Effectiveness of Wavelet Denoising on Electroencephalogram Signals

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ABSTRACT
Analyzing Electroencephalogram (EEG) signal is a challenge due to the various artifacts used by Electromyogram, eye blink and Electrooculogram. The present de-noising techniques that are based on the frequency selective filtering suffers from a substantial loss of the EEG data. Noise removal using wavelet has the characteristic of preserving signal uniqueness even if noise is going to be minimized. To remove noise from EEG signal, this research employed discrete wavelet transform. Root mean square difference has been used to find the usefulness of the noise elimination. In this research, four different discrete wavelet functions have been used to remove noise from the Electroencephalogram signal gotten from two different types of patients (healthy and epileptic) to show the effectiveness of DWT on EEG noise removal. The result shows that the WF orthogonal meyer is the best one for noise elimination from the EEG signal of epileptic subjects and the WF Daubechies 8 (db8) is the best one for noise elimination from the EEG signal on healthy subjects.

Keywords: electroencephalogram, discrete wavelet transform, denoising, root mean square.

1. Introduction

Electroencephalogram (EEG) has been long utilized to diagnose different disorders of the nervous system such as epilepsy, classifying stages of sleep in patients, seizures and brain damage. EEG is the electrical activity recorded from the scalp surface, which is picked up by conductive media and electrodes [1, 2]. EEG has been performing a vital role to investigate brain activities in clinical application and scientific research for several years [3-5].

The current de-noising techniques, that are based on the frequency selective filtering, suffer from a substantial loss of the EEG data. Preventing patients from a normal work is not considered a feasible solution.,In fact, this may have major impacts in recording EEG. Considering the problems, frequency selective filtering technique for eliminating noise from EEG is regarded as a challenging task nowadays [6]. An attractive substitute is the Wavelet based filtering considering the capability of studying both frequency and time maps simultaneously [7-9]. Stationary wavelet transform (SWT) is utilized for de-noising EEG signal by Zikov *et al.* [10]. Reconstructed signal in SWT technique is not a good approximation for original EEG because artifacts associated to recorded EEG signal are considerably uncorrelated. A different way of de-noising EEG signal utilizing HAAR wavelet of higher order is portrayed by Venkataramanan *et al.* [11]. However, the technique is valid for eliminating noise associated to eye movements.

In this research, a discrete wavelet-based noise elimination is carried out to get rid of artifacts from EEG signal. In de-noising physiological signals, Wavelet de-noising is efficient as it has a tendency for preserving signal characteristics while reducing noise, this is favored over signal frequency domain filtering [12]. The reason is that the threshold strategies are available which allows reconstruction based on chosen coefficients [13].

Daubechies (db8, db6, db2), Meyer (dmey) and wavelet functions (WF) are utilized in this research for the period of the wavelet transform for noise elimination. These WFs are selected based on mother wavelet shapes [12, 14]. Figure 1. shows the meyer wavelet. Utilizing these wavelets, RMS difference was worked out to calculate the noise removal effectiveness.

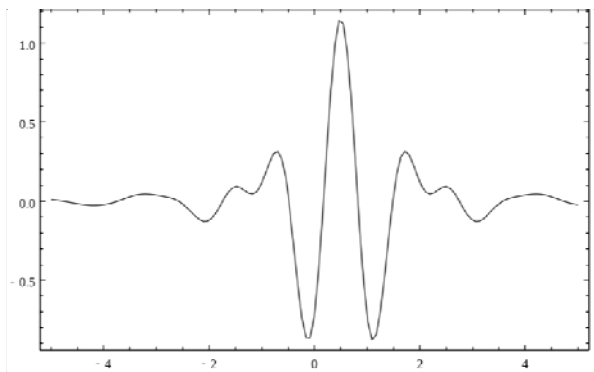

Figure 1. Meyer wavelet.

From the results it can be seen that the WFs db8 offers the most excellent noise elimination from raw EEG signal of a healthy subject, WF orthogonal meyer provides high RMS divergence in contrast to other 3 WFs for epileptic subjects. These results enhance noise elimination for the EEG signal.

2. Methodology

2.1 Data and acquiring techniques

Four sets which are indicated from A to D, consisting each one of twenty single channel of 23.6 second duration of EEG segments were composed for experimentation, which was accumulated from the University of Bonn, Germany (Department of Epileptology) database. A and B are comprised of parts from surface EEG acquisition. Utilizing standardized electrode placement scheme, these were done on 5 healthy awake volunteers. Set A data was recorded with open eyes, set B data, was recorded in a closed eye condition. Set C and D data were taken from 5 subjects under complete seizure control. Set C data was recorded during the seizure interval and set D data was recorded during seizure. The entire EEG signals were taken with the same 128-channel amplifier system utilizing an average common reference. Data were stored constantly at 173.61 Hz sampling rate after conversation of 12 bit analog to digital [15].

Utilizing a threshold technique and discrete wavelet transform (DWT), the EEG signals were de-noised and implemented using the MATLAB Wavelet toolbox.

2.2 Noise Removal

Wavelets usually utilized to de-noise biomedical signals comprising orthogonal meyer wavelet and Daubechies, ‘db8’ ‘db6’ and ‘db2’ wavelets. These are normally selected from the shapes similar to those EEG signals [12].

A wavelet decomposes a signal in various multi-resolution parts in accordance with a basic function. This is known as wavelet function. The most extensively utilized signal processing functions are filters. The filtering operations determine the resolution of the signal, which is a calculation of detailed information in the signal. The scale is stabilized by downsampling or subsampling and the upsampling operations. DWT is calculated with consecutive highpass and lowpass discrete time-domain signal filtering, which is illustrated in Figure 2.

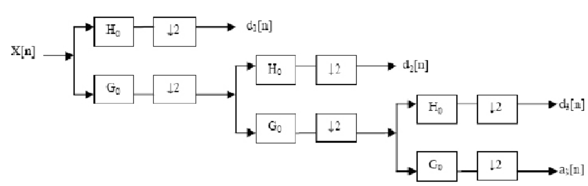

Figure 2. Three-level wavelet decomposition tree.

In Figure 1. The signal is indicated by sequence *x[n]*, where *n* is an integer. G_0 indicates the low pass filter and H_0 indicates the high pass filter. The high pass filter generates detail information *d[n]* at every level. Coarse approximations *a[n]* is generated by the low pass filter connected to scaling function. The time resolution turns arbitrarily excellent with this approach at high frequencies, where at low frequencies, the frequency resolution turns arbitrarily excellent.

A threshold is determined for the raw EEG signals which is applied on the wavelet coefficients ($d_1[n]$, $d_2[n]$, $d_3[n]$, $d_4[n]$, $a_4[n]$) after the WT. The WT coefficients used are to estimate the noise and calculate the threshold.

Calculate the *median absolute deviation,* δ_{mad} on the largest coefficient spectrum by

$$\delta_{mad} = \frac{median\{|c_0|,|c_1|,...,|c_n - 1|\}}{0.6745} \quad (1)$$

where $|c_0|,|c_1|,...,|c_n - 1|$ are the wavelet coefficients and 0.6745 in the denominator rescales the numerator so that it is a suitable estimator for the standard deviation for Gaussian white noise.

The noise threshold, τ is determined by

$$Threshold, \tau = \delta_{mad}\sqrt{\ln(N)} \quad (2)$$

where δ is the estimated noise. N is the total number of samples.

Assuming raw EEG signal (f) is equivalent to original EEG signal (s) and noise (n). The threshold method works under the following assumptions, where T_s is the signal threshold and T_n (threshold, τ) is the noise threshold. The threshold method that has been applied in this research is described below:

1. Original signal energy s is efficiently acquired at a higher percentage. This is done by transforming values where magnitudes are larger than threshold ($T_s>0$).

2. Transform values of raw signal have magnitudes. These lie under a raw threshold T_n satisfy $T_n < T_s$.

Noise in f can be eliminated by thresholding transform. Entire transform values which magnitude is less than the noise threshold (T_n) are put equivalent to 0.

A good approximation of f has been provided by executing an inverse transform. Reconstruction is the opposite process to decomposition. Detail coefficients and approximation at each stage are upsampled by 2, passed by high and low pass synthesis filters and added afterwards. To get the original signal, the process is continued by similar amount of steps like decomposition process.

Equation 1 defines the RMS difference of raw EEG signal (f) compared with EEG (noise free) signal (s).

$$RMS\ Difference = \sqrt{\frac{(f_1 - s_1)^2 + (f_2 - s_2)^2 + ... + (f_N - s_N)^2}{N}} \quad (3)$$

RMS difference was computed for 4 WFs. Where N is samples number, s is de-noised signal and f is noisy EEG signal.

3. Results and Discussion

At various physical conditions (during and after seizure, open and closed eyes), wavelet denoising technique is applied to raw EEG. Each WFs (dmey, db8, db2 and db6) RMS variation was computed through entire physical states. Table 1. lists the calculation result.

It was found from RMS difference values in Table 1, that WFs dmey, db4 and db6 gives same RMS difference for healthy subjects with open and closed eyes, while using db8 WF, the RMS variation is high. Therefore, it can be said that db8 WF is more useful for noise elimination process for healthy subjects EEG signal. On the other hand, it was found from the RMS difference values in Table 1, that orthogonal Meyer wavelet function gives highest RMS difference during and after seizure, which shows that the orthogonal Meyer WF is more useful for noise elimination process for epileptic subjects EEG signal. For a sample EEG signal, the outcome of de-noising technique utilizing various WFs with 4 levels of decomposition is shown in Figure 3.

4. Conclusion

Wavelet theory has already achieved huge success. For EEG signals, it is estimated to offer a dominant complement to conventional noise-elimination methods such as frequency selective filtering and stationary wavelet transform. All 4 WFs are able to eliminate noise from EEG signal efficiently. But the most proficient one to eliminate noise from the healthy subject's EEG signal is the WF db8. On the other hand, WF orthogonal meyer is the best for the epileptic patient. To analyze and characterize EEG signal for various brain activities, wavelet based noise elimination method is also useful.

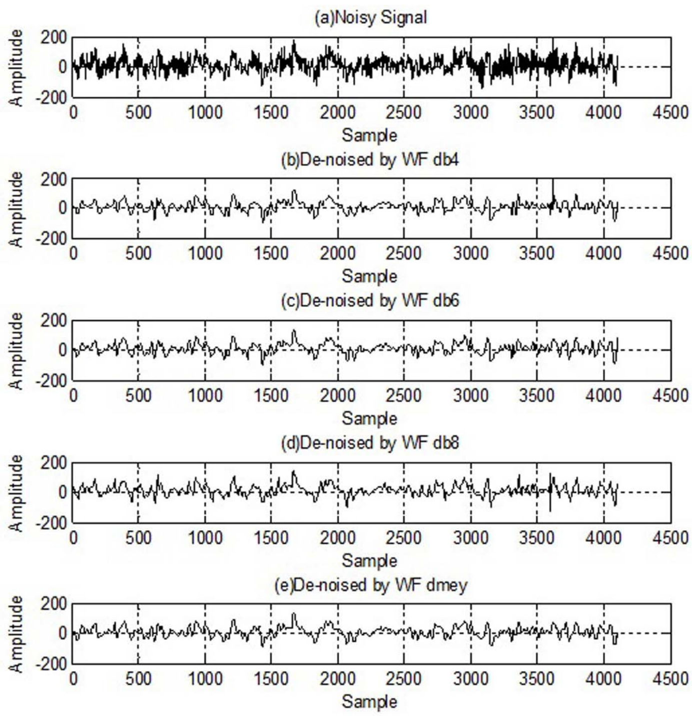

Figure 3. (a) Raw EEG signal of healthy person, (b) wavelet de-noising utilizing db4, (c) wavelet de-noising utilizing db6, (d) wavelet de-noising utilizing db8, and (e) wavelet de-noising utilizing dmey.

Subjects	Condition of Body	dmey	db8	db6	db4
Healthy	(Set A) Eyes open	26.24	26.32	26.22	26.25
	(Set B) Eyes closed	56.25	56.89	56.90	56.68
Epileptic	(Set C) After seizure	23.39	22.96	22.99	22.45
	(Set D) During seizure	255.83	255.59	254.19	248.89

Table 1. RMS Difference of electroencephalogram signal at different body conditions

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