Error-based Analysis of VEP EEG Signal using LMS

by

Lee Ban Siong
14227

Dissertation submitted in partial fulfilment of
the requirements for the
Bachelor of Engineering (Hons)
(Electrical & Electronics)

SEPTEMBER 2014

Universiti Teknologi
PETRONAS Bandar Seri
Iskandar
31750 Tronoh
Perak Darul Ridzuan

CERTIFICATION OF APPROVAL

Error-based Analysis of VEP EEG Signal using LMS

by

Lee Ban Siong
14227

A project dissertation submitted to the
Electrical & Electronics Engineering Programme
Universiti Teknologi PETRONAS
in partial fulfilment of the requirement for the
BACHELOR OF ENGINEERING (Hons)
(ELECTRICAL & ELECTRONICS)

Approved by,

_____

(Dr. Vijanth Asirvadam)

UNIVERSITI TEKNOLOGI PETRONAS

TRONOH, PERAK

September 2014

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

_____

LEE BAN SIONG

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

Electroencephalography (EEG) involves the usage of electrodes placed on the human scalp to record electrical impulses generated by the brain. One of the many components that are present in EEG signals is the Visually Evoked Potential (VEP), whereby brief electrical impulses are generated as a result of the presence of visual stimuli. The aim of this project is to analyse EEG signals that contain VEP using the least-mean squares (LMS) method and differentiate between alcoholic and non-alcoholic subjects based on the resultant error signal. This LMS method is a form of adaptive filter that minimizes the mean square of the cost function for every iteration it undergoes and is widely used in many signal imaging applications due to its simplicity in implementation and low computational complexity. The EEG recording with VEP components is already available so the scope of the project only covers the adaptation of the LMS adaptive filter and the analysis of the VEP EEG error signals for 5 alcoholic and non-alcoholic subjects. The analysis of the results indicate that there is a certain range of standard deviation values in which it is possible to classify the condition of the subject into either alcoholic or non-alcoholic condition.

ACKNOWLEDGEMENT

I would like to extend my deepest gratitude and appreciation to everyone who has been responsible for assisting me in my final year project over the course of 8 months.

I would like to acknowledge my supervisor, Dr. Vijanth, for assisting me and providing guidance in completing my project. I would also like to mention Hussam, who gave me some advice regarding my project.

I am deeply indebted towards my family, for giving me their full support during times of doubt. Though there were many difficulties in finishing this particular project, I managed to overcome the problems and complete the project successfully. This is due in no small part to the people who have supported me through the good times and the bad times.

Thank you.

CHAPTER 1
INTRODUCTION

1.1 Background of Study

Our brain processes and transmits information using billions of neurons. Each neuron produces a miniscule amount of voltage when sending signals, usually measured in microvolts. To record this electrical activity of the human brain, the electroencephalogram (EEG) is used [1]. Also called electroencephalography, this method of measurement is just one of the many medical imaging techniques. This measurement technique is a non-invasive procedure that can be done frequently without any risk to the subject [2].

A single neuron does not generate sufficient voltage to be detected by electrodes. Thus, EEG recordings often display the summation of the synchronous activity of a large group of neurons, usually numbered in the millions. A typical human brain contains a hundred billion neurons [3]. One of the main intentions of using the EEG is to study the condition of the brain for clinical and physiological purposes.

EEG is carried out by first applying electrolyte on the scalp and then placing electrodes on the scalp to record any electrical impulses generated by nerves in the brain. The arrangement and placement of electrodes has to follow certain systems, one of them being the 10-20 system which includes 21 electrodes as shown in Figure 1.

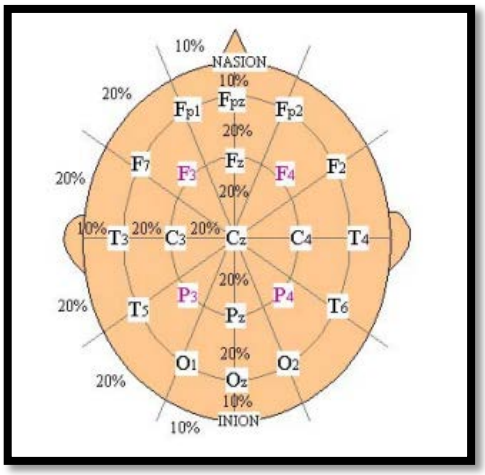

Figure 1. The 10-20 system [2]

The purpose of the electrolyte is to transform the current flow in the brain into electron flow that can be read by the electrodes. There are two types of electrodes: needle and surface. Needle electrodes are implanted on the surface of the brain during surgery and are able to read intracranial EEG. Surface electrodes, on the other hand, are placed on the scalp and are able to read scalp EEG.

Once the electrodes have recorded the electrical signals, amplifiers are used to boost the amplitude of the readings in order to increase the accuracy by which the readings can be converted into digital signals. This conversion is carried out by an analog-to-digital converter and the output from this converter goes to a computer where the data can be stored and displayed [2]. Filters are also used together with amplifiers in order to remove artefacts from the signal or to obtain a desired component. Common filters include Butterworth, Chebyshev and Fast Fourier Transform (FFT). The gain of the common filters can be seen in Figure 2.

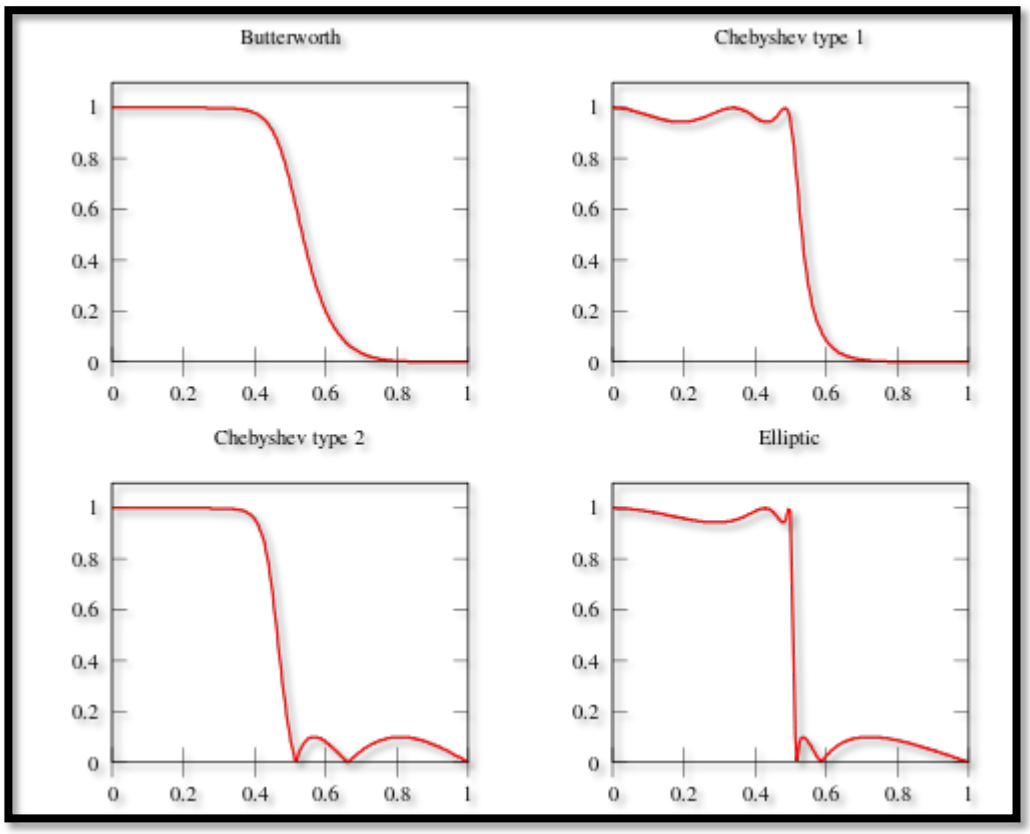

Figure 2. Signal Processing Filters [3]

There are a number of frequency bands in EEG signals:-

i) Delta (<4 Hz): deep sleep stage for adults

ii) Theta (4-8 Hz): infants and children, sleep stage for adults

iii) Alpha (8-14 Hz): relaxed state for adults

iv) Beta (14-30 Hz): ranges from state of calm to state of tension

v) Gamma (>30 Hz): not of clinical/physiological interests, normally filtered

These frequency bands can be seen in Figure 3.

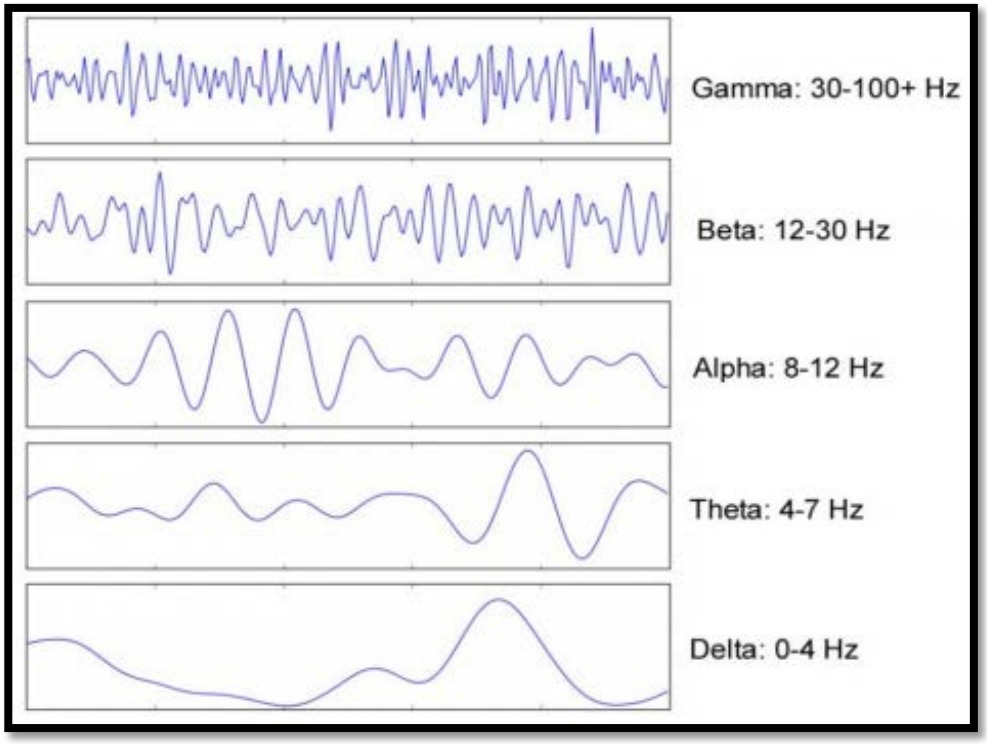

Figure 3. EEG Frequency Bands [5]

The term visually evoked potential (VEP), which refers to electrical potentials, is an offshoot of EEG and is initiated by brief visual stimuli. These potentials are recorded from the scalp overlying the visual pathway and cortex [6].

VEPs are used primarily to measure the functional integrity of the visual pathways from the retina via the optic nerves to the visual cortex of the brain. Optical abnormalities which affect a person's visual cortex can be identified by examining the VEP. The most commonly used stimuli to initiate VEPs are normally in the form of flash lights or patterned shapes. However, VEP waveforms have low amplitude and are therefore distinguished from EEG signals by a train of stimuli and signal averaging.

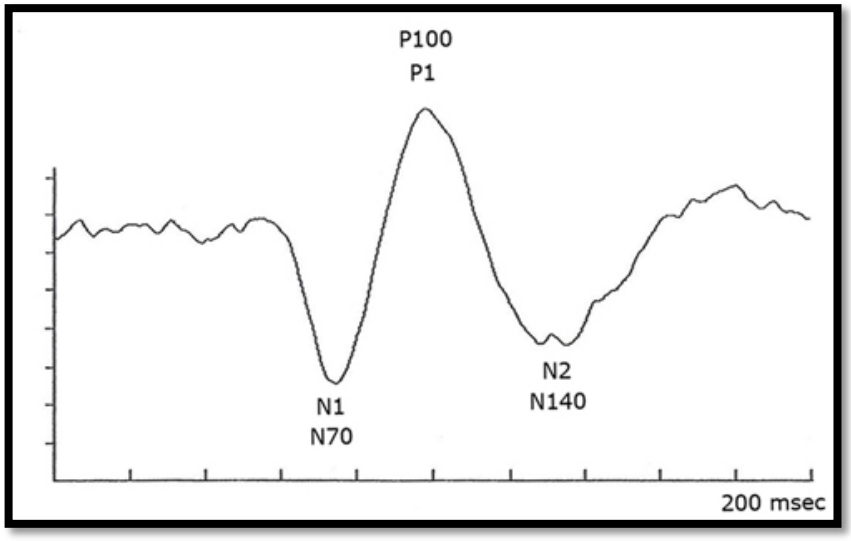

Figure 4. Example of VEP [7]

1.2 Problem Statement

VEP components are found in EEG signals whenever a visual stimuli is presented to a subject. The response of the subject depends upon the condition the subject is in. Thus, it is possible to differentiate between the VEP EEG signals of alcoholic and non-alcoholic subjects using an adaptive algorithm.

1.3 Objectives and Scope of Study

There are two objectives for the project:-

- To adapt a least-mean squares (LMS) adaptive filter to analyse the VEP EEG signals for alcoholic and non-alcoholic subjects.
- To differentiate between alcoholic and non-alcoholic subjects based on their resultant error signal from the LMS adaptive filter.

The scope of the project covers the adaptation of the LMS adaptive filter using MATLAB. The EEG data is readily available so analysis of the VEP EEG signal can be carried out once adaptation of the LMS adaptive filter has been completed. The visual stimuli is in the form of a single object shown to subjects. The error signals for 5 alcoholic and 5 non-alcoholic subjects will be analysed in order to properly differentiate between both conditions. Only nodes FPZ, FP1, FP2, OZ, O1 and O2 are covered in the analysis.

CHAPTER 2
LITERATURE REVIEW

Many methods have been used in imaging for the purposes of extraction of the desired signals, each with their own advantage and disadvantage. In this section, two different aspects that are related to the project will be analysed. The first one is about the methods used to extract VEP from EEG signals. The second one concerns the diverse applications of the LMS adaptive filter in imaging.

The oldest method for VEP extraction was carried out way back in 1951 and involved the repetitive recording and summation of EEG signals within a certain time period after visual stimulus [7]. This cancels out the EEG activity, resulting in the formation of the VEP signals. This technique is known as 'signal averaging'.

One of the recent methods is to use Partial Least Squares (PLS) regression for a single trial extraction of a VEP [8]. As a result of averaging signals from all trials, information that exist in each trial will be lost. Thus, by using the single trial estimation scheme, it is possible to preserve the unique characteristics of each trial. The PLS regression works by estimating a pair of uncorrelated variables that produce the maximum covariance with independent variable A and dependent variable B. The results of the evaluation indicate that for the real EEG signals, around half of the subjects have mean peak estimation close to the ensemble averaging. The artificial EEG signals, meanwhile, were compared to another method known as Generalized Eigenvalue Decomposition (GEVD) which involves the alteration of the input signal to reduce the colored noise. It was found that the PLS-based P100 estimations are comparable to the GEVD ones in term of latencies. Further comparisons can be seen in Table 1.

Table 1. Statistical values for artificial PLS-based EEG signals and GEVD [8]

SNR (dB)	Average Error Rate					
	P100		P200		P300	
	PLS	GEVD	PLS	GEVD	PLS	GEVD
0	3.68	3.35	2.69	3.7	2.55	5.23
-5	3.51	4.04	2.95	5.56	2.49	5.99
-10	3.29	3.93	2.88	7.82	2.58	6.97

An imaging method employs the usage of a linear Multi-Layer Perceptron (MLP) for identifying the harmonic contents [9]. Artificial sinusoidal signals were inputted into the neural network and the analysed signals were taken as the output and compared against other measured signals. The results obtained illustrate the accuracy and efficiency of the MLP in classifying the signals based on frequency features. Besides that, the MLP is also able to acclimatize and compensate for conditions with high noise.

The least-mean squares (LMS) method, which is the method that will be used for this project, has been extensively used in signal and imaging applications and can also be applied on VEPs. The LMS filter adapts by minimizing the error signal and fine-tuning the filter coefficients towards an optimum value. This goes on until steady-state conditions are achieved. Advantages of this method include simplicity in term of formulation and efficiency of computation.

It has been used in power systems for frequency estimation [10]. A complex signal was derived from three-phase voltages and the LMS algorithm in complex form was applied to this signal in order to estimate the frequency of a power system. The complex weight vector was recursively modified for each iteration. The result of the LMS algorithm can be seen in Figure 5. This application displays the versatility of the LMS technique.

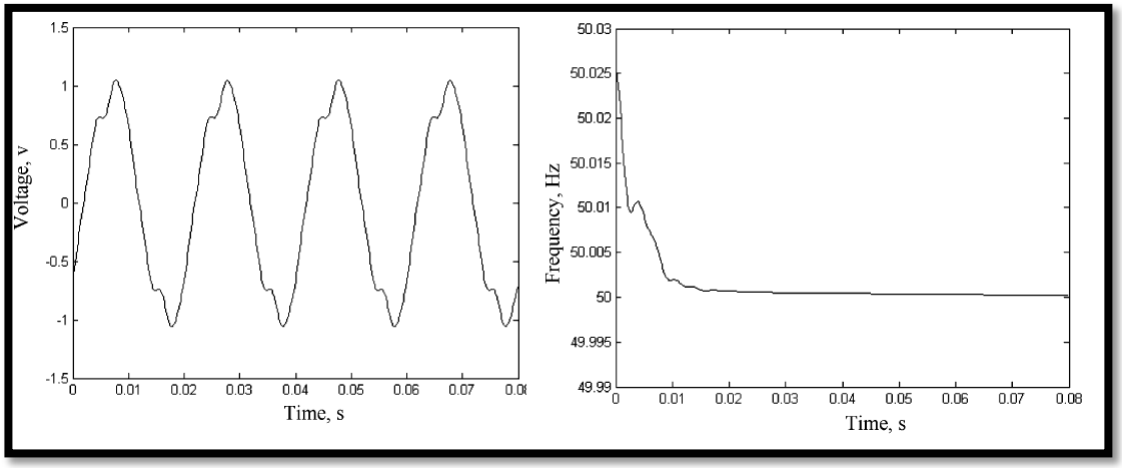

Figure 5. Frequency estimation (right) of voltages (left) using LMS [10]

Besides that, the LMS algorithm has been employed for noise cancellation purposes and as an adaptive estimator of Fourier coefficients. This coefficients are used for a dynamic Fourier series to estimate time-varying evoked potentials [11]. Figure 6 shows the result for the estimation of cortical somatosensory evoked potential.

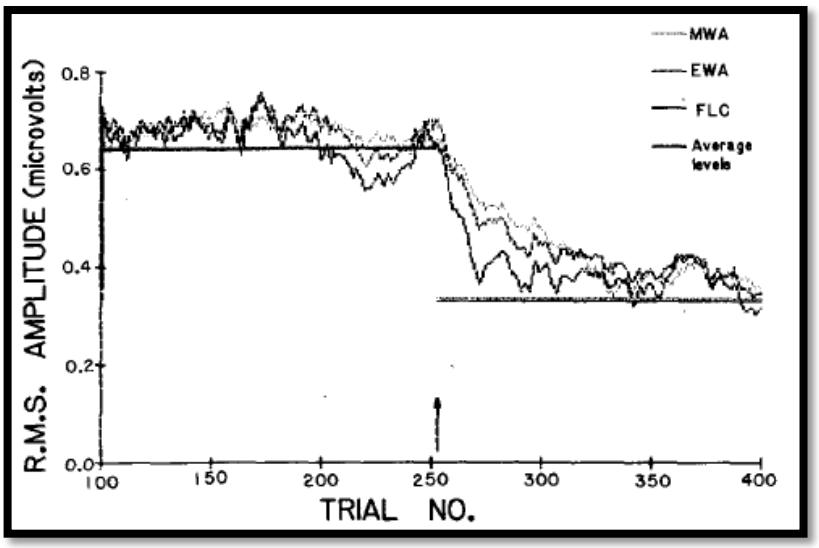

Figure 6. Cortical SEP estimation [11]

Finally, the LMS algorithm was derived for an optimal time-varying filter for evoked potential estimation [12]. It was found that many current methods were ineffective in extracting evoked potentials as an adaptive filter will be reduced to a processor with minimum-variance when the evoked potentials behave randomly for each iteration. Thus, a basic adaptive time-varying filter was developed based on the LMS algorithm. The results can be seen in Figure 7, whereby the filter was able to extract the evoked potentials from a simulated EEG signal.

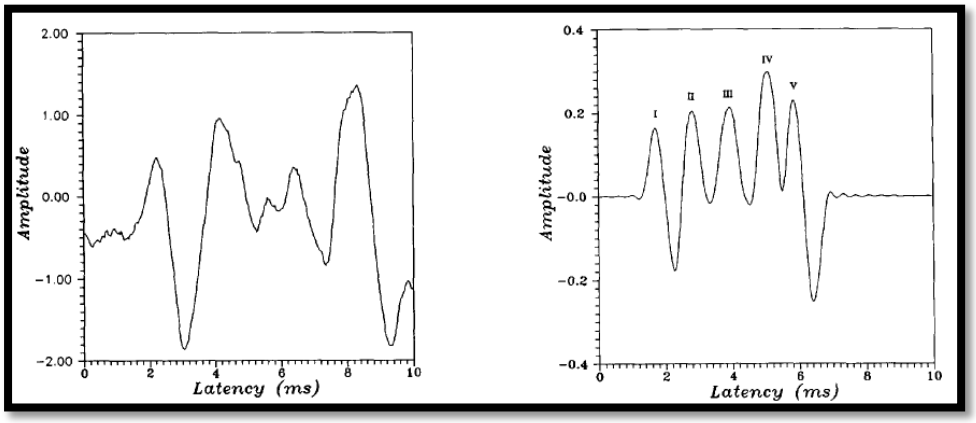

Figure 7. Evoked potential (right) obtained from simulated EEG (left) [12]

CHAPTER 3
METHODOLOGY

3.1 Project Activities

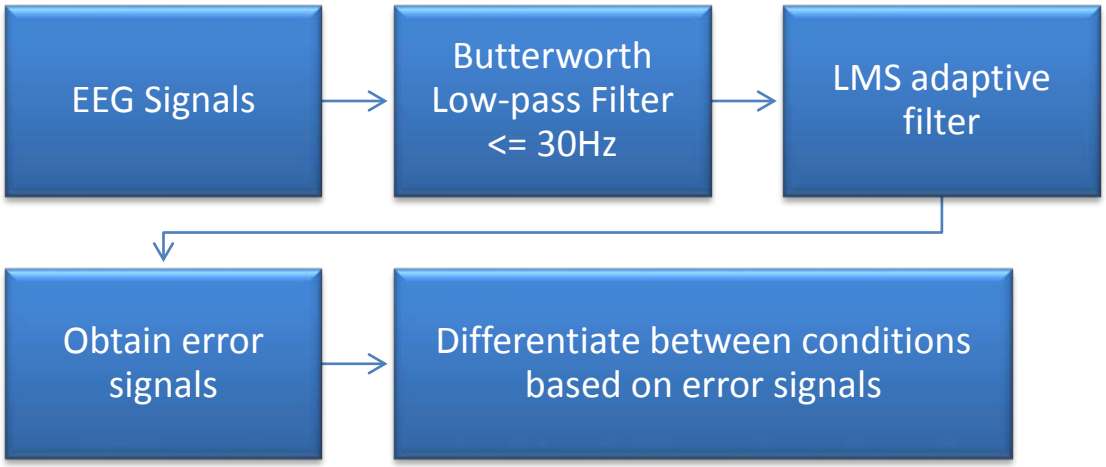

Figure 8. The flow of the process

The first step involves obtaining the EEG signals. As the recording for EEG data is already available, this task can easily be accomplished.

Next, the EEG signals have to undergo filtering. Filtering of EEG signals has to be carried out in order to obtain the desired frequency bands. Sometimes there are EEG artifacts that are either physiological (due to subject) or non-physiological (due to environment/equipment) in nature. These artifacts have to be removed as well. For the purposes of VEP EEG analysis, only the frequency bands of 0-30 Hz are taken into account. The other frequency bands will be filtered out.

For low-pass filtering, the Butterworth low-pass filter will be employed. This filter is designed to have a frequency response that is as flat as possible in the pass band, which means no ripples, and zero roll-off response in the stop band. It is fast and easy to implement. The main disadvantage of this filter lies in its wide transition band. An ideal frequency response will be a ‘brick wall’ response, as seen in Figure 9.

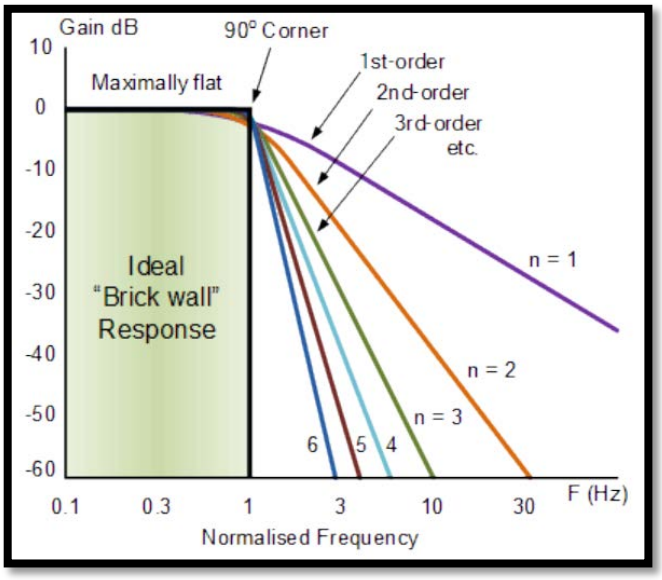

Figure 9. The effect of filter order on the Butterworth low-pass filter

The structure of a typical adaptive filter can be seen in Figure 10. The LMS algorithm adopts the same structure, the only difference being the adaptive algorithm employed which is to minimize the error signal squared [10]. As mentioned earlier, this algorithm is widely used due to its simplicity. However, one of the many things that have to be taken into account is its convergence time which increases as the step size decreases [13]. For this project, the LMS filter is used to obtain the error signals of the VEP EEG signals of subjects under alcoholic and non-alcoholic conditions.

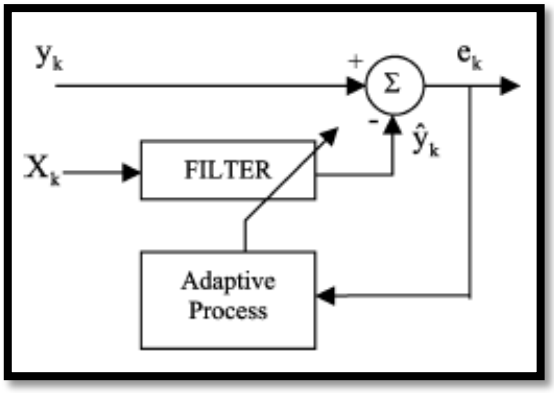

Figure 10. LMS filter structure [10]

The LMS algorithm is based on the stochastic gradient descent method which means that the filter coefficients are updated based on the error of the input signal relative to the desired signal at the current time. These filter coefficients are used to minimize the cost function.

From Figure 10, X_k is the input data vector while y_k is the desired signal. Note that k is the instant. To estimate the proper signal, an appropriate value of the filter coefficient W_k can be obtained through the minimization of the squared error signal, e_k. The error of the signal is calculated using the following equation:

$$e_k = y_k - \widehat{y_k}$$

Two other things to factor in the calculation is the adaptation parameter, μ, and the gradient of the error performance surface, ∇_k. The weight vector can be computed as:

$$W_{k+1} = W_k + \mu\nabla_k$$

And the gradient can be computed from this equation:

$$\hat{\nabla}_k = -2e_k X_k$$

Thus, it can be seen that the weight coefficients of the filter are constantly updated based on the error between the desired signal and the filtered signal.

After adapting and applying the LMS adaptive filter on the EEG signal, the error signals can be obtained. The input to the filter is a single VEP EEG trial while the desired signal is an ensemble average of 10 VEP EEG trials. The output of the filter will try to mimic the desired signal as closely as possible. The difference between the output of the filter and the desired signal results in the error signal.

Once filtering is done, the analysis of VEP EEG signals for subjects under different conditions can be carried out. These conditions include subjects under alcoholic and non-alcoholic conditions.

For VEPs, the main area of concern of a subject's brain lobes are the frontal parietal and occipital lobes. The parietal lobe is concerned with the processing of sensory information from the eyes that are obtained in other lobes. The occipital lobe, on the other hand, processes visual input that is sent by the retinas to the brain. These areas are where VEP activity is concentrated. Therefore, analysis of VEPs will be focused on the readings of electrodes placed at these locations.

3.2 Key Project Milestones

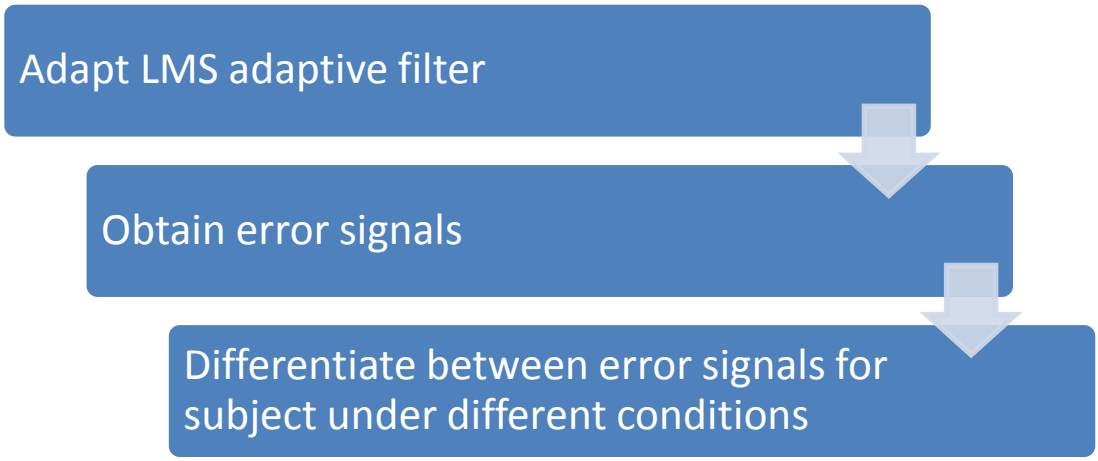

Figure 11. Key project milestones

By referring to the Project Activities process flow in Figure 9, three key project milestones are identified. These three milestones can be seen in Figure 11.

Completing any one of these milestones represent a huge step in finishing this project. However, the milestones have to be carried out in the order shown in Figure 11 as the next step relies on the basis that the previous step has been completed.

As the LMS adaptive filter plays a major role in producing the error signals and is the central tool used in the project, it is considered a key milestone when adaptation of it is done. Complete adaptation of the LMS adaptive filter represents a huge leap in the project progress. Obtaining the error signals of the LMS adaptive filter is one of the main objectives of this project, thus, it is also a key milestone. Finally, the other objective is the analysis for error signals of subjects under different conditions. Therefore, it is also a key milestone for the project.

For the purposes of error-based analysis of subjects under different conditions, one group of data will be chosen as the control group. This control group (non-alcoholic) will then be compared against another group, in this case, the alcoholic group. The changes between these groups will be analysed to determine the effects the state of a subject has on VEP EEG signals.

3.3 Project Timeline

Detail/Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Selection of Title														
Preliminary Research														
Extended Proposal														
Proposal Defense														
Adapt LMS adaptive filter														
Interim Draft														
Interim Report														

Figure 12. FYP I Gantt-Chart

Detail/Week	15	16	17	18	19	20	21	22	23	24	25	26	27	28
Adapt LMS adaptive filter														
Analyse error signals														
Progress Report														
Pre-SEDEX														
Technical Paper														
Viva														
Dissertation														

Figure 13. FYP II Gantt-Chart

CHAPTER 4
RESULTS AND DISCUSSION

The dataset that was used for signal analysis was taken from UCI KDD Archive that can be accessed online. This data arises from a large study aimed at examining genetic predisposition of EEG relating to alcoholism. It contains measurements from 64 electrodes placed on scalps of the subjects which were sampled at 256 Hz for 1 second.

There were two groups of subjects which were control and alcoholic. Each subject was exposed to either a single stimulus (S1) or to two stimuli (S1 & S2). These stimuli were in the form of pictures of objects chosen from the 1980 Snodgrass and Vanderwart picture set. When two stimuli were shown, they were presented in either a matched condition (S1 identical to S2) or non-matched condition (S1 differs from S2). The dataset contains a total of 122 subjects with 120 trials each where different stimuli was shown. Once one of the many files in the dataset has been imported into MATLAB, it can be represented in the form of a table as seen in Figure 14.

	1	2	3	4	5
1	'# co2a0000364.rd'	[]	[]	[]	[]
2	'# 120 trials, 64 chans, 416 samples 368 post_stim samples'	[]	[]	[]	[]
3	'# 3.906000 msecs uV'	[]	[]	[]	[]
4	'#'	'S1'	'obj'	','	'trial'
5	'#'	'FP1'	'chan'	'0'	[]
6	'0'	'FP1'	'0'	'-8.921'	[]
7	'0'	'FP1'	'1'	'-8.433'	[]
8	'0'	'FP1'	'2'	'-2.574'	[]
9	'0'	'FP1'	'3'	'5.239'	[]
10	'0'	'FP1'	'4'	'11.587'	[]
11	'0'	'FP1'	'5'	'14.028'	[]
12	'0'	'FP1'	'6'	'11.587'	[]
13	'0'	'FP1'	'7'	'6.704'	[]
14	'0'	'FP1'	'8'	'1.821'	[]
15	'0'	'FP1'	'9'	'-1.109'	[]
16	'0'	'FP1'	'10'	'-2.085'	[]
17	'0'	'FP1'	'11'	'-1.597'	[]
18	'0'	'FP1'	'12'	'0.356'	[]
19	'0'	'FP1'	'13'	'2.309'	[]
20	'0'	'FP1'	'14'	'2.797'	[]

Figure 14. The extracted data

As seen from Figure 14, the first four lines are header data. In the first line, the fourth letter indicates whether that particular data belongs to a subject from the alcoholic group (a) or a subject from the control group (c). The fourth line identifies the matching conditions which are a single object shown (S1 obj), object 1 and 2 shown in a matching condition (S2 match), and object 1 and 2 shown in a non-matching condition (S2 nomatch). Meanwhile, line 5 signifies the start of the data from electrode FP1. The four columns of data, from left to right, are the trial number, electrode position, sample number (0-255), and sensor value (in µV). Once plotted, the data is represented in the form of 64 separate graphs (1 for each electrode), as seen in Figure 15. The graphs below are of a subject from the alcoholic group.

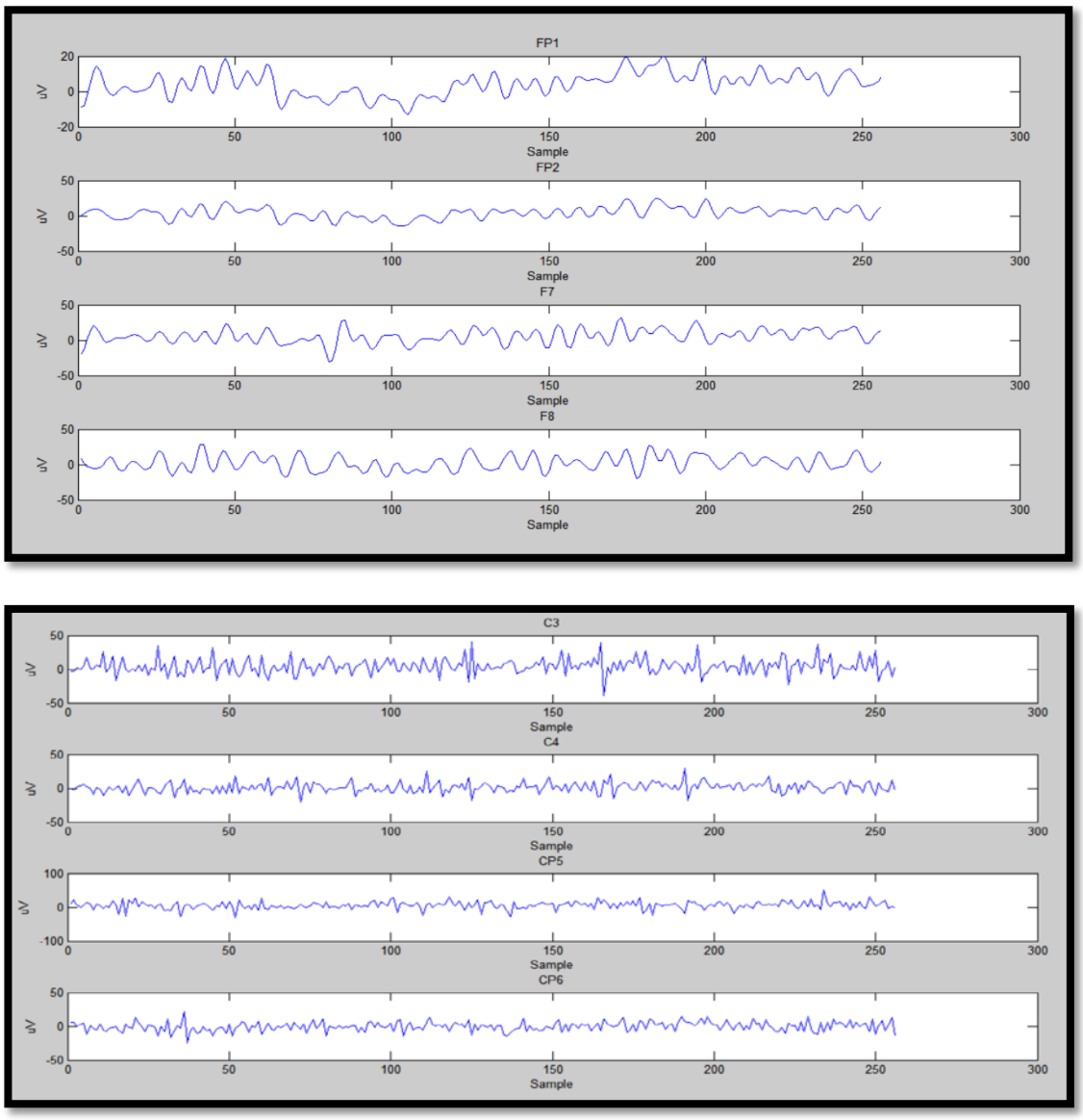

Figure 15. An example of eight graphs showing the voltage reading at different electrode positions

4.1 Results

As mentioned earlier, VEPs are only concerned with electrodes placed at the frontal parietal and occipital lobes. For this reason, only six electrodes will be analysed further. These six electrodes are OZ, O1, O2, FP1, FP2, and FPZ. The Z in the notation indicates that the electrode was placed in the middle while odd numbers mean that the electrodes were placed on the left side and even numbers indicate that the electrodes were placed on the right side.

5 random subjects from both alcoholic and non-alcoholic groups were chosen. These subjects undergo multiple trials involving a single visual stimuli (S1). As mentioned earlier, a single VEP EEG trial from a subject was used as the input signal to the LMS adaptive filter while an ensemble average of 10 VEP EEG trials from the same subject was used as the desired signal. 20 iterations of LMS filtering were carried out.

A Butterworth low-pass filter was used to remove frequencies above 30 Hz. The signals are then filtered using the LMS adaptive filter to obtain the error signals. The results are shown in the following figures. Figures in time domain are a combination of the output from all 6 nodes (FP1, FP2, FPZ, O1, O2, OZ) and result in a total of 1536 samples.

The arrangement of the nodes according to sample number is as follows:

Table 2. Order of node output according to sample number

Node	Sample number
FP1	1 to 256
FP2	257 to 512
O2	513 to 768
O1	769 to 1024
FPZ	1025 to 1280
OZ	1281 to 1536

Alcoholic Subjects

Subject 1

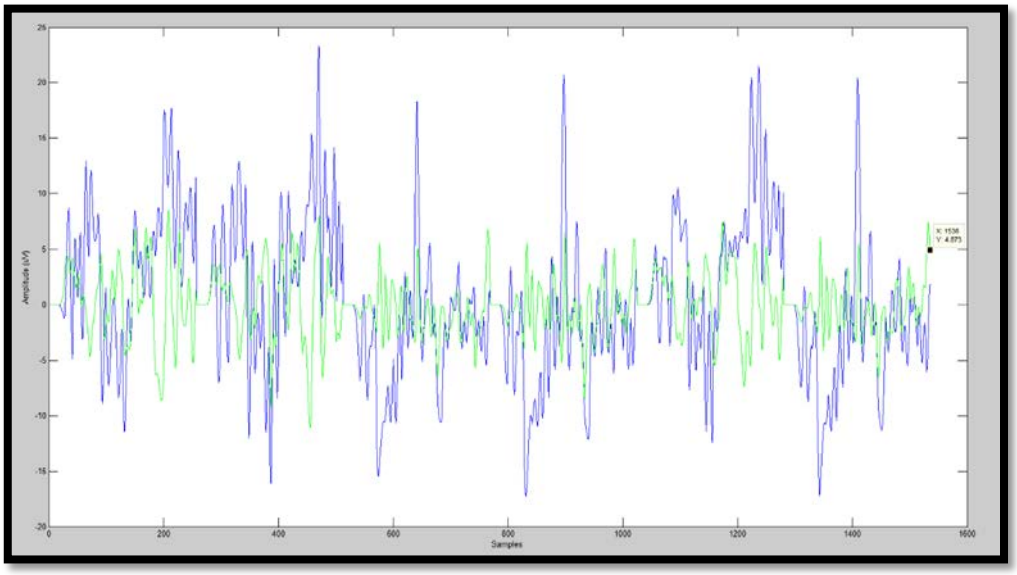

Figure 16. The input signal (blue) and error signal (green) of alcoholic subject 1 in time domain

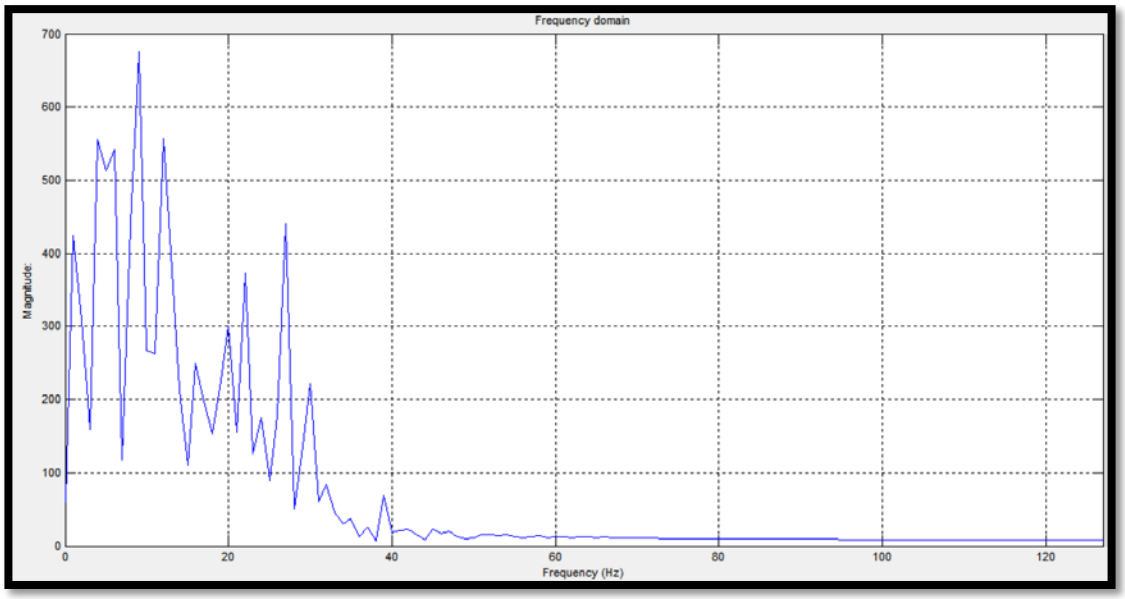

Figure 17. The magnitude of error signal of alcoholic subject 1 in frequency domain

Figure 16 and Figure 17 shows the time domain response and frequency domain response of alcoholic Subject 1 respectively. From Figure 16, it can be observed that, in time domain, the error signal (green) of the subject has erratic waveforms but it has relatively lower peak-to-peak amplitude compared to the input signal (blue). In Figure 17, it can be seen that the harmonic components are mostly in the band of 0-30 Hz.

Subject 2

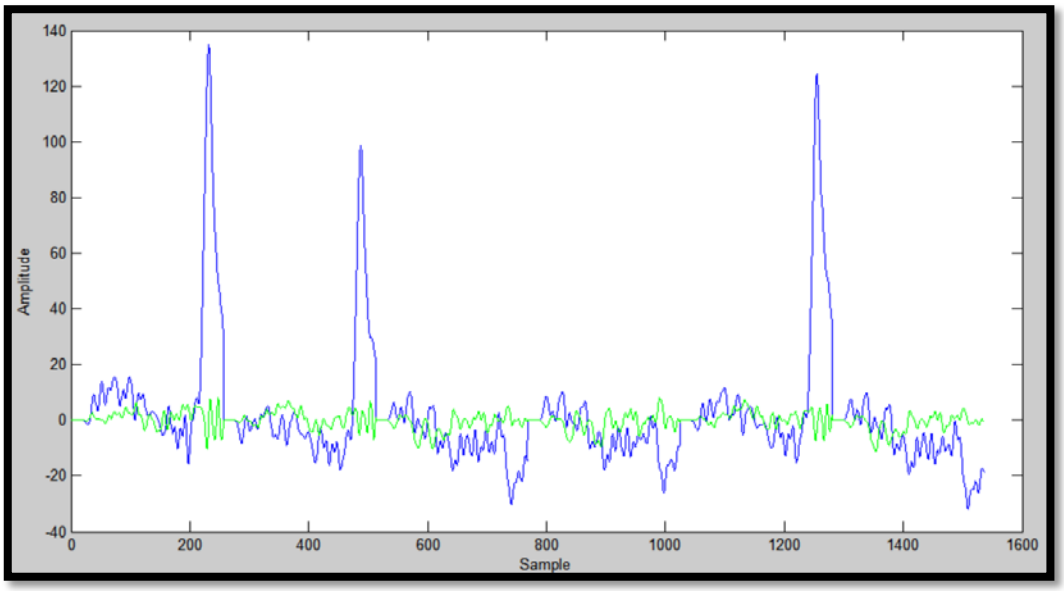

Figure 18. The input signal (blue) and error signal (green) of alcoholic subject 2 in time domain

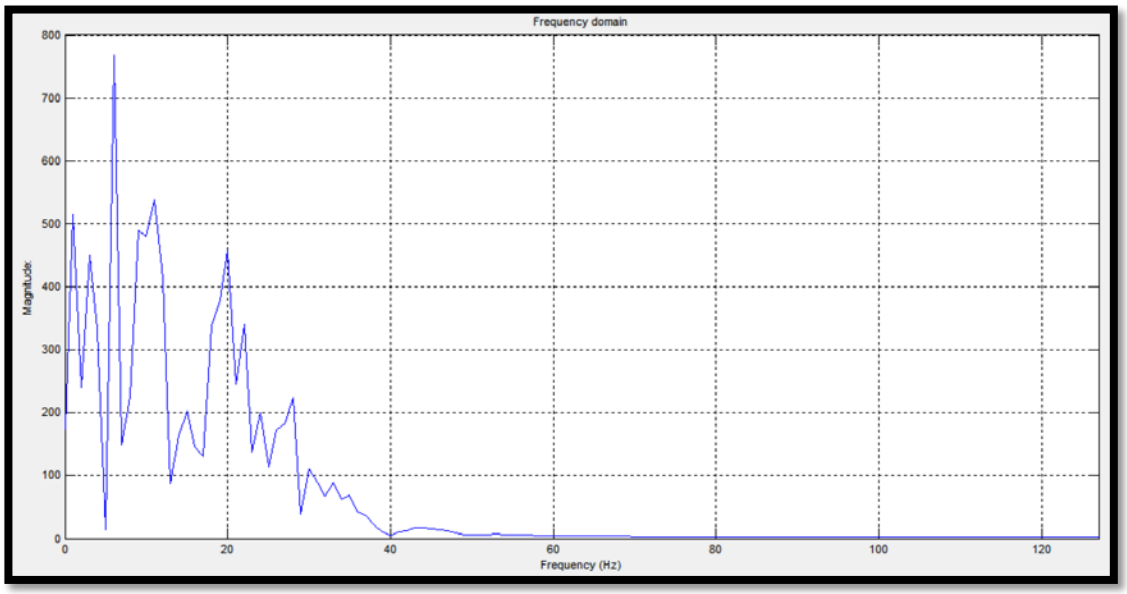

Figure 19. The magnitude of error signal of alcoholic subject 2 in frequency domain

Figure 18 and Figure 19 shows the time domain response and frequency domain response of alcoholic Subject 2 respectively. From Figure 18, it can be seen that the error signal (green) has none of the peaks or dips of the input signal (blue). Its-peak-to-peak amplitude is also much reduced compared to the input signal. In Figure 19, it can be observed that the harmonic components of the error signal are mostly centered in the frequency region of 0-30 Hz.

Subject 3

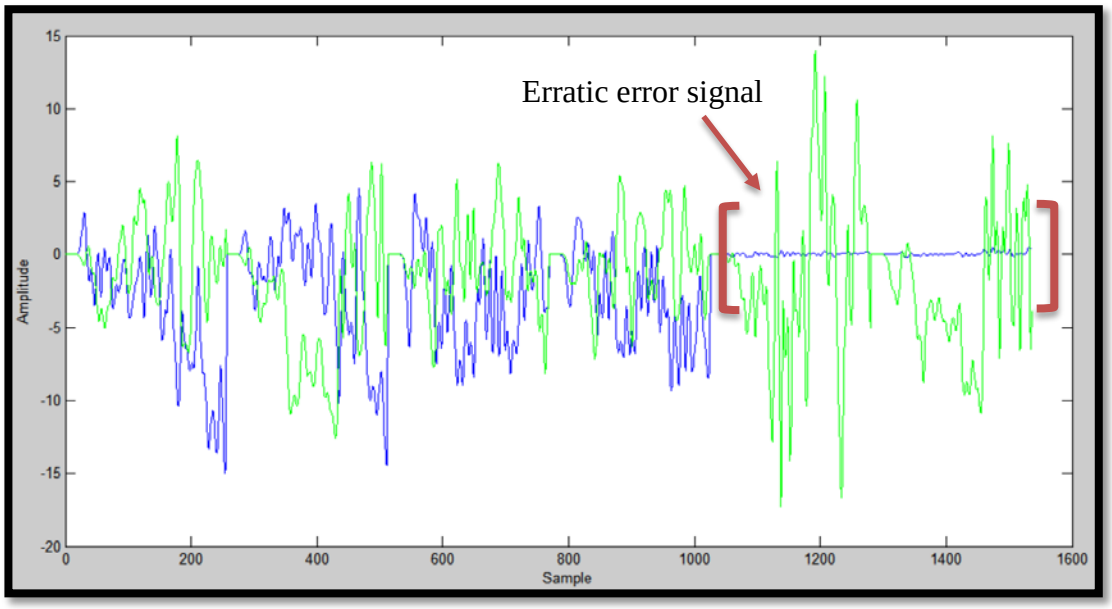

Figure 20. The input signal (blue) and error signal (green) of alcoholic subject 3 in time domain

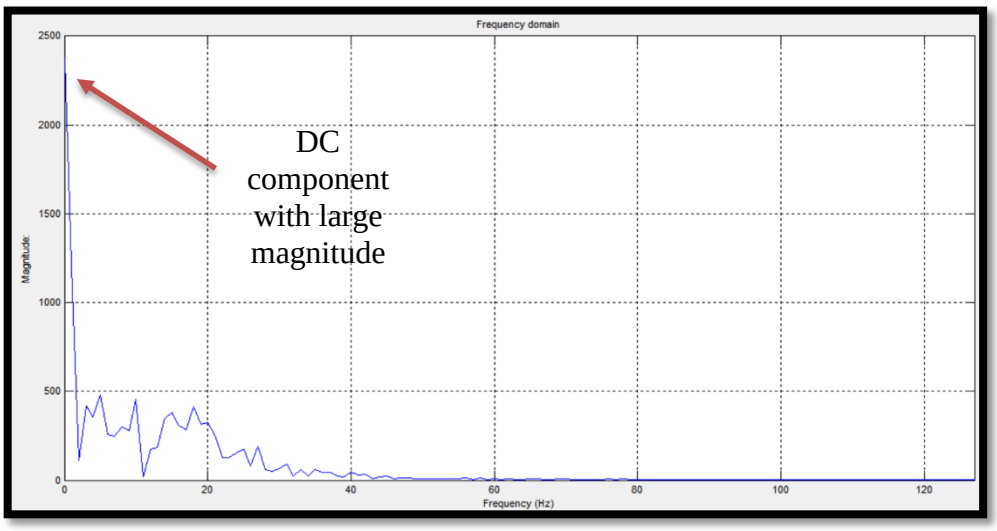

Figure 21. The magnitude of error signal of alcoholic subject 3 in frequency domain

Figure 20 and Figure 21 shows the time domain response and frequency domain response of alcoholic Subject 3 respectively. In Figure 20, the error signal (green) has extremely erratic behavior. It can be seen that at nodes FPZ (sample number 1025 to 1280) and OZ (sample number 1281 to 1536), the error signal behaves erratically even though there is minimal amplitude from the input signal (blue). The peak-to-peak amplitude of the error signal is actually higher than that of the input signal. In Figure 21, it can be seen that the DC component of the error signal has a very high magnitude.

Subject 4

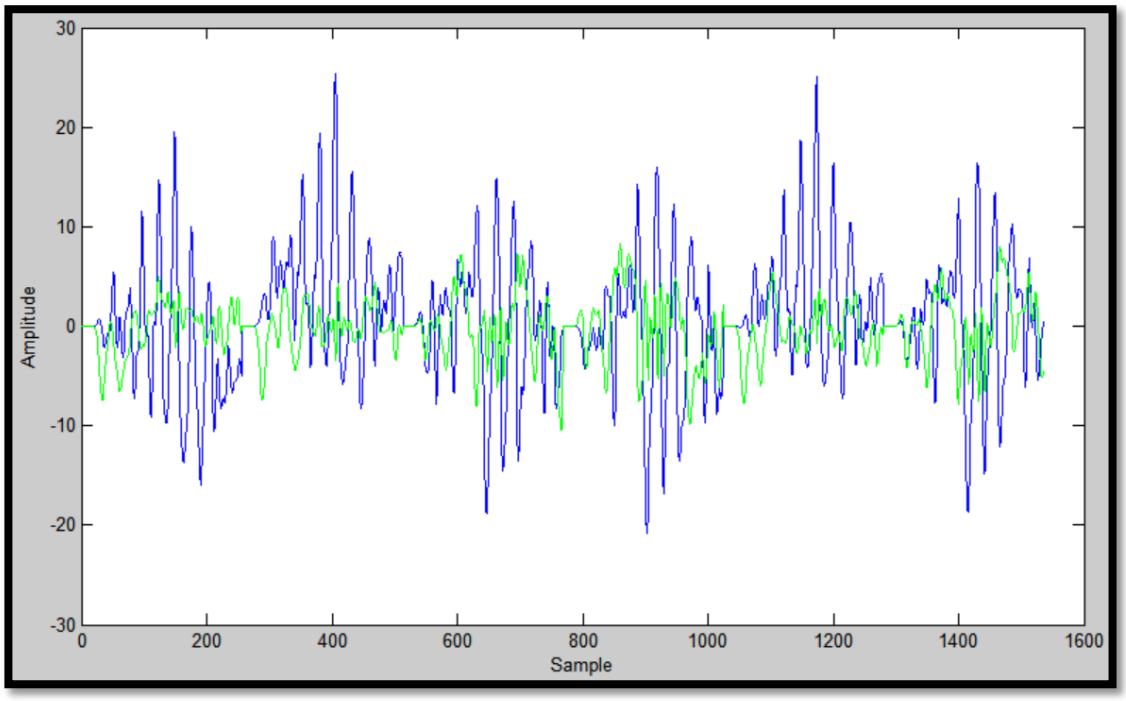

Figure 22. The input signal (blue) and error signal (green) of alcoholic subject 4 in time domain

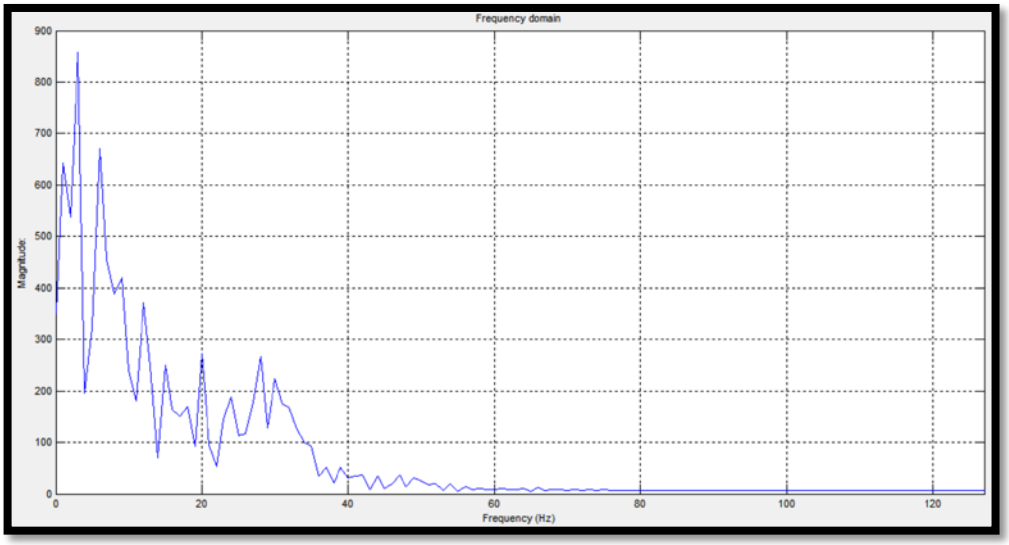

Figure 23. The magnitude of error signal of alcoholic subject 4 in frequency domain

Figure 22 and Figure 23 shows the time domain response and frequency domain response of alcoholic Subject 4 respectively. It can be observed in Figure 22 that the error signal (green) has reduced peak-to-peak amplitude compared to the input signal (blue). In Figure 23, it can be seen that the harmonic components are mostly in the region of 0–30 Hz.

Subject 5

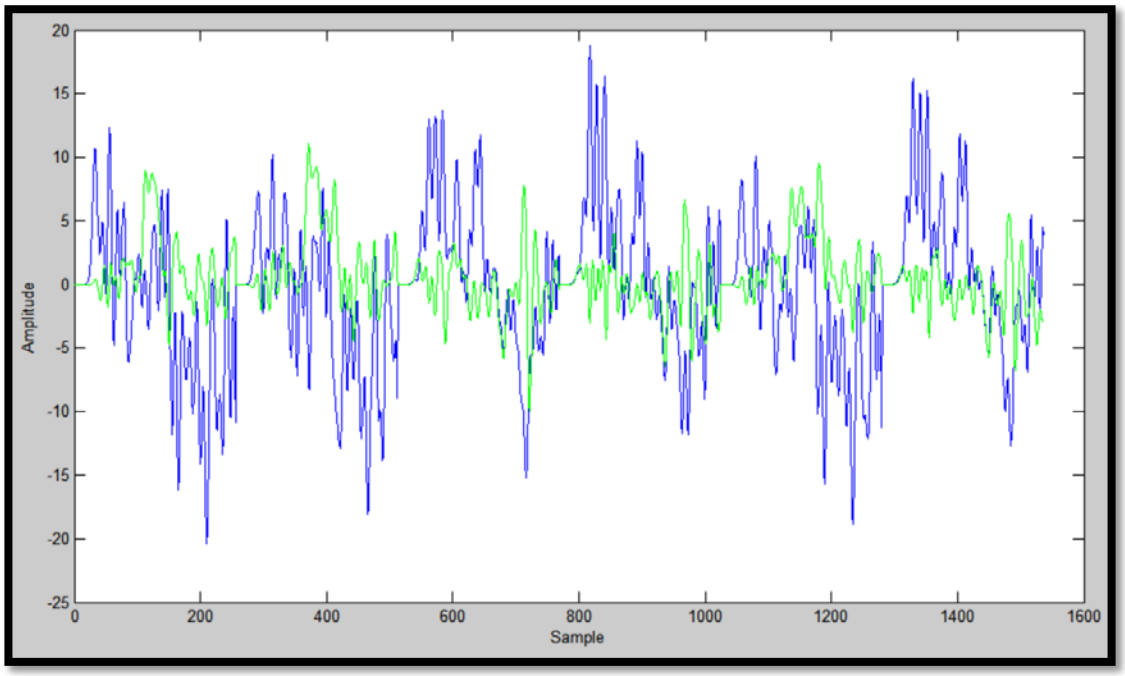

Figure 24. The input signal (blue) and error signal (green) of alcoholic subject 5 in time domain

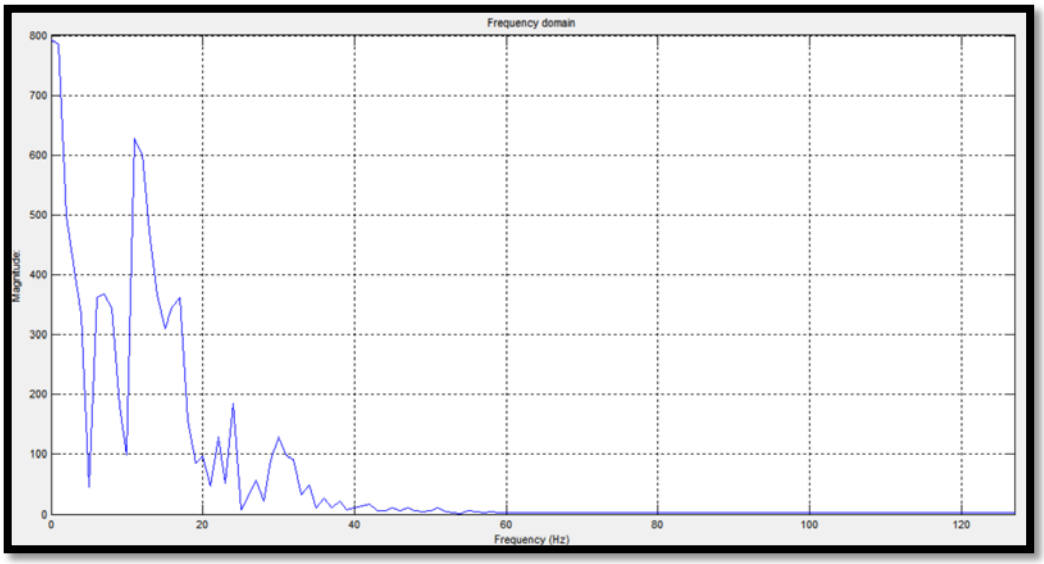

Figure 25. The magnitude of error signal of alcoholic subject 5 in frequency domain

Figure 24 and Figure 25 shows the time domain response and frequency domain response of alcoholic Subject 5 respectively. Like most of the error signals of the other alcoholic subjects, in Figure 24, the error signal (green) of the subject has lower peak-to-peak amplitude compared to the input signal (blue). The harmonic components of the error signal, as seen in Figure 25, are located mainly in the region of 0-30 Hz.

Non-alcoholic Subjects

Subject 1

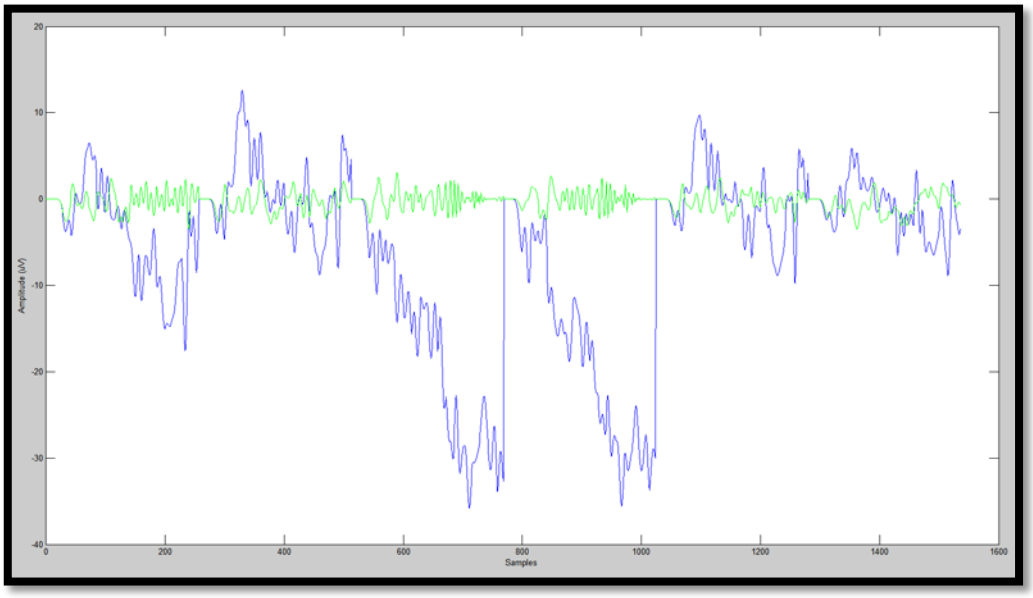

Figure 26. The input signal (blue) and error signal (green) of non-alcoholic subject 1 in time domain

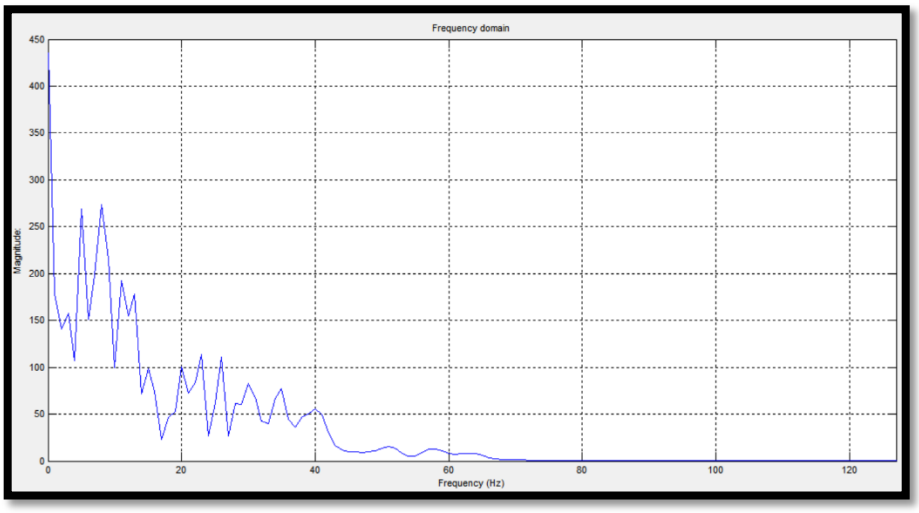

Figure 27. The magnitude of error signal of non-alcoholic subject 1 in frequency domain

Figure 26 and Figure 27 shows the time domain response and frequency domain response of non-alcoholic Subject 1 respectively. From Figure 26, the error signal (green) has none of the negative peaks of the input signal (blue). It also has significantly reduced peak-to-peak amplitude when compared to the input signal. The harmonic components of the error signal are mostly concentrated in the frequency band of 0-30 Hz.

Subject 2

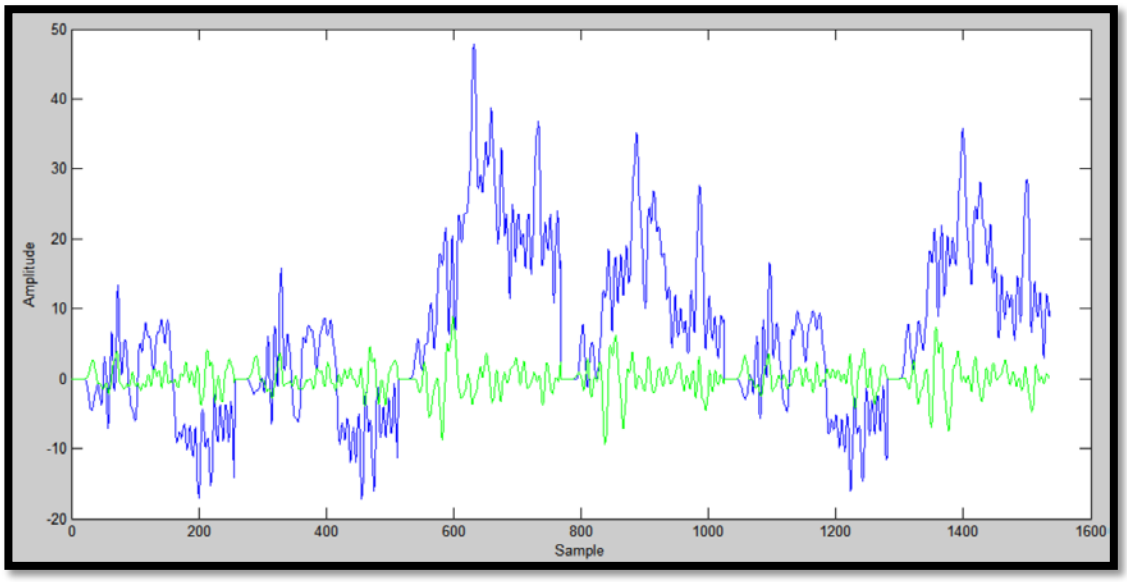

Figure 28. The input signal (blue) and error signal (green) of non-alcoholic subject 2 in time domain

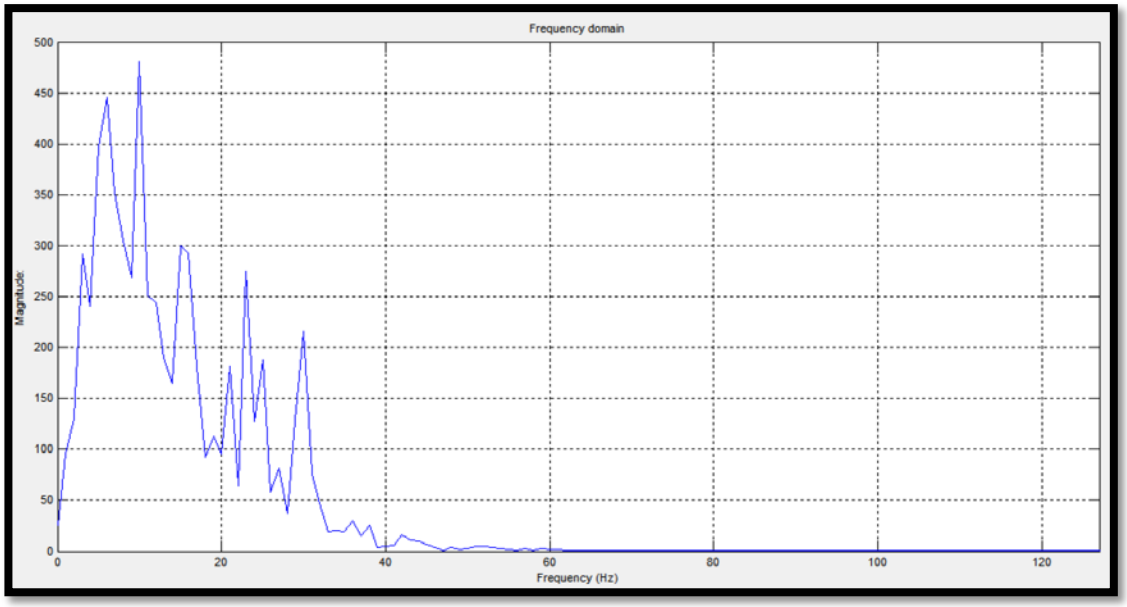

Figure 29. The magnitude of error signal of non-alcoholic subject 2 in frequency domain

Figure 28 and Figure 29 shows the time domain response and frequency domain response of non-alcoholic Subject 2 respectively. Like the previous subject, the error signal (green) has lower peak-to-peak amplitude compared to the input signal (blue), as seen in Figure 28. Similarly, by referring to Figure 29, the magnitude of the error signal is also focused in the region of 0-30 Hz.

Subject 3

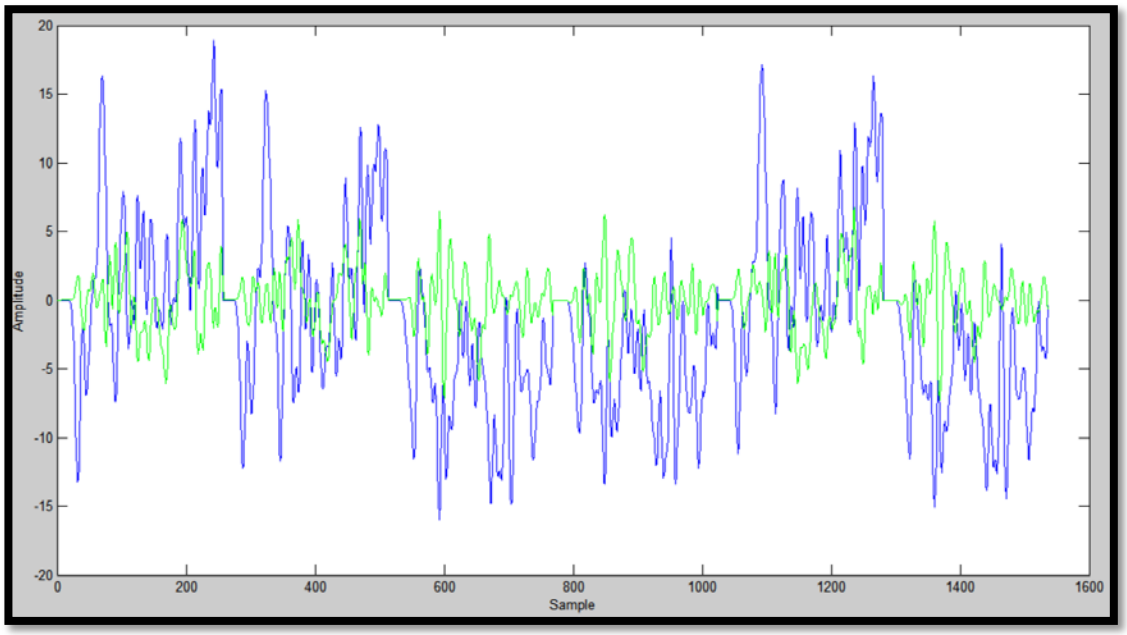

Figure 30. The input signal (blue) and error signal (green) of non-alcoholic subject 3 in time domain

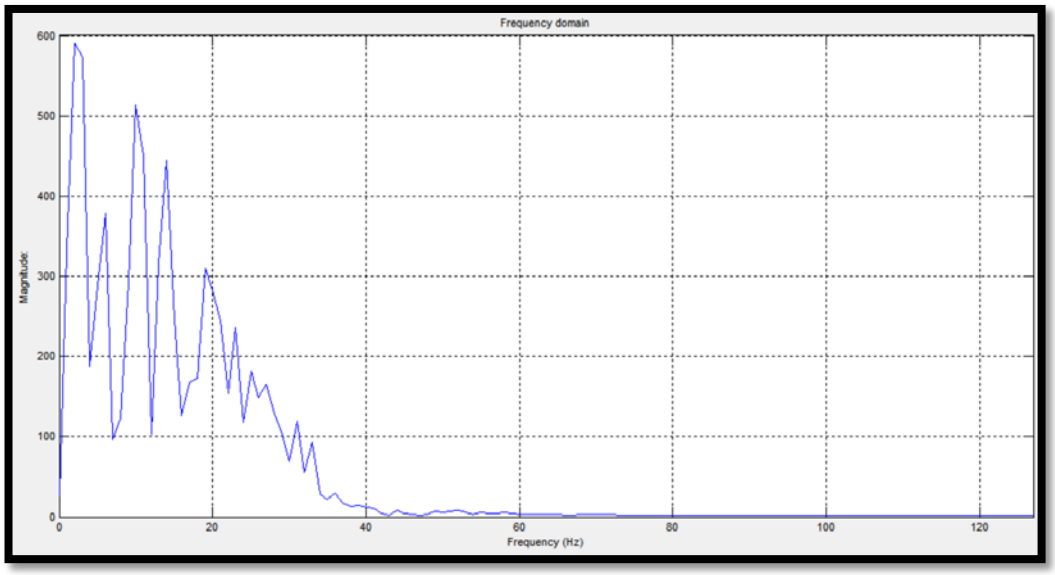

Figure 31. The magnitude of error response of non-alcoholic subject 3 in frequency domain

Figure 30 and Figure 31 shows the time domain response and frequency domain response of non-alcoholic Subject 3 respectively. From Figure 30, it can be observed that the error signal (green) has lower peak-to-peak amplitude compared to the input signal (blue). From Figure 31, the harmonic components of the error signal are found mainly to be residing in the frequency range of 0-30 Hz.

Subject 4

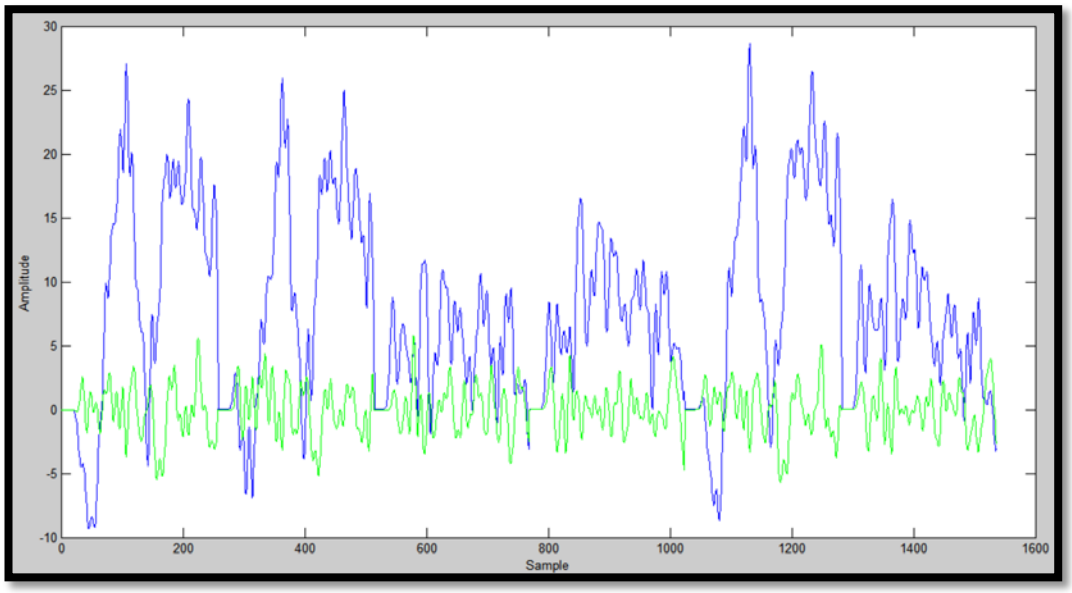

Figure 32. The input signal (blue) and error signal (green) of non-alcoholic subject 4 in time domain

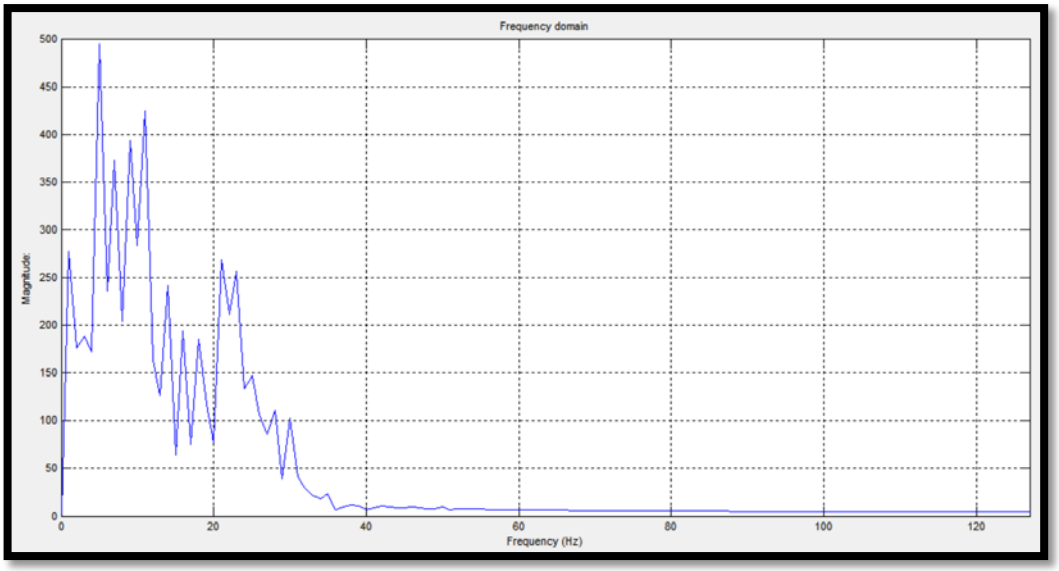

Figure 33. The magnitude of error signal of non-alcoholic subject 4 in frequency domain

Figure 32 and Figure 33 shows the time domain response and frequency domain response of non-alcoholic Subject 4 respectively. Figure 32 illustrates how many of the peaks of the input signal (blue) were not carried over to the error signal (green). The peak-to-peak amplitude of the error signal is greatly reduced when compared to the input signal. From Figure 33, it can be observed, like many other error signals in frequency domain, that the harmonic components are mostly in the band of 0-30 Hz.

Subject 5

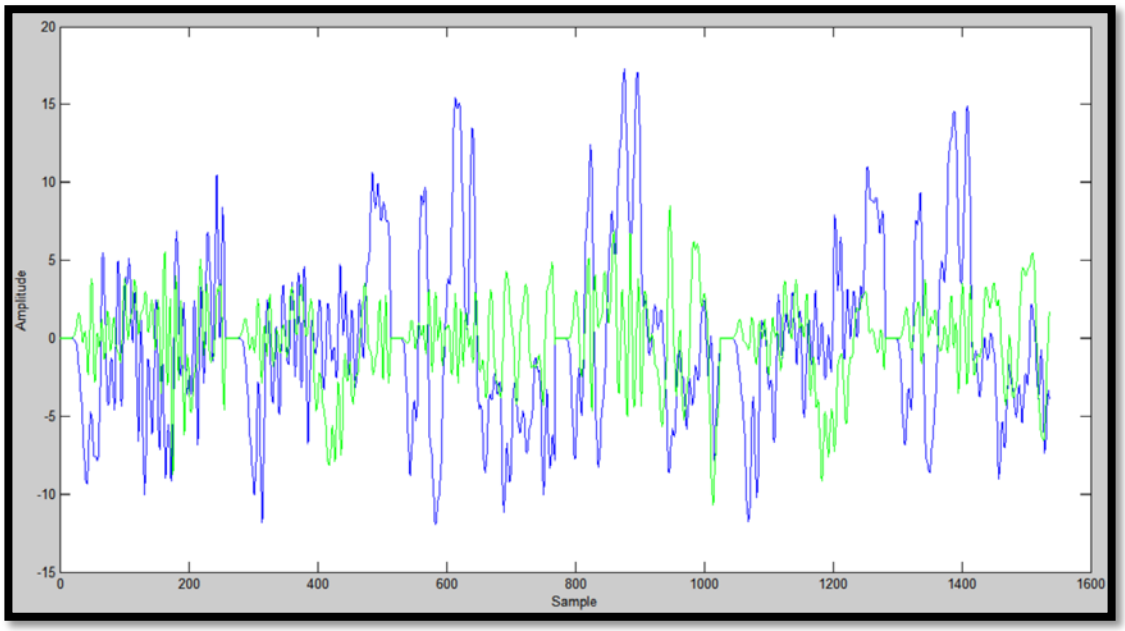

Figure 34. The input signal (blue) and error signal (green) of non-alcoholic subject 5 in time domain

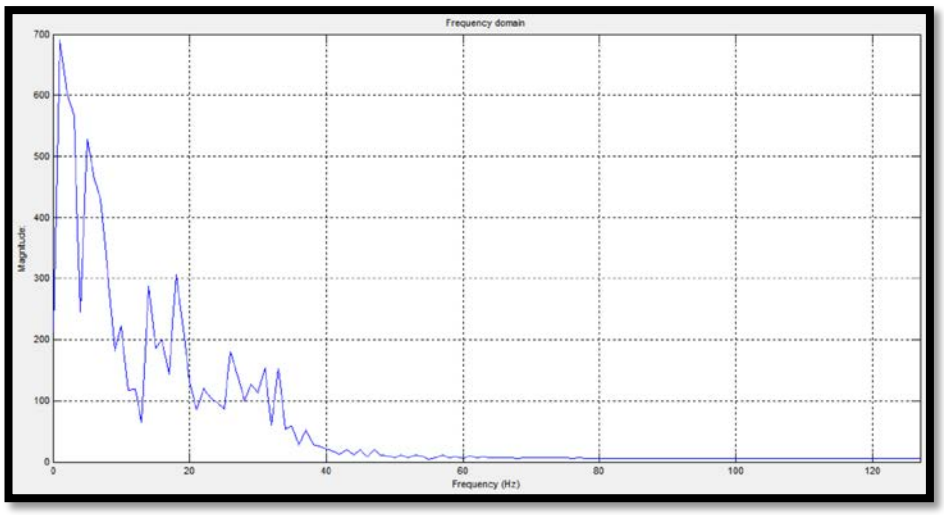

Figure 35. The magnitude of error signal of non-alcoholic subject 5 in frequency domain

Figure 34 and Figure 35 shows the time domain response and frequency domain response of non-alcoholic Subject 5 respectively. From Figure 34, the error signal (green) has noticeably lower peak-to-peak amplitude compared to the input signal (blue) but there are some spikes and dips. Like the previous subjects, the harmonic components of the error signal are concentrated in the region of 0-30 Hz, as seen in Figure 35.

When comparing alcoholic subjects with non-alcoholic subjects, it can be observed that the error signals in time domain from the alcoholic subjects are slightly more erratic than the error signals from the non-alcoholic subjects. Besides that, the error signals of the alcoholic subjects have a marginally higher peak-to-peak amplitude compared to the non-alcoholic subjects. These differences could be attributed to the genetic predisposition of the subject. It can also be observed that alcoholic subjects have a higher magnitude in frequency domain compared to the non-alcoholic subjects.

Table 3. Standard deviation and mean of the error signals for alcoholic and non-alcoholic subjects

Subject	Alcoholic		Non-alcoholic	
	Standard Deviation	Mean	Standard Deviation	Mean
1	2.9170	0.0957	1.1408	-0.2833
2	3.1606	-0.1135	2.0394	-0.0163
3	4.1219	-1.5487	2.1415	-0.0166
4	3.0430	-0.2285	1.8497	-0.0020
5	2.7081	0.5157	2.6922	-0.1384

Table 3 details the standard deviation and mean of the error signals from all the alcoholic and non-alcoholic subjects. Note that each condition has their own separate 5 subjects, e.g. Subject 1 for alcoholic condition and Subject 1 for non-alcoholic condition are not the same person. The same goes for all the other subjects.

It can be observed that the error signals from alcoholic subjects have a generally higher standard deviation as compared to the error signals from the non-alcoholic subjects. However, there is only a slight difference in standard deviation between alcoholic Subject 5 and non-alcoholic Subject 5.

Meanwhile, when comparing alcoholic and non-alcoholic subjects in terms of mean of the error signal, there is not enough observable difference to properly differentiate between both conditions. Based on this observation, it is safe to conclude that using the mean of the error signal from the LMS adaptive filter is not suitable enough to differentiate between subjects under alcoholic and non-alcoholic conditions.

4.2 Discussion

The computation time needed for the LMS algorithm was very short; the filtering of the EEG signal was completed in a matter of seconds. This is one of the benefits of using LMS adaptive filter as it will be very useful in situations where time is a constraint. The speed can be adjusted by changing the step size of the filter. A smaller step size increases the time taken for the filter to converge on a set of coefficients but increases its accuracy. On the other hand, a larger step size reduces the time taken but a step size that is too large may cause the filter to diverge, becoming unstable and unable to converge. For this filter, a miniscule step size was chosen to maximize accuracy.

The similarity shared by the error response obtained from both alcoholic and non-alcoholic subjects is a reduction in amplitude in time domain compared to the input signal. This is due to the adaptive filter filtering the input signal using coefficients that are iteratively updated based on the LMS algorithm in order to obtain the desired signal.

Generally, when error signal of all the subjects was transformed from the time domain to the frequency domain, the harmonic components are concentrated in the region of 0-30 Hz. This is due to the input VEP EEG signals going through a Butterworth low-pass filter before being used as input signals to the LMS adaptive filter. As explained earlier, this is because most of the important brain activities are focused in this frequency band. Frequencies that are above this range are irrelevant to the current objective of this project.

Based on the results, the standard deviation of the error signal for each subject was obtained. From this, it can be seen that there is a certain range of values whereby the condition of a subject could be confidently classified. For example, for values of standard deviation below 2, it can be deducted as most likely belonging to a subject with a non-alcoholic condition. On the other hand, for values of standard deviation above 3, it can assumed that these belong to a subject with an alcoholic condition. However, for values of standard deviation between 2 and 3, it can be harder to classify a subject into alcoholic or non-alcoholic conditions.

CHAPTER 5
CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The study of VEPs contained in EEG signals has numerous applications, from detecting disorders in the visual pathways to studying the reaction of the visual cortex to visual stimuli. An example would be a situation where a doctor who is treating a patient requires information regarding the brain activity of the patient in response to visual stimuli. A fast and accurate depiction of the evoked potentials present in the patient's brain activity would be vital in this case.

VEPs are produced when a visual stimuli is presented a subject. The waveform of the VEP depends on what stimuli is presented and the condition of the subject. For this project, the stimuli is kept constant while the condition of the subject is manipulated into alcoholic and non-alcoholic. One way to differentiate between subjects under these two conditions is to analyse the error response of the subjects. The LMS adaptive filter was used to obtain the error response of the subjects under different conditions as it is simple to implement and has low computational complexity.

From the results obtained, it can be seen that the waveform of the error response from the alcoholic subjects has a slightly more erratic behaviour, marginally higher peak-to-peak amplitude, and higher magnitude when compared to the non-alcoholic subject. Error signals from alcoholic subjects also have generally higher standard deviation compared to non-alcoholic subjects.

As a conclusion, it has been proven that it is possible to differentiate between subjects under alcoholic and non-alcoholic conditions based on their error response using LMS adaptive filter within a certain range of values. Further study may be necessary to further improve the definition of the range of values of standard deviation that define whether a subject is under alcoholic or non-alcoholic conditions.

5.2 Recommendations

The LMS algorithm is not perfect and there are many ways to improve it. As mentioned earlier, the step size used for the LMS adaptive filter affects the convergence time. A compromise between two opposing aspects, fast convergence rate and low maladjustment is necessary [13]. One method that can be used to overcome this is by using time-varying step size can be implemented [10]. This solution works by using large step size values when the optimal solution is still far away from being achieved, thus increasing the rate of convergence. Once the optimal solution is near, the step size values are reduced to small values in order to reduce inaccuracies. Therefore, better performance can be produced.

The differences in standard deviation of error signal between alcoholic and non-alcoholic subject require a larger sample size to obtain a more defined range. With a higher sample size, it would be easier get a clearer picture of the values of standard deviation that belong to subjects under alcoholic and non-alcoholic conditions.

Another possible usage for the LMS algorithm that was adapted during the course of this project is the extraction of VEP components from EEG signals. This is possible if the desired signal is an EEG signal containing VEP components while the input signal to the filter has all the other components in the desired signal minus the VEP components. Since the output of the filter will try to mimic the desired signal as possible in terms of correlated variables, the error signal from the filter will be the VEP signal itself without any background EEG noise. However, both the input signal and desired signal must have some correlation with each other in terms of components for this to work. Simulations aimed at accomplishing this was done and it was found that it is possible to do so if both the input signal and desired signal were created artificially. Unfortunately, application of this adaptive filter on real signals turn out to be unsuccessful due to the lack of a proper input signal that is correlated to the desired signal.

REFERENCES

[1] A. C. Enache, C. Cepisca, A. M. Paraschiv, and C. K. Banica, "Virtual instrument for electroencephalography data acquisition," in *7th International Symposium on Advanced Topics in Electrical Engineering (ATEE)*, pp. 1-4, 2011.

[2] M. Teplan, "Fundamentals of EEG measurement," *Measurement science review*, vol. 2, pp. 1-11, 2002.

[3] P. Podder, M. M. Hasan, M. R. Islam, M. Sayeed, "Design and Implementation of Butterworth, Chebyshev-I and Elliptic Filter for Speech Signal Analysis," *International Journal of Computer Applications*, vol. 98, pp. 12-18, July, 2014.

[4] S. Herculano-Houzel, "The human brain in numbers: a linearly scaled-up primate brain," *Frontiers in Human Neuroscience*, vol. 3, November 9, 2009.

[5] G. Krishan, "Brain Signals and Alcoholism," *International Journal of Engineering Trends and Technology (IJETT)*, vol. 4, pp. 1998-2002, 2013.

[6] S. Tong and N. V. Thakor, *Quantitative EEG Analysis Methods and Clinical Applications*: Artech House, 2009.

[7] D. J. Creel, "Visually evoked potentials," *Webvision: The Organization of the Retina and Visual System. Salt Lake City: University of Utah Health Sciences Center*, pp. 201-229, 2012.

[8] D. K. Yanti, M. Z. Yusoff, and V. S. Asirvadam, "Single Trial Visual Evoked Potential Extraction using Partial Least Squares-based Approach," *IEEE Journal of Biomedical and Health Informatics*, vol. PP, no. 99. doi: 10.1109/JBHI.2014.2367152.

[9] T. Nguyen and P. Wira, "A Linear Multi-Layer Perceptron for Identifying Harmonic Contents of Biomedical Signals," in *Artificial Intelligence Applications and Innovations*. vol. 412, ed, pp. 262-271, 2013.

[10] A. K. Pradhan, A. Routray, and A. Basak, "Power system frequency estimation using least mean square technique," *IEEE Trans. Power Delivery*, vol. 20, pp. 1812-1816, 2005.

[11] C. A. Vaz and N. V. Thakor. "Adaptive Fourier estimation of time-varying evoked potentials," *IEEE Trans. Biomed. Eng. 36(4)*, 448-455, 1989.

[12] Y. Xiao-Hu, Z. Y. He, and Z. Yi-Sheng, "Time-varying adaptive filters for evoked potential estimation," *IEEE Trans. Biomed. Eng.*, vol. 41, pp. 1062-1071, 1994.

[13] T. Aboulnasr and K. Mayyas, "A robust variable step-size LMS-type algorithm: analysis and simulations," *IEEE Trans. Signal Processing*, vol. 45, pp. 631-639, 1997.

[14] D. O. Olguın, F. Bouchereau, & S. Martınez, "Adaptive notch filter for EEG signals based on the LMS algorithm with variable step-size parameter," in *Proc. of the 39th International Conference on Information Sciences and Systems*, March, 2005.

[15] F. Bi, T. Qiu, and N. Yu, "Robust Adaptive Estimator for Evoked Potentials Based on Non-Linear Transform Under Impulsive Noise Environments," *Journal of Medical and Biological Engineering*, vol. 32, no. 6, pp. 443-452, 2012.

[16] R. Palaniappan and P. Raveendran, "Recursive digital filter for fast visual evoked potential estimation and classification," Electronics Letters, vol. 37, pp. 990-992, 2001.