# Investigation of Bispectral Index Filtering and Improvement Using Wavelet Transform Adaptive Filter

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***Abstract*—Electroencephalogram (EEG) signals are often contaminated with artifacts such as electromyography (EMG), eye blink and eye ball movement. These contaminated EEG signals may give incorrect values of Bispectral Index. If fixed band-pass filter is used to filter the overlapping signals between the EEG and the artifacts, the useful information in EEG signal could be lost. This paper proposes a method to filter the EEG signals using wavelet adaptive techniques. The preliminary result shows that this technique is capable to remove the artifacts from the EEG signal more efficiently.**

***Keywords- EEG; Bispectral Index; wavelet transform; adaptive filter***

## I. Introduction

Inter-operative awareness or anesthesia awareness happens throughout general anesthesia. It is defined as an explicit recall to some event during surgery [1]. Inter-operative awareness and experiencing bad dream during anesthesia could affect patients mentally and also potentially long term psychological damage [2,3]. These incidents could be prevented by monitoring the effect of anesthetic drugs and the depth of anesthesia to reduce the inter-operative awareness.

An incorrect amount of anesthetic agents may cause a patient to be overdosed or under dosed. Inter-operative awareness during surgery may occur if the patient has received an inadequate anesthetic drug dosage. Conversely, overdose may result in longer recovery time due to effect of the anesthetic agent and could be harmful for the brain and or may cause brain damage [1]. Therefore, monitoring the depth of anesthesia (DoA) has become an important part of surgery.

There are only a few techniques and algorithms to analyse the EEG signal for depth of anesthesia. The most popular one is Bispectral Index (BIS). BIS has been introduced by Aspect Medical System. It has been used widely in hospital and health education around the world. According to Bowdle [1], without BIS monitored patients tend to have more intra operative awareness incidents.

## II. 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 [4], which algorithm is a combination of several techniques to derive one single value of consciousness level [4]. A single BIS index is drawn from three components. These components are burst suppression, Beta ratio, and SyncFastSlow [4]. 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 in titrating the anesthetic agent.

### *A. Limitations of Bispectral Index*

Although BIS is the most popular method of DoA monitoring, its algorithm has limitations. For example, the index does not response properly to all anesthetics agent such as nitrous oxide, ketamine and opioids [1]. Furthermore, noises such as eye movement and EMG could affect the BIS value. The increasing values of EMG raise the BIS index. The BIS index drops in absence of EMG [1]. Moreover, the BIS value gives false measurement of the depth of anesthesia because it measures the increasing value of electromyography (EMG) activity [5].

Noises in EEG signals could cause error calculation of DoA. Electromyography (EMG), eye ball movement and eye blinking which is considered as electrooculogram (EOG) are some of the noises that might be exist in EEG signals. Those signals overlapping each other with the pure EEG signal. The EEG signal is in the ranges of 0 to 30 Hz which may be contaminated by EOG ranges from 0 to 16 Hz and the EMG signal ranges 0 to more than 200 Hz [6,7]. 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. Fig. 1 shows the power spectrum of EEG and EMG [8]:

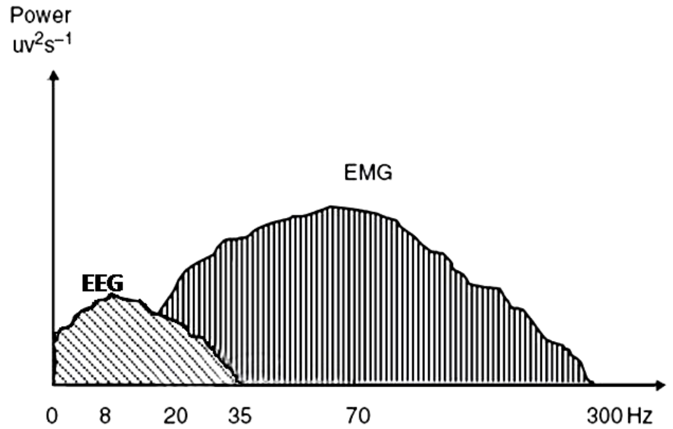


Figure 1. Power Spectrum of EEG and EMG. [8]

There are limitations of BIS and other DoA monitoring devices. Reference [1] listed several limitations of BIS and DoA monitoring device such as:

- DoA monitoring not responding properly to all anesthetic agents
- EMG and other high frequency devices interfere with EEG
- Data processing time produces a lag in computation of DoA monitoring Index
- "Frequently the EEG effects of anesthetic agents are not good predictor of movements in response to a surgical stimulus because the main site of action for anesthetic drugs to prevent movement is the spinal cord."
- The use of DoA monitoring in children is not as well established as in adults.

### B. *Bispectral Index Filtering*

The noises and useful information in EEG signals are overlapping each other. Minimizing the error by removing some noises from EEG signal using low pass filter and high pass filter has been introduced by [9]. This filtering technique works well in some cases with particular frequency sampling. However, according to [10] band-pass filtering technique did not solve the filtering problems of EEG signal. Removing the noises such as EMG, EOG and ECG artifacts from EEG signal using band-pass filter could remove the useful information in EEG signal as well. This type of filtering eliminates the noises as well as important information of EEG signal [5].

Reference [4] introduced BIS filtering technique to filter the EEG signal. The signal has put through the band pass filter with 0.3 to 30 Hz [4]. In this type of filter, low frequency EMG signal could still contaminate the EEG signal [11]. Moreover, the electrocardiogram (ECG) might exist in EEG frequency range 0.5 to 30 Hz. Furthermore, the EOG within range 0-16 Hz could contaminate the EEG signal as well [7]. Therefore, band-pass filter is not reliable to remove the noises that exist in EEG signal.

Filtering the noises out might minimize the error in analyzing 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 the BIS decreases [13]. 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.

## III. METHOD

Filtering method is important for further analyzing the EEG signal. Identification, removing noise and feature extraction from the signal will be achieved through filtering. In this paper the wavelet adaptive filter method has been used to remove the noises from EEG signal. This filtering method has been proposed because the variable of EEG signal itself is unknown and the signal is varying with time.

### A. *Wavelet Transform*

The characteristic of wavelet analysis is to deal with time varying modes. Wavelet analysis 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 [15]. EEG signal is one of the non-stationary signals because this signal is vary in time. Therefore wavelet transform is become popular for analyzing the biomedical signal in general.

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

$$\psi_{a,b} = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \tag{1}$$

where a>0 is the scale and b is the translation. Wavelet transform of the function ψ(t) which is called the mother wavelet is translate the function across time (t) and vary the time scale of the ψ(t), and then the signal x(t) is describe as follows [16] :

$$WT_{a,b} = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{+\infty} x(t)\,\psi^*\left(\frac{t-b}{a}\right)dt, a > 0 \tag{2}$$

The equation (2) is known as continues wavelet transform (CWT). The CWT is in continues form so it is infinitely redundant. Moreover, the CWT provides the original signal oversampling [17]. With the intention of reducing the redundant of the wavelet transform the discrete wavelet transform (DWT) will be using. The scales and translation in DWT is restricted to the power of two or dyadic wavelet transform. The dyadic scales and translation from the discrete sets {a=$2^k$; b=$2^k l$ ; $k,l$   Z}. The DWT is describing of its recovery transform as:

$$x(t) = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} d(k,l) 2^{-k/2} \psi(2^{-k} - l) \qquad (3)$$

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 sampling of W(a,b) at discrete points $k$ and $l$. Using Mallat's fast algorithms the gradual decomposition of the original signal become:

$$A_j(n) = \sum_{k=-\infty}^{\infty} g(k-2n) A_{(j-1)}(k) \qquad (4)$$

$$D_j(n) = \sum_{k=-\infty}^{\infty} h(k-2n) A_{(j-1)}(k) \qquad (5)$$

Hence, $A_j(n)$ represents the approximation at level j and $D_j(n)$ correspond to the details of the signal at level j. The g (4) is the high-pass filter and the h (5) stand for low pass filter.

### *B. Wavelet Denoising*

There are few steps to denoising the signals using wavelet which is first the decomposing and second is thresholds to select the coefficients for removing unwanted signal. Wavelet denoising technique [19] is proposed to reconstruct the signal from the noisy signal. The technique is based on calculating the noise from translating wavelet coefficient and setting the threshold to remove the noise from the wavelet coefficient [19]. The signal with noise is describe as:

$$Yt = f(t) + \varepsilon t, \quad t=1,\dots,n-1 \qquad (6)$$

The analysis of Y is equal to the sum of the analyses signal f(t) and the noise εt . The proposed method of denosing signal in this paper used soft threshold. The soft thresholding function based on [19] is:

$$Ts = \varepsilon 1 \sqrt{2\log(n)} \qquad (7)$$

Where Ts is the threshold and ε1 is define as ε1=γ.σ/ . By using the γ as a constant, then σ = MAD/0.6745; MAD is represent the median absolute value of the normalized fine scale wavelet coefficient. The simplified threshold function from above that can be used to threshold is:

$$Ts = \varepsilon 1 \sqrt{2\log(n)} \qquad (8)$$

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 will 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. In this stage signal is reconstructed using up-sampling method [20].

## IV. ADAPTIVE FILTER

As the explanation above that the EEG signal is overlapping spectra with the noises. The reason that we used the combined wavelet transform with adaptive filter because the filter parameters are unknown and the signal parameter are vary in time. The adaptive filter algorithm has been used is Least Mean Square (LMS). The simple diagram of LMS filter is described below [21]:

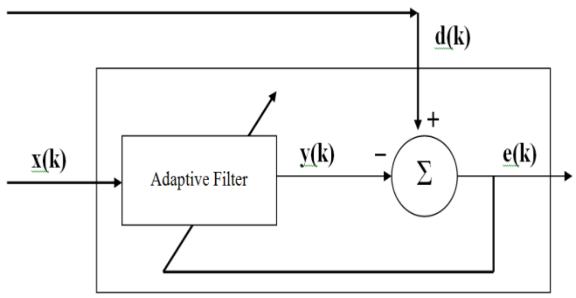


Figure 1. Adaptive filter

LMS is considering low in complexity calculation and simple compare to the other adaptive filtering [22,16]. In general the adaptive filtering algorithm structure is depicting in Figure 1. Signal x(k) is the reference signal for the adaptive filter. The desire signal d(k) is the signal with noises. Reference signal x(k) as an input to the system to produce the output signal y(k). Signal y(k) and d(k) is subtracted to compute the error e(k). LMS algorithm is to adjust the weight of adaptive filter to minimize the error and estimate the output signal. This algorithm can be defined as a function:

$$y(k) = W^T(k)x(k) \qquad (9)$$

$$e(k) = d(k) - y(k) \qquad (10)$$

$$W(k+1) = W(k) + 2\mu\, e(k)x(k) \qquad (11)$$

Where k is the time index; y(k) is the output from the adaptive filter; e(k) is the output error; μ is the adaptation of the step size and W(k) is the vector of filter weight.

## V. SIMULATIONS AND RESULT

Wavelet filtering is an advance method in band-pass filter technique for filtering the EEG signal. Mallat [18] has introduced the technique of filtering using wavelet method. This filtering method divides the signal into two separate signals, and then the signals can be decomposed further down. In Multi-level decomposition method, calculation of the signal is broken down into lower resolution component [23].

In this work we have used the Daubechies 3 (db3) wavelet transform and decomposed the signal to five levels. The first stage of wavelet adaptive filtering is to remove the high frequency in the signal. To remove the high frequency we use the denoising method with the adjustment in the threshold. The threshold boundary is adjusted to get the best result of the first stage EEG signal filtering. Figure 2 below shows the decomposition of EEG signal.

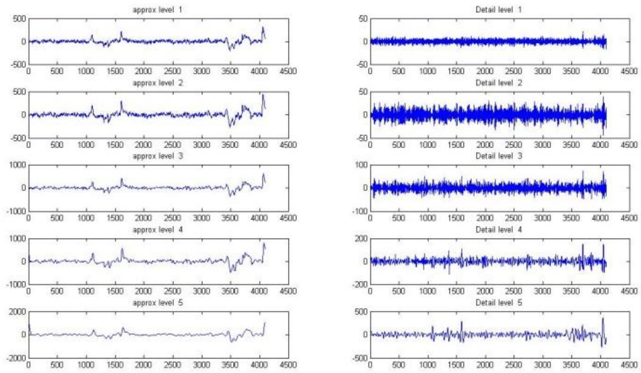


Figure 2. Decomposed signal at level five

The adaptive filter removes the other noises from the signal. The output signal from the wavelet denoising will become an input reference in adaptive filter. This signal is then put through the LMS filter with the adjustment of the weight of adaptive filter to estimate the output. By comparing the coefficient of signal y(k) and d(k) to further remove the noise and resulting the clean signal e(k). The signal e(k) is the desire signal which is EEG signal free artifact.

Figure 3 shows the result of the process of EEG signal filtering using wavelet adaptive filter. In Figure 3(a) is the raw EEG signal, (3b) is the EEG signal after denoising process with wavelet and the (3c) is the result of combine wavelet adaptive filter. The EEG signal after denoising demonstrates the first stage of the filtering. The difference between the signal before and after the denoising is shown in the Figure 4. It is clear that after first stage of filtering the noise is still exist (4a). Further, using adaptive filter for that signal shows that the noises in that signal are completely removed (4b). The extracted noises from the signal depicted in (4c), the result signal is consider free of artifact (4d).

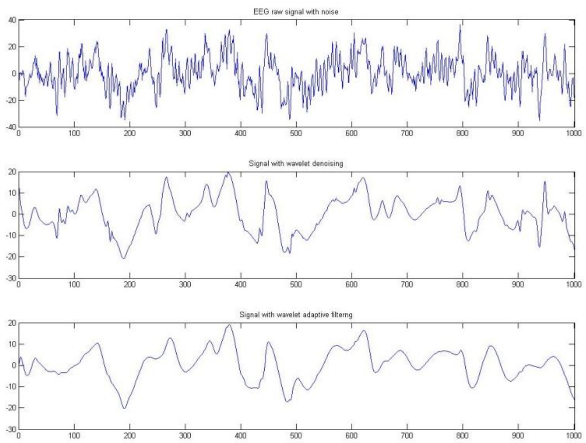


Figure 3. (a) EEG signal with noise, (b) Signal after denoising with wavelet, and (c) clean signal after wavelet adaptive filter.

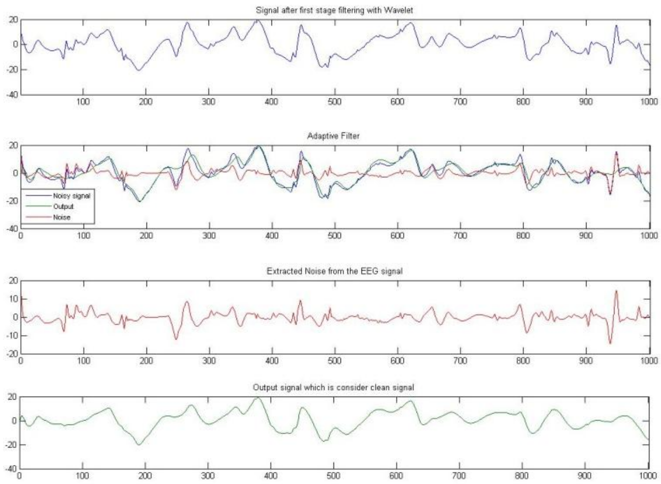


Figure 4. (a) First stage filtering with wavelet; (b) Signal with adaptive filter; (c) the reconstruct noise from the adaptive filter; (d) is the EEG signal which is consider clean.

In signal processing to measure the ratio of how dominant the signal relative to the noise, the signal to noise ratio (SNR) is used [16]. 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 noise we also use SNR. Table I show the performance of the filtering technique. The results shows that the filtering technique using wavelet adaptive filter is much better compare 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 I. THE PERFORMANCE OF THE FILTERING TECHNIQUE

| **Wavelete adaptive Filter** | |
|---|---|
| **Denoising** | **SNR** |
| Wavelet denoising | 81.8868 |
| Wavelet adaptive filter | 102.1010 |

## VI. CONCLUSION

The proposed method of EEG signals filtering using wavelet transform adaptive filter is explained in this paper. The adaptive noise cancelation method based on least mean square has been combined with wavelet to filter out the noises from EEG signals. The first stage of this method was to remove the high frequencies in EEG signals which were considered as the EMG signals. At this stage, the EMG signalsare removed by wavelet denoising threshold algorithm. The next stage of filtering is to put through the adaptive filter to filter out some other artifacts. The result shows that this technique is more efficient to remove the artifacts from EEG signal.

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