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DESIGN OF WAVELET THRESHOLDING MODEL FOR EPILEPTIC EEG SIGNAL DENOISING

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Abstract:

EEG plays a vital role for detecting various neurological disorders and for investigating scientific researches in human computer interaction applications. Raw EEG data through motor imagery of a BCI user is entrenched with non-Gaussian noise. In the growing field of EEG denoising, numerous researches have been carried out to give optimum results. In this paper, a denoising model has been proposed for finding optimum wavelet function with thresholding technique in terms of performance matrices like RRMSE (Relative Root Mean Square Error), RMAE (Relative Mean Absolute Error), SNR (Signal to noise ratio) and PSNR (Peak SNR). It has been shown that soft thresholding offers excellent results than hard thresholding. The evaluation parameters have been analyzed for Haar, db2, db4, db8, dmey and other functions corresponding to soft thresholding.

Keywords: EEG, Brain Computer Interface, Signal Processing, Wavelet, Thresholding.

1. Introduction

Electroencephalogram (EEG) is employed for detecting different neurological disorders like epilepsy, sleep disorders, seizure attacks, brain injuries and also for BCI (Brain Computer Interface) applications. BCI permits individuals with rigorous movement disability to have communication with outside assistive procedure such as a wheelchair by decoding the brain signals. There are four steps carried out in a BCI system such as signal acquisition, signal pre-processing (supervise and enhance raw signal), feature extraction & selection and classification [1-2]. There are certain extraneous sources and artifacts, for example, cardiovascular pulse wave from vessels in brain generated in the neocortex, extra cerebral artifacts like EOG (Electro ocular) and EMG (Electromyography) due to neck, shoulders, faces movements and eye blink that may add up to the signal at particular recording electrode site, making successful control over signal mystified. In addition, various technical artifacts and power line interference signals distort the original recorded signal. Therefore, experimental measured signal is linear mixture of multi brain activities so pre-processing of EEG data plays an important role in EEG signal analysis. There is need for fast data processing techniques including detection and handling of artifacts [3- 4].

Extensive research has been carried out for EEG artifacts removal or denoising alongwith maintaining the useful information from the original data but still lot of improvements are required in denoising of corrupted EEG signals. Wavelet transforms played a vital role in image denoising but there are very limited applications for biological signals like ECG and EEG signal denoising. In this paper, the main aim is to perform EEG denoising using DWT and analyzing the wavelet thresholding technique. Various performance matrices have been considered to compare the performance of different wavelet functions using MATLAB Simulink generated model.

2. EEG Signal Analysis

2.1 EEG Brainwave Patterns

An EEG recording is taken from the scalp electrodes that contain the brain activity in terms of electric potentials. The internal language of mind can be understood using different EEG patterns from mind's EM (electromagnetic) field activity. Different frequency bands characterize brain activities. Raw EEG data is characterized by delta (0- 4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13- 30 Hz) and gamma (greater than 30 Hz) bands [5]. Figure 1 gives a description of these frequency rhythms without including the gamma waves. Gamma waves are higher frequency waves that maintain abstract visual profiles in short term memory and higher in focused stimuli. Sometimes gamma waves are of no clinical interest and are filtered out in EEG recordings as muscle artifacts.

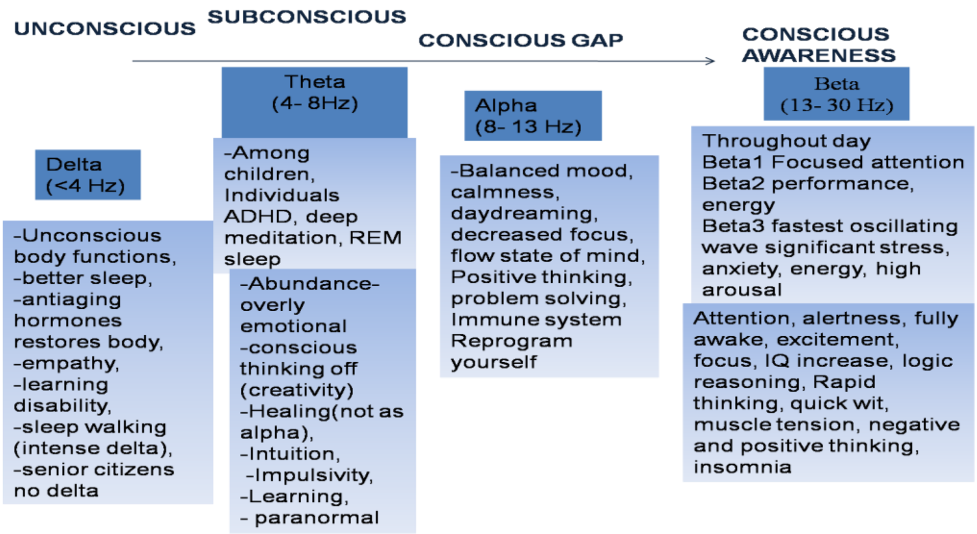


Fig. 1. EEG brainwave patterns.

2.2 EEG Denoising: Literature Review

By remarkable encroachment in brain function imaging since past 15 years, temporal resolution of < 100 ms has been offered for M/EEG. One of the major limitations in EEG is SNR. The signals are generated by superposition of large number of neurons. SNR estimates remain a putative confounder albeit assessment is possible [6]. Denoising is the term used to describe the procedure of removing noise present in the signal. Also, visual signal processing builds tiredness and considerable SNR may hinder with subject's natural performance. So, since last decades, limitations of EEG are being highlighted. For that, spatial filters like large laplacian filter, average referencing filter and comb filters can be used [7]. A vast number of SP (Signal Processing) techniques have made source localization of EEG possible such as array signal processing, digital filtering, reconstructing and modeling images, BSS (Blind Source Separation) and phase synchrony estimation etc [8].

Various denoising methods have been studied such as PCA (Principal Component Analysis), ICA (Independent Component Analysis), Wavelet based denoising, and Wavelet packet based denoising and so on. In [9], a new algorithm based on a combination of ICA and Translation Invariant Wavelet Transform has been studied. Efficacy was evaluated by comparing performance of three ICA algorithms (EFICA, FastICA, and Pearson-ICA) using amari performance index, signal to distortion ratio, MSE and PSNR. In [10], ICA denoising was studied for muscular artifacts in epileptic simulated data. However, the disadvantages of the PCA and ICA are that there is analysis for time domain signals only. Also in case of PCA, size of the signal to be denoised has to be considered. A striking replacement is the Wavelet based filtering that takes into accounts both frequency and time maps simultaneously [11]. Lower noise amplitude signals can be denoised.

Large body of evidence has concluded wavelets for giving the best denoising results. It has been used to study the sleep disorders also [12]. Stationary wavelet transform (SWT) is not a high-quality approximation as noise is highly uncorrelated. Wavelet based denoising gives significantly improved judgment of the latencies and amplitudes in the simulated ERPs (Event Related Potentials) [13]. A combination of wavelet denoising and ICA has been proposed in [14]. The study has included the concept of the spatially constrained ICA (SCICA) to remove independent components (ICs) having artifacts and WD (wavelet denoising) to denoise cerebral activity from these ICs. It was effective in terms of computational speed.

The role of an extra inclusion of wavelet denoising (WD) and the interactions between BSS, denoising and classification have been explored in [15].

Wavelet thresholding is another extensively used term for wavelet domain denoising. The denoising technique of SURE (Stein's unbiased risk estimate) has been employed to fix thresholding function in [16]. Wavelet approximation using thresholding allows an adaptive representation of signal discontinuities [17]. Therefore, in the present work, wavelet thresholding has been used to perform a non-linear denoising. In this work, discrete wavelet transform (DWT) has been studied for signal pre-processing. The main focus is to check and evaluate different discrete wavelet functions (WFs) by using thresholding technique.

2.3 Wavelet transform

Unlike the fourier transform based sine functions, wavelets are greatly determined in time. They frequently give an investigation of the signal, localized in both time and frequency, while fourier transform is restricted in frequency domain analysis. In wavelet transform, a correlation analysis is performed in which maximum output is predicted when input signal mainly looks like the mother wavelet. Wavelets decompose signals according to wavelet functions that make denoising possible. DWT is performed using consecutive HP (High pass) and LP (Low pass) signal filtering as shown in figure 2 [18-20].

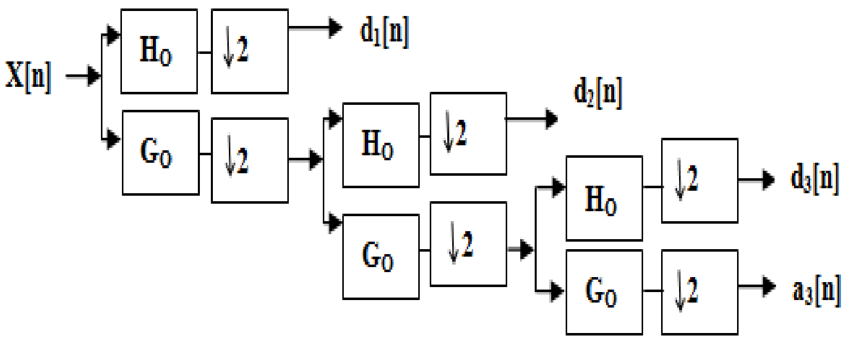


Fig. 2. Wavelet tree structure for decomposition at level 3 [20].

Here, x[n] denoted the input signal that gives d[n] as detailed information corresponding to each level using low pass and high pass filters. The opposite process of decomposition gives reconstruction. Each stage approximations and coefficients are upsampled and passed through low and high pass filters and summed afterwards.

2.4 Wavelet thresholding

The soft and hard thresholding techniques give an approximation of wavelet coefficients during wavelet threshold denoising. Smaller coefficients are cancelled in hard thresholding thus providing an efficient representation whereas in soft thresholding, coefficients above the threshold are reduced. The coefficients equal to or less than threshold are made equal to zero and also, coefficients above this threshold level are softened out by the value equal to threshold value [21]. Defing the threshold level is a tedious task. Although mathematically hard thresholding is simpler but better performance in terms of denoising is attainable with soft thresholding [22].

3. Methodology

This paper has been focused to analyze wavelet functions and denoising results with DWT transform for soft thresholding. EEG dataset has been used from Project BCI which has been freely made available from SCCN (Swartz Center of Computational Neuroscience). It was the motor imagery data set in matlab format. It consisted of single subject EEG data where actual left and right hand movements were recorded (with no control on swallowing or breathing). Recording was performed using 19 electrodes at sampling rate of 500 Hz. Room was not EM shielded. Neurofax system using daisy chain montage was used for recording purpose [23].

In the present work, a denoising model is proposed for finding optimum wavelet function (WF) with soft thresholding applied to coefficients obtained by DWT at level 4. The evaluation parameters like RMSE, MAE, SNR and PSNR have been analyzed for HAAR, db2, db4, db8, db meyer and other functions corresponding to thresholding after analyzing soft and hard thresholding methods. Figure 3 shows the process of implementing wavelet denoising. Thresholding technique is applied to wavelet coefficients obtained after DWT. Then inverse transform is executed to give approximate description of original EEG signal.

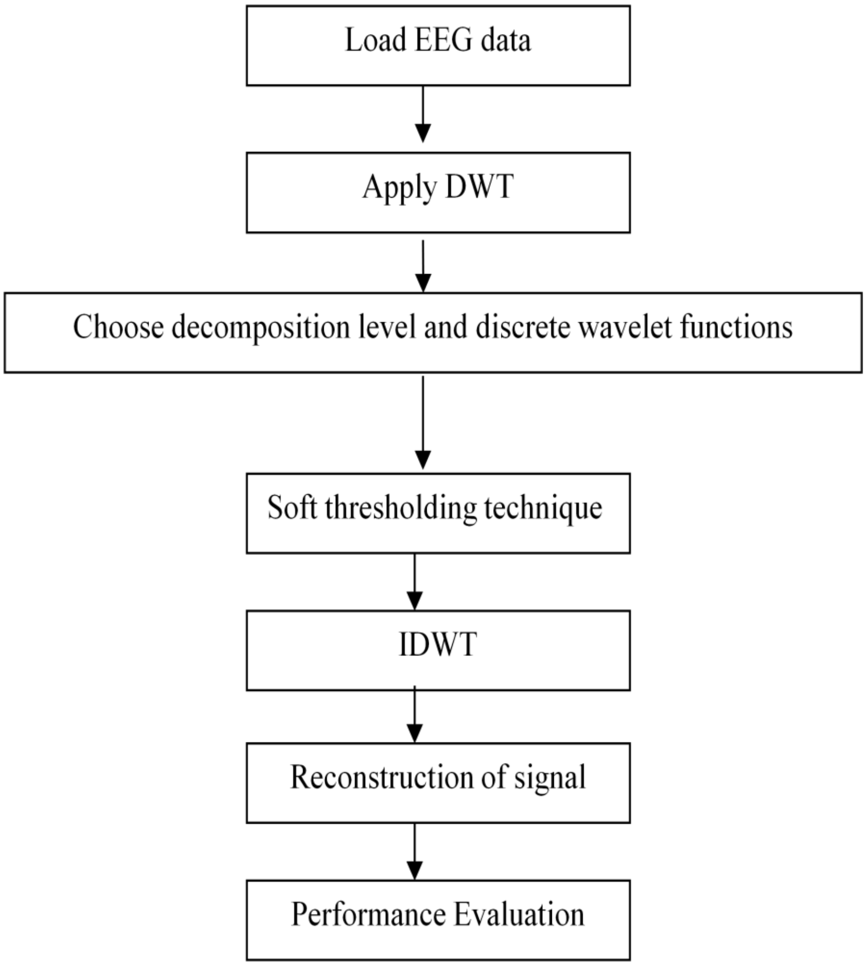


Fig. 3. Flowchart of wavelet denoising process.

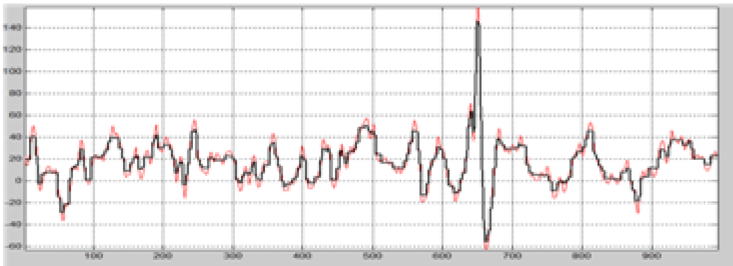
4. Results and Discussion

The concept of thresholding has been considered in this work as various thresholding techniques allow reconstruction of physiological signals based on chosen coefficients. A comparative analysis for soft and hard thresholding for a variety of thersholding selection methods such as fixed, Rigorous Sure, Heuristic Sure and minimax shows that soft thresholding performs better than hard thresholding. Table 1 lists the results of thresholding in terms of RMSE and SNR.

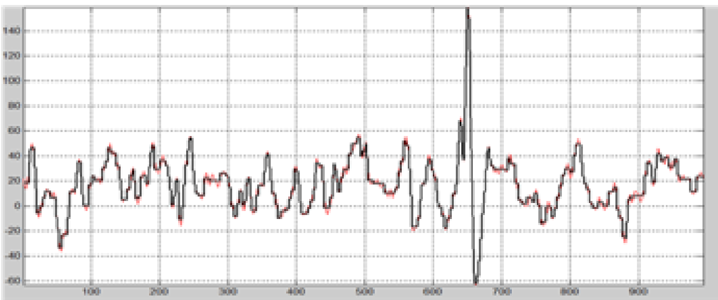
Table 1. Comparison of various thresholding techniques for soft and hard thresholding for Haar and db8 wavelet decomposition.

Wavelet Function	**Thresholding Selection Method**	**RMSE**		**SNR (db)**	
		Soft Thresholding	**Hard Thresholding**	**Soft Thresholding**	**Hard Thresholding**
HAAR	Fixed from threshold	19.43	21.44	21.13	20.69
	Rigorous Sure	21.52	21.61	20.25	20.21
	Heuristic Sure	21.51	21.57	20.25	20.23
	Minimaxi	20.19	21.56	20.80	20.80
db8	Fixed from threshold	21.46	21.64	21.12	20.21
	Rigorous Sure	21.53	21.64	20.31	20.20
	Heuristic Sure	21.54	21.64	20.30	20.20
	Minimaxi	21.53	21.64	20.42	20.42

Using table 1, it can be concluded that minimum RMSE and maximum SNR is attained by soft thresholding using fixed threshold selection technique for both HAAR and db8 wavelet decomposition. Minimum RMSE of 19.43 and highest SNR equal to 21.12 db has been observed for fixed thesholding selection method. Figures 4 shows the original and denoised signals corresponding to HAAR decomposition at level 5 with thresholding set at 8.552.



(a)



(b)

Fig. 4. Original (red) and denoised (black) signals at HAAR wavelet at LEVEL 5 with (a) soft thresholding set at fixed level = 8.552 and (b) hard thresholding set at fixed level = 8.552.

EEG Denoising Model

Based on these results, a DWT based EEG denoising model using soft thresholding has been designed using MATLAB SIMULINK as shown in figure 5.

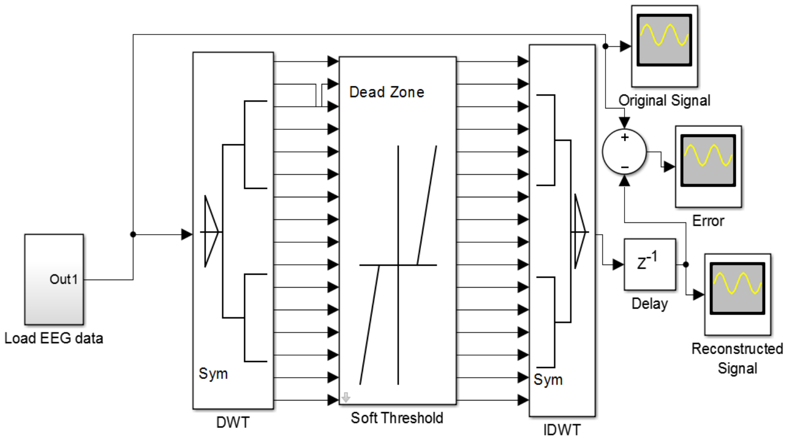


Fig. 5. Wavelet denoising model for EEG signals with transform DWT at decomposition level 4.

The simulation and computation of the performance parameters has been performed for DWT transform at decomposition level of 4 using soft thresholding. Wavelet functions like haar, db2, db4, db6, db8, dmey, sym4, sym 8, bior1.1, bior1.3, bior2.2, bior3.3 and bior4.4 have been used for decomposition. Table 2 concludes that best overall performance is achieved by haar and bior 1.1 wavelet decomposition for DWT transform at level 4. Both yield same results for the noise removal process of epileptic EEG signals.

Table 2. Comparative analysis of different performance evaluation parameters for different wavelet decompositions at level 4.

Wavelet Function	**RRMSE**	**RMAE**	**SNR (db)**	**PSNR (db)**
HAAR	**0.7669**	**0.725**	**2.304**	**17.17**
db2	0.8217	0.7555	1.705	16.57
db4	0.8793	0.8489	1.117	15.96
db6	0.9386	0.9384	0.5487	15.41
db8	0.8864	0.8734	1.046	15.91
dmey	0.9247	0.9083	0.6791	15.54
Symlets 4	0.8834	0.857	1.075	15.94

		3		
Symlets 8	0.8849	0.8804	1.062	15.93
Bio- orthogonal 1/1	**0.7669**	**0.725**	**2.304**	**17.17**
Bio- orthogonal 1/3	0.8686	0.8023	1.223	16.09
Bio- orthogonal 2/2	0.8693	0.8012	1.216	16.08
Bio- orthogonal 3/3	0.8850	0.8573	1.06	15.93
Bio- orthogonal 4/4	0.8809	0.8651	1.101	15.97

Conclusion

Wavelet transforms are already gaining great success in the field of signal processing. In this work, a denoising model has been proposed for finding optimum wavelet function with thresholding technique after applying level 4 DWT in terms of performance matrices like Relative RMS error, Relative MAE, SNR and PSNR for epileptic subjects' EEG signals. Soft thresholding gives better performance than hard thresholding as shown by lower RMSE and higher SNR values. Also, all the wavelet functions perform denoising efficiently, but it has been observed that Haar and Bioorthogonal 1/1 perform best as they show minimum values of RRMSE and RMAE as 0.7669 and 0.725 respectively, with maximum values of SNR and PSNR as 2.304 db and 17.17 db respectively as compared to other decompositions. So, various WFs have been concluded for analyzing EEG signal in this work at the levels of decomposition equal to 4. Also, more efficient algorithms can be developed by increasing the levels of decompositions. So, this analysis can be extended for analyzing other levels of decompositions also.

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