectral analysis techniques are considered as the best technique which transformation between time and frequency domains however with time-shift invariant. The Fourier transform pairs expressed as:

$$X(f) = F\{x(t)\} = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}\, dt \qquad a.3.1$$

The Fourier transform (FT) converts time domain signals into frequency domain illustrations and similarly; the discrete Fourier transform (DFT) converts discrete time sequences into discrete frequency versions derived by (a.3.2.) respect to k $= 0, 1, 2, \ldots, \mathrm{N} - 1$.

$$X_k = \sum_{n=0}^{N-1} x_n e^{-j2\pi kn/N} \quad = \sum_{n=0}^{N-1} x_n \, W_N^{kn} \qquad a.3.2$$

Where the signal *x(t)* present the time domain signal, and *X(f)* presenting the FT, since *xth* of input sequence signal, since the X_k in DFT present the n number of samples. Nonetheless, the Fast Fourier Transform (FFT) is an optimized implementation of a DFT that takes less computation to perform. In 1965 J.W.Cooley and J.W.Tuckey reinvented the FFT for fast computation of the DFT [2]. However, the twiddle factor W is notation by $e^{-j\frac{2\pi}{N}}$ whereas often to use at more compact form. This equation is identical FFT and simple to use an efficient programming method to implement it [137]. Furthermore, the inverse of DFT or FFT defined by:

$$x_n = \frac{1}{N} \sum_{n=0}^{N-1} x_k e^{-j2\pi kn/N} \quad = \frac{1}{N} \sum_{n=0}^{N-1} x_n \, W_k^{-kn} \qquad \mathrm{a}.3.3$$

The factor of $1/N$ is defined rather inverse or not; however, this factor is used to adjust the scale of reversibility. Cooley and Tukey are constructed approach beyond FFT technique, which described through the length N of DFT is not prime number, the calculation component can be decomposed into a number of shorter length using DFTs [137].

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Further, the work contained in this thesis has not been previously submitted for a degree or any other higher education institution.

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Advanced knowledge	Analog technology, CAD systems, construction, microelectronics, information technology, computer technology, microcomputer, microprocessor technology, microcontroller, communications technique

IT and computer concept

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Additional information

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