UNIVERSITY OF SOUTHERN QUEENSLAND

Removing Noise From Electroencephalogram Signals For BIS Based Depth of Anaesthesia Monitors

A Dissertation submitted by

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For the award of
Master of Engineering Research (MENR)

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2011

ABSTRACT

The assessment of patient has changed from the physical assessment to digital assessment. One significant example is the assessment of the depth of anaesthesia (DoA). It has changed from physical to digital assessment using DoA monitor. DoA monitor uses the electroencephalogram (EEG) signal as its input. The processes include the digitising, filtering and signal analysing. This study focuses on filtering process to reduce noise in the EEG signal.

Noises in EEG signals could affect the accuracy of DoA monitor. The noises in EEG signal are from the muscle, eye movement and blinking, power line, and interference with other device. Those noises are overlapped each other. Hence, monitoring of DoA without removing the noise may result in an incorrect assessment. A simple filtering process such as band pass filter is not able to remove all noise from EEG signals.

There are three methods which are introduced to remove noise from EEG signals. The first technique is adaptive least mean square technique, which is able to find the best output of the signal through the iteration. In this method ANOVA technique is employed to define the best coefficient of the signal in the adaptation. This technique is chosen to find the significant output from the iteration. The result shows that the adaptive least mean square with the ANOVA is able to remove the noise from EEG signal effectively.

The second method is Wavelet transform. In this technique, EEG signal is decomposed into five levels using the Stationary Wavelet Transform (SWT). The first step of this filtering is to eliminate high frequency noise in the EEG signal. The next step is to remove the low frequency noise using the soft threshold method. The final step is to reconstruct the signal. The result from this method shows that there is a significant improvement of the signal quality after the filtering.

The third method is a combination of adaptive LMS and wavelet transforms method. The result from this study shows that the wavelet transform adaptive filter is able to remove both the low frequency noise and high frequency noise in the EEG signal. Compare to the previous two other methods, the combined method is also more robust. Filtering the noise in EEG signal with wavelet transform adaptive filter technique could minimise false prediction of DoA.

CERTIFICATION OF DISSERTATION

I certify that the ideas, experimental work, results, analyses, software and conclusions reported in this dissertation are entirely my own effort, except where otherwise acknowledged. I also certify that the work is original and has not been previously submitted for any other award, except where otherwise acknowledged.

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Signature of Candidate Date

ENDORSEMENT

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Signature of Supervisor/s Date

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ACKNOWLEDGEMENTS

"It is God who arms me with strength, He makes my way perfect" (2 Samuel 22:33 NIV)

I would like to thank my supervisor, Associate Professor Paul Wen. I really appreciate his advice, guidance, support and encouragement. I cannot make it without his guidance.

The advice and support from Mr Steven Goh as associate supervisor are also acknowledged and wholly appreciated.

For all the precious help and friendship of the biomedical engineering research team, Mr Richard Landers, Shahab Abdulla, Tai Nguyen-Ky, Syed Salman Shahid, and Siuly. I am really thankful.

I would like also to acknowledge the generous tutorial help from Mr Richard Landers in MATLAB programming.

Special thanks for my dear wife and daughter, Adriana and Kearney, for their love and cheering.

For all the people who have provided assistance and support, thank you very much.

Special thanks to the Indonesian government which financially supported me through Indonesian DGHE (DIKTI) Scholarship.

TABLE OF CONTENT

TABLE OF FIGURE

LIST OF ABBREVIATION

AP	= Action Potential
BIS	= Bispectral Index
CBF	= Cerebral blood flow
CSM	= Cerebral State Monitor
DoA	= Depth of anaesthesia
DWT	= Discrete Wavelet Transform
EEG	= Electroencephalogram
EMG	= Electromyography
EOG	= Electrooculogram
MAC	= Minimum Alveolar Concentration
MLAEP	= Mid-Latency Auditory Evoked Potential
MSE	= Mean square error
MSG	= Mean square
PSA	= Patient state Analyser
SNR	= Signal to noise ratio
SWT	= Stationary Wavelet Transform

I. INTRODUCTION

I.1 Background

Brain signal is an electrical activity of neuron. It can be monitored and recorded. Brain signals are known as electroencephalogram (EEG) signal. EEG signal from the brain can be affected by medicine (drugs) intake, diseases, deficiency or disability. Therefore, the information obtained from EEG signal is beneficial to identify clinical related problem such as brain injury, coma, head injury, stroke, epilepsy, sleep disorder, and depth of anaesthesia.

EEG signal activity reflects the effect of anaesthetics agents. The effect of anaesthetics agents (contain analgesic and hypnotic agents) on the brain could depress the brain activity and cause the person unconscious which causes different EEG pattern (Kelley, 2003; Sice, 2005). The changing pattern in EEG signal under the effect of anaesthetics agent is an indicator of level of consciousness. As the amount of anaesthetics agent increases, the signals changed from low amplitude high frequency to high amplitude low frequency (Gelb et al, 2009). The variability of this signal gives different level of consciousness of the patient. Then, the varying pattern of the EEG signal is translated into an index of the level of consciousness.

The level of consciousness or unconsciousness under general anaesthesia is defined as depth of anaesthesia (Gelb et al, 2009). Maintaining the specific level of consciousness with DoA monitor may reduce the inter-operative awareness and overdose (Sebel et al, 2004). Inter-operative awareness is defined as the recall of events during surgery (Bowdle, 2006). Inter-operative awareness happened if the persons does not receive sufficient anaesthetic agent. The inter-operative awareness may affect mental anxiety of the patients and physiological effects (Lennmarken et al., 2002; Avidan et al., 2008). On the other hand, the overdose of anaesthetics agent also could cause brain death and longer recovery time (Bowdle, 2006).

A number of DoA monitors have been developed to help anaesthetists in the operation room. Those monitors use different techniques of digital signal processing to produce an index of DoA. The DoA equipment available in the market includes (Bowdle, 2006):

1. Bispectral Index (BIS)
2. Narcotrend
3. Cerebral state analyser
4. SNAP index
5. AEP or AAI (Mid-latency auditory-evoked potential=MLAEP)

Although all those monitors are available in the market BIS monitor is the most widely used in hospitals around the world (Musizza, 2010). Figure 1 shows the BIS monitor. This monitor uses the EEG signal directly to derive the DoA index. The components of the BIS are the BIS sensor, monitor, BISx (EEG signal pre-processing and filtering), and patient interface cable (PIC) (Aspec Medical System, 2009). The BIS monitor indicates the level of consciousness using an index from 100 (awake) to zero (isoelectric) (Kelley, 2003).

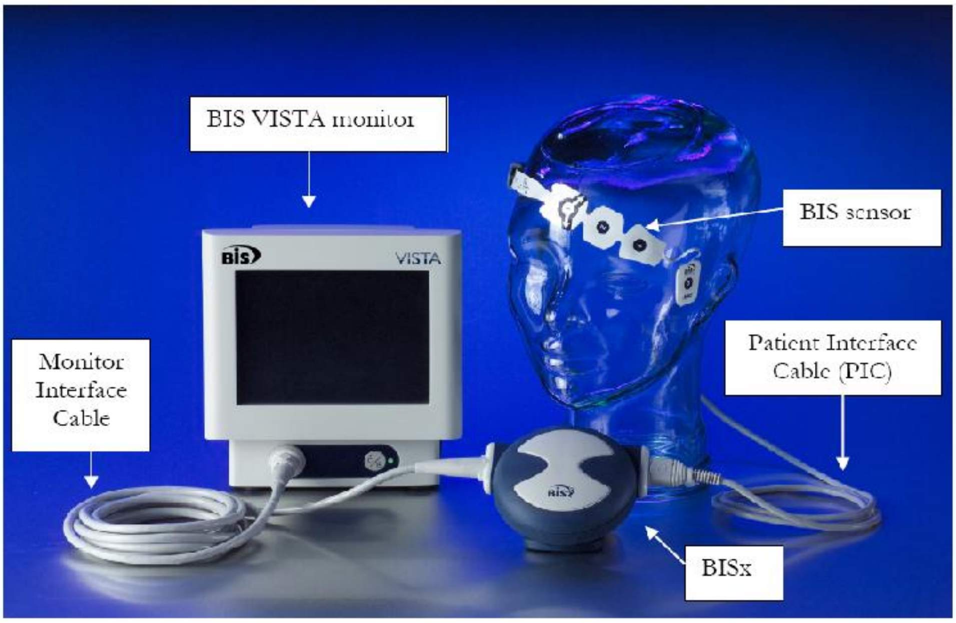


Figure 1. BIS Monitor (Source: Aspec Medical System, 2009)

Figure 2 shows the Cerebral State Analyser, Narcotrend and AEP monitor. Those monitoring also uses EEG signal as a source to measure the DoA. Cerebral state Analyser was introduced in 2004 by the Danmeter Company, Denmark. The Narcotrend monitor was developed by Monitor-Technik, Germany and it was first introduced in 2000. The AEP is produced by Danmeter Company. The AEP monitor-1 uses the auditory evoked potential signal as an input to produce the DoA index. The company has improved the first AEP monitor with the combining auditory evoked potential and EEG signal analysis, which is known as AEP monitor-2 (Bowdle, 2006).

Figure 2. Cerebral state Analyser, Narcotrend and AEP Monitor (Source: Various)

The signal processing technique in DoA monitor consists of the pre-processing segment for the input signal. The pre-processing segment includes the digitizing and signal filtering. Those two processes are significant for further analysing the signal. However, the filtering process is the most important one to the reliability of the DoA monitor (Musizza, 2010).

EEG signal is more often contaminated with noises. The most common noise in EEG is from the muscle or electromyogram (EMG), power line frequency (50 Hz or 60 Hz), and electrooculogram (EOG) (Johansen, 2006; Krishnaveni, 2006). The EOG signal comes from the eye movement and eye blinking. Eye movement causes the electrical field around the eye and it interfere the EEG signal over the scalp (Croft & Barry, 2000). Removing a noise with simple filtering technique will remove some important information from the signal as well.

Ranges of filtering techniques have introduced to remove noise in EEG signal. Existing filtering techniques used such as the adaptive filtering using recursive least square, discrete wavelet transform technique, a combination of the adaptive filtering and discrete wavelet transform has widely used. Most of the existing techniques can only remove either EOG signal or EMG signal, but not both.

Kumar (2009), introduced the adaptive method using wavelet transform to remove noise. This technique uses the recursive least square (RLS) and wavelet transform. The first step is to decompose the contaminated EEG signal. The second step is to feed the decomposed signals to the adaptive RLS filter. The final step is to subtract the contaminated EEG signal with the output from the RLS filter, the output of the final step is considered as clean EEG signal (Kumar, 2009). However, the proposed technique by Kumar only removes EOG noise from the EEG signal. Therefore it is necessary to improve the filtering technique so it is able to remove all the noise in EEG signal.

I.2 Research Problems

BIS is widely used in hospitals around the world. However, there are some limitations such as (Bowdle, 2006; Johansen, 2006; Frey, 2007-2011):

1. Does not respond properly to all anaesthetics agent such as nitrous oxide, ketamine and opioids.

2. The filtering technique is not able to remove noise such as EMG, ECG and EOG (Johansen, 2006). Bowdle (2006) explained that the increasing value of EMG could raise the BIS index.
3. The uncertainties of the BIS value make it difficult to compare the result with other version of BIS monitor. In addition, the index is not consistent with the anaesthetics agent type and patients (Frey, 2011).
4. Problems for validating the BIS monitor in children.

BIS monitor analyses the EEG signals in the ranges of 0 to 60 Hz. These signals are often contaminated by the EOG signal ranges from 0 to 20 Hz and the EMG signal ranges from 0 to more than 200 Hz (Krishnaveni, 2006 ; Dauwels, Vialatte & Cichocki, 2010). Those signals are overlapping to each other. Simpler filters such as band-pass filter could remove useful information.

Based on the problems have listed previously, research question of this work are: Is it possible to develop a new filtering technique to remove noise from EEG signal using Wavelet transform and adaptive filter? How to design more efficient filters and evaluate them in comparison to the other filtering techniques?

This research focuses on the improvement of filtering process of EEG signal.

I.3 Objectives

- Identify the noise and their features in EEG signal.
- Analyse and improve the existing filtering techniques of DoA monitor in simulation.

- Develop new filtering techniques using wavelet transform, and adaptive technique.
- Apply the developed new filtering technique to the EEG signal, and evaluate their performance.

The contribution of the research could improve the DoA monitor by removing the noise from EEG signal. It is expected that the filtering technique could minimise false prediction in DoA.

I.4 Thesis Outline

The thesis consists of six chapters. Chapter one presents the background of developing new filtering techniques for DoA monitor. This chapter also includes the research problems and objectives of this research.

Chapter two is a literature review of DoA monitor and EEG signal. It also introduce the assessment of DoA, different methods for DoA monitoring and BIS index.

Chapter three investigates the filtering process using adaptive least mean square technique with analysis of variance to define the best coefficient of the filter.

Chapter four studies the wavelet transform technique to remove noise in EEG signal and the SWT technique to remove high frequency noise and low frequency noise in EEG signal.

Chapter five is to combine wavelet adaptive filter and least mean square technique. This chapter shows wavelet adaptive filter is more robust and advance in filtering compare to the other filtering techniques.

Chapter six covers the discussions, conclusion and recommendation for the future work.

I.5 Publication

Palendeng M.E, Wen P, Goh S, "Investigation of BIS Index Filtering and Improvement Using Wavelet Transform Adaptive Filter“, *IEEE International Conference on Nano/Molecular Medicine and Engineering 2010 (4th IEEE-NANOMED)*, Hongkong, 5-9 December 2010.

Palendeng M.E, Wen P, Goh S, “Removing ocular artifact from EEG using Stationary Wavelet Transform”, *Engineering and Physical Sciences in Medicine and the Australian Biomedical Engineering Conference (EPSM-ABEC) 2011*, Darwin, 14-18 August 2011. (Accepted)

II. DEPTH OF ANAESTHESIA MONITORING

II.1 Depth of Anaesthesia Assessment

During a surgery, it is common to use anaesthetics agent. However, it is important to administer the correct amount of anaesthetic agent. If the amount is inadequate, the patient may experience inter-operative awareness. Inter-operative awareness is defined as the explicit recall of events during surgery (Bowdle, 2006). In simple words, it means the condition where the patient is not fully unconscious so that the patient seems to dream or slightly aware what had happen during operation. Conversely, if the amount is more than required, the patient may stay unaware for longer time. In addition, an overdose may harm or damage the brain (Bowdle, 2006). A long term brain damage can lead to paralysed or death (Myles, 2007; Braz, 2009).

Over the years, the numbers of incident of awareness has been reduced from 1-2 % to 0.1% (Myles, 2007; Musizza, 2010). Moreover, the number of mortality rate related to general anaesthesia in the operation room in developed countries has reduced to lower than 1 per 10,000 patients (Braz, 2009). In contrast, the mortality rate in developing country ranging from 3.30 to 5.70 per 10,000 patients (Braz, 2009; Musizza, 2010).

II.1.1 Physical Assessment

The first known method for DoA monitoring is physical assessment. In medical term, this physical assessment is called autonomic sign. The physical assessment includes the assessment of heart rate, pupil dilation response, breathing pattern, increased blood pressure, and absence of movement (Kelley, 2003; Myles, 2007). Figure 3 illustrates the schematic process of physical assessment.

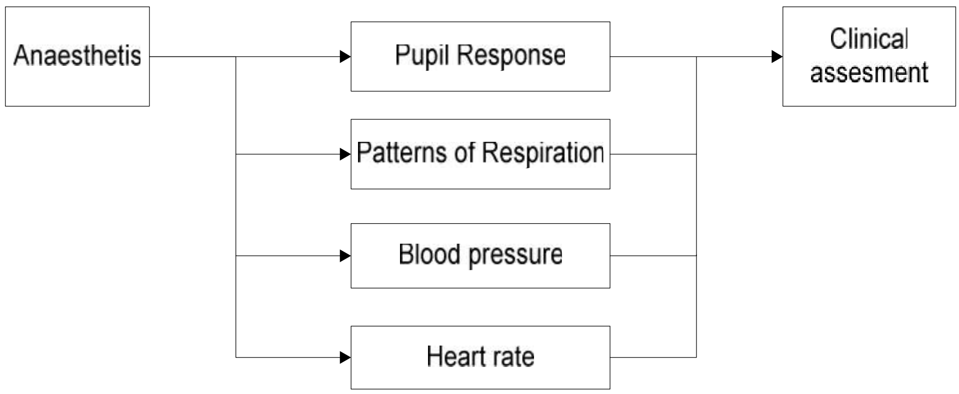


Figure 3. Physical assessments for Depth of Anaesthesia Monitoring

Physical assessment is less reliable in measuring the depth of unconsciousness. The reason is that different patients may response differently to the stimulus and the effect of anaesthetics agent is also different among each patient. For example, under the same amount of anaesthetics agent, two patients at similar age group may have different heart rate. Kaul (2002) reported that the blood pressure remained constant on the first hour of Halothane anaesthetics, therefore the blood pressure is not reliable for monitoring DoA. Moreover, for a typical healthy person the pupil dilation can give response to light but for a person under anaesthetic, the dilation of pupil may not response properly (Myles, 2007; Gelb, 2009). Therefore, it is difficult to translate the physical signs into to a certain level of consciousness.

II.1.2 Monitoring with DoA device

A more advance assessment method to monitor DoA during the administration of anaesthetics agent is the use of digital monitoring. The digital monitoring produces a more accurate and reliable result. The monitor gives a prediction of patient response to stimuli (Kissin, 2000). In addition, it will help in administering correct amount of anaesthetics agent.

DoA assessment is more complicated in the conjunction anaesthetics agent with muscle relaxant. An incident of awareness is reported approximately between one per 500 patients and one per 1000 in administering muscle relaxant during anaesthesia (Maclaurin, 2002; Sneyd cited in Sice, 2005, p.1). Absent of movement in a response of painful stimuli to assume the person unconscious is not reliable when muscle relaxant is applied (Sice, 2005). Patient movement in physical assessments is reflecting the analgesic agent instead of hypnotic agent (Myles, 2007). Therefore, it is necessary to measure the DoA with DoA device.

The classical concept of minimum alveolar concentration (MAC) is a golden standard for inhaled anaesthetics concentration. Some researcher believes administration of at least 0.5 MAC inhaled agent prevents the awareness (Myles, 2007; Musizza, 2010). However, the relative value of MAC is less similarity among the intravenous hypnotic (Gelb, 2009). This is because of the estimation of plasma concentration using pharmacokinetics are different (Sice, 2005).

Assessing patient movement and response to stimuli uses the isolated forearm technique previously has been used to monitor the DoA. The isolated forearm technique is applied to the patient upper arm with a tourniquet (Kaul, 2002). The arm movement will indicate the consciousness of the patient even though this movement not explicit awareness (Sice, 2005). However, there are no closely linked between the movement and hypnosis (Bowdle, 2006). The isolated forearm technique is not practical to monitor the DoA accurately.

Assessing DoA in the operation room is in-line with administering the anaesthetics agents. Figure 4 shows the relevant stimuli and response as the increasing of the anaesthetics dose. There are ten responses in rank order of difficulty to suppress and fourteen stimuli of approximately increasing intensity. The stimuli are divided into two groups, known as benign and noxious stimuli (Gelb, 2009). The stimuli such as calling name, light touch, shouting and shouting - shaking are grouping in benign stimuli. The benign stimuli are not physical pain stimuli (Gelb, 2009). On the other hand, the noxious stimuli is a physically pain stimuli (Gelb, 2009). The increasing of physical stimuli means the depth of anaesthesia is increase too. This is also indicating that the central nervous system has suppressed as the result of administering anaesthetics agents. Therefore EEG signal has been used for DoA monitoring because of the relation between the administering of anaesthetics agents and the brain activities.

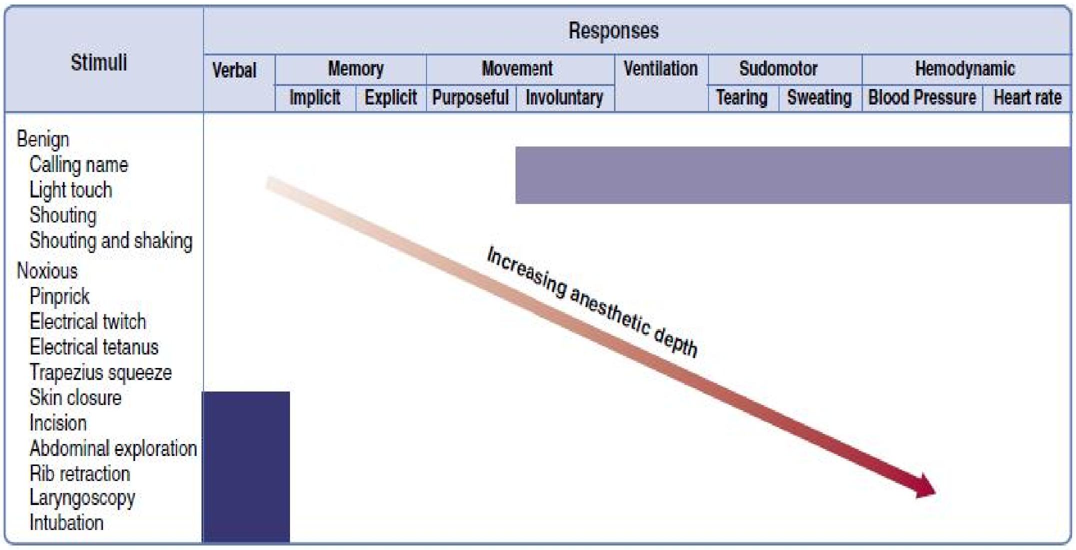


Figure 4. Matrix of Relevant stimuli and response (Gelb, 2009)

II.2 Electroencephalogram (EEG)

The first recorded electrical activity of human brain or EEG was achieved in 1875. Hans Berger in 1929 succeeded in recording brain signal on paper for one to three minutes. This technique is leading to advance in neurological disease and disorder diagnosis. The fundamental method of EEG continues to be used in the current fully computerized EEG signal recording system (Sanei & Chambers, 2007).

Figure 5 shows the neuron structure according to (Sanei & Chambers, 2007). In the central nerve system, the synaptic electrical potential is between 60-70 mV (Sanei &

Chambers, 2007). The EEG has also been used to assess the central nerve system activity from the impact of any drugs or disease (Rampil, 1998). For example, the

EEG signal under the effect of anaesthetic agents increases in average amplitude and decreases in average frequency (Kelly, 2003).

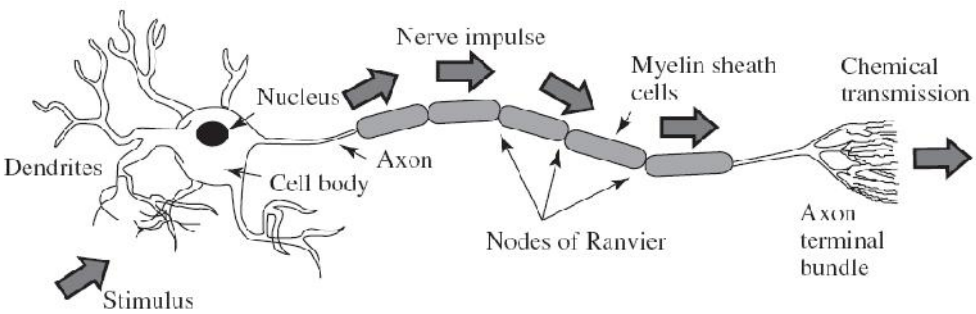


Figure 5. Neuron structure (Sanei & Chambers, 2007)

According to Rampil (1998), there are two sources of electric potential in neurons. The first is action potential (AP) and the second postsynaptic potential (PSP). Action potential is information transmitted by nerve cell and causes an ion exchange on the neuron membrane. The spike in EEG signal appears if there is a change in membrane potential, and the resulting action lasts 5-10 ms (Sanei & Chambers, 2007). This phenomenon is illustrated in Figure 6. On the other hand, the postsynaptic potential arises if there is a permeability in the ion channel and in the membrane cell (Rampil, 1998). "The permeability of ion channel in the postsynaptic neuron's cell membrane, altering its transmembrane ionic concentration gradients and thus it trans membrane voltage" (Rampil, 1998). Rampil (1998) explained that the polarity of the trans-membrane could be positive and negative.

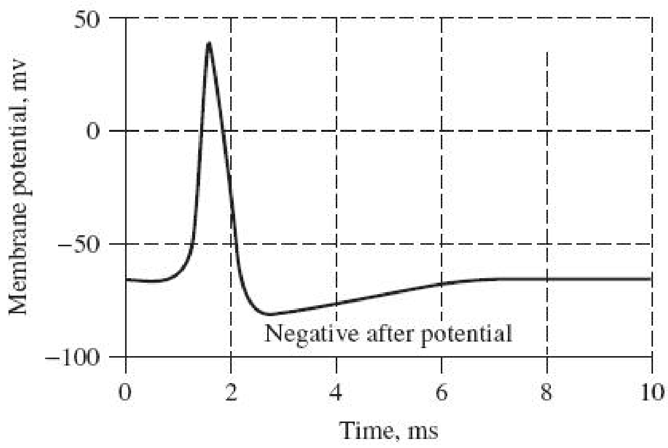


Figure 6. Action Potential spike (the changing of membrane potential).

(Source: Sanei & Chambers, 2007)

Monitoring the patient conditions based on the EEG signal is more popular than other techniques such as MAC (Minimum Alveolar Concentration) and physical assessment in anaesthesia (Johansen, 2006; Li et al., 2007). This is because EEG signal from the brain contains a lot of information related to human body and it could be used to analyse the depth of anaesthesia (Sigl & Chamoun, 1994). Monitoring DoA using EEG signal is also preferred in clinical situation because the effect of anaesthetic agent could depress some function of central nervous system and would cause decreasing activity of the brain. Moreover, the EEG patterns are different between the consciousness and unconsciousness. In addition, the EEG monitoring is a non-invasive technique.

In clinical practice, bi-frontal electrodes are used as EEG monitor sensors. These electrodes are placed in the forehead. The bi-frontal electrode method is more convenient in emergency situation rather than using the 19 electrodes method which is time consuming in placing the electrodes (sice, 2005). However, the 19 electrodes method is still used in brain analysis, autism disorder, seizures analysis in epilepsy, and Alzheimer’s disease (Escudero, 2006; Acar, 2007; Benham, 2007; Sanei, 2007; Saleh, 2009).

In DoA monitoring EEG signal is used for the assessment of pharmacodynamic drug effect in central nervous system. Pharmacodynamic is the analysis of physiological effect of drug concentration in the body (Gelb, 2009). As general anaesthesia affects different neurotransmitter receptors in the brain, different types of anaesthetics agents correlated with different part in the central nervous system; “such as hypnosis linked with cerebral cortex, lost of memory linked with limbic system, and immobility and pain killer linked with spinal cord” (Mashour, 2006; Sanei, 2007). The changing wave pattern in central nervous system is the indication of the effect of anaesthetics agent. EEG signal changing from high frequency and low amplitude to low frequency and high amplitude is the indication of the increasing of anaesthetics agent concentration (Bischoff, 2000; Kelley, 2003). The wave changing pattern can be seen in Figure 7, which shows that the wave patterns are varying as the increasing titration of anaesthetics agents in the body. It is shown that the awake wave is low amplitude and high frequency and under deep anaesthesia the signal wave is changed to high amplitude and low frequency.

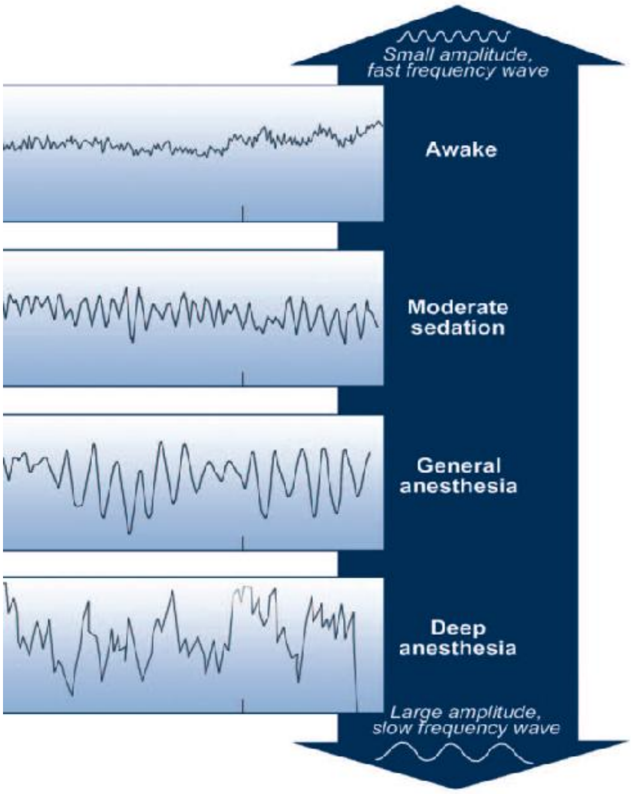


Figure 7. Changing wave pattern as the increasing of anaesthetics agents (Kelly,2003)

The main reasons that EEG is considered to measure the depth of anaesthesia are (Gelb, 2009):

a) It represents the cortical activity of the brain.

b) The effect of anaesthetics is connected to cerebral blood flow and cerebral metabolism which is related to different state of the brain activity (Kuramoto, 1979).

c) The EEG patterns, metabolism, and cerebral blood flow are affected by anaesthetic agents and surgical stimulus. As the result of administering anaesthetics agents, the EEG pattern characteristics change.

In normal state (the patient is awake), the EEG waveform amplitude is approximately *20 to 200 micro volts* and the variable frequency approximately *0* to *50 Hz*. Kelly (2003) reported that during general anaesthesia, the average amplitude is increasing and the average frequency is decreasing. The change in EEG patterns characteristics is shown in Figure 7.

Cerebral blood flow (CBF) is the flow of blood supply to the brain, which is measured from the velocities of the arterial blood flows. CBF is related to brain metabolism. The blood flow will change as the response of body movement and increasing activities of the brain (Healthcare, 2004). Brain metabolisms depend on the oxygen from the blood in order to process glucose for neurons activity (Alkire, 1998). Anaesthetic agent could depress the activity of central nervous system in the brain, resulting in the decreasing activity of the brain metabolism (Kelly, 2003).

II.3 Depth of Anaesthesia Technique

Most existing DoA monitors in the market employ EEG signal to analyse the level of consciousness, although each of them has different algorithm. The majority parameter to evaluate EEG signal in DoA monitor are power spectrum, spectral edge frequency, and median power frequency (Bischoff, 2000; Bard, 2001). The algorithms are developed based on the assumption that anaesthetics agent are propofol, midazolam, and isoflurane (Bowdle, 2006). EEG signal and Mid-latency auditory evoked potential (MLAEP) signal are both commonly employed, while other techniques are a combination of EEG and MLAEP signals. As illustrated in the Figure 8 existing EEG based monitors are SNAP Index, Cerebral State Monitor (CSM), Patient State Analyser (PSA), Bispectral Index (BIS), Narcotrend Index, and State response entropy.

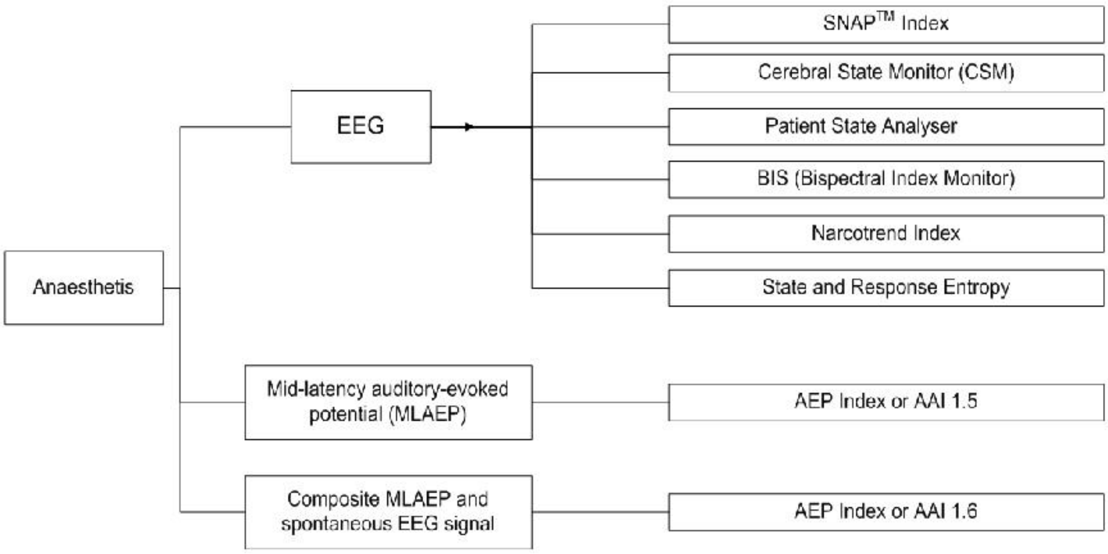


Figure 8. Enhanced assessment techniques for Depth of Anaesthesia Monitoring

The features of EEG signal in time domain such as burst suppression are collaborated with other component to derive DoA index. The burst suppression appears in the deep anaesthesia (Rampil, 1998). The characteristic of the features is amplitude changing from normal wave to a burst and back again to normal wave in a short period of time (Sarkela, 2002). The burst suppression can be seen in Figure 9.

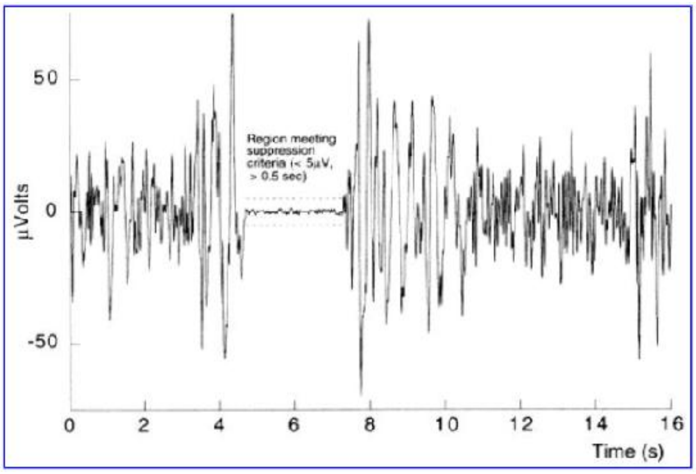


Figure 9. Burst Supreesion (Rampil, 1998)

In frequency domain, signal information such as amplitude, phase angle and frequency spectrum of the signal are analysed (Musizza, 2010). Raw EEG signal in time domain can be transformed into frequency domain signal using Fast Fourier transform (FFT) (Rampil, 1998).

The most popular DoA monitor is the Bispectral Index (BIS) (Johansen, 2006). It uses both time domain signal and frequency domain information to get the BIS value (Rampil, 1998). The BIS algorithm has a range from 0 (isoelectric) to 100 (awake). This indicates the level of consciousness of the patient during surgery and dictates the requirement for anaesthetic agent titration.

II.4 Bispectral Index (BIS)

BIS is an index for DoA monitor released by Aspec Medical (now Covidien). The BIS index is derived from a complex analysis of EEG signal using several parameters and techniques. Bispectral analysis includes the calculation of bicoherence, bispectrum and real triple product as its sub parameters. The method of analysing the signal starts from digitization of the raw EEG signal, then low pass filter *40 Hz* and high pass filter *0.3 Hz* are used to eliminate the artifacts (Sigl & Chamoun, 1994). Fourier transform to convert the signal from time domain *[x(t)]* to frequency domain *[(x(f)]*. The signals can be expressed in several frequency bands after the Fourier transform. The frequency bands of the signal are shown in Table 1 below.

Table 1. EEG frequency band

EEG bands	**Frequency (Hz)**	**Amplitude (mV)**
α (alfa)	7 – 13	20 – 60
β (beta)	13 – 30	2 – 20
γ (gama)	30 – 70	3 – 5
δ (delta)	0.5 - 3.5	20 - 200
θ (theta)	3.5 – 7	20 - 100

According to Sigl & Chamoun (1994), each sample of signal can be defined in Fourier transforms as:

$$x(f) = 2/\mathrm{M} \sum_{k=1}^{M-1} x(\mathrm{k})\mathrm{e}^{-\mathrm{ik}2\pi\mathrm{f}} \qquad (1)$$

where:

M is the number of sample data; *x(k)* is a function in time domain for *k= 1,2,...,M-1*.

In order to analyse the signal, the series of signal are divided into several epochs.

Bispectral analysis is used to analyse the phase coupling of the signals (Sigl, 1994). It is capable of calculating the quadratic non-linear and deviation from normality (Rampil, 1998). The fluctuation of the EEG signals defers the changes of bispectrum. Thus, triple product is used to detect the relationship of the phase between each epoch (Rampil, 1998):

$$X(f_1)X(f_2)X^*(f_1 + f_2) \tag{2}$$

X^* = Complex conjugate of the spectral value $X(f_1)$ and $X(f_2)$

The bispectrum is determined from the degree of average of the triple product. The bispectrum analyses the phase coupling of each epochs and also analyses the quantity of phase coupling between any pair of frequencies.

To compute the bicoherence of the signal, the following formula will be used to calculate the real triple product (RTP) (Rampil, 1998):

$$RTP(f_1, f_2) = \sum_{i=1}^{L} P_i(f_1)P_i(f_2)P_i(f_1 + f_2) \tag{3}$$

$$P_i(f) = \mathit{Power\ spectrum\ of\ each\ frequency}$$

The degree of phase coupling from the frequency tripled is defined as the *bicoherence (BIC):*

$$BIC\ (f_1, f_2) = \frac{B(f_1, f_2)}{\sqrt{RTP\ (f_1, f_2)}} \tag{4}$$

where the square root of *RTP* is a joint amplitude of the triplet.

Sub parameter Beta ratio and SyncFastSlow (new function for BIS analysis introduced by Aspec Medical System) are calculated for each epoch of the signal (Rampil, 1998). Beta ratio derived from the log ratio:

$$\log\left(\frac{P_{30-47}\ Hz}{P_{11-20}\ Hz}\right) \tag{5}$$

$P_{30-47}\ Hz$ is a power spectrum in the range frequency band *30 – 47 Hz* and $P_{11-20}\ Hz$ is power spectrum in frequency range *11 – 20 Hz*.

The SyncFastSlow sub parameters are the log of sum of all bispectrum peaks, defined as:

$$\log\left(\frac{B_{0.5-47}\ Hz}{B_{40-47}\ Hz}\right) \tag{6}$$

$B_{0.5\text{-}47\ Hz}$ *is defined as log power in the frequency band 0.5 to 47 Hz.*

$B_{40\text{-}47\ Hz}$ *is defined as log power in the frequency band 40 to 47 Hz.*

Burst suppression parameter is calculated from time domain. Suppression is a periodic signal at least *0.5 second* and the amplitude of the signal ± *5 (μV)* (Rampil, 1998). Burst suppression is defined as the sum of the interval in the epoch divided by the number of epoch length.

$$\text{BSR} = \frac{l}{n} \tag{7}$$

where l is the sum of interval suppression and n is the epoch length.

The anaesthetic agent could depress the central nervous system and will cause a decrease in the bispectral index value. The bispectral index value has a scale from 0 to 100, scale 100 corresponds to awake and 0 is isoelectric, as illustrated in Figure 10.

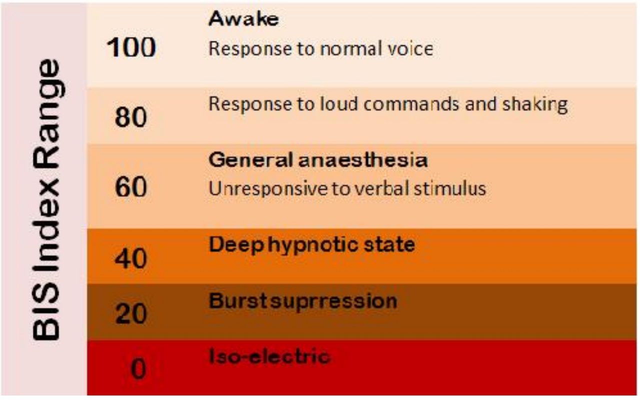


Figure 10. BIS index range (Kelly, 2003)

As the result of increasing anaesthetic agent, the level of consciousness declines and the activities of brain metabolism decrease. The decreasing activities of brain metabolism reflect the decreasing of BIS index value. The correlation between brain metabolism activity and BIS index values are shown by PET (Positron emission tomography) in the Figure 11 (Pomfrett, 1998).

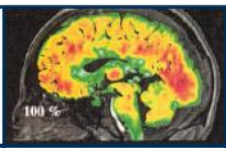
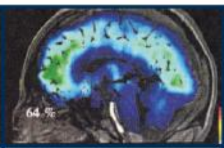
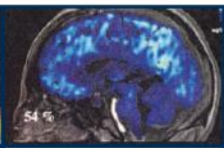
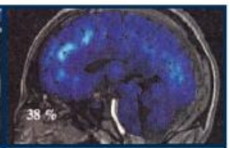
PET				
% BMR	100	64	54	38
BIS	95	66	62	34

Figure 11. Correlation of BIS with brain metabolism (Kelly, 2003)

III. EEG FILTERING BASED ON ADAPTIVE LEAST MEAN SQUARE

III.1 Adaptive Least Mean Square

Most Applications of signal processing need to remove the unwanted noise from the signal. The noise often corrupted the important information in the signal. In general, noise comes from the transmission medium of the signal such as wires (copper wires, fibre wires) (Poularikas, 2006). Also, noise comes from the device for gaining information, sensors, power line frequency, and interference with other electronics device. In biological signal such as EEG, the noise comes from the electrical activity in the body caused by muscle movements. The electrical activity in the muscle interfere the brain signal. The variation properties of the noise signal are often unidentified.

Filtering process basically is to retain frequency component of the specific signal. For example in low pass filter, the filter retains the high frequency and put through the low frequency according to the parameter settings. The adaptive filter defines as the system attempting to find the best parameter to meet the target of the filtering process (Farhang-Boroujeny, 1998). Most of the adaptive filter is achieved through the iteration to get the best result for its parameter.

The least mean square (LMS) adaptive filter was first introduced by Widrow and Hoff in 1990. The LMS has been used in many applications because of the less calculation and simpler comparing to other adaptive method (Farhang-Boroujeny, 1998; Poularikas, 2006). Moreover, the computational is faster because of the simplicity in calculation (Widrow, n.d). The LMS algorithm can be defined as a function:

$$y(n) = W^T(n)x(n) \tag{8}$$

$$e(n) = d(n) - y(n) \tag{9}$$

$$W(n+1) = W(n) + 2\mu\, e(n)x(n) \tag{10}$$

where n is the time index; $y(n)$ is the output from the adaptive filter; $e(n)$ is the output error; μ is the adaptation of the step size and $W(n)$ is the vector of filter weight, and $d(n)$ is the desire signal.

$$w(n)=[w_0(n) \;\; w_1(n) \;\; \ldots \;\; w_{M-1}(n)]^T \tag{11}$$

$$x(n)=[x(n) \;\; x(n-1) \;\; x(n-2) \;\; \ldots \;\; x(n-M+1)]^T \tag{12}$$

where $w(n)$ is the filter weight and $x(n)$ is the input signal. The output from the adaptive filter $y(n)$ is the multiplication of the weight filter and the input of adaptive filter $x(n)$. The LMS algorithm continues to identify the input signal by adapting the filter weight. Filter weight coefficients $w(n)$ is trying to minimise the error by subtracted the output of the adaptive filter $y(n)$ with $d(n)$. Step parameter μ in LMS algorithm needs to be selected properly to reach the best performance of the adaptive filter (Bellanger, 2001; Poularikas, 2006).

III.1.1 System Identification

Model application of the LMS algorithm is divided based on the purpose of the algorithm. Figure 12 shows the application of LMS in system identification. In system identification model the adaptive filter coefficients *w(n)* is trying to adapt as similar as possible with the response signal of unknown system *d(n)* (Bellanger, 2001; Poularikas, 2006). System identification input signal *x(n)* is fed into both reference signal and desire signal. If the *e(n)* is very small, the output adaptive filter *y(n)* and unknown system *d(n)* will be almost similar. The signal error is calculated from the differences of the adaptive filter *y(n)* and the unknown system *d(n).* The calculation can be seen in equation (9). The filter coefficient *w(n)* will change in attempt to minimise the error of the system.

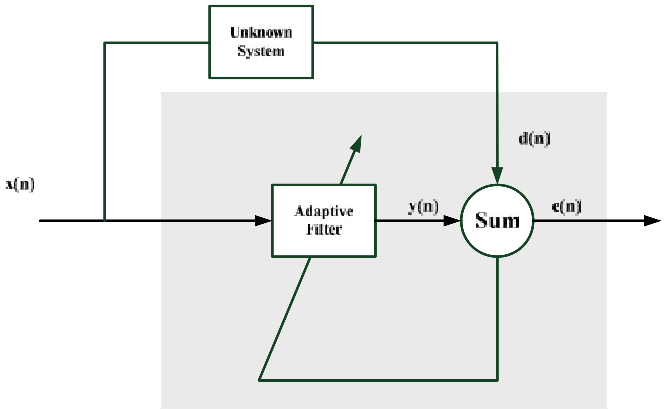


Figure 12. Adaptive filter System identification

The application of system identification adaptive filter uses to response the unknown communication channel or frequency response (Mathworks, 2001). This system is mostly used in close loop control system, where the output of the adaptive filter is trying to match the response of unknown system.

III.1.2 Inverse system identification

Inverse system identification uses delay to keep the summation synchronise. Furthermore, the adaptive filter is trying to adapt the $y(n)$ with the response of unknown system $x(n)$. However, the output of the adaptive filter has a lag time because there is an unknown series before it. Without the time delay, filtering process will not reach the adaptation (Mathworks, 2001). The diagram of inverse system identification is depicted in Figure 13. The unknown system output is define as $x(n)$. The output of the adaptive filter $y(n)$ is subtracted with the response of time delay $d(n) = s(n-\Delta(t))$ (Douglas, 1999).

The adaptive filter adjusts the coefficients to minimise the error of the output filter. The time delay feeds in parallel with the unknown system to enable the output of the adaptive filter reach as close as possible with the unknown system. The error of the adaptive filter $e(n)$ is the summation of the response of time delay $d(n)$ and the output of the adaptive filter $y(n)$.

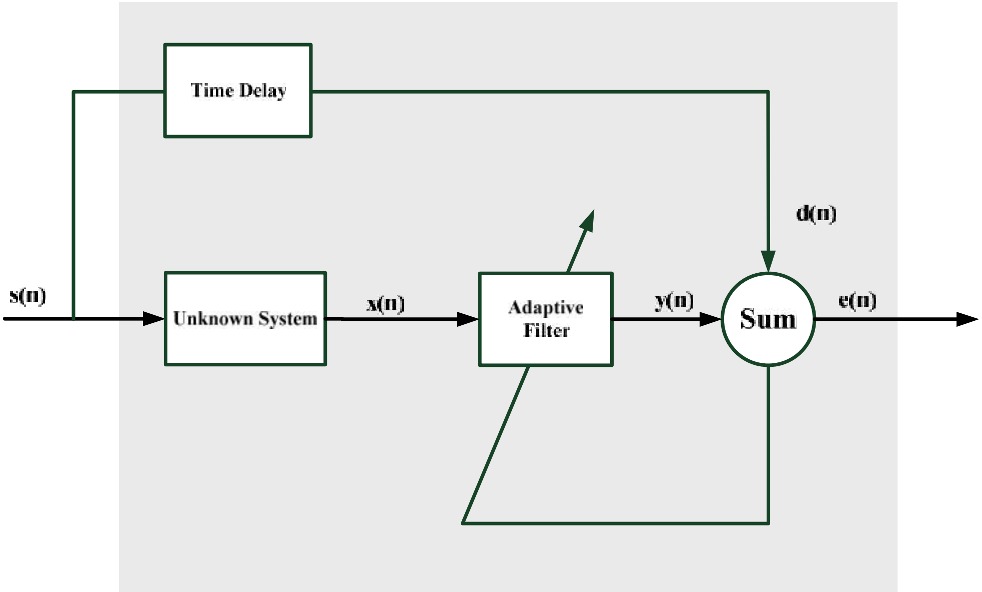


Figure 13. Inverse system identification

III.1.3 Noise Cancellation

Noise cancellation is popular in signal processing because it works in real time. The noise cancellation technique uses reference signal as an input to the adaptive filter. The reference signal is usually the pure noise correlate with the input in desire signal. Figure 14 illustrates the noise cancelation method. The desire signal is the signal input with noise. This signal can be put into a simple function $d(n)=s(n) + r(n)$. Reference signal input for adaptive filter $r(n)$ is a noise. This noise is correlated with the $d(n)$.

The adaptive filter is adapted the filter coefficients with the reference signal to reduce the noise. The filter component *w(n)* is adapted with input signal *r(n)* to reduce the error between *y(n)* and *d(n)* in order to produce the clean signal. This method is considered able to remove noise in real time and better to remove overlapping noise in the signal (Kumar, 2009).

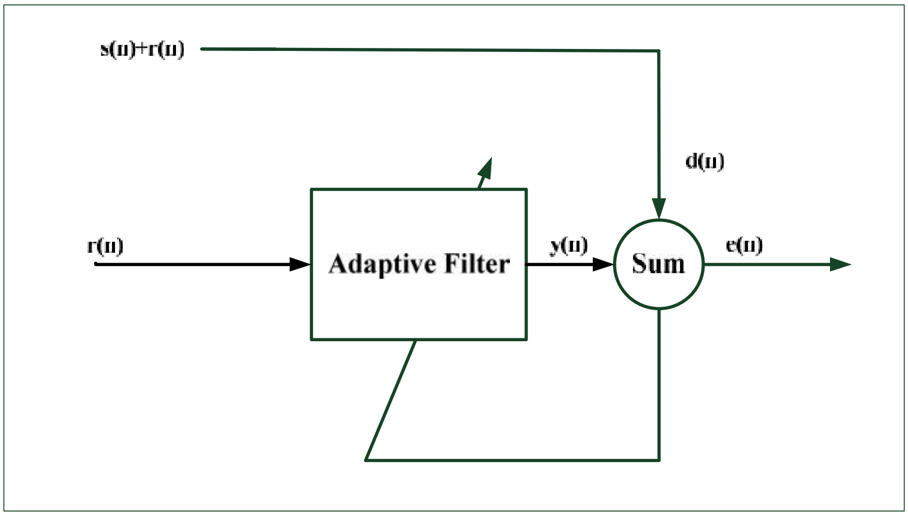


Figure 14. Noise cancelation

III.2 One way ANOVA

ANOVA has been used to analyse the variability of data in order to determine the significant outcome of filter adaptation. The ANOVA technique compares the experiment data by using mean of the sample and after that compares to each sample in the group to find the significant from the experiment (Moore, 1995). One way ANOVA is used to specify the significant from the group of sample by analysing the *F value*. The *F value* is the ratio of mean squares variance. The probability of

F value indicates how significant the outcome data from the filter adaptation. ANOVA technique is used in the LMS adaptive filter to determine the output of the filter. ANOVA analysis compares all data from the iteration of LMS adaptive filter, in order to find the significant outcome of the filter adaptation.

The ANOVA *F* defines as:

$$F = \frac{\text{variation among the sample means}}{\text{variations among individuals in the same sample}} \quad (13)$$

The *ANOVA F* defines as the variations from among the sample means divided by the variations each individual in sample group. In mathematical model the variations among the sample means denoted as *MSG* and the variations among individual in the sample symbolize as *MSE*.

$$F = \frac{MSG}{MSE} \quad (14)$$

MSG is the mean square of the sample from the experiment. The *MSG* calculates the variance of the group sample means, then multiplying that variance with the number of sample (n). *MSG* is defined as:

$$MSG = \frac{n_1(\overline{x_1} - \overline{x})^2 + n_2(\overline{x_2} - \overline{x})^2 + \ldots + n_i(\overline{x_i} - \overline{x})^2}{i-1} \quad (15)$$

where n_i is the number of sample and $\overline{x_i}$ is the sample mean.

MSE is the mean square error. The *MSE* calculate the variance of each group of sample individually than compute the variance of the entire group. *MSE* defines as:

$$MSE = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2 + ... + (n_i - 1)s_i^2}{N - i} \quad (16)$$

where n_1 is the number of sample and s_i is the sample standard deviation.

The ANOVA *F*, tests all the data in the group to examine the significant value from the group of data. Adaptive filtering with ANOVA method is employed to find the best coefficients in the adaptive filter.

III.3 Filtering using adaptive filter with ANOVA

The LMS adaptive filter does the adaptation process by using iteration. The adaptation process is based on the number of iteration that feed in the filter. ANOVA technique has applied in this filtering to classify which coefficient is best from the iteration. The ANOVA is justifying the filter coefficient one by one then combining each result with the entire sample mean. Figure 15 shows the filtering technique use in this study. The result shows there is an improvement in the signal after filtering (result section III.4).

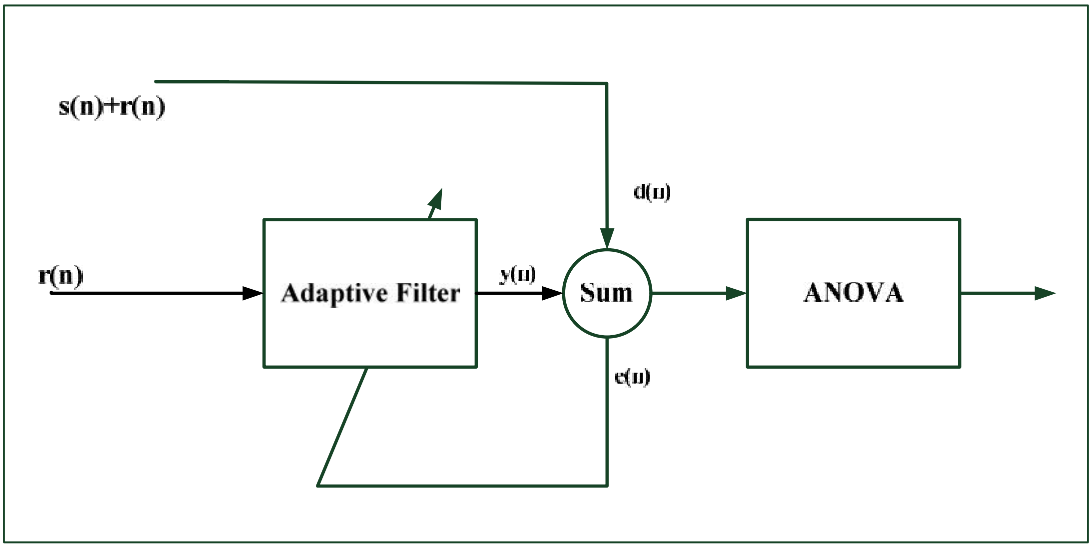


Figure 15. Filtering Method

The filtering process of ANOVA technique uses the generated EEG signal as an input. Signal *s(n)* is a pure signal and *r(n)* is a noise. The EEG signal with noise is indicated with *d(n)=s(n)+r(n)*. Reference signal for the adaptive filter *r(n)* is the same noise which is added to the input signal. The adaptive filter coefficients attempt to reduce error between the output of the adaptive filter *y(n)* and the desire signal *d(n)*. The numbers of iteration and step parameter μ are defined for the adaptation process. The iteration of the filter adaptation continues until the iteration reaches the defined iteration number. The ANOVA technique is employed to define the best coefficient from the numbers of iterations. Then, ANOVA is applied to determine the significant filter coefficient from the group of iteration of the LMS adaptive filter in order to produce clean EEG signal. The flowchart from this method is depicted in Figure 16.

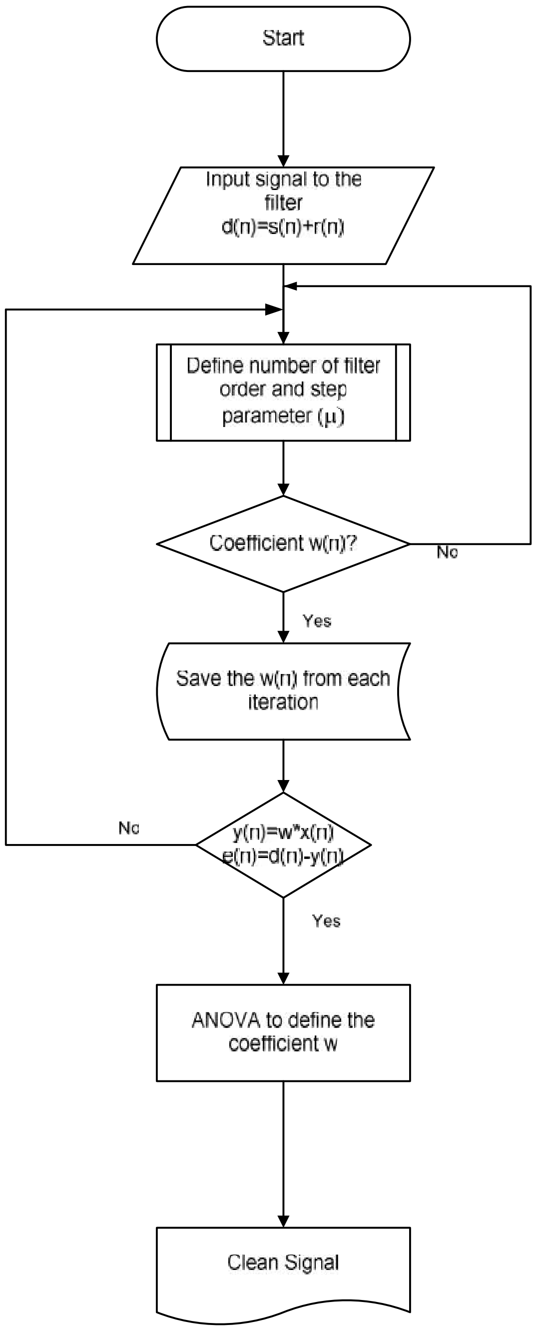


Figure 16. LMS adaptive filter with ANOVA Flowchart

The simulation process of adaptive filter with ANOVA in this study uses MATLAB software and Statistics toolbox in MATLAB. The LMS adaptive filter algorithm is modified by the writer from Poularikas (2006).

III.4 Simulation and Result

The simulation of the adaptive filter with ANOVA uses the synthetic EEG signal. The signal is derived using MATLAB. Figure 17 shows the raw signal. The raw EEG signal is contaminated with noise.

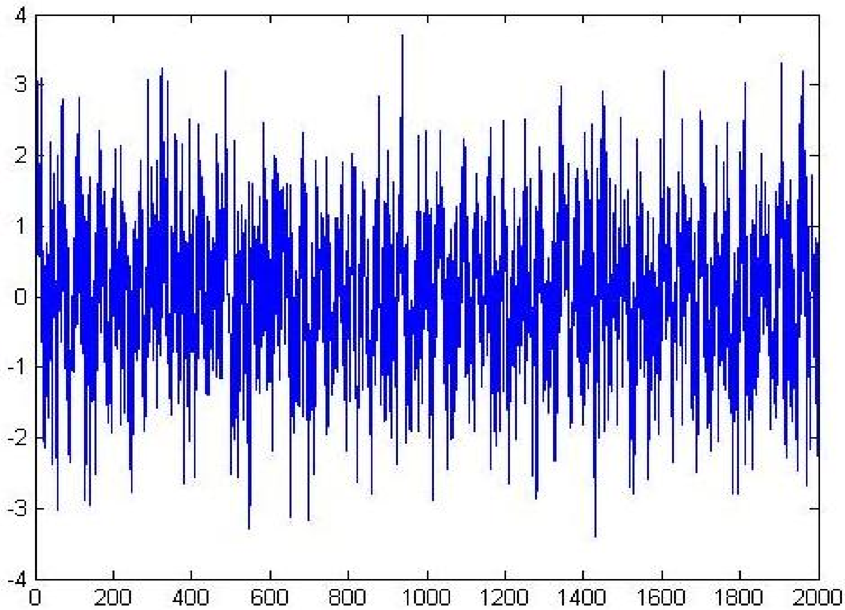


Figure 17. Raw signal contaminated with noise

The result shows the adaptive LMS filter able to remove noise from the corrupted EEG signal. The Filtering technique significant reduced the noise by getting the coefficients in adaptive filter using ANOVA. Filter coefficient *w(n)* from the adaptive filter has chosen by comparison between each signal with the ANOVA and finds the best coefficients. The coefficient is defined by finding the significant value of the ANOVA. Figure 18 shows the output of the adaptive filtering process using ANOVA.

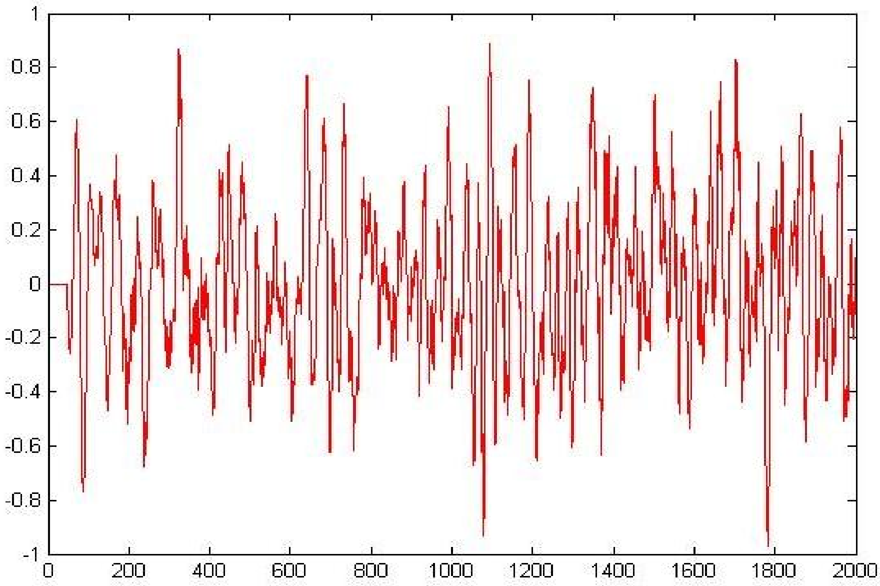


Figure 18. Output of the adaptive filtering

The output of the adaptive filtering process shows the improvement of the raw signal. This improvement of the signal can be achieved because the ANOVA technique is able to choose the best value from the iteration to define the output of the filtering process. As explain above, the ANOVA method finds the degree of comparison using the mean square error between each signal. This technique is capable to define which coefficient is the best from the iteration process of the adaptive filter.

Figure 19 shows the signal power before the filtering process. As explained earlier that the noise in EEG signal could raise the signal power. By removing the noise from the signal the power of the signal will reduce. It indicates the noise from the signal has removed.

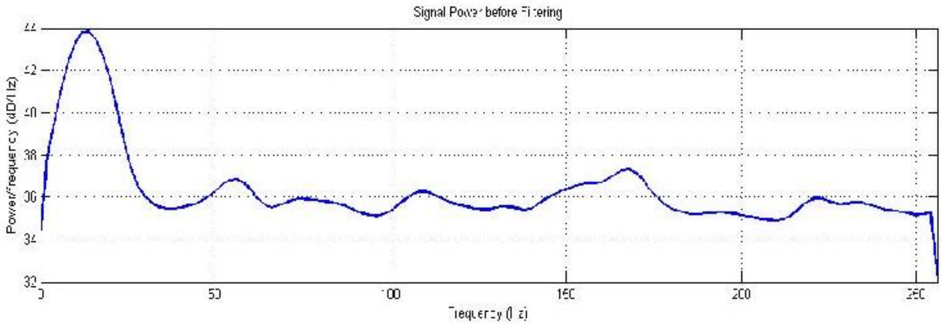


Figure 19. Signal Power of the raw signal

Figure 20 illustrates the differences of the signal power between the signals input and output using the Welch Power Spectral Estimation. The power of the raw signal is decreased, which indicates the noise in the signal removed. The result shows that the filtering method is able to remove the high frequency noise efficiently.

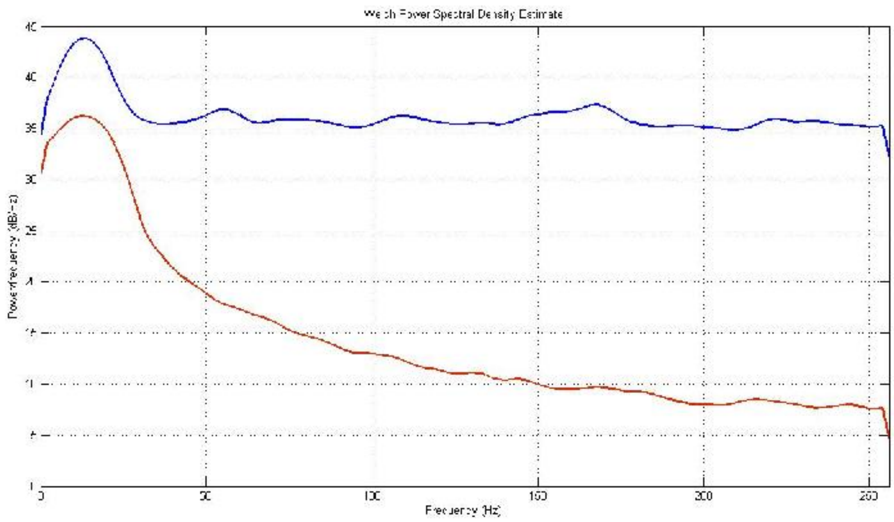


Figure 20. Differences between the clean signal and the raw signal.

IV. EEG SIGNAL FILTERING USING WAVELET TRANSFORM

Signals in time domain usually only provide the information of signal amplitude and time information. A raw signal in time domain needs to be processed to find out more information in that signal. Figure 21 shows the signal in time domain. The Fourier transform is a technique to transform a signal from time domain to frequency domain. The raw signal in time domain is then transfers to different frequency spectrum signal. As illustrated in Figure 22.

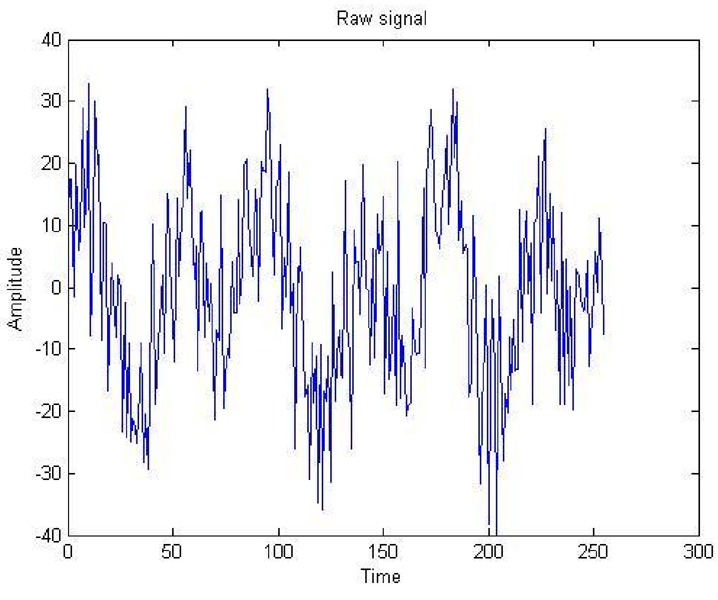


Figure 21. Raw signal in time domain

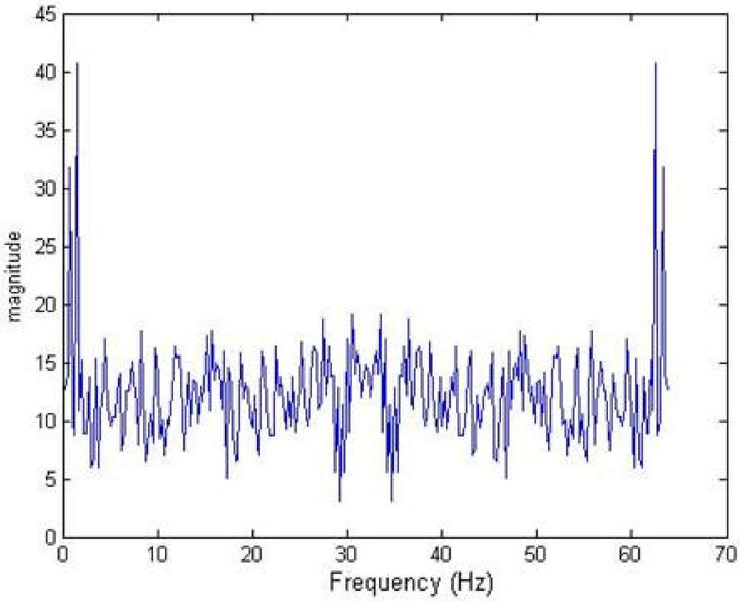
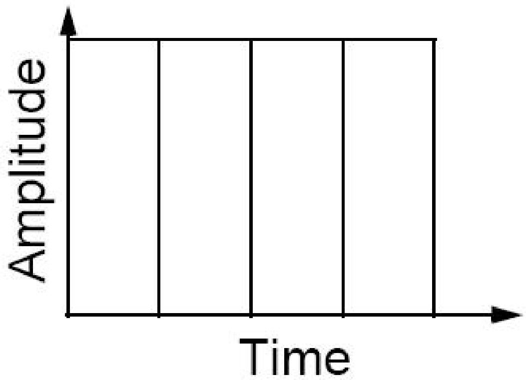


Figure 22. Signal in frequency domain

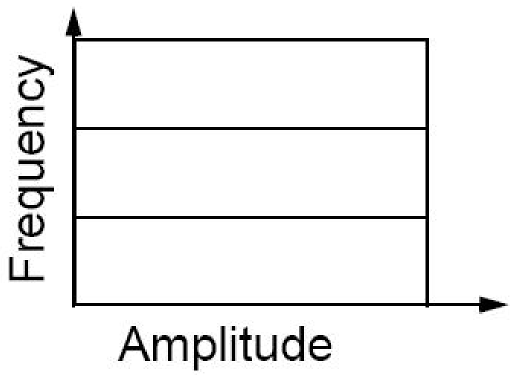
Specific frequency spectrum from the signal can be found using Fourier Transforms. This is very useful in spectral analysis, filtering and communication. However, there is a major drawback of the Fourier Transform which is in transforming to frequency domain signal, the time information of the signal is lost (Mathworks, 2009). The signal in Figure 22 shows that it is hard to define on which time the specific frequency occurs. Moreover, biological signal such as EEG, EMG and ECG are not suitable to use the Fourier transform (Polikar, 2001). Time and frequency information of the signal are mostly needed in analysing biological signal. Furthermore, the biological signals are grouping in the non-stationary signal. This signal needs to analyse the drift, trend, abrupt changes, the start and finish of the event (Mathworks, 2009; Misiti, 2009). All this information is important to classify the signal. Wavelet transform is the advance technique to classify the biological signal.

IV.1 Wavelet Transform

Wavelet transform is a powerful method to analyse the signal. This method could present the time – scale information of the signal. Frequency and time information of the signal can be obtained using this method. Wavelet is able to perform a different time and scale resolution, so the user could choose which particular signal they want. The other advantage of the wavelet is capable to localise the area of larger signal.



Time Domain



Frequency Domain

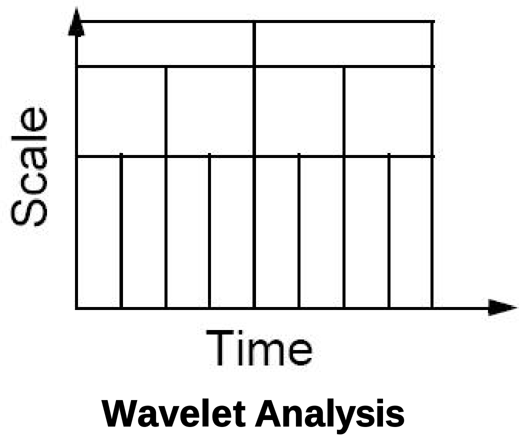


Figure 23. Differences between Fourier Transform, and Wavelet analysis

(Misiti, 2008)

Wavelet analysis characteristic is to deal with time varying modes. It is more robust in non-stationary signal analysis. "In general non stationary signal means the signal has statistical characteristic with vary in time and it is not essentially periodic over some interval"(Kronenburger, 2008). EEG signal is one of the non-stationary signals because this signal is vary in time. The benefit of wavelet analysis is capable to disclose information contain of the signals. The disclose information of the signal are trends, breakdown points, discontinuities and self similarity (Misiti, 2009). In addition, wavelet is able to filter or denoise the signal as well as classify the signal.

IV.1.1 Continuous Wavelet Transform

Wavelet transform is defined as the sum over all time of the signal multiplied by scaled, shifted or translate versions of the wavelet function. The basic wavelet function *ψ(t)* which is called the mother wavelet is defined in Equation (17):

$$\cdot_{a,b}(t) = \frac{1}{\sqrt{|a|}} \cdot \left(\frac{t-b}{a}\right) \qquad (17)$$

where $a>0$ is the scale parameter which measure the degree of scaling. Scaling in wavelet function is the stretching or compressing of the wavelet. The parameter b is the translation which determines the location of the wavelet. The factor of $\frac{1}{\sqrt{|a|}}$ preserves the norm of mother wavelet (·)(Lewis, 1998). The higher the scale factors, the more stretch the wavelet; on the contrary the smaller the scale factor, the more compress the wavelet. Wavelet scale is related to frequency of the signal (Misiti, 2009).

Wavelet transform in Equation (18) shows the function *ψ(t)* is translated function across time *(t)* and vary the time scale of the *ψ(t),* and then *x(t)* is the signal to be analyse. Wavelet transform is described as follow (Wang, 2009; Mohammadpour, 2009) :

$$WT_{a,b} = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t) \cdot^{*} \left(\frac{t-b}{a}\right) dt, \quad a > 0 \qquad (18)$$

The continuous wavelet transform function is producing wavelet coefficient in different scale and time. Figure 24 illustrates an example of signals analyse using

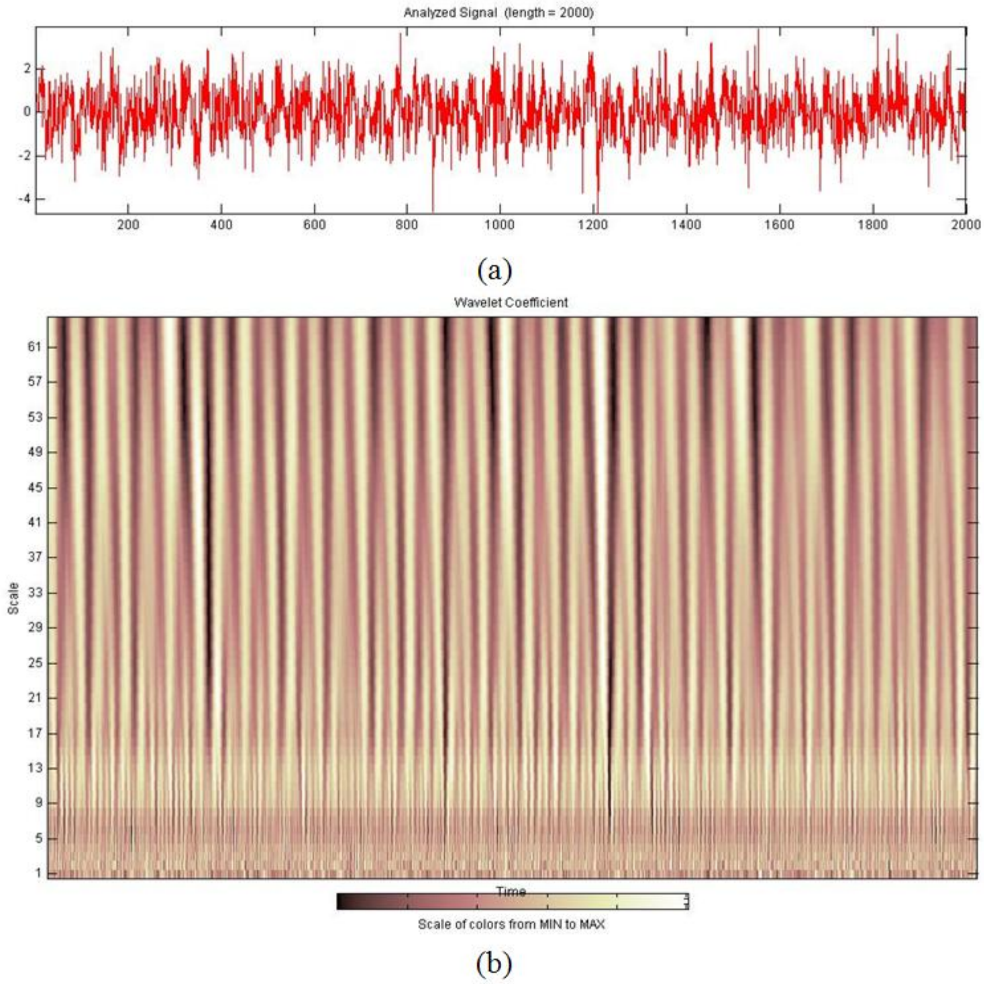


Figure 24. (a) Generated raw signal. (b) Signal coefficient using continuous Wavelet transform

continuous wavelet transform. Figure 24a is the raw signal and Figure 24b the coefficient of wavelet transform. Wavelet coefficient in the figure 24 shows the brighter the colour, the higher the coefficient of the wavelet. The equation (18) known as continuous wavelet transforms (CWT). The continuous wavelet transforms (CWT) is in continuous form so it is infinitely redundant. The CWT also provides the original signal oversampling. In addition, the redundancy of the CWT is its coefficient (Semmlow, 2004). Masuda (2002) explained that the redundancy of CWT exists because it maps the one dimensional signal to a two dimensional time scale plane. Therefore, it is a time consuming process to recover the original signal from continuous wavelet transforms (CWT). With the intention of reducing the redundancy of the CWT, discrete wavelet transform (DWT) technique is introduced.

IV.1.2 Discrete Wavelet Transform

Discrete wavelet transform (DWT) is introduced to overcome the drawback of the CWT. DWT uses multi-resolution analysis to present information of the signal. The Wavelet coefficients in CWT are computed by changing the window scale, and then translate it across the time and multiply by the signal. Signal in DWT is computed by using the low pass filter and high pass filter in the different scale.

The composite signal is derived from the approximation and details by down sampling the original signal and pass to different cut of frequency. The Approximation contains the low frequency component of the signal and the detail contains the high frequency of the signal. The original signal is passing through the low pass filter to derive the approximation signal. On the other hand, the details signal is formed by passing the original signal to high pass filter. Figure 25 illustrates the composite signal derived from the original signal (Misiti, 2009).

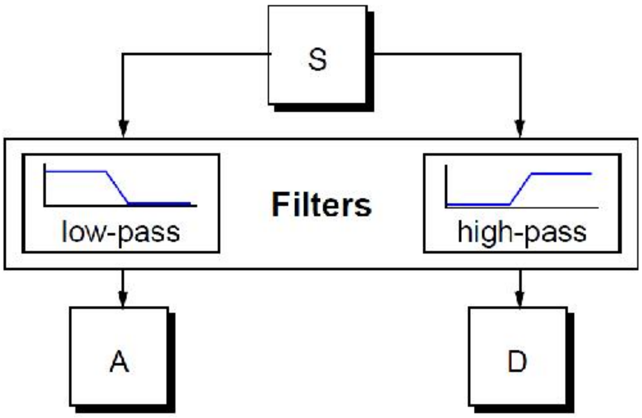


Figure 25. Approximation and details derived by passing through the different cut-off frequency (Mathworks, 2009).

The discrete version of CWT is the DWT. The continuous function in equation (18) with parameter *a, b* can be converted into discrete function. The *a, b* parameter is assuming only take the integral value of the CWT. This function defines as (Mallat, 2009):

$$\cdot_{a,b}(t) = m_0^{\frac{-a}{2}} \cdot (m_0^{-a}x - bn_0) \qquad (19)$$

Where m_0 and n_0 are the positive constants, *a* is the scale parameter and *b* is the scale parameter $(a,b \in \; Z)$. The DWT is defining by (Mallat, 2009):

$$W_{a,b}\; x(t) = \int_{-\infty}^{\infty} x(t) \cdot {}^{*}_{a,b}(t)dt \qquad (20)$$

$$W_{a,b}\; x(t) = m_0^{\frac{-a}{2}} \int_{-\infty}^{\infty} x(t) \cdot {}^{*}(m_0^{-a}x - bn_0)dt \qquad (21)$$

The scales and translation in DWT is restricted to the power of two or dyadic wavelet transform. The dyadic wavelet transform is intended to reduce the time consuming calculation in signal filtering. The dyadic scales and translation from the discrete sets are $\{a=2^k;\ b=2^k\,l;\ k, l \in Z\}$. The DWT equation is described as:

$$x(t) = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} d(k,l)\, 2^{-k/2} \cdot (2^{-k} - l) \tag{22}$$

where k is related to a as: $a=2^k$ and b related to l as $b=2^k\,l$; and $d(k,l)$ is a sampling of $W(a,b)$ at discrete points k and l. Using Mallat's fast algorithms the gradual decomposition of the original signal become:

$$A_k(n) = \sum_{l=-\infty}^{\infty} g(l-2n)\, A_{(k-1)}(l) \tag{23}$$

$$D_k(n) = \sum_{l=-\infty}^{\infty} h(l-2n)\, A_{(k-1)}(l) \tag{24}$$

Hence, $A_k(n)$ represents the approximation at level k and $D_k(n)$ correspond to the details of the signal at level k. The g in equation (23) is the low-pass filter and h in equation 24 stands for high pass filter. The parameter n is the number of sample in the wavelet. Figure 26 depicts the decomposition of a raw signal into 5 levels. This decomposition is using db3 wavelet family.

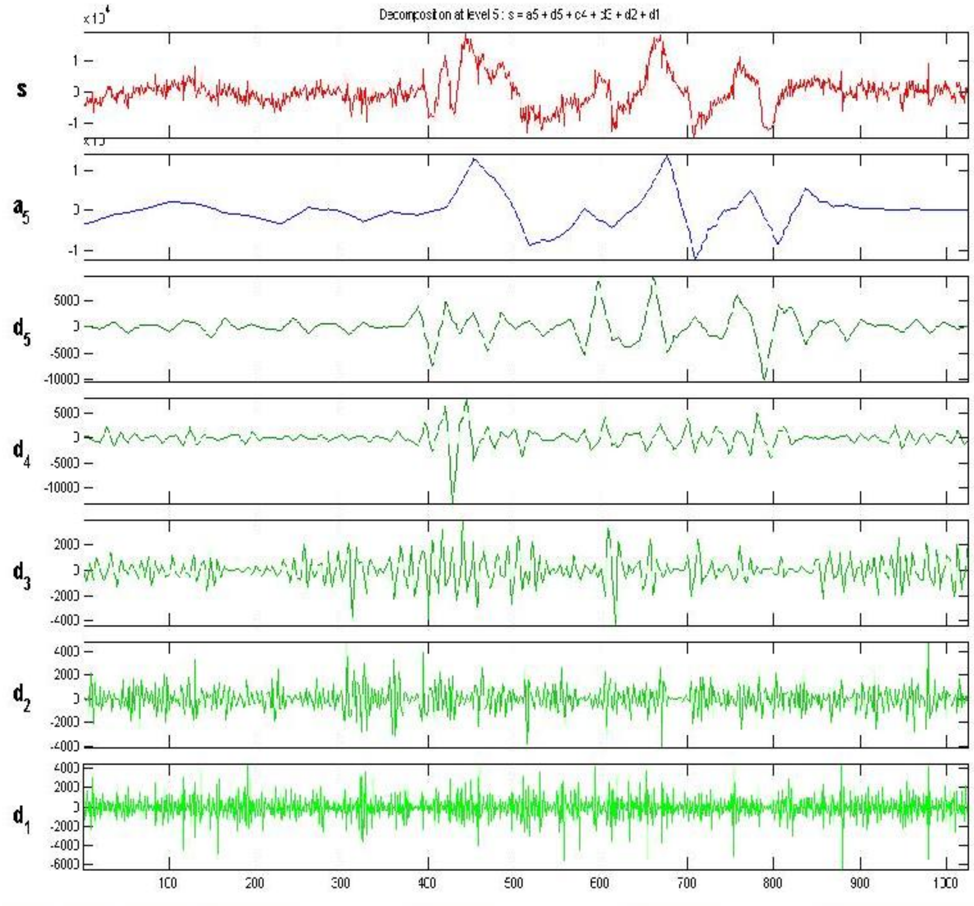


Figure 26. Five level DWT decomposition

The decomposition of DWT is using down sampling method. This method decompose the original signal by passing through the filter which is low pass filter and high pass filter then the resulting signal is divided into approximation and details. In the filtering process DWT method uses down sampling technique to reduce the numbers of sample produce by the separation signal. For example, suppose the signal have 1024 number of sample in original signal. The original signal is passed through low pass filter and high pass filter. The outputs of both filter without down sampling are 2048 samples, that are twice the number of the original signal (Misiti, 2009).. This is illustrated in Figure 27.

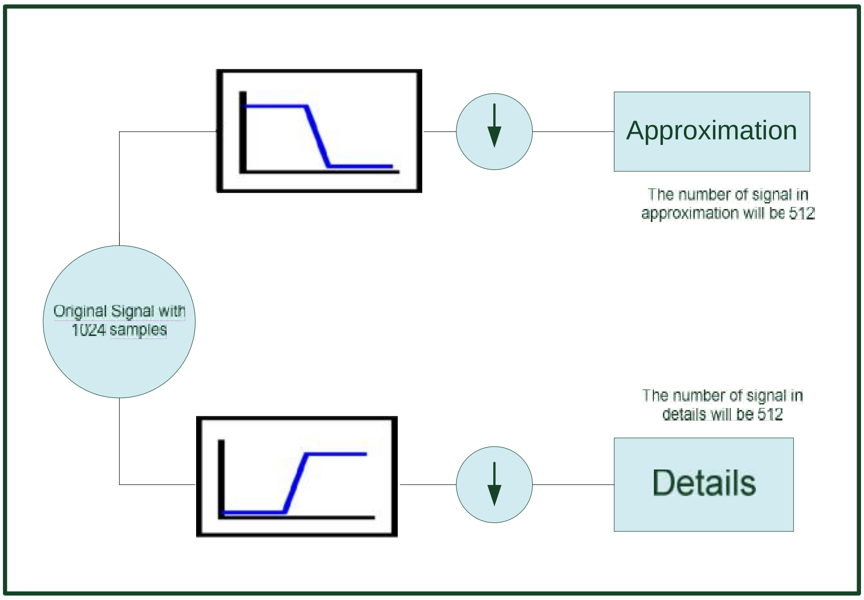


Figure 27. Illustrations of decomposition signal (Mathwork, 2009)

For that reason, the DWT has introduced using down sampling method to reduce the number of sample after filtering. The down sample is used to reduce the number of sample in each approximation and details to produce the coefficient of DWT. This is illustrating in Figure 28. The result of the decomposition is the signal with different frequency band. Figure 28 shows one level of DWT decomposition. The source signal is feed into the low pass filter and high pass filter then by using down sampling method to derive the approximation and details of the signal. The signal is separated into high frequency and low frequency band. The high frequency band is in the details and the low frequency band is in the approximation.

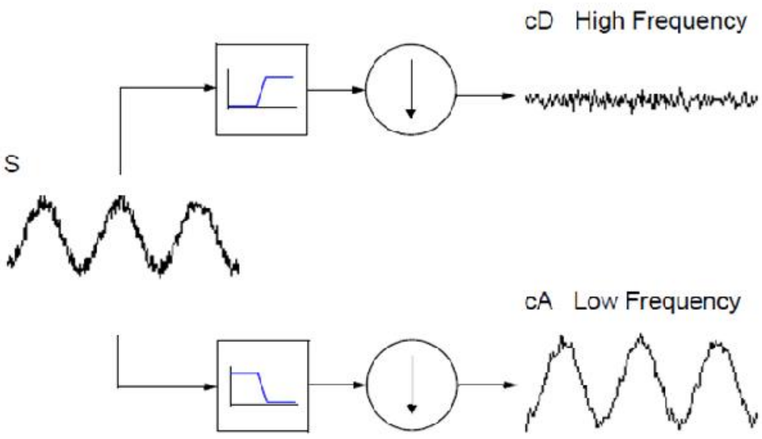


Figure 28. The DWT decomposition (Mathworks, 2009)

IV.1.3 Stationary Wavelet Transform

"The Discrete Wavelet Transform method involved with the down-sampling method to reduce half length of the coefficients of the signal after decomposition" (Misiti, 2009). This is one of the redundant of DWT which is losing the time invariant property on its decomposition (Morsi, 2008). Time invariance property is very important in signal processing to help identify and detect the changes or transient characteristics of the signal. EEG signals Analysis is essential to retain the time invariance property for further defining the uniqueness of the signal.

SWT technique is an improved technique from wavelet transform. It is capable for signal with time invariant to decompose and improve the power of the signal denoising. SWT also uses up sampled method at each level of decomposition for the signal (Suyi, 2009). The decomposition of SWT produces the coefficients of approximation and details in the same length with the original signal. Unlike the DWT as explain before, the SWT on its decomposition uses up sample method applied to its filtering process. The original signal is convolved with the up sample appropriate filter for each coefficient. Figure 29 shows one level decomposition of the SWT and filter computations at level *j*. The approximation is produced by convolves the original signal with up sample low pass filter *(g_j)*. On the other hand the detail is derived from convolving with up sampling high pass filter *(h_j)* to construct the coefficient.

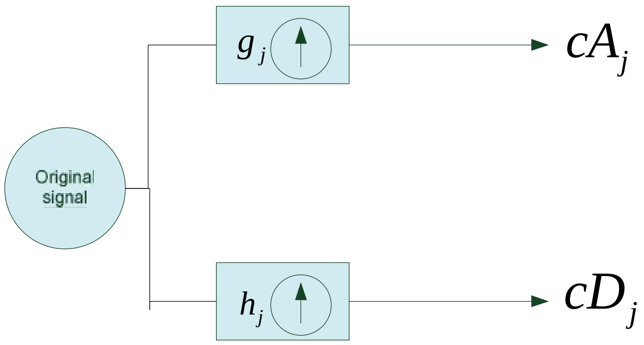


Figure 29. SWT Decomposition

SWT is introduced to analyse the signal without losing the time invariant of the signal. The time invariant of the signal still retains because the SWT technique does not use down-sampling on its decomposition. The decomposition in SWT is applied up-sampling to derive the approximation and details coefficients. The approximation and details are both the same length with the original signal. The decomposition of SWT can be computed by (Morsi, 2008; Naon, 1995).

$$cA_{j,k}^{SWT} = \sum_{n} cA_{j-1,k+2^{j}(n)}^{SWT} g(n) \tag{25}$$

$$cD_{j,k}^{SWT} = \sum_{n} cD_{j-1,k+2^{j}(n)}^{SWT} h(n) \tag{26}$$

The $cA_{j,k}^{SWT}$ is the approximation coefficient of SWT, $cD_{j,k}^{SWT}$ is the details of SWT and the *j*,*k* is the number of level decomposition and the position. The parameter *g(n)* stands for low pass filter and *h(n)* stands for high pass filter. The decomposition hierarchy of SWT is depicted in Figure 30.

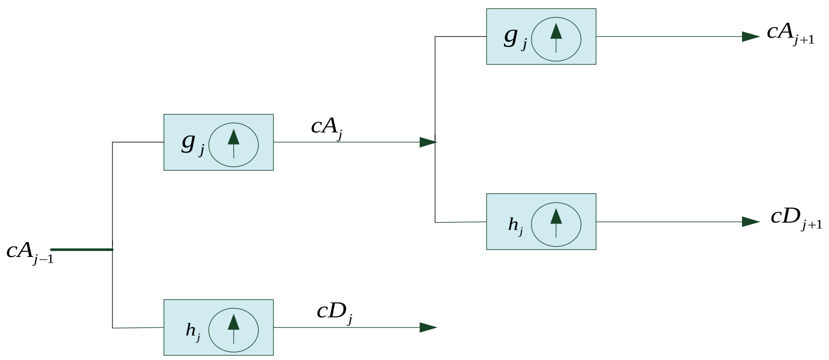


Figure 30. Decomposition hierarchy of SWT

IV.2 Wavelet Denoising

Wavelet denoising technique will be used to filter the signal. There are few steps for denoising the signals using wavelet. Wavelet denoising technique is used to remove the unwanted signal. The unwanted signal is known as noise signal. Generally the wavelet denoising steps is divided into three parts, which is:

1. Decompose the signal from the original signal to different level composition

2. Threshold the signal based on the boundary of the noise

3. Reconstruct the signal

Removing noise from the signal is based on the wavelet denoising steps above. The signal with noise is describe as:

$$Y(t) = f(t) + £\,(t), \quad t = 1, \ldots, n-1 \tag{27}$$

The analysis of Y is equal to the sum of the analyses signal *f(t)* and the noise ε_t . The proposed method of denosing signal in this proposal used soft threshold. The soft thresholding function based on (Donoho, 1995) is:

$$T_s = £1\sqrt{2\log(n)} \tag{28}$$

where T_s is the threshold and ε_1 is define as $\varepsilon_1 = \gamma.\sigma/\sqrt{n}$. By using the γ as a constant, then σ = MAD/0.6745. MAD represents the median absolute value of the normalized fine scale wavelet coefficient at level *k*. To estimate the variance of noise ε_t from the data $Y(t) = f(t) + \varepsilon_t$ in equation (27), the signal *Y* of size *t* has *n/2* wavelet coefficients ($\psi_{k,l}$). This can be defined as $\{|Y, \psi_{k,l}|\}\ 0 \le l < n/2$ at the finest scale 2^{l}=$2n^{-1}$. MAD is the median of the absolute value of the normalized fine scale wavelet coefficient $\{|Y, \psi_{k,l}|\}\ 0 \le l < n/2$. The *0.6745* is the *75 percents* of standard normal distribution. The simplified threshold function from above that can be used to threshold is (Donoho, 1995):

$$T_s = \pm\sqrt{2\log(n)/n} \tag{29}$$

where T_s is the threshold and σ = $MAD/0.6745$; n is array of wavelet coefficient. Based on the wavelet transform algorithm, there are three steps to denoise the signal. The first step is decomposing the signal. In this stage the signal is split into two parts by passing through low pass filter and high pass filter. Then, the signal is broken down into different resolution components. The second step is threshold the boundary of the artifact as a coefficient to remove the unwanted signals. The last step is reconstructing the signal.

IV.3 EEG Filtering using Wavelet Denoising

IV.3.1 Contaminated EEG Signal

EEG signal is often contaminated by ECG, electromyography (EMG), and eye blinking (Rampil, 1998). Analysing depth of anaesthesia using corrupted EEG signals may result in an incorrect result. Most of the contaminated signal comes from the eye ball movement and blinking which is known as electrooculogram EOG and EMG signal from the muscles (Sanei & Chambers, 2007). Therefore it is necessary to filter the noise from EEG signal.

The major noise source of EEG signal is EOG. It is because of the movement of the eye ball causes an electric field around the eye and affected the electric field of the scalp (Croft & Barry, 2000). This electric field could contaminate neurons potential of the brain and as a result EEG signal is contaminated. EOG is considered as a signal with high amplitude and low frequency. This signal is usually affected the lower band of EEG signal (Kavitha, Lau & Premkumar, 2007). Also, the EOG signal could increase the power of low frequency band (Croft & Barry, 2000). Based on the characteristics of EOG, the appearance of EOG signal could affect the accuracy of DoA. Consequently, analyse the depth of anaesthesia (DoA) with contaminated EOG could give incorrect result. Sample of EOG signal is shown in Figure 31.

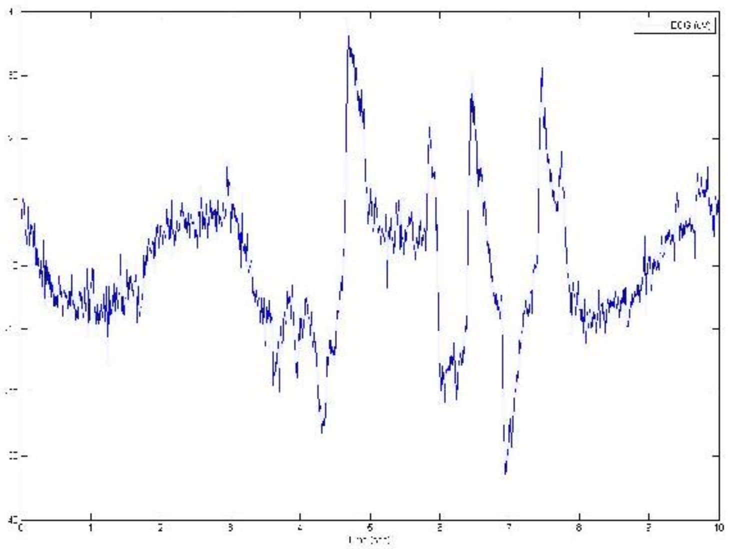


Figure 31. Sample of EOG signal

Signal generated by muscles known as EMG signal. This signal is also considered as a noise that could affect DoA analysis. The increasing values of EMG may raise the BIS index. Bowdle, explain that the BIS index may drop in absence of EMG signal (Bowdle, 2006). Moreover, the BIS value may give false measurement of the depth of anaesthesia because it measures the increasing value of electromyography (EMG) activity (Bruhn et al., 2000). Removing the EMG signals from the EEG is difficult because the EMG signals vastly overlap with EEG signals and the intensity of the signals are larger than EEG signals. Sample of EMG signal can be seen in Figure 32.

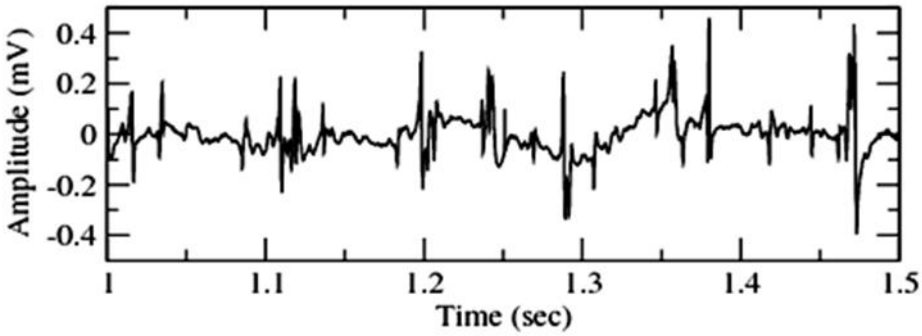


Figure 32. EMG signal (Physionet, 2011)

IV.3.2 Removing noise from EEG Signal

There are many techniques to remove the artifacts from EEG signal, such as adaptive filter, frequency domain regression technique, wiener filter technique, FIR filter, independent component analysis (ICA), and Discrete Wavelet Transform. However, each technique has its own ability to remove one particular artifact. For instance the popular technique to remove the EOG artifact is adaptive filter (Kavitha, Lau & Premkumar, 2007). Kumar has used the adaptive filter technique combined with wavelet to remove the EOG (Kumar et al., 2009). On the other hand the most popular technique to filter EMG artifact from the EEG signal is discrete wavelet Transform (DWT) (Lanlan, 2009). Furthermore, in order to remove the EMG signal from the EEG signal, Lanlan used the db4 wavelet and decomposed it using 8 layers (Lanlan, 2009). The result shows that the wavelet is more effective to remove the noise from the EEG signal. However, this technique works only in removing the

EMG signal from the EEG signal. Different to the method used by Lanlan (2009), Araghi used the bior3.3 discrete wavelet transform (DWT) and decomposed it using six layers to remove the artifact from the EEG signal (Araghi, 2010). In contrast, Palendeng et al. explain that the Wavelet transform technique which is combine with adaptive least Mean Square (LMS) able to remove the EMG artifact as well as other artifact in low frequency (Palendeng, Wen & Goh, 2010).

Filtering the EEG signal is essential before analyse it. Removing artifact from the EEG signal would reduce the error in calculations. In this chapter Stationary Wavelet Transform (SWT) is proposed to remove the artifact from the EEG signal using Daubechies 3 (db3). The method is using SWT because of its time invariant and it has better sampling rates in the low frequency bands (Kumar et al., 2009). Also SWT could improve power of the wavelet transform and effectively eliminates noise in signal denoising. It has good ability in filtering the noise and retains the information (Yuan & Hongwei, 2009). As a result it could provide good signal filtering.

This filtering technique uses db3 mother wavelet and decomposed the signal to five levels. The reason uses the db3 wavelet transform because it is capable to detect and localise the spike in the EEG signal. For that reason, the db3 wavelet is more suitable for denoising the EEG signal. The mother wavelet db3 is shown in Figure 33. The reason to use db3 mother Wavelet transform is that noises in EEG signal such as the EOG and EMG have a spiky characteristic. The Daubechies wavelet orders 4 or higher are more stretched in time axis and the mother wavelet more sinusoidal like (Sarkela et al., 2007). Figure 34 depicts the other family of db.

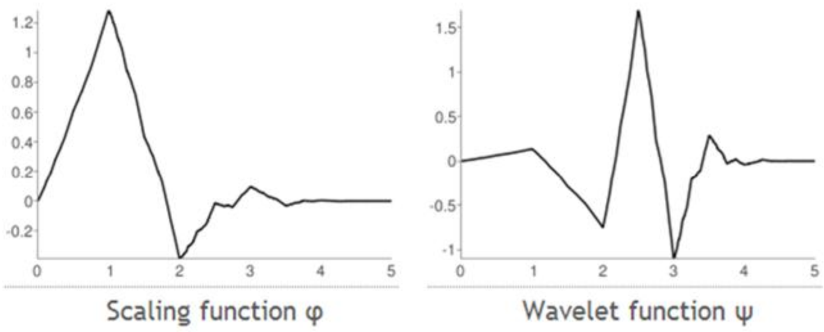


Figure 33. Mother wavelet db3 (http://wavelets.pybytes.com/wavelet/db3/)

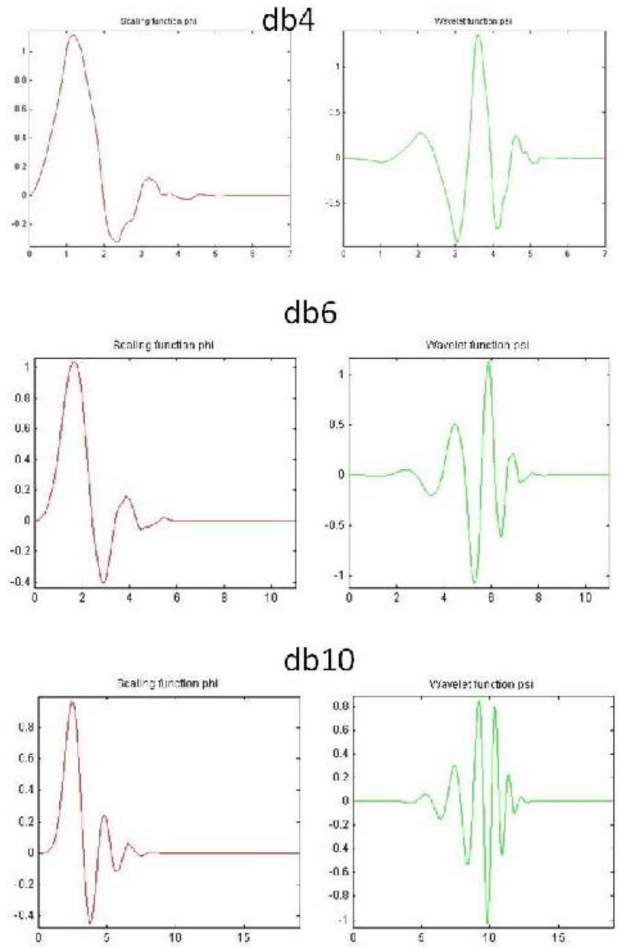


Figure 34. Family of db mother Wavelet

The technique in this research is based on the wavelet transform algorithm. There are four steps applied in order to remove the EMG signal and EOG signal. The first step is decomposing the signal into five levels. In this stage the signal will be split into two parts which is approximation and details by passing through low pass filter and high pass filter. The signal is broken down into different frequency resolution components. Then, the second step is to eliminate the high frequency of the signal based on the frequency band in the details. After removing the high frequency component of the signal which consider the EMG signal, followed by reconstruct the signal. The last step is to threshold the boundary of the artifacts as a coefficient to remove the EOG signals. Finally after threshold the signal is considered clean. The filtering process is illustrated in Figure 35.

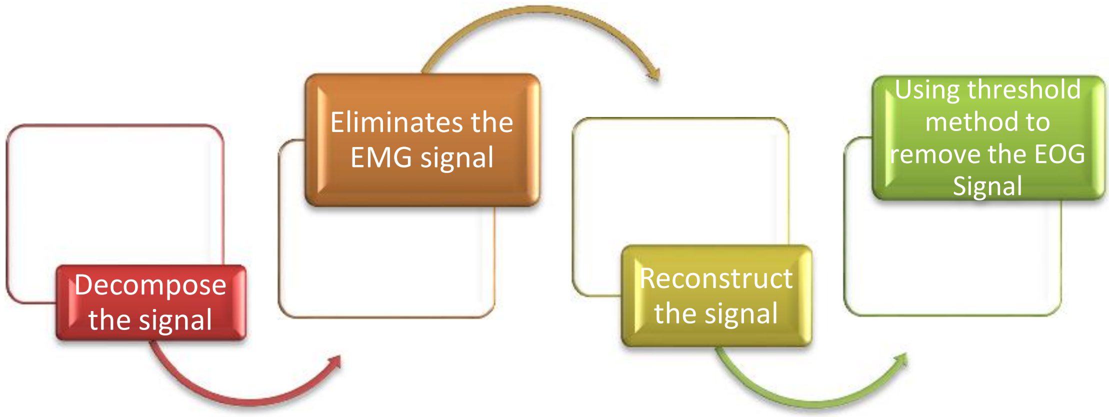


Figure 35. Filtering Process

IV.4 Simulations and Result

SWT technique is a powerful technique to decompose EEG signal because it has better sampling rate. This will provide good result in removing artifact from EEG signal. By using Daubechies 3 (db3) wavelet, the EEG signal will be decomposed into five levels. The EEG signals in this simulation are downloaded from Physionet (Physionet, 2011). The EEG signal is taken from the person with no record of brain injury and sampled at 125 *Hz*. The recorded pure EEG signal *x(t)* has mixed with EMG signal and EOG signal *e(t)*, it is define as:

$$Y(t) = x(t) + e(t) \tag{30}$$

Figure 36 shown the corrupted EEG signal,

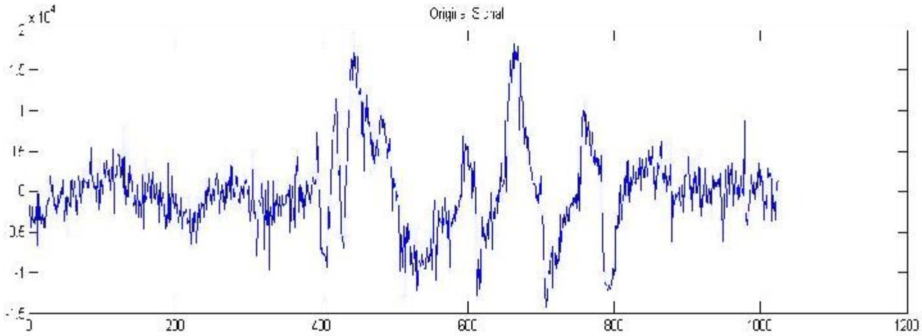


Figure 36. Corrupted EEG signal

The signal is a contaminated EEG signal with arifact such as EOG and EMG. The simulation below shows the wavelet transforms filtering is able to remove the artifact from the EEG signal. The first step of this technique is to decompose the signal into five levels.

The next step after the decomposition is to remove the high frequency in the signal. In order to remove the high frequency in the signal, this research introduces the signal elimination technique. Signal elimination technique is applied to EEG signal after its decomposition. First and second decomposition of details is considered high frequency and related to EMG. The elimination signal method is applied to the first and second level of detail decomposition because it is considered as a noise. The signal is shown in the Figure 37.

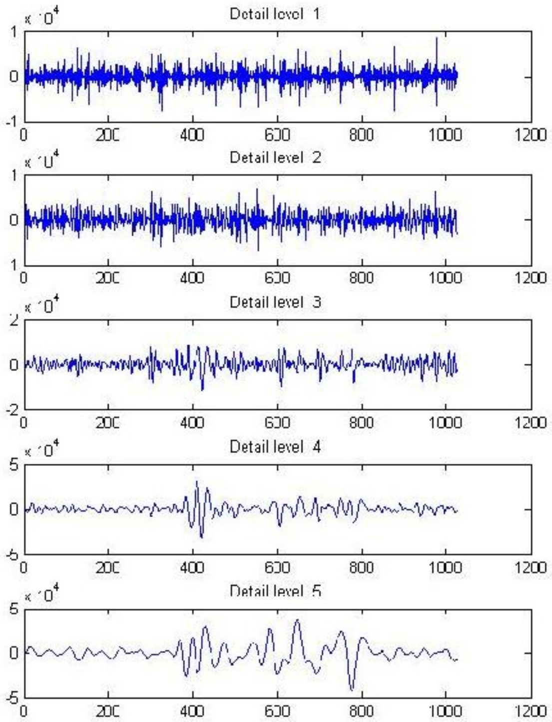


Figure 37. The details of the signal

The next step of this technique is to reconstruct the rest of the signal. Then the reconstructed signal is applied the threshold method to remove low frequency signal which is consider EOG. The Soft threshold method has been applied in this technique to remove noise from the signal. This method is capable to remove noise from EEG signal. The frequency spectrum of the residual signal after threshold is correlated with the EOG noise frequency. The EOG frequency spectrum is between *0-16 Hz* (Krishnaveni, 2006). Figure 38 shows the frequency spectrum of the removed noise.

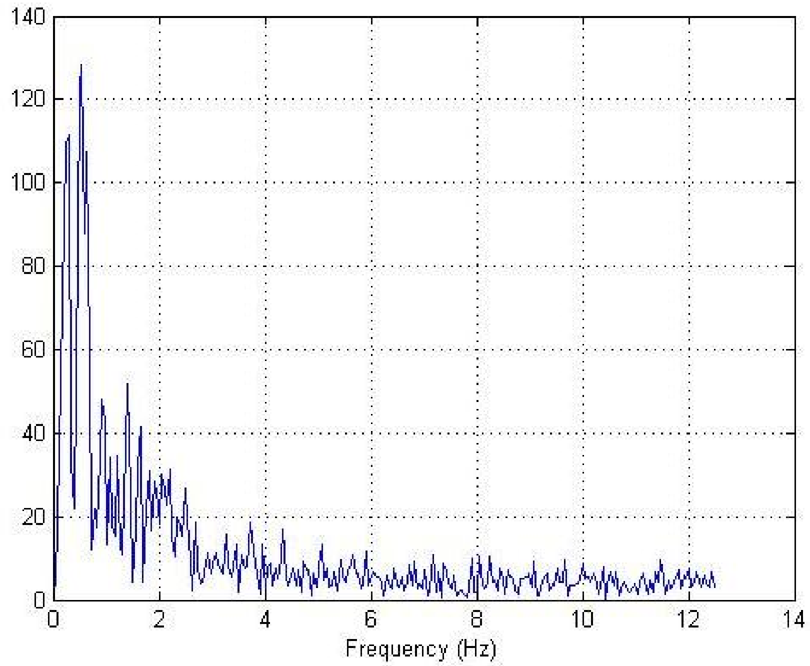


Figure 38. Residual Spectrum after Threshold

The result shows that this technique is able to remove noise from the EEG signal effectively. Figure 39 below shows the result after denoising using this technique.

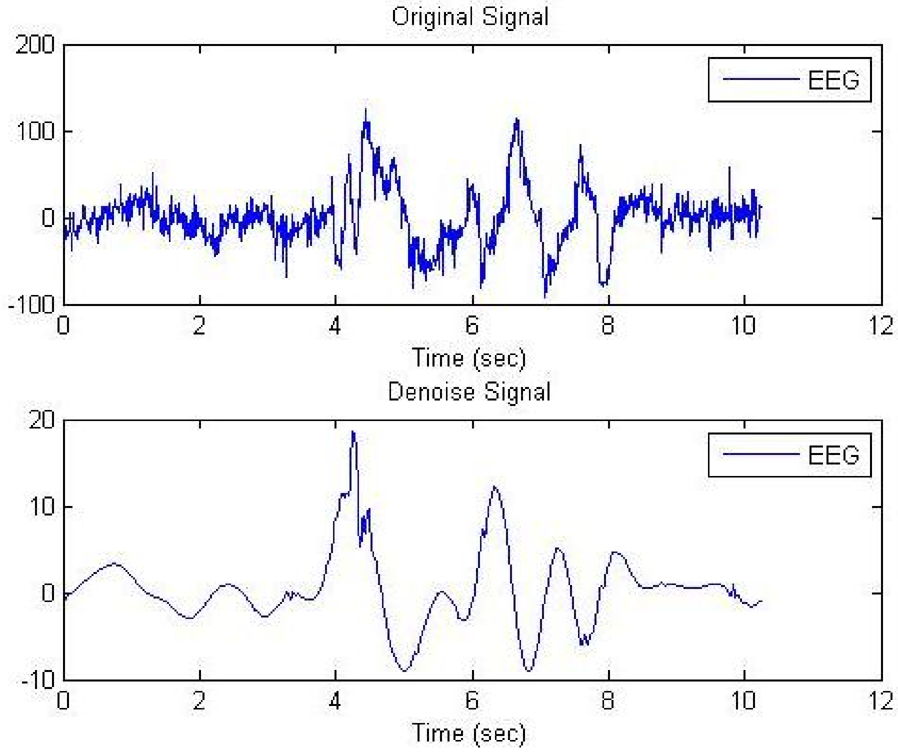


Figure 39. Result of signal denoising

From that result, the residual of the signal extracted from the EEG signal is correlated with the noise which is EOG and EMG signal. Figure 40 is shown the signal residual after filtering. This signal is a noise signal that could elevates the index of DoA monitor. The filtering technique in this research is able to remove noise in EEG signal.

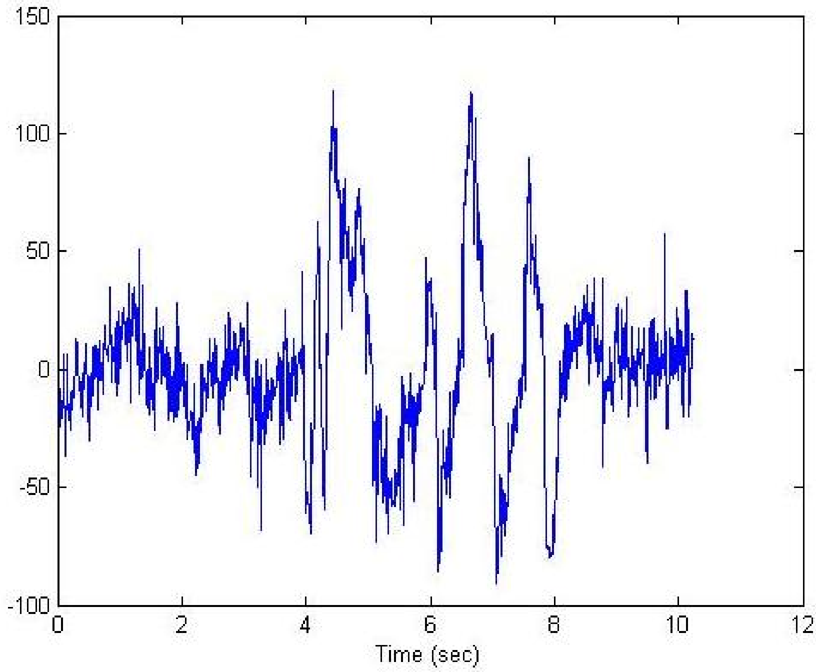


Figure 40. Residual signal

Validating the signal uses the cross correlation to see the relationship between EEG signal with noise and the clean signal. The cross correlation between the EEG signal with noise and the signal after filtering are correlated. Figure 41 shows the cross correlation of signals. The graph shows a balance in the data, this means that there is a strong correlation between the original signal and the clean signal. In another word, the frequency information in both signals are still the same. The result also shows there is a strong correlation between the signal after removing noise and the signal before removing noise.

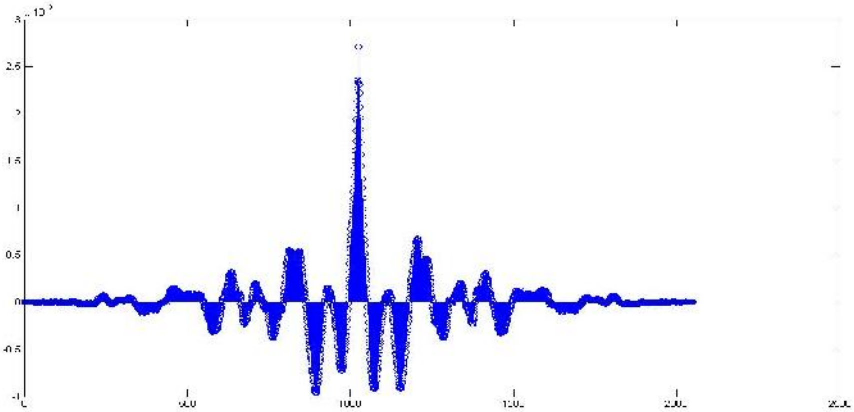


Figure 41. Cross Correlation of the signal

Signal after filtering is known as clean signal. The result from the filtering confirms that the high frequency from the signal vanish and also remove the noise in low frequency. The noise in low frequency is known as eye movement and blinking. This filtering technique also reduces the spike which is high amplitude in low frequency causes by eye blinking. Figure 42 illustrates the spectrum of the clean signal. The graph shows the desire frequency for analysing the DoA in a range frequency *0-60 Hz* free from high frequency. The amplitude power in the range frequency *60-130 Hz* is reduce to approximate zero. The filtering technique also reduces the amplitude power of the signal that could cause misinterpretation DoA.

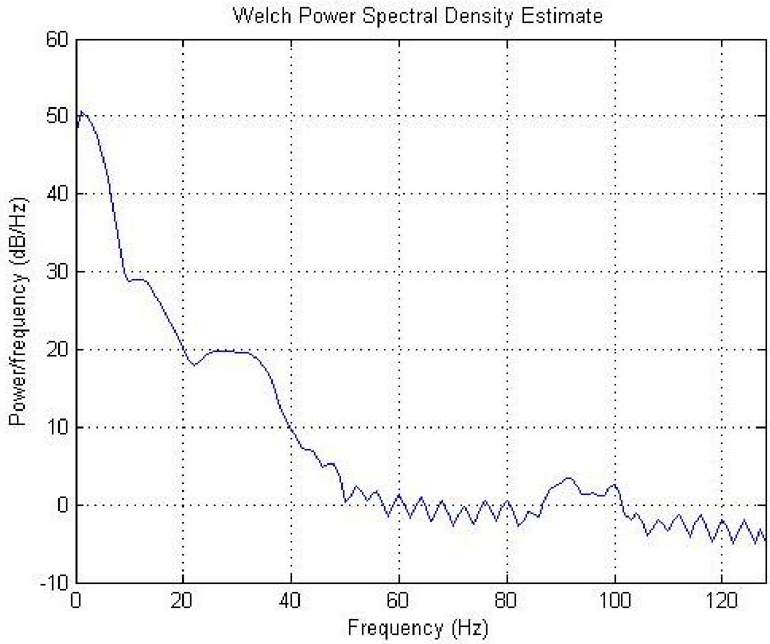


Figure 42. Spectrum of the clean signal

Figure 43 shows the result of this filtering technique compared to the result from research by Kumar (2009). The figure explains that the filtering technique in this study is more robust compared to the other technique introduced in the previous sections. The filtering technique introduced by Kumar (2009) using SWT technique and *symlet* mother wavelet containing higher amplitude power in the high frequency band. Higher amplitude power in the high frequency correlates with the EMG noise.

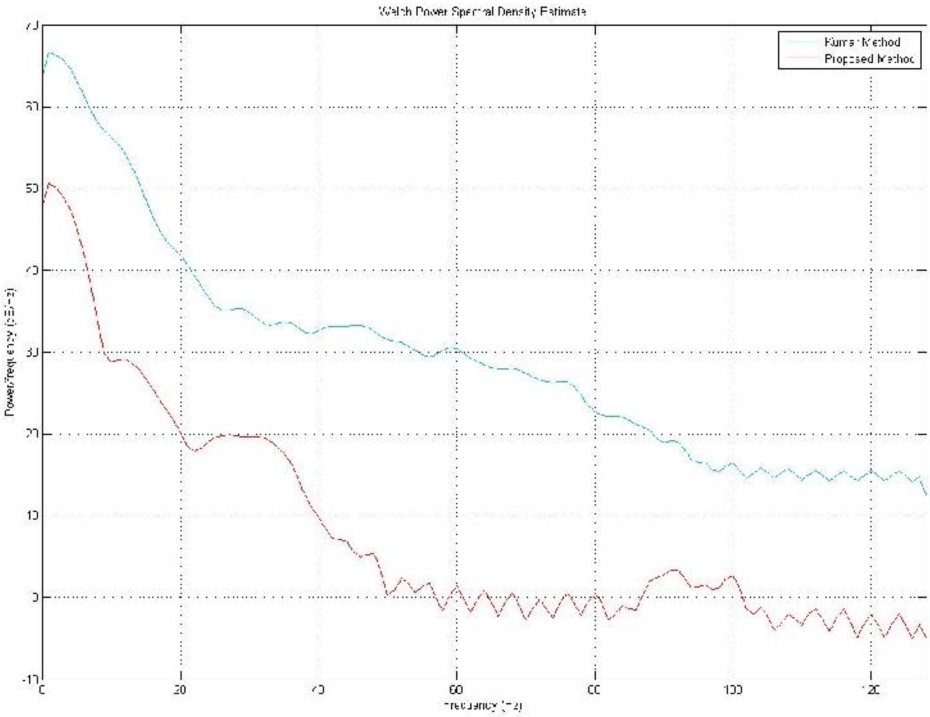


Figure 43. Comparison with other technique

Based on the result, the filtering technique introduced in this thesis is able to remove EOG and EMG noise from the EEG signal effectively. The cross correlation result shows that the frequency information of the signal did not lose in the filtering process.

V. IMPROVEMENT OF BISPECTRAL INDEX FILTERING

V.1 Bispectral Index

V.1.1 Limitation of Bispectral Index

The BIS is a medical device to monitor DoA based on EEG signals. BIS uses time domain and frequency domain information of EEG signal to derive the BIS value (Rampil, 1998). A single value of BIS is drawn from three components. These components are burst suppression, Beta ratio, and SyncFastSlow (Rampil, 1998). The index classifies the level of consciousness from 0 (isoelectric) to 100 (awake). It indicates the level of consciousness of the patient and helps the doctors for titrating anaesthetic agent.

There are limitations of DoA monitoring monitoring device. The limitations listed by (Bowdle, 2006) are:

1. Not responding properly to all anaesthetic agents
2. EMG and other high frequency interfere with EEG
3. Data processing time produces a lag in computation of DoA monitoring Index

4. “Frequently the EEG effects of anaesthetic agents are not good predictor of movements in response to a surgical stimulus because the main site of action for anaesthetic drugs to prevent movement is the spinal cord.” (Bowdle, 2006)

5. The use of DoA monitoring in children is not as well as in adults.

Although BIS is the most popular method of DoA monitoring, its algorithm has limitations. For example, the index does not response properly to all anaesthetics agent such as nitrous oxide, ketamine and opioids (Bowdle, 2006). Furthermore, noises such as eye movement and EMG could affect the BIS value. The increasing values of EMG raise the bispectral index. In addition, the BIS index drops in absence of EMG (Bowdle, 2006). Moreover, the BIS value gives false measurement of the depth of anaesthesia because it measures the increasing value of electromyography (EMG) activity (Bruhn, 2000).

Noises in EEG signals could cause error calculation of DoA. The EMG, EOG are some of the noises that might be exist in EEG signals. That signal overlaps each other with the pure EEG signal. Figure 44 shows the EEG signal overlap with EMG signal. The power of EMG signal is much higher than the EEG signal. Consequently, EMG signal could raise the EEG signal power as well.

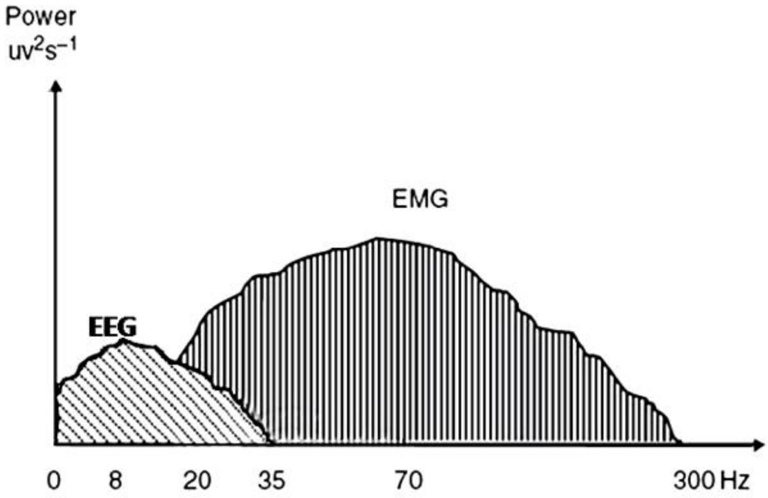


Figure 44. Power Spectrum of the EEG and EMG. (Jensen et al., 2004)

V.1.2 Bispectral Index Filter

The noises and useful information in EEG signal are overlapping each other. Minimising the error by removing some noises from EEG signal using low pass filter and high pass filter was introduced by Sigl (1994). This filtering technique works well in some cases with particular frequency sampling. However, according to Plourde (2002) band-pass filtering technique does not solve the filtering problems of EEG signal. Removing the noises such as EMG, EOG and ECG artefacts from EEG signal using band-pass filter, some useful information in EEG signal could also be removed as well. This type of filter eliminates the noises as well as important information of EEG signal (Bruhn, 2000).

BIS monitoring uses filter to remove the noise. The filtering technique in BIS is revealed by Rampil (1998) using band pass filter. The band pass frequency is within range 0.3 to 30 Hz (Rampil, 1999). This type of filter is completely cut of the frequency which is also containing EEG signal information (Johansen, 2006). Moreover, the electrocardiogram (ECG) might exist in EEG frequency range 0.5 to 30 Hz. Furthermore, the EOG within range 0-16 Hz would also contaminate the EEG signal as well (Krishnaveni, 2006). Therefore, the band-pass filter is not reliable to remove the noises that exist in EEG signal because it will also cut remove some information in EEG signal.

Filtering the noise out could minimise the error in analysing the EEG signal. The DoA analysis with impure EEG signal could cause incorrect result. Increasing activity of EMG signal will also increase the BIS value whereas following administering the neuromuscular blocker decreases the BIS value (Vivien, 2003). Consecutively, as EMG elevates the BIS value will increase, which might be a misleading to the real situation. Hence, to filter out the noise from the EEG signal will improve the robustness of the BIS index.

Specific Filtering method is important for further analysing the EEG signal. Identification, removing noise and feature extraction from the signal will be achieved through filtering. The filtering method used in this filtering technique is the wavelet adaptive filter method to remove the noises in EEG signal. The technique is able to overcome the noise exist in EEG signal. The EEG signal itself is overlapping with the noise and to remove the noise needs specific technique. The wavelet adaptive filter is robust in filtering the signal because it could retain the frequency information in EEG signal and remove the unwanted signal.

V.2 Adaptive Filter

As the explanation above that the EEG signal is overlapping spectra with the noises. The reasons that the combined wavelet transform with adaptive filter is used in this research because the signal parameters are unknown and also the signal is vary in time. The adaptive filter algorithm method used in this technique is Least Mean Square (LMS). The simple diagram of LMS filter is described Figure 45(Gao, 2010).

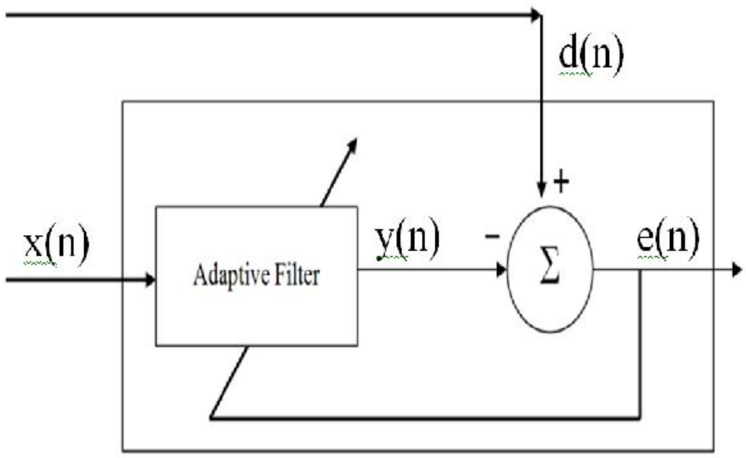


Figure 45. Adaptive Filter Method

LMS is considering low in complexity calculation and simple compare to the other adaptive filtering (Poularikas, 2006; Wang et.al., 2009). Signal *x(n)* is the reference signal for the adaptive filter. The desire signal *d(n)* is the signal with noises.

Reference signal *x(n)* as an input to the system to produce the output signal *y(n).* Signal *y(n)* and *d(n)* is subtracted to compute the error *e(n).* LMS algorithm is to adjust the weight of adaptive filter to minimise the error and estimate the output signal. The algorithm of the LMS filter applied to this filtering technique is based on the LMS adaptive filter.

V.3 Wavelet Adaptive Filter

As explain in previous chapter, Wavelet technique is able to extract information in EEG signal and also remove the noise in EEG signal. Wavelet filtering is an advance method in removing the noise in the signal. The filtering technique using wavelet is introduced by Mallat (1989). This filtering method divides the signal into two different groups (approximation and details), and then decomposes the signal to different level. In Multi-level decomposition method, the signal is broken down into different frequency resolution component (Mathworks, 2010).

The wavelet transforms method uses db3 wavelet transform and decomposed the signal to five levels. In this section the SWT has been chosen based on the explanation in previous chapter. Moreover, SWT has better frequency resolution and capable for signal with time invariant.

In wavelet transform, signal is divided into two groups which are approximation and detail component. Most of the High frequency component of the signal is in details group. Removing the high frequency in the wavelet denoising method by adjust the threshold. Soft threshold method uses in the denoising technique. The soft threshold method is explained in the previous chapter. Raw EEG signal contaminated with artifact shows in Figure 46.

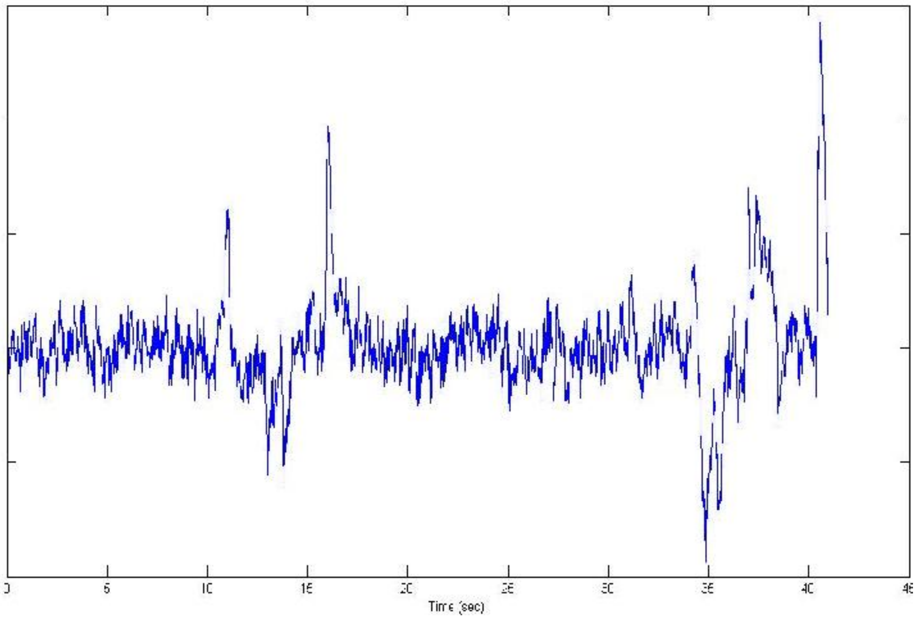


Figure 46. Raw EEG signal with noise

The first stage of EEG signal filtering is achieved by removing high frequency with the SWT technique. Figure 47 shows the decomposition of EEG signal.

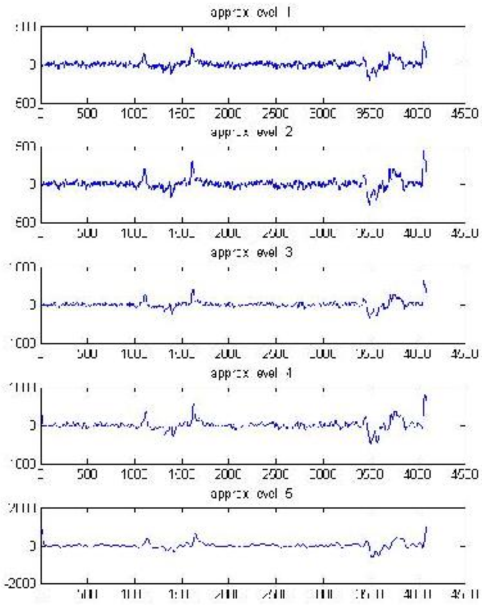


Figure 47 (a). Approximation coefficients

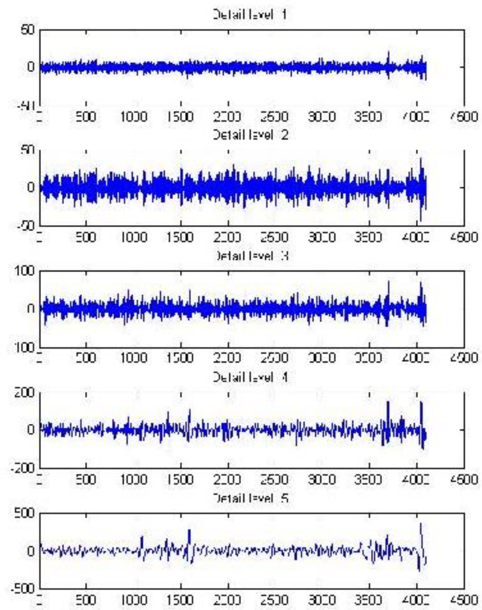


Figure 47 (b). Details coefficiets

Figure 47 (a) shows the approximation coefficients in five levels decomposition. Figure 47 (b) illustrates the details coefficients. Both decompositions use the db3 mother wavelet.

Filtering process in wavelet adaptive method is divided int o two steps. The first step is to remove the high frequency noise in the EEG signal uses wavelet transform. The second step is to remove the low frequency noise using LMS adaptive filter. Figure 48 depicts the Wavelet adaptive filter. The reference signal for the adaptive filter uses the approximation level 5. The reason to use approximation level 5 as a reference signal is because the approximation level 5 is in the lower band and the emergence of EOG signals is mostly in the low frequency band *(0-16 Hz).* The output of the wavelet transform is fed into the adaptive filter as a desire signal. Filter coefficient in adaptive filter is attempted to adapt with the desire signal from the wavelet transform. The summation error between the output of the adaptive filter and the desire signal is then considered as a clean signal.

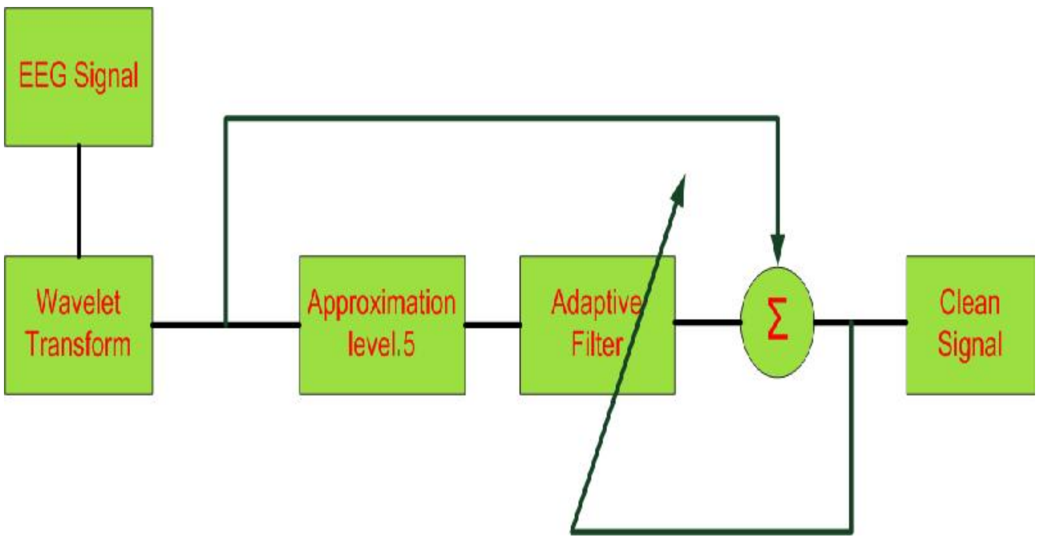


Figure 48. Wavelet Adaptive Filter

V.4 Simulation of filtering technique

The simulation program of wavelet transform filtering technique uses MATLAB software with the Wavelet toolbox. The first stage of wavelet adaptive filter is to remove the high frequency from the EEG signal. The threshold method of wavelet denoising is applied. Figure 49 shows the result after removing the high frequency of the signal.

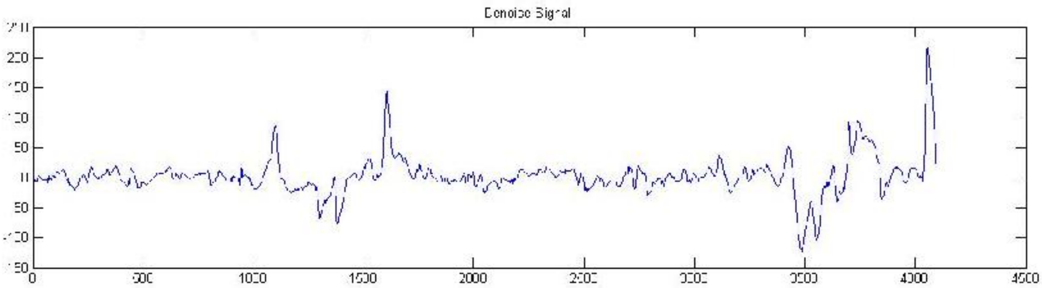


Figure 49. First stage filtering with wavelet

Figure 50 illustrates that the high frequency noise has removed from the raw EEG signal. The next step is to remove the low frequency noise from the signal. Removing the low frequency noise from the signal uses the adaptive LMS filter technique. The output signal from the wavelet denoising is put through the adaptive LMS filter as an input. The reference signal for the LMS filter is the approximation decomposition level five. This level is considered as a reference because the frequency components of this signal low frequency and high amplitude. Frequency of this signal is between *0 to 16 Hz*. This signal is then put through the LMS filter with the adjustment of the weight of adaptive filter to estimate the output. The response of the adaptive filter *y(k)* is comparing with the desire signal *d(k)* for further removing the noise and resulting the clean signal *e(k).* The signal *e(k)* is the desire signal which is EEG signal free artifact. The result signal after filtering is depicted in Figure 50.

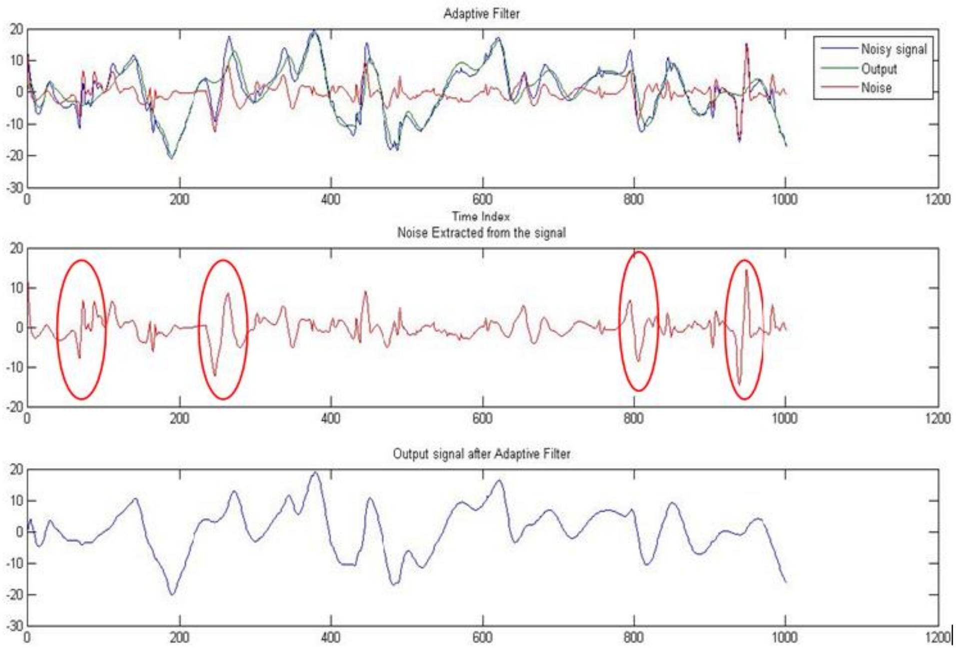


Figure 50. Adaptive Filter

Figure 50 shows the filtering process of the adaptive filtering technique. Figure 50 (a) shows the result of the adaptive LMS process, Figure 50(b) is the noises extracted from the corrupted EEG signal and the Figure 50(c) is the output of the wavelet adaptive filter. Noise extracted from the EEG signal shows that the low frequency noise has taken out as well as other noise such as the ECG signal (marked with circle).

V.5 Result and Analysis

Figure 51 shows the result of the process of EEG signal filtering using wavelet adaptive filter. In Figure 51(a) is the raw EEG signal. Figure 51(b) is the EEG signal after denoising process with wavelet and the Figure 51(c) is the result of combine wavelet adaptive filter. The performance of wavelet adaptive filter technique shows that the filter is able to remove noise from the EEG signal effectively. The difference between the signal before and after the denoising is shown in the Figure 51. It is clear that after first step of filtering the noise still exist Figure 51(b). Furthermore, combine wavelet and adaptive filter shows that the noises in that signal are completely removed. The result is depicted in (c).

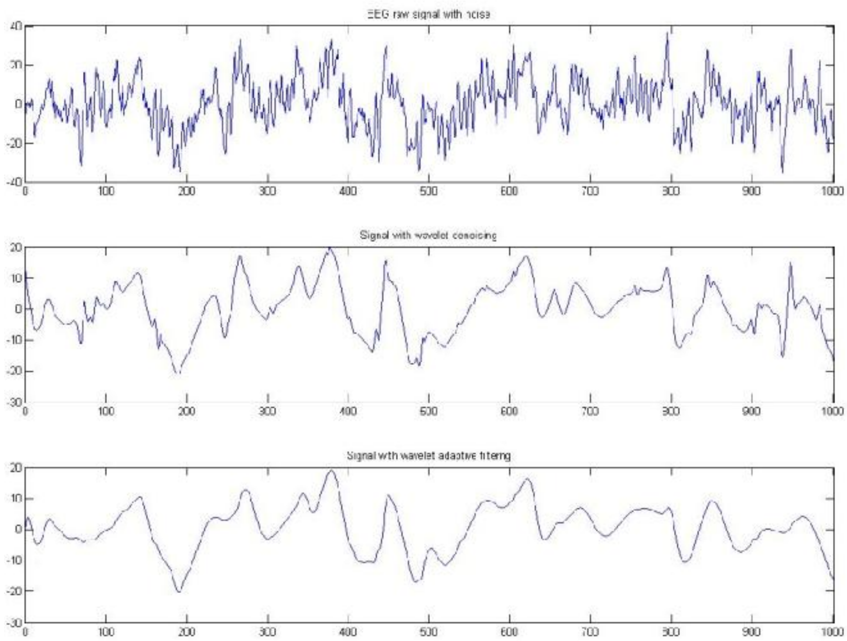


Figure 51 (a) EEG signal with noise, (b) Signal after denoising with wavelet, and (c) clean signal after wavelet adaptive filter

Signal to noise ratio (SNR) is used to measure how dominant the signal relative to the noise (Wang, 2009). The ratio is expressed in dB. The ratio value of the SNR is linear with the performance of the filtering technique. The higher the ratio value of SNR means the performance of the filtering is good.

In order to compare the performance of the filtering technique of the EEG signal before and after wavelet adaptive filter also use SNR. Table I shows the performance of the filtering technique. The results shows the filtering technique using wavelet adaptive filter is much better comparing to the wavelet denoising. Also, it is illustrated that the combining techniques of wavelet adaptive filter is more robust in removing the noise from the EEG signal.

Table 1. The Performance of the Filtering Technique

WAVELETE ADAPTIVE FILTER	
FILTERING TECHNIQUE	**SNR**
WAVELET ADAPTIVE FILTER	102.1010
WAVELET DENOISING	81.8868

The result shown a filtering with wavelet adaptive filter is able to remove noise from the EEG signal. The comparison of the result with other research shows that the filtering technique is significant compare with other technique. Table 2 shows the comparison between other researches method.

Table 2. Comparison between other research method

WAVELETE ADAPTIVE FILTER	
Filtering Technique	**SNR (dB)**
Wavelet adaptive filter	102.1010
SWT filter in Chapter 4	98.08
Wang, 2009	85.6640
Wavelet denoising	81.8868

The comparison between other methods shows the wavelet adaptive filter gives better result in filtering the EEG signal. The SWT filter introduced in the previous chapter has 98.08 dB. On the other hand, Wang (2009) method using adaptive filter based on discrete wavelet transform shows the SNR lower than the SWT filter technique in chapter 4. However, wavelet adaptive filter in this chapter confirm that it has better performance compared to the other method.

A cross correlation method is used to analyse the relationship of the signal before and after filtering. It helps to validate the signal after filtering, whether it is still retained frequency information or not. The result shows that the filtering technique using wavelet adaptive filters still retain frequency information of the signal. The cross correlation of the first stage filtering output shows that the signal information is highly correlated with the input signal. Figure 52 depicts the correlation between the output of the first stage filtering and the input signal. It is shown the peak of the histogram is in zero and there is a balance lag between left and right, which is means there is a significant correlation.

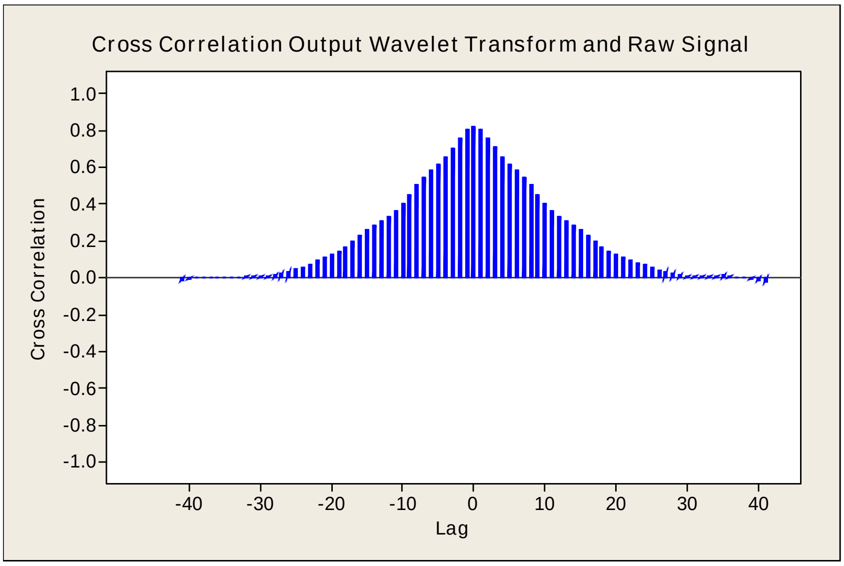


Figure 52. Cross correlation of output wavelet transform and the input signal

The output signal from the second stage of the wavelet adaptive filter technique shows that there is a correlation between the output of the filter and the input signal. In other words, frequency information of the signal after filtering still contains information from the original signal. Figure 53 shows the cross correlation between the raw signal and the output of wavelet adaptive filter. These analyses validate the efficiency of the filtering technique using wavelet adaptive filter is more robust compare to the wavelet transform filter and adaptive LMS filter. It is also confirmed that the noise in EEG has removed and frequency information of the signal is still retain.

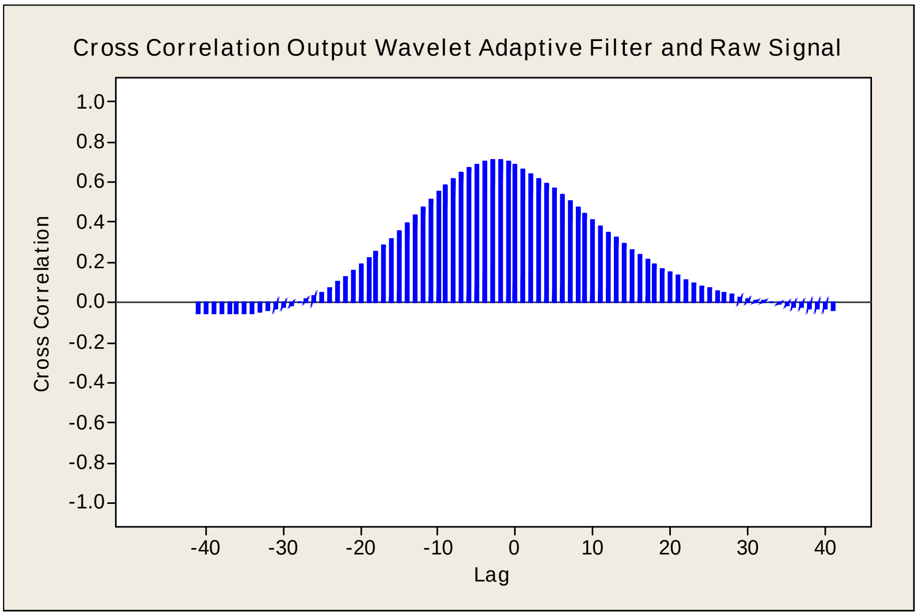


Figure 53. Cross correlation of the output of wavelet adaptive filter and raw signal

The combining wavelet adaptive filter technique able to removes noise in EEG signal. In the simulation above shows the capability of the wavelet adaptive filter to removes noise from EEG signal. Three filtering simulations below is to demonstrate the reliability of Wavelet adaptive filter in removing noise in EEG signal. The simulations of wavelet adaptive filter technique uses the recorded EEG signal contaminated with EMG, EOG and ECG noise. The recorded EEG signals are downloaded from Physionet organisation website (Physionet, 2011).

Figure 54 shows the original signal before filtering and after the first stage of the filtering using wavelet. In this stage the high frequency of the signal has removed. Signal power and amplitude is still the same with the original signal.

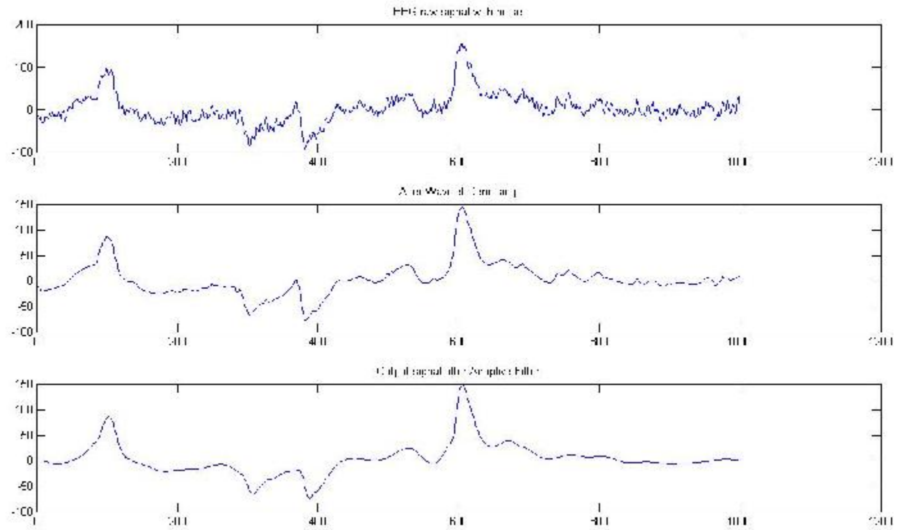


Figure 54. Comparison of filtering different filtering technique

The final result of wavelet adaptive filter in removing noise depicted in Figure 55. It shows the filter capability in removing the high frequency noise and low frequency noise as well as the ECG noise in the signal.

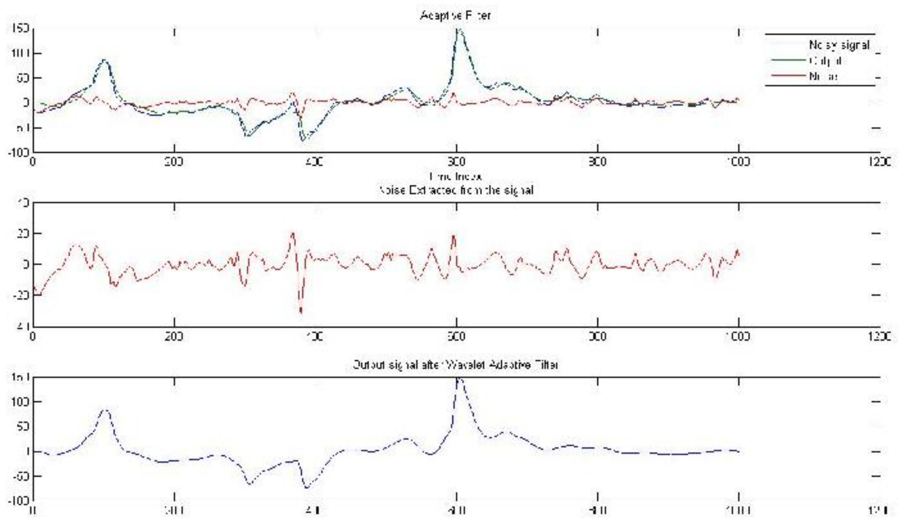


Figure 55. Wavelet adaptive filter output

Next two simulations demonstrate the performance of the wavelet adaptive filter technique in removing noise from the EEG signal.

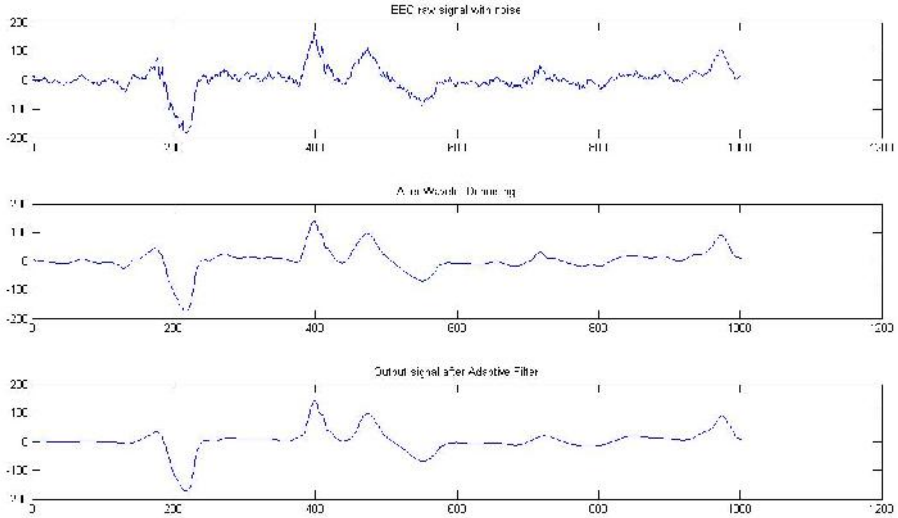


Figure 56. Original signal and denoise signal.

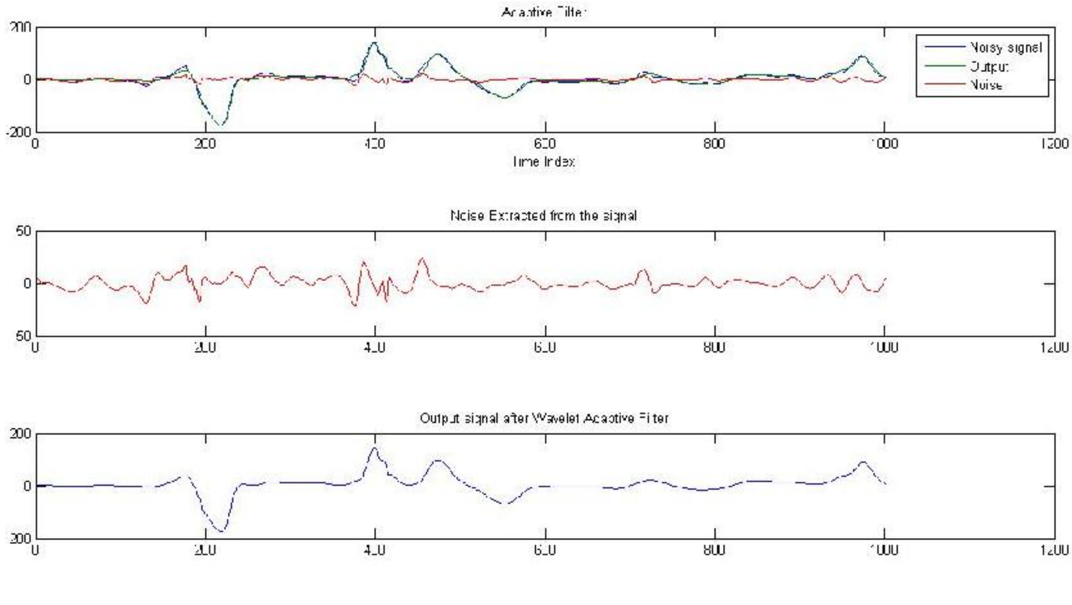


Figure 57. Filtering after the wavelet adaptive filter

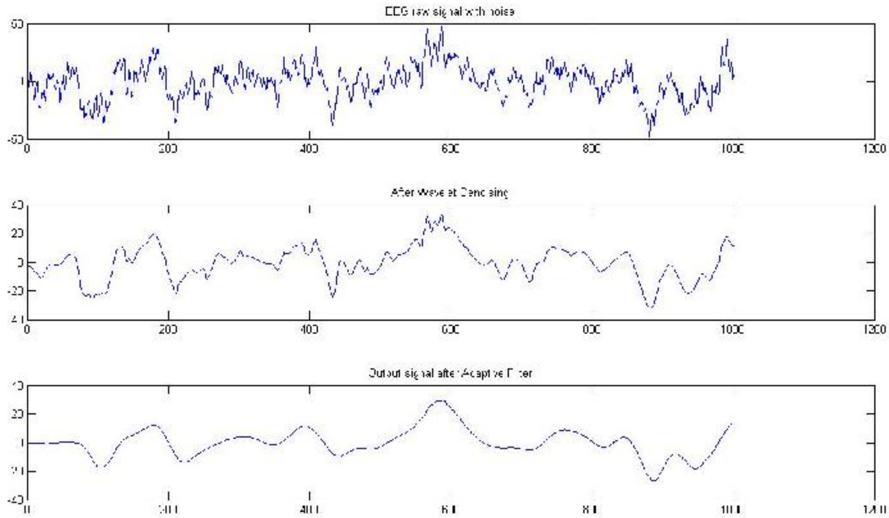


Figure 58. Original signal and denoise signal after filtering process.

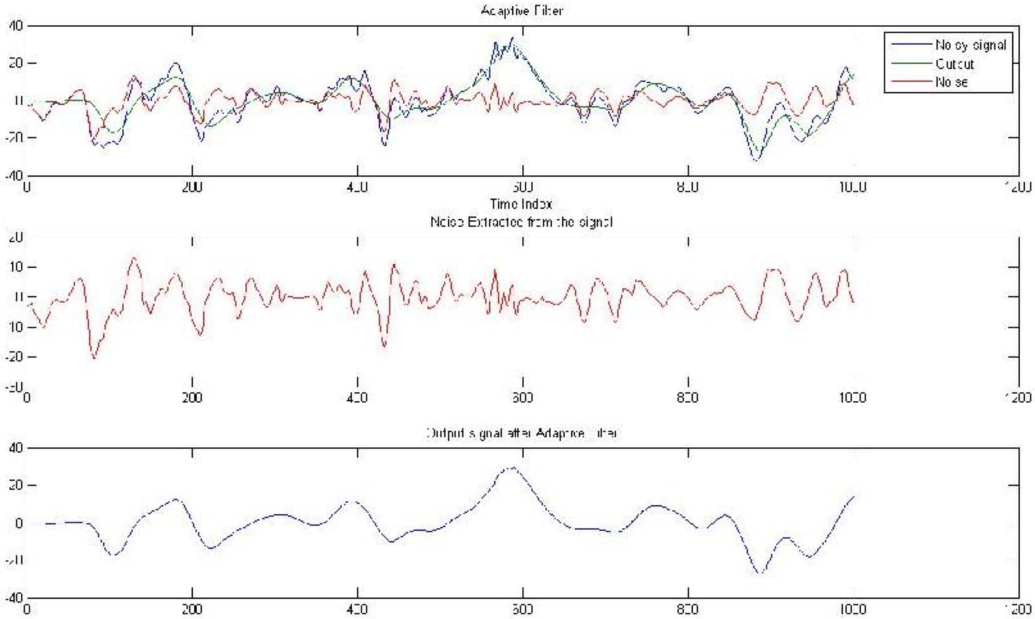


Figure 59. Output of the wavelet adaptive filter

The reliability of the Wavelet Adaptive filter technique can be seen from the result of the filtering simulations. The result of these experiments is higher compare to the other filtering technique as discuss in section V.5. Table 3 shows the result of the Wavelet adaptive filtering technique.

Table 3. Result of Wavelet adaptive filtering technique simulations

WAVELETE ADAPTIVE FILTER	
Filtering Technique	**SNR (dB)**
Experiment 1	102.1010
Experiment 2	156.0055
Experiment 3	116.7837
Experiment 4	80.8922

From the table above, the SNR is relative higher compare to the result in Table 2. Table 3 shows, the experiment 2 has higher value compare to the other experiments. Experiment 4 has less SNR value compare to the other simulations. However, the Figure 59 shows the simulation of experiment 4 is able to remove noises in the EEG signal.

VI. DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

VI.1 Discussions

EMG, EOG and ECG noise in EEG signal are overlapping each other (Jensen, 2004). Simple filtering process such as band pass filter for removing noises from the EEG signal might remove some useful information of the signal (Plourde, 2002; Krisnaveni, 2006). Review by Rampil (1998), the BIS monitor uses the band pass filter to eliminate noise in EEG signals. The band pass filter from 0.3 to 30 Hz might cause inconsistence result of the monitor.

The LMS adaptive filter introduced in the previous chapter is able to remove the high frequency noise such as EMG from EEG. The appearance of this noise could raise the BIS index value (Vivien, 2003; Bonhome, 2007). The LMS adaptive filter eliminates EMG noise with the filter adaptation by putting the reference signal.

DoA monitor using contaminated EEG signal often results in an incorrect outcome. Removing the EMG and EOG noise from the EEG signal could minimise error result in analysis. EMG signal noise affects the high frequency band of the EEG signal (Sanei & Chamber, 2007). On the other hand the EOG signal could also raise the power of lower frequency band (0 – 16 Hz) (Croft & Berry 2000; Kavitha et al., 2007). Wavelet transform filtering technique is introduced in this research to overcome the EEG filtering problem. The result shows that the wavelet transforms technique is able to remove EMG and EOG noise from the contaminated EEG signal. The result of the wavelet transform filtering technique is much better comparing to the technique proposed by Kumar (2009).

A combined filtering technique of wavelet transform and LMS adaptive filter has been introduced in this research. The combined Wavelet adaptive filter technique shows that it is more robust and efficient in removing noise from EEG signal. The result in chapter five shows this filtering technique is able to remove low frequency noise, high frequency noise and ECG signals. The proposed wavelet adaptive filter provides better result comparing to Kumar (2009) and Wang (2009) filtering technique.

VI.2 Conclusions

Noise in EEG signal causes the incorrect reading of DoA monitor. The noise such as EMG comes from muscle which emerges as high frequency signal that could raise the EEG signal frequency. Another underlying noise that is difficult to detect in general anaesthesia is EOG. The existence of EOG also could increase the power in low frequency band. All these noises need specific filtering technique to be removed.

Three different filtering methods are investigated in this research. The first one is adaptive least mean square technique with analysis of variance (ANOVA). The second one is wavelet technique, which uses SWT method. Finally the advanced technique is a combination of the Wavelet transform and adaptive least mean square.

Adaptive LMS technique has been chosen for the filtering because of the simplicity in calculation. Thus, the time consuming for the filtering process is more efficient. This filtering method needs certain iteration for the adaptation to get better result. However, justification of iteration to find the best coefficients value is required. The ANOVA is employed to justify the best coefficients for the output. The result shows that the LMS adaptation technique with ANOVA is able to find the best value for the filter. In addition, the output of the adaptive filter with ANOVA is able to remove the high frequency noise in EEG signal, which is correlated with EMG noise.

The SWT filter removes the noise in two steps. The first step is to eliminate high frequency noise. In this step high frequency which is considered as EMG noise is removed. The second stage is to remove the low frequency noise. Wavelet transform filtering technique removes both EMG and EOG signal from the EEG signal. This filtering method able to removes noise and retain the frequency information of the signal.

The most advanced technique in this research is the filtering technique using both the wavelet transform and adaptive method. The result shows the filtering technique is able to remove underlying noise in the EEG signal. The comparison among other techniques shows that this technique is also more robust. The SNR method is used to compare the performance of filtering method. Result shows that the Wavelet adaptive filter is much better (102.1010 dB) comparing to the existing filtering method.

VI.3 Future Work

Adaptive LMS filtering technique with ANOVA can be further improved to define filter weight coefficient on the adaptive filter. The filtering method with ANOVA can be further optimised to define the step function of the adaptive filter.

The Wavelet transform filtering can be improved with development of new mother Wavelet rather than using the available one. The defining of a new mother Wavelet should be based on the characteristics of the EEG signal artifact. The development of new mother Wavelet could improve the efficiency of EEG signal filtering and classification.

The application of combined wavelet transform adaptive filter can be further improved by placing the filter in a real time with DoA monitor.

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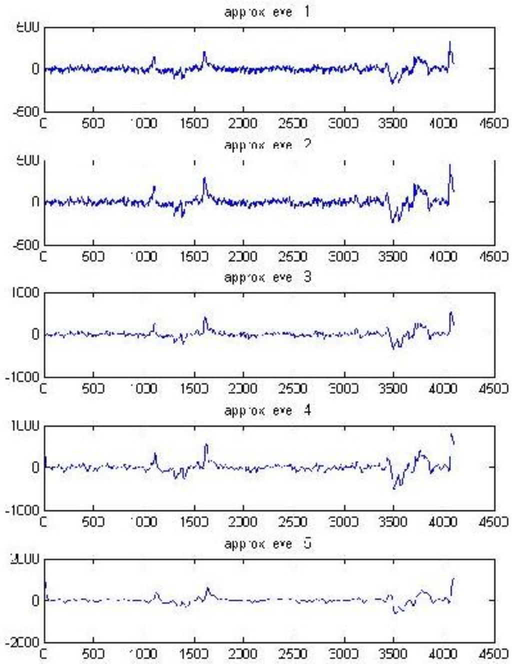
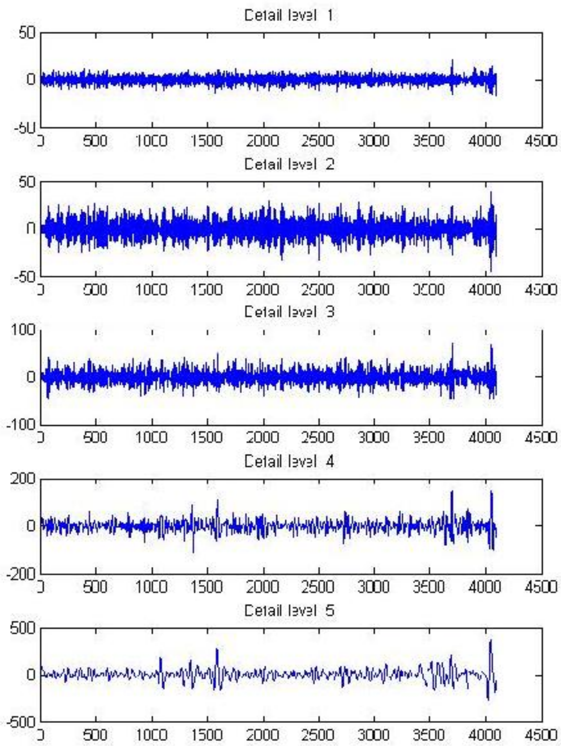
APPENDIX A - STATIONARY WAVELET DECOMPOSITION

```
%% load raw EEG data
load EEG.txt;
c=EEG(:,2);
d=c';
g=d(1:4096);      %take sample in order to calculate

%% Decomposed using wavelet,  Stationary Wavelet Decomposition
%SWC = SWT(X,N,'wname') computes the stationary wavelet
%    decomposition of the signal X at level N, using 'wname'.
% this stage I am using db3 al level 5
[wa,wd]=swt(g,5,'db3');

%% Plot the wavelet decomposition
figure(1);
kp=0;
for i=1:5
   subplot(5,2,kp+1), plot(wa(i,:));
   title(['approx level  ',num2str(i)])
   subplot(5,2,kp+2), plot(wd(i,:));
   title(['Detail level  ',num2str(i)])
   kp=kp+2;
end
```

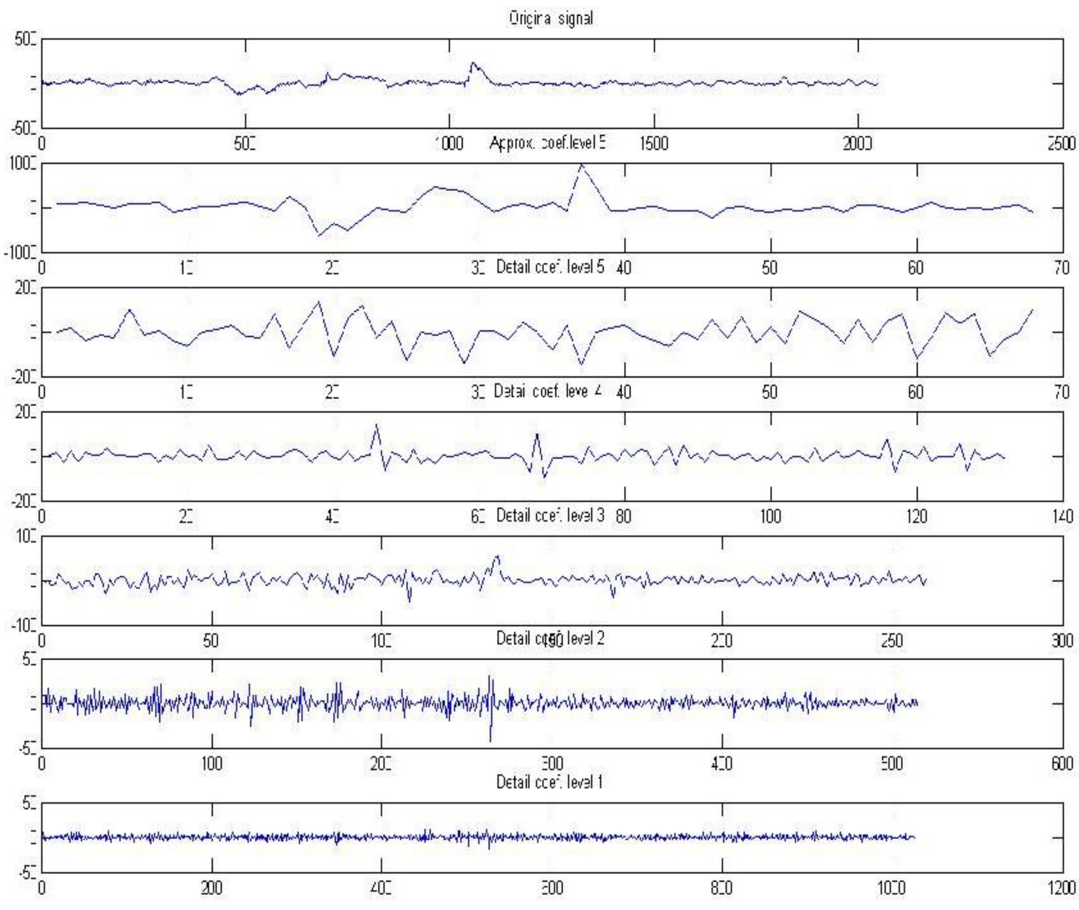



Detail level 1
Detail level 2
Detail level 3
Detail level 4
Detail level 5

APPENDIX B - DISCRETE WAVELET DECOMPOSITION

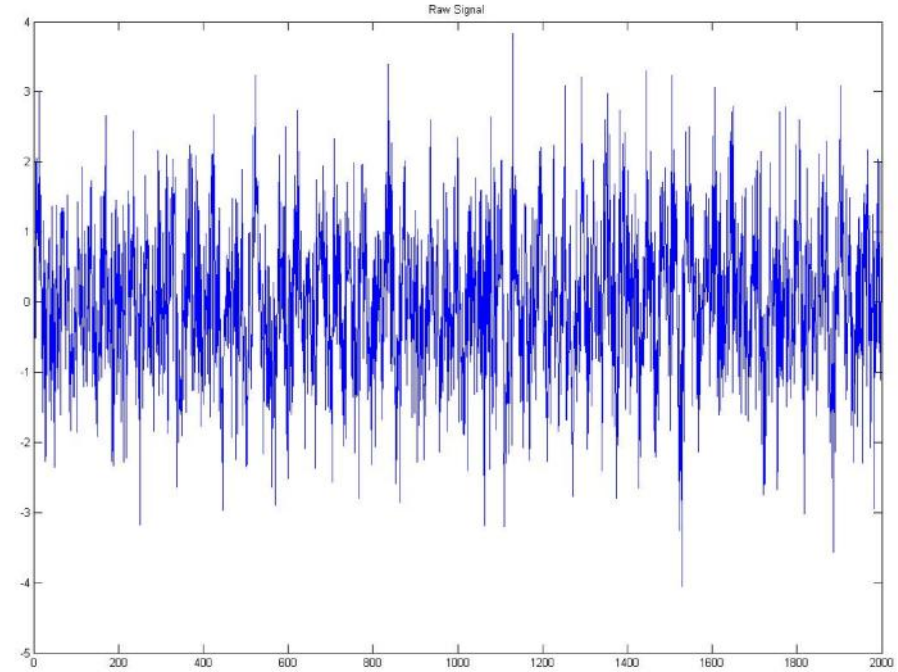
```
clear all;

%% Load signal for decomposition

load EEGraw.mat

tim=3000:5047;

x=EEG(tim);

 %% Decomposed using wavelet, Multilevel Stationary Wavelet Decomposition

%[A,D] = DWT(X,N,'wname') computes the stationary wavelet

%    decomposition of the signal X at level N, using 'wname'.

% this stage I am using db3 wavelet and decompose to level 5

[A,D]=wavedec(x,5,'db3');


%% Plot the wavelet decomposition

figure(1);

A5=appcoef(A,D,'db3',5);

[D1,D2,D3,D4,D5]=detcoef(A,D,[1,2,3,4,5]);


subplot(711); plot(x); title('Original signal');

subplot(712); plot(A5); title('Approx. coef.level 5 ');
```

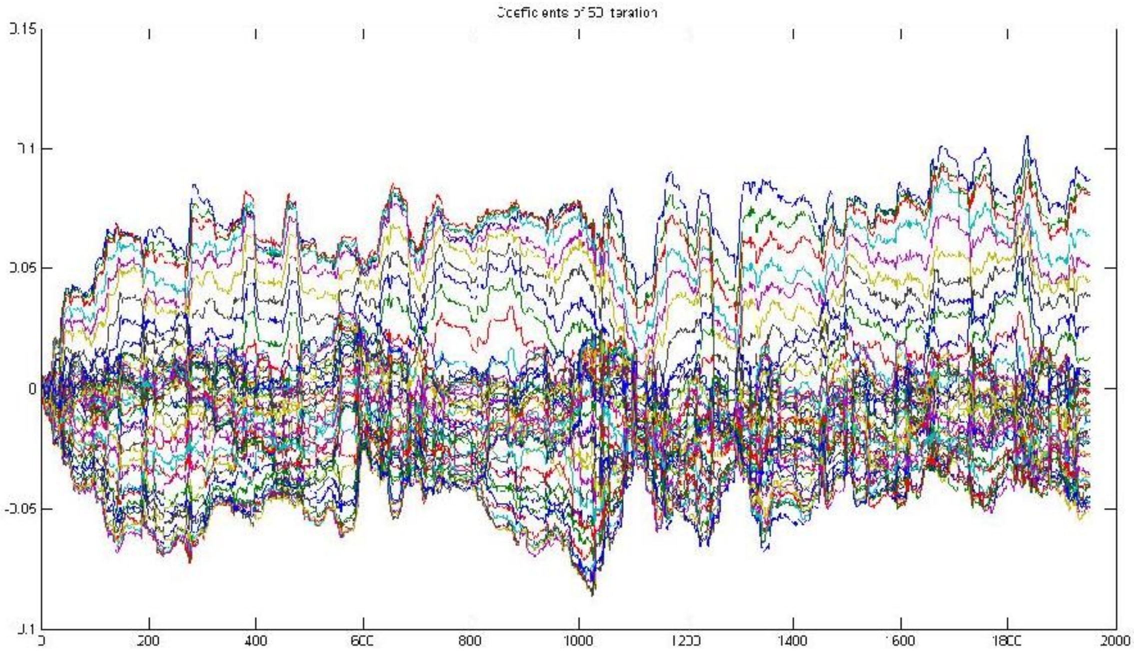
```
subplot(713); plot(D5); title('Detail coef. level 5');

subplot(714); plot(D4); title('Detail coef. level 4 ');

subplot(715); plot(D3); title('Detail coef. level 3');

subplot(716); plot(D2); title('Detail coef. level 2');

subplot(717); plot(D1); title('Detail coef. level 1');
```

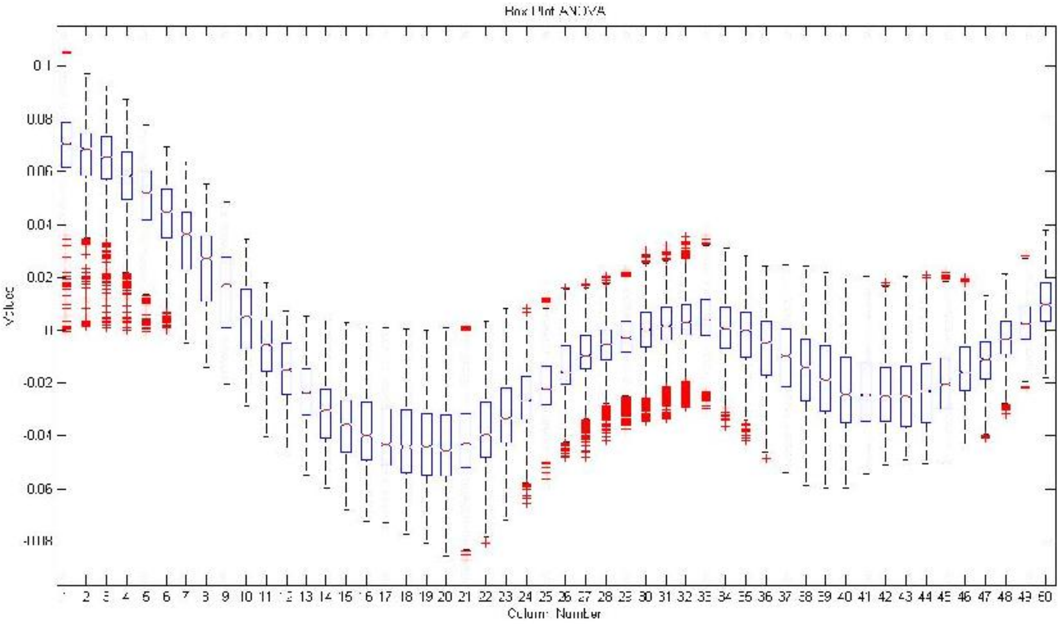


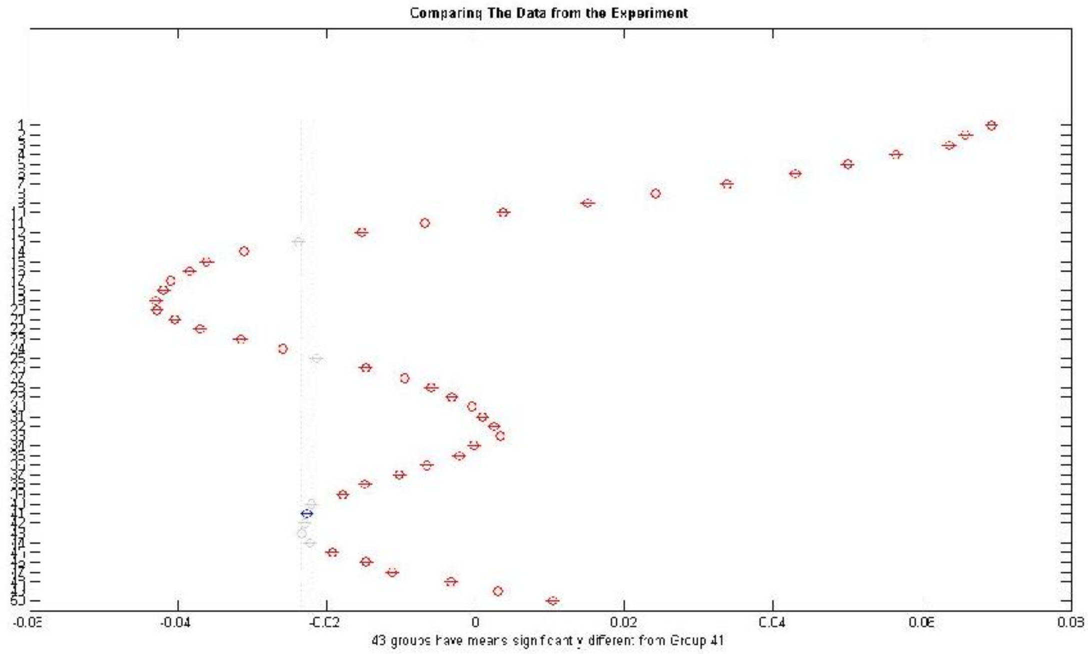
APPENDIX C – ADAPTIVE LMS WITH ANOVA

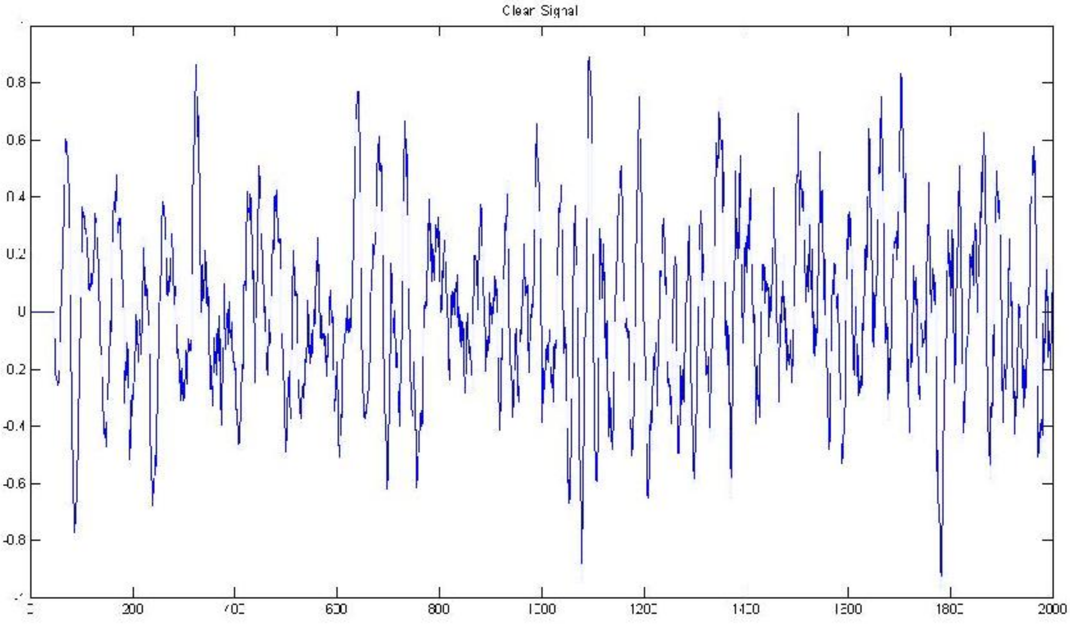
```
%% Import Generate Signal

load EEG.mat
dn=x;

nois=randn(size(dn));
os=dn+nois;   % output signal


%% LMS adaptive filter

%x=input data to the filter; dn=desired signal;
%M=order of the filter;
%mu=step size; x and dn must be of the same length;
%each column of the matrix w1 contains the history of each
%filter coefficient;
M=50;
mu=0.002;   %works good
N=length(os);
y=zeros(1,N);
w=zeros(1,M); %initialized filter coefficient vector;
for n=M:N
    xl=os(n:-1:n-M+1); %for each n the vector xl is produced
                     %of  length  M  with  elements  from  os  in  reverse
order;
    y(n)=w*xl';
    e(n)=dn(n)-y(n);
    w=w+2*mu*e(n)*xl;
    w1(n-M+1,:)=w(1,:);
end;

%% Statistics

[p,table,stats]=anova1(w1);   % this is the right one
figure;
[c,m] = multcompare(stats);

%% find the minimum of the data

[AA,yy] = finditer(w1,c,m,e)   %Minimum value from iteration

%% Plot Data
figure;
plot(w1(:,AA));
```


Raw Signal
4
3
2
1
0
-1
-2
-3
-4
-5
0
200
400
600
800
1000
1200
1400
1600
1800
2000


Coefficients of 50 iteration
0.15
0.1
0.05
0
-0.05
-0.1
0
200
400
600
800
1000
1200
1400
1600
1800
2000

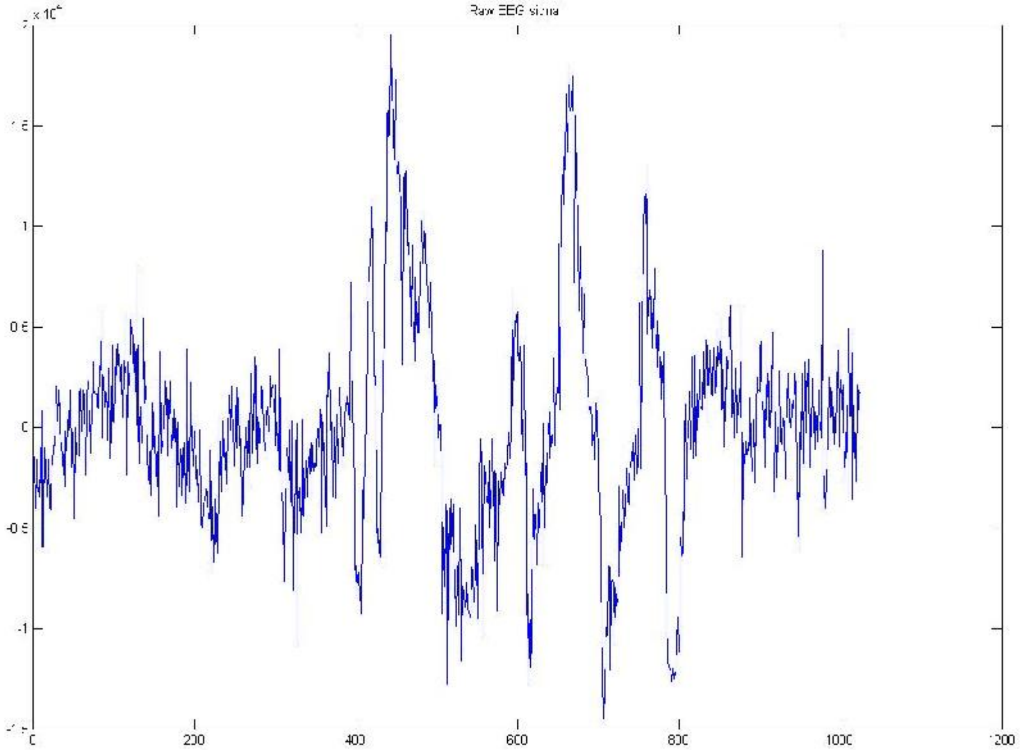

Box Plot ANOVA
Values
Column Number

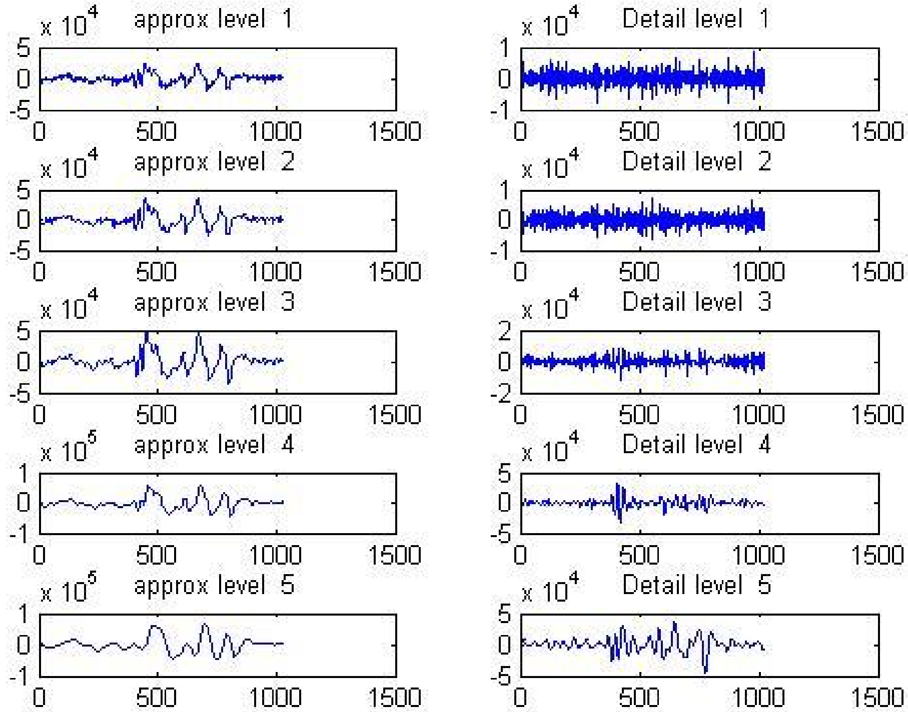

Comparing The Data from the Experiment
43 groups have means significantly different from Group 41


Clear Signal
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
200
800
1800
2000

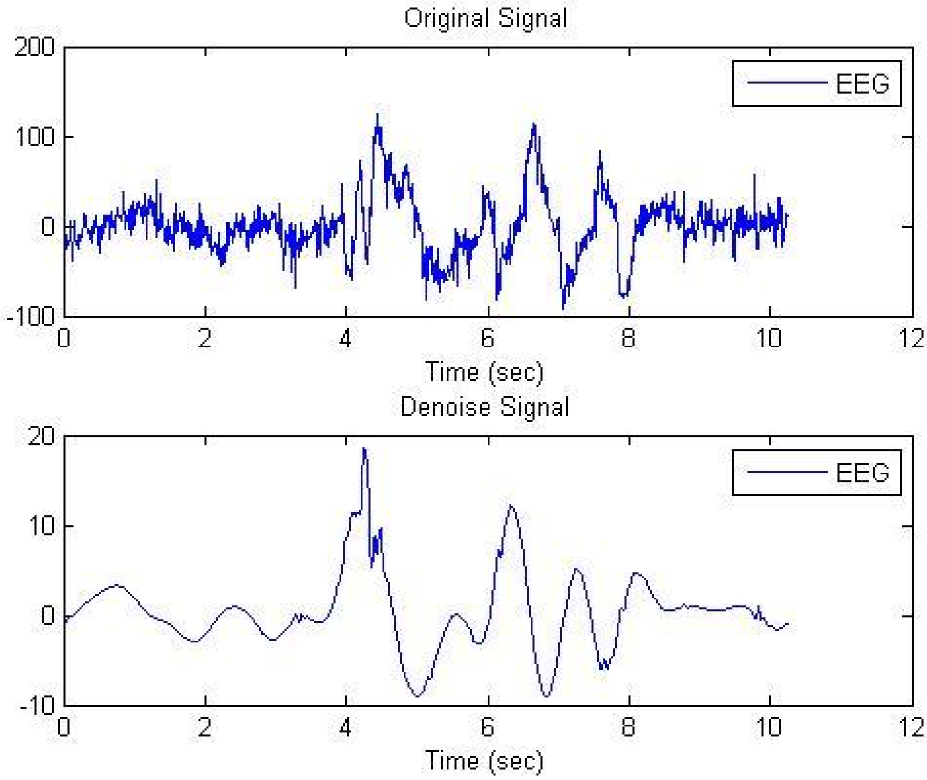
APPENDIX D - FILTERING USING WAVELET TRANSFORM

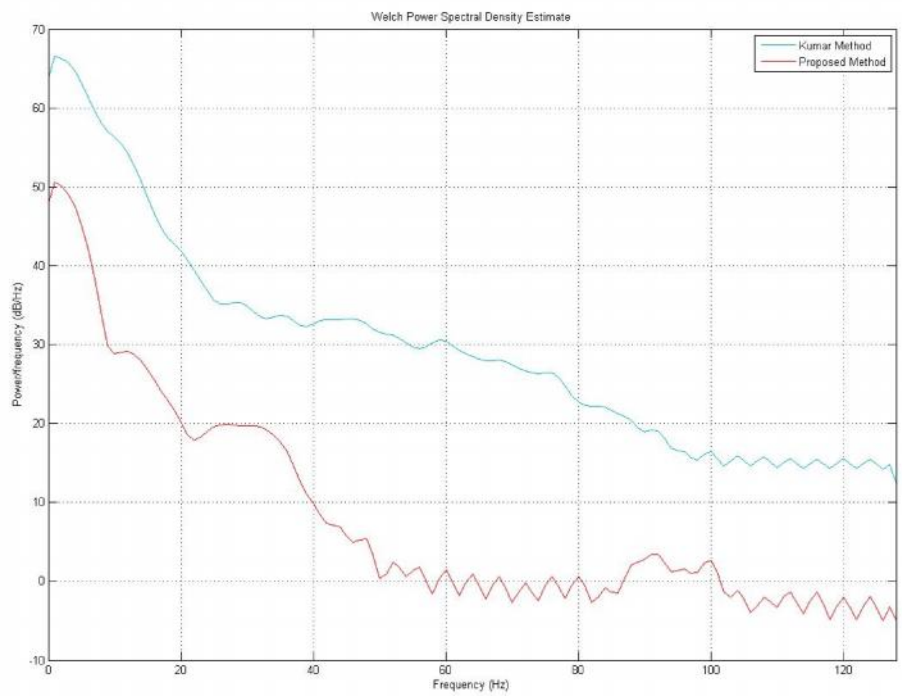
```
%% load raw EEG data
load 'signoiscampuran.mat'; % EEG signal with EOG and EMG noise
g=x;
%% Decomposed using wavelet,Stationary Wavelet Decomposition
%SWC = SWT(X,N,'wname') computes the stationary wavelet
%    decomposition of the signal X at level N, using 'wname'.
%
% this stage I am using db3 al level 5
[wa,wd]=swt(g,5,'db3');

%% Plot the wavelet decomposition
figure(1);
kp=0;
for i=1:5
    subplot(5,2,kp+1), plot(wa(i,:));
    title(['approx level  ',num2str(i)])
    subplot(5,2,kp+2), plot(wd(i,:));
    title(['Detail level  ',num2str(i)])
    kp=kp+2;
end

%% Reconstruct the Signal

%% Reconstruc the approximation from level 1 to 5
snol=zeros(size(wd));
A=snol;
for i=1:5
    A(i,:)=iswt(wa,snol,'db3');
end

%% Reconstruc the details from level 3 to 5
D=snol;
for i=3:5
    D(i,:)=iswt(snol,wd,'db3');
end

%% Denoise the signal
% Remove the Noise

[clean,tt]=synal(x,wa,wd,A,D,f2);


%% display the original and denoise signal
figure(10);
subplot(2,1,1), PlotEEG(g);
title('Original Signal');
subplot(2,1,2), PlotEEG(clean);
title('Denoise Signal')
```





x 10^4 approx level 1
x 10^4 approx level 2
x 10^4 approx level 3
x 10^5 approx level 4
x 10^5 approx level 5
x 10^4 Detail level 1
x 10^4 Detail level 2
x 10^4 Detail level 3
x 10^4 Detail level 4
x 10^4 Detail level 5
0 500 1000 1500

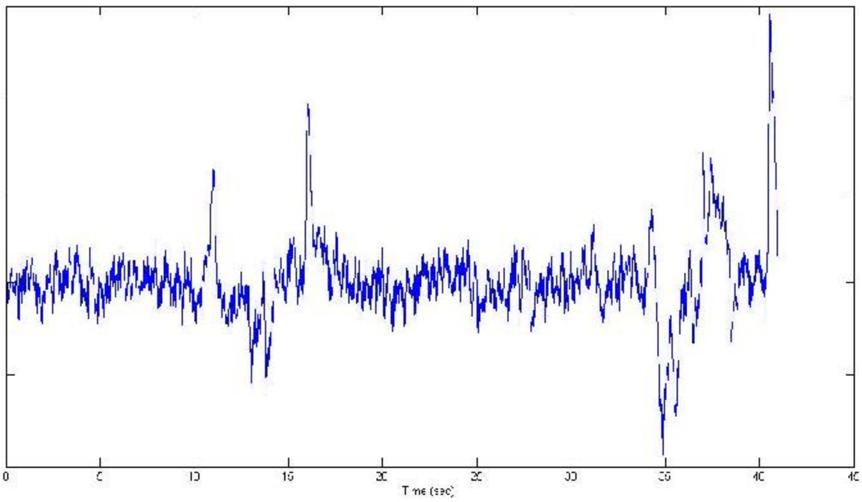

Original Signal
EEG
Time (sec)
Denoise Signal
EEG
Time (sec)

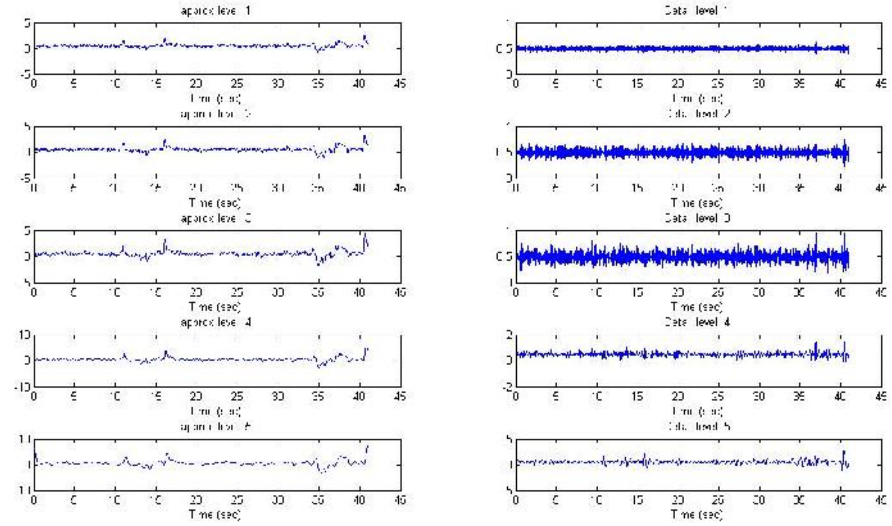

Welch Power Spectral Density Estimate
Kumar Method
Proposed Method
Power/frequency (dB/Hz)
Frequency (Hz)

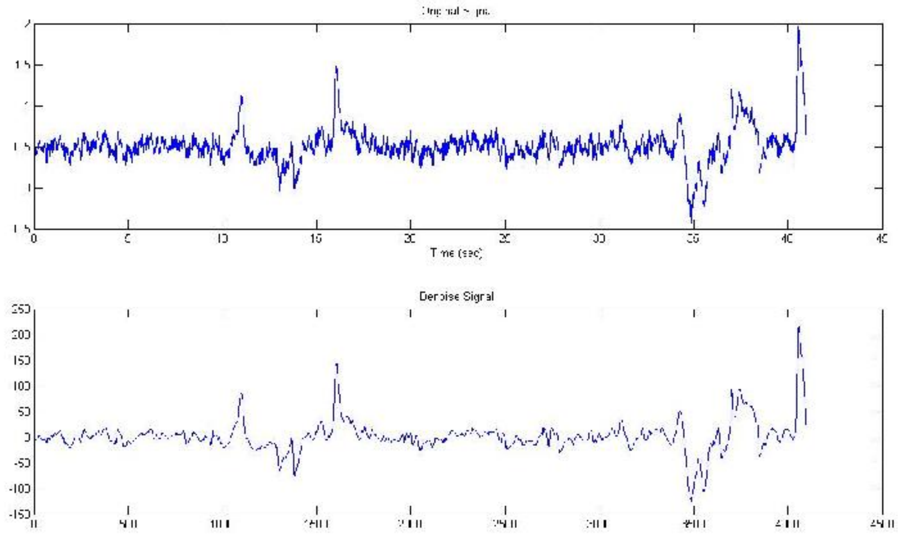
APPENDIX E - FILTERING USING COMBINED ADAPTIVE FILTER AND WAVELET TRANSFORM

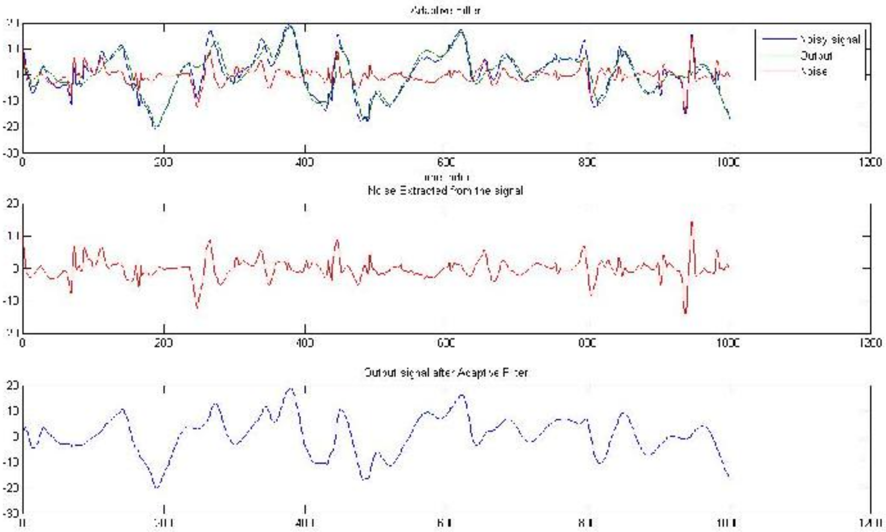
```
%% load raw EEG data
load EEG.txt;
c=EEG(:,2);
d=c';
g=d(1:4096);      %take sample in order to calculate
%% Decomposed using wavelet,  Stationary Wavelet Decomposition
%SWC = SWT(X,N,'wname') computes the stationary wavelet
%    decomposition of the signal X at level N, using 'wname'.
%    N must be a strictly positive integer (see WMAXLEV for more
%    information). 2^N must divide length(X)
% this stage I am using db3 al level 5
[wa,wd]=swt(g,5,'db3');

%% Plot the wavelet decomposition
figure(1);
kp=0;
for i=1:5
    subplot(5,2,kp+1), plot(wa(i,:));
    title(['approx level  ',num2str(i)])
    subplot(5,2,kp+2), plot(wd(i,:));
    title(['Detail level  ',num2str(i)])
    kp=kp+2;
end

%% Reconstruct the Signal
% This EXERCISE only reconstruct the approximation and detail
% from 2 to 5

%% Reconstruc the approximation from level 2 to 5
snol=zeros(size(wd));
A=snol;
for i=2:5
    A(i,:)=iswt(wa,snol,'db3');
end

%% Reconstruc the details from level 2 to 5
D=snol;
for i=2:5
    D(i,:)=iswt(snol,wd,'db3');
end

%% display the approximation at level 2 to 5
figure(2);
kp=0;
for i=2:5
    subplot(5,2,kp+1), PlotEEG(A(i,:));
    title(['approximation lvl  ',num2str(i)]);
    subplot(5,2,kp+2), PlotEEG(D(i,:));
```

```
    title(['Detail lvl  ', num2str(i)]);
    kp=kp+2;
end

%% Denoise the signal
% Remove the Noise

[clean,tt]=synal(x,wa,wd,A,D,f2);


%% adaptive filter
 x  = A(5,[1:1001]);      % A5 as Input to the desire signal
 d  = clean(1:1001);       % after denoise as input to the filter

 [y,e] = waveletadapt(x,d,mu);

figure(3)
%subplot(3,1,1);plot(d);title('Raw EEG Signal');
subplot(3,1,1); plot(1:1001,[d;y;e]);
title('Adaptive Filter');
legend('Noisy signal','Output','Noise');
xlabel('Time Index');
subplot(3,1,2); plot(e,'r');
title('Noise Extracted from the signal');
subplot(3,1,3); plot(y);
title('Output signal after Adaptive Filter');

%% Plot comparing the signal
figure(4)
subplot(3,1,1);plot(g(1:1001));
title('EEG raw signal with noise');
subplot(3,1,2); plot(d);
title('After Wavelet Denoising');
subplot(3,1,3); plot(y);
title('Output signal after Adaptive Filter');
```




aprox level 1
Time (sec)
aprox level 3
Time (sec)
aprox level 4
Time (sec)
Deta level 3
Time (sec)
Deta level 4
Time (sec)


Time (sec)
Denoise Signal


Noisy signal
Output
Noise
Noise Extracted from the signal
Output signal after Adaptive Filter