

Performance Analysis of wavelet Thresholding for Denoising EEG Signal

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Abstract— Electroencephalogram (EEG) is used for detecting problems in the electrical activity of the brain associated with brain disorders. During acquisition of EEG signals various noises like electrocardiogram (ECG), electromyogram (EMG), electrooculogram (EOG) and power line interference etc. contaminates the signal, which makes the proper analysis of the signal difficult. Therefore, noise removal is an integral part of preprocessing step before signal analysis. In this paper, wavelet transform using different kind of filters like db2, db4, coif2, coif4, sym2 and sym4 is used to decompose the signal into low and high frequency components. Then, high frequency components have been thresholded at each level of decomposition. The denoised signal is reconstructed using the thresholded coefficients and the approximation coefficients. Thresholding methods such as minimaxi, Sure (Heuristic and rigorous) and Square-Root-Log are investigated to compute the threshold value. The coiflet filter at level 4 with minimax thresholding method performed better than other wavelet filters and thresholding methods in terms of Peak Signal-to-Noise Ratio (PSNR) value.

Keywords— Electroencephalogram, Wavelet Transform, Threshold, Denoising, Peak Signal-to-Noise Ratio

I. INTRODUCTION

Electroencephalography (EEG) is used to measure electrical activities in the brain caused by the synaptic current generated by the activated brain cells. The skull attenuates the EEG signal, which is later amplified to display. The amplitude of the brain signal lies between $0.5\mu\text{V}$ to $100\mu\text{V}$ [1]. EEG signals are classified into different frequency bands as delta (δ), theta (θ), alpha (α), beta (β) and gamma (γ). Delta waves lies between (0.5-4 Hz) and is primarily associated with the deep sleep, theta waves exists within the range of (4-7.5 Hz), appear in children and during drowsiness or sleepiness in adults but the presence of theta waves in waking adult are abnormal and caused by pathological problem. The frequency of alpha waves lies between (8-13 Hz), these waves exists in both relaxed and awareness without attention. It is eliminated in the active state. Beta waves vary within the range of (14-30 Hz), associated with the active thinking state of a normal adult. The frequencies above 30 Hz constitute gamma range. The acquired EEG signal may be used in the diagnosis of many neurological disorders and other abnormalities. Brain signal is often contaminated by various artifacts such as ocular, cardiac, muscle, power line noise etc. Noise removal is an indispensable task for proper analysis of EEG signal to diagnose the abnormalities. Several denoising techniques have been developed for extracting actual signal from noisy signal.

Wavelet transform is a widely used technique in denoising images and signals because wavelet localizes the features in data at different scales, preserves the signal while removing the noise [2]. It concentrates signal features in large magnitude wavelet coefficients while the coefficients having low magnitude represents noise and these coefficients are removed without affecting the signal quality.

In this paper, discrete wavelet based denoising has been carried out to eliminate the noise from the EEG signal. In wavelet analysis, signal is decomposed in to low frequency and high frequency components, which represents noise. These high frequency components are thresholded without affecting the significant features of a signal. Denoising is achieved using hard and soft thresholding of wavelet coefficients. Different wavelet filters such as db2, db4, sym2, sym4, coif2 and coif4 have been used at different level of decomposition.

Denoising based on thresholding was proposed by Donoho and Johnston [3]. In hard thresholding the coefficients below the threshold value are set to be zero, while in soft thresholding wavelet coefficients are shrunk by a quantity equal to the threshold value. In the research work DWT has been used to decompose and reconstruction of a signal.

The paper is organized as follows. Section 2 presents the literature review of wavelet based thresholding methods for signal denoising. In section 3, wavelet based denoising is

presented. Section 4 provides experimental results Finally, conclusion is presented in section 5.

II. LITERATURE REVIEW

Md. Mamun et al.[2], presented that four discrete wavelet functions as db4, db6, db8 and dmey, have been used to denoise the EEG signals taken from the normal and epileptic patients. Author observed that orthogonal meyer (dmey) gives the best result in denoising signal of epileptic patients and the Daubechies (db8) provides best result for eliminating noise from the healthy subjects.

Verma et al. [4], presented a comparative analysis of well-known thresholding methods for denoising audio signals of Indian musical instruments and measured the performance regarding Peak Signal to Noise Ratio (PSNR), the authors state that best PSNR values were achieved using Coif5 wavelet transform and heursure and gives minimum distortion as compared to other thresholding methods.

In [5,6] ocular artifact EOG rejection method is proposed using wavelet transform. Adaptive thresholding has been performed on ocular artifact zone rather than using the entire EEG signal which does not affect the low frequency components. Performance is evaluated using power spectral density and frequency correlation.

Al-Qazzaz et al.[7], presented various thresholding techniques such as rigrsure, heursure, sqtwolog and minimaxi with Daubechies (dB), Symlet (sym) wavelet filters for denoising EEG signals. Author used four qualitative measures such as Signal to Noise ratio (SNR), PSNR, Mean Square Error (MSE) and Cross-Correlation (XCorr) to evaluate the performance of the signal. The best results were achieved using rigrsure on soft thresholding technique.

Independent component analysis (ICA) has been widely used in denoising the signal. In [8], ocular artifact (EOG) has been removed from the EEG signal using ICA. Author state that ICA performed better than PCA and regression.

In this paper [9], EMD-DWT-CLS method has been used for denoising physiological signal of human and animals. Signal decomposition was performed using EMD, DWT for thresholding or denoising, and Constrained Least Squares (CLS) to recover the denoised signal by estimating the weights. It was observed that the proposed method outperform EMD-DWT in terms of SNR and MSE.

III. WAVELET BASED DENOISING METHOD

The objective of this research is to recover the noise less signal as compare to original signal using mother wavelet and thresholding methods. The steps involved in reducing the noise are:

- i. Decompose the noisy signal upto level N

- ii. Threshold is selected and applied to detail coefficients at each level
- iii. Reconstruct the signal from the thresholded coefficients

A. Discrete Wavelet Transform

Discrete Wavelet transforms analyze the signal at a finer scale due to its multiresolution property. DWT decomposes the signal into approximation and detail coefficients by convolving the signal with low pass and high pass filter. Low frequency components are called approximation coefficients while details coefficients are high frequency components. After decomposition, the signal can be reconstructed using inverse discrete wavelet transform. A three level decomposition structure is shown in figure 1.

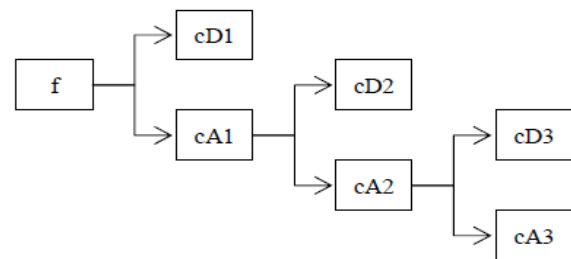


Fig. 1. Three level wavelet decomposition

DWT produces two coefficients at each level of decomposition, which are detail and approximation coefficients respectively. Approximation coefficients are further splitted at higher level of decomposition. Detail coefficients are then thresholded and the signal is reconstructed from the thresholded coefficients.

B. Threshold selection method

Threshold selection is done by mathematical calculation to provide the threshold value for denoising. In this study, four thresholding methods such as rigrsure, heursure, sqtwolog and minimaxi have been considered:

1) Sqtwolog

Threshold values are calculated by using the universal method given in (1) [4]

$$T_i = \sigma_i \sqrt{2 \log(N_i)} \quad (1)$$

where σ_i is the mean absolute deviation (MAD) and N_i is the length of a noisy signal, σ_i can be expressed as (2)

$$\sigma_i = \frac{MAD_i}{0.6745} = \frac{\text{median}|\omega|}{0.6745} \quad (2)$$

where, ω represents wavelet coefficients at i^{th} level

2) Rigrsure:

This threshold selection method is based on Stein's Unbiased Risk Estimation (SURE), which calculates an estimate of the risk for a particular threshold value (T). Minimum risk can be calculated as given in (3) [4]

$$R = \{r_i\}_{i=1,2,\dots,N} = \left[N - 2i + (N - i)\omega_i + \sum_{k=1}^i \omega_k \right] \quad (3)$$

The threshold can be calculated as, σ is the standard deviation of the noisy signal, ω_k is the wavelet coefficient square (minimal risk coefficient) chosen from the vector $W = [\omega_1, \omega_2, \dots, \omega_n]$, where $\omega_1, \omega_2, \dots, \omega_n$ are the square of the wavelet coefficient arranged in ascending order.

3) Heursure

Heursure is a combination of rigrsure and sqtwolog thresholding methods, when signal to noise ratio is very small. In this case, rigrsure estimation is very poor but sqtwolog provides the better threshold value.

4)Minimaxi

Minimaxi uses a fixed threshold value that yields a minimx performance for mean square error against an ideal procedure. The Minimax principle is used in statistics in order to design estimators.

$$T = \begin{cases} \sigma(0.3936 + 0.1829 \log_2 N) & N > 32 \\ 0 & N < 32 \end{cases} \quad (4)$$

Where N is the length of the noisy signal and σ is mean absolute deviation of the wavelet coefficients as given in equation 2.

C. Thresholding Rule

After selecting the appropriate threshold, it is applied to the details coefficients at each level. There are two types of thresholding such as hard and soft.

1) Hard Thresholding

In hard thresholding, the coefficients whose absolute values are less than the threshold value, are set to be zero. Otherwise the coefficients remain unchanged. This is also known as keep or kill method [11].

$$D^H(d|\lambda) = \begin{cases} 0 & |d| \leq \lambda \\ d & |d| > \lambda \end{cases} \quad (5)$$

where d is the value of wavelet coefficients, and λ is the threshold value.

2) Soft Thresholding

In softthresholding, the coefficients whose absolute values are less than the threshold value, are set to be zero. Otherwise the coefficients are shrunk as given in the equation 6.

$$D^S(d|\lambda) = \begin{cases} 0 & |d| \leq \lambda \\ d - \lambda & d > \lambda \\ d + \lambda & d < -\lambda \end{cases} \quad (6)$$

After calculating the threshold value the noisy signal is denoised, block diagram and algorithm is given below.

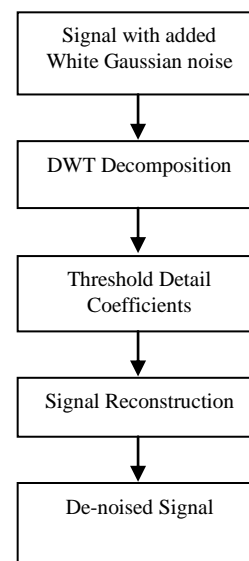


Figure 2. Block diagram of signal denoising

Algorithm

1. Add White Gaussian Noise to the signal
2. Select a wavelet filter and decomposition levels (k)
3. Take the kth level discrete wavelet transform (DWT) of the input signal X, decomposing it into k decomposition levels resulting into k detail coefficients and the kth Approximation component.
4. Calculate the noise threshold for the k detail components.
5. Apply noise thresholding to the k selected detail components.
6. Reconstruct the signal using thresholded k detail coefficients and the kth approximation component.
7. Evaluate the performance using the quality measure PSNR

IV. EXPERIMENTAL RESULTS

The comparison of the well known threshold selection methods as rigrsure, heursure, sqtwolog and minimaxi with wavelet filters (db2, db4, sym2, sym4, coif2, coif4) at different level of decomposition is given in table 1 to table 6. Initially White Gaussian noise is added to the original signal with different noise levels. Then the noisy signal is decomposed, thresholded and reconstructed to get the denoised signal.

A. Dataset

The dataset used in this work has been taken from Bonn University, Germany which is publicly available. The dataset consists of five sets (A-E) each set contains 100 single channel EEG signal. The sampling frequency of the signal is 173.61 Hz with a duration of 23.6s. A and B consist of EEG signals recorded from the healthy subjects with eyes open (A) and eyes closed (B). Sets C and D contain only EEG signal taken from the epileptic patients during seizure-free intervals while set E contains signal during seizure.

B. Quantative Measure

The signal quality measure such as Peak Signal to Noise Ratio (PSNR) has been used to evaluate the performance between original signal S_i denoised signal S_d . [4] PSNR can be calculated as given in equation 7.

$$PSNR = 10 \log_{10} \left(\frac{S_{max}^2}{MSE} \right) \tag{7}$$

where S_{max} is the maximum value of the signal calculated as

$$S_{max} = \max(\max(S_i), \max(S_d)) \tag{8}$$

MSE is calculated as given in equation 9. Where N is the length of the signal

$$MSE = \frac{1}{N} \sum_{k=1}^N [S_d(k) - S_i(k)]^2 \tag{9}$$

The comparison results of denoising EEG signal corrupted by White Gaussian noise with various thresholding methods using wavelet filters (db2, db4, sym2, sym4, coif2 and coif4) at different level of decomposition are presented in following tables:

In summary, the performance of the Coif4 wavelet with soft thresholding at second level of decomposition gives the better result as compared to other wavelet filters and hard thresholding. It is clearly understood from the above tables that among all the wavelet filter coif4 outperforms in terms of PSNR.

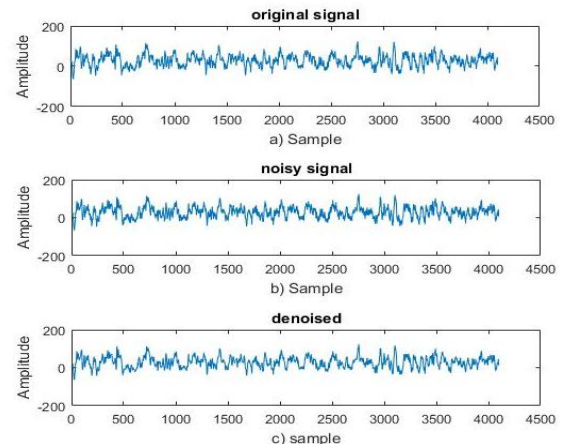


Figure 3. (a) Original signal (b) White Gaussian noise added signal (c) Denoised signal

TABLE 1. WITH ‘DAUBECHIES’ WAVELET AT LEVEL 2

Wavelet name	Threshold Rule	Rigrsure	Heursure	Sqtwolog	Minimaxi
		PSNR			
Db2	Hard	30.46	30.45	30.22	30.38
	Soft	30.58	30.57	30.37	30.85
Db4	Hard	30.46	30.45	30.89	31.24
	Soft	30.61	30.61	30.89	31.25

TABLE 2. WITH ‘SYMLET’ WAVELET AT LEVEL 2

Wavelet Name	Threshold Rule	Rigrsure	Heursure	Sqtwolog	Minimaxi
		PSNR			
Sym2	Hard	30.46	30.45	30.22	30.37
	Soft	30.58	30.57	30.38	30.85
Sym4	Hard	30.46	30.45	30.34	30.42
	Soft	30.60	30.60	30.86	31.18

TABLE 3. WITH ‘COIFLET’ WAVELET AT LEVEL 2

Wavelet name	Threshold Rule	Rigrsure	Heursure	Sqtwolog	Minimaxi
		PSNR			
Coif2	Hard	30.46	30.45	30.35	30.58
	Soft	30.60	30.61	30.35	30.58
Coif4	Hard	30.45	30.44	30.41	30.61
	Soft	30.62	30.62	31.07	31.77

TABLE 4. WITH ‘DAUBECHIES’ WAVELET AT LEVEL 3

Wavelet name	Threshold Rule	Rigrsure	Heursure	Sqtwolog	Minimaxi
		PSNR			
Db2	Hard	30.44	30.44	30.00	30.29
	Soft	30.58	30.58	29.21	30.21
Db4	Hard	30.44	30.45	30.15	30.35
	Soft	30.61	30.61	29.59	30.53

TABLE 5. WITH ‘SYMLET’ WAVELET AT LEVEL 3

Wavelet Name	Threshold Rule	Rigrsure	Heursure	Sqtwolog	Minimaxi
		PSNR			
Sym2	Hard	30.45	30.45	30.00	30.30
	Soft	30.59	30.57	29.20	30.22
Sym4	Hard	30.46	30.42	30.78	31.13
	Soft	30.59	30.57	30.63	31.28

TABLE 6. WITH 'SYMLET' WAVELET AT LEVEL3

Wavelet Name	Threshold Rule	Rigrsure	Heursure	Sqtwolog	Minimaxi
		PSNR			
Coif2	Hard	30.45	30.45	30.14	30.35
	Soft	30.61	30.61	29.54	30.50
Coif4	Hard	30.45	30.45	30.20	30.38
	Soft	30.62	30.61	30.29	30.65

V. CONCLUSION and Future Scope

In this paper, EEG signal denoising using discrete wavelet transform based on thresholding is performed. Initially, White Gaussian noise is added to the signal at noise level 20db and DWT is used to decompose the noisy signal into approximation and detail coefficients at different levels. Details coefficients at each level are then thresholded using hard and soft thresholding. It is observed that minimaxi threshold estimation with soft thresholding using wavelet filter coif4 performs better in terms of PSNR. The result shows that as the level of decomposition increases, PSNR does not improve.

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Dipali Sinha was born in Kanpur, Uttar Pradesh (UP), India, in 1981. She received the Bachelor of Science degree from chhatrapati shahuji maharaj university kanpur, UP, India, in 2000 and Master of Computer Applications from U.P. Technical University, Lucknow, India in 2005. She obtained her M.E. degree from Vinayaka Mission University, Salem in 2014. She is currently pursuing Ph.D. in the Department of Computer Science, Periyar university, Salem.



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