Performance Analysis of Mother Wavelet Functions and Thresholding Methods for Denoising EEG Signals during Cognitive Tasks

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Abstract—**Artifact reduction is a major challenging task in the analysis of Electroencephalography signals. Wavelet denoising is one of the efficient techniques for rejecting artifacts and it has been employed in the detection of various brain diseases. The selection of the most suitable wavelet function and the thresholding method, which varies with the nature of the task performed, are important steps in the process of wavelet denoising. In this study, the effects of wavelet denoising on Electroencephalograph (EEG) signals during reading and mental arithmetic tasks were investigated. The effectiveness of each of the 46 wavelet functions including Daubechies- db, Symlet- sym, Coiflet- coif and Discrete Meyer- dmey, was examined for denoising the EEG signals recorded during reading and mental arithmetic tasks. EEGs of ten healthy subjects were recorded during reading and mental arithmetic tasks. The performance evaluation of wavelet function and thresholding method were done on the basis of peak signal to noise ratio (PSNR), root mean square error (RMSE), percentage root square difference (PRD), and cross correlation coefficient (CC). Subsequently, the EEG signals were decomposed into different frequency bands, and variations in EEG band power were computed before and after denoising. The wavelet function "dmey" was found to be the most efficient wavelet function for denoising EEG signals during cognitive tasks. Rigrsure thresholding method was found to be the best thresholding method in this study. A significant difference in EEG rhythmic activity (P < 0.05) was observed after denoising the EEG signal.**

Keywords— EEG artifact, wavelet denoising, cognitive task, wavelet function, thresholding.

I. Introduction

Electroencephalography (EEG), a non- invasive technique that records the electric activity of brain, is being widely used in medical and research fields. It finds application in diverse disciplines such as cognitive neuroscience, medical diagnosis, brain-computer interface, artificial intelligence, etc. EEG is divided into several rhythms based on the frequency- delta (1- 4 Hz), theta (4- 8 Hz), alpha (8-13 Hz), beta (13- 30 Hz) and gamma (30- 50 Hz) [1-3]. The delta activity occurs during deep sleep, while theta activity is dominant during drowsiness and mental workload. Alpha activity represents relaxed state, and gets attenuated during attentive state [4]. Beta activity is observed during states of attention and consciousness [5]. Gamma activity represents selective attention, cognition and perceptual activity [6].

The recorded EEG signals, which are generally weak in the order of microvolts, are mostly contaminated with artifacts. Artifacts are unwanted signals of non-cerebral origin, which interfere with EEG signals causing misinterpretation of the brain activity. There are different types of artifacts including eye blinks, eye movements, muscle activity, cardiac activity, electrode movements, power supply noise, etc. [7-8]. Most of the artifacts lie in the frequency range of EEG signals and mimic brain activity. Artifact rejection is an essential task in the analysis of EEG signals as it alleviates misinterpretation of the mental state or faulty diagnosis of brain disorders. The rejection of artifacts is performed during pre-processing of EEG signals, following which the EEG features are extracted.

There are several techniques for reducing artifacts such as wavelet denoising [9-11], regression analysis [12], blind source separation [13-14], principal component analysis [15], independent component analysis [16-17], etc. Wavelet denoising is one of the most efficient techniques for artifact removal since it detects any abrupt transients in the EEG [18-19]. Basically, wavelet denoising involves the selection of proper wavelet function and thresholding, which in turn, depends on the nature of the experiment. Studies have identified the most compatible wavelet functions for denoising EEG signals during various tasks and mental states. Al-Qazzaz *et al.* [20] examined the performance of forty-five wavelet functions from Daubechies, Symlets, and Coiflets families for denoising EEG signals during working memory tasks. They observed that the wavelet function 'sym9' provided the best results. Mamun *et al.* [21] demonstrated that the wavelet function 'dmey', with the evaluation parameter root mean square difference, has been efficient for denoising the EEG of epileptic patients [21].

Our study focused on identifying the most compatible wavelet function for denoising the EEG signals of healthy subjects during reading and mental arithmetic tasks. The most effective thresholding method was evaluated in terms of peak signal to noise ratio (PSNR), root mean square error (RMSE), percentage root mean square difference (PRD), and cross-correlation coefficient (CC). Further, the spectral variations in EEG frequency bands were computed before and after the denoising process.

II. METHODS

A. Ethical Clearance

The study was approved by the Institutional Ethics Committee duly constituted according to the guidelines of Indian Council of Medical Research (ICMR). The procedure was explained in detail and written informed consent was obtained from all the participants.

B. EEG Recording

Ten healthy volunteers (6 males, 4 females) aged 18- 31 years (mean age 22.90) participated in this study. The subjects had no neurological or psychiatric illness. The experiments were conducted in an electrically shielded room with subjects in a sitting position. EEG was recorded during the rest state, reading task and mental arithmetic task, each having 3 minutes duration. During the reading task, the participants were instructed to read a scientific article related to the basics of brain functions. The arithmetic tasks included showing moderately complex arithmetic calculations in the screen, and the subject had to respond to the correct answer using a response key. EEG was recorded using BE Plus LTM 128 channel EEG acquisition system. All the EEG channels were recorded in an averaged reference and electrode impedance was kept lower than 5kohm. EEG signals from 18 channels Fp1, Fp2, Fpz, F3, F4, F7, F8, Fz, T5, T6, P3, Pz, P4, C3, Cz, C4, O1, and O2 were used for the analysis. EEG signals were digitized online at 128 Hz sampling rate and exported to MATLAB-compatible format for further processing. EEG data were band pass filtered between 1Hz and 64Hz and an additional notch filtering was performed to eliminate 50Hz power line noise interference. EEG signal was divided into several epochs of one second duration and were applied for wavelet denoising. EEG epochs contained various artifacts such as ocular artifacts, muscular artifacts, and power line interference, which were observed when plotting the power spectrum of the EEG signal.

C. Wavelet Denoising

Wavelet analysis is a very effective technique for time-frequency analysis of non- stationary signals like EEG and it provides a good time- frequency resolution [18-19]. Wavelet transform can detect any transient events occurring in the signal, and it decomposes the given signal using a set of oscillating functions known as wavelets. Different families of wavelet functions '$\boldsymbol{\psi_{a,b}(t)}$' are formed as scaled and shifted versions of a unique mother wavelet '$\boldsymbol{\psi(t)}$' according to (1).

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

where, a, b $\in R, a \neq 0$, 'a' is the scaling parameter, 'b' is the shifting parameter and 't' is the time variable. Discrete wavelet transform (DWT) is a discrete version of continuous wavelet transform, defined by assigning discrete values to wavelet parameters 'a' and 'b' ($a = 2^{-j}$ and $b = k\,2^{-j}$, where j and k are integers representing the scale and translation) as illustrated by (2) [18]. Discrete wavelet transform has been widely employed for denoising and feature extraction of EEG signals.

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^j t - k) \quad (2)$$

The process of wavelet denoising consists of three phases namely decomposition of EEG signal into high frequency and low frequency coefficients, thresholding of coefficients based on the noise level, and finally reconstruction of denoised EEG signal from the wavelet coefficients. Discrete Wavelet Transform (DWT) decomposes the digitized EEG samples into detail and approximation coefficients as indicated in Fig. 1. The detail coefficients and approximation coefficients represent high frequency components and low frequency components respectively. Various EEG bands- delta, theta, alpha, beta, and gamma are extracted from the detail and approximation components. Two functions, scaling functions (l_d) and wavelet functions (h_d), are used for producing details 'D' and approximations 'A' respectively, according to (3) and (4).

$$D[n] = \sum_{k=-\infty}^{k=+\infty} h_d[k]x[2n-k] \quad (3)$$

$$A[n] = \sum_{k=-\infty}^{k=+\infty} l_d[k]x[2n-k] \quad (4)$$

where n and k represent discrete time coefficients and x denotes the signal to be decomposed.

The decomposition of the EEG signal is influenced by the selection of proper mother wavelet function and the level of decomposition. Forty-six wavelet functions from wavelet families Daubechies (db1- 20, Symlet (sym1- 20), Coiflet (coif1- 5) and Discrete Meyer (dmey) (Rafiee et al., 2011) were examined for identifying the most suitable wavelet to denoise the EEG signal. The level of wavelet decomposition was chosen as four based on sampling rate of EEG signal (128 Hz) and all EEG frequency bands were extracted using four decomposition levels. In the thresholding phase, the value of the threshold is computed according to threshold selection rules.

Thresholding selection rules include Sqtwolog, Minimax, Heursure, and Rigrsure and each method was examined to identify the best thresholding selection rule for denoising EEG signal [23-24]. 'Sqtwolog' technique calculates the threshold value using mean absolute deviation, while 'Rigrsure' method is based on Stein's Unbiased Risk Estimator (SURE), computing an estimate of the risk for a particular threshold value. 'Minimax' uses a fixed threshold providing minimax performance for mean square error against an ideal procedure. 'Heursure' is a combination of Sqtwolog and Rigrsure methods and it is used when the signal to noise ratio of the signal is very small.

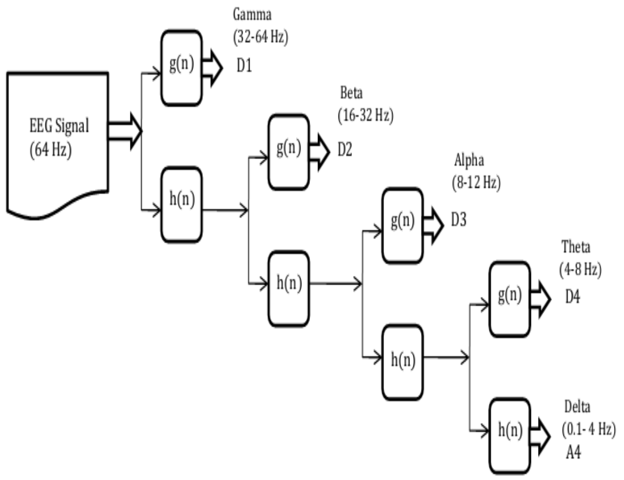

Fig. 1. Four- level Wavelet Decomposition of EEG into different frequency bands

D. Performance Metrics

The effectiveness in denoising of EEG signal was evaluated for different wavelet functions and thresholding methods using the performance metrics- root mean square error (RMSE), peak signal to noise ratio (PSNR), percentage root mean square difference (PRD) and cross-correlation coefficient (CC). These are computed as follows (5)- (8).

$$RMSE = \sqrt{\frac{1}{N}\sum_n (x(n) - x'(n))^2} \tag{5}$$

where $x(n)$ = Original signal
$x'(n)$ = Denoised signal
N= Total number of signal samples

$$PSNR = 20 \log \frac{\max[x(n)]}{RMSE} \tag{6}$$

$$PRD = 100 \times \sqrt{\frac{\sum_n (x(n)-x'(n))}{\sum_n (x(n))^2}} \tag{7}$$

$$CC = \frac{E[(x-\mu_x)(y-\mu_{x'})]}{\sigma_x \sigma_{x'}} \tag{8}$$

where μ_x *and* $\mu_{x'}$ represent mean values of signals x and x' respectively, and σ_x and $\sigma_{x'}$ represent standard deviations of x and x' respectively.

PSNR indicates the ratio of the strength of the signal content to that of noise content. RMSE and PRD indicate the error difference between the original signal and the denoised signal. Cross-correlation coefficient (CC) describes the degree of correlation between the original EEG signal and the denoised signal. Higher values of PSNR and CC and lower values of RMSE and PRD indicate the better performance of each wavelet denoising technique.

EEG rhythms- delta, theta, alpha, beta, and gamma were extracted using discrete wavelet decomposition in order to evaluate the effect of wavelet denoising for each rhythm. Relative power for each band was computed as the ratio of the absolute power of each band to the absolute power in the whole EEG spectrum and expressed in percentage.

E. Statistical Analysis

Wilcoxon Signed-Rank test was used to examine the significant difference (P value, $p<0.05$) in each EEG rhythmic activity between the original EEG signal and its denoised form.

III. RESULTS

The performance of each wavelet function from 46 wavelet functions for denoising EEG signal during the reading and mental arithmetic tasks has been measured in the study. The variations in EEG rhythmic activity due to wavelet denoising were also computed.

The wavelet function Discrete Meyer "dmey" was found to be the most compatible wavelet for denoising EEG signal during the reading task and mental arithmetic task. The PSNR, RMSE, PRD, and CC of wavelet functions with the highest performance are illustrated in Table I. The wavelet dmey provided the highest PSNR the lowest RMSE. The larger values of PSNR and CC and the lower values of RMSE and PRD indicate better performance of a given method in denoising EEG signals. EEG signal before and after wavelet denoising is illustrated in the Fig. 2.

TABLE I. PERFORMANCE EVALUATION OF DIFFERENT WAVELET FUNCTIONS IN DENOISING EEG SIGNALS DURING THE READING TASK FOR THE REPRESENTATIVE SUBJECT (CHANNEL FP1)

Wavelet Function	PSNR	RMSE	PRD	CC
dmey	52.756	0.0192	0.708	0.9999
db20	50.952	0.0237	0.872	0.9999
db13	45.662	0.0436	1.604	0.9998
db19	44.819	0.0480	1.768	0.9998
sym19	43.763	0.0542	1.996	0.9998
db18	43.622	0.0551	2.029	0.9997
sym20	41.869	0.0675	2.483	0.9996
db16	40.023	0.0834	3.070	0.9995
db15	39.972	0.0839	3.089	0.9995

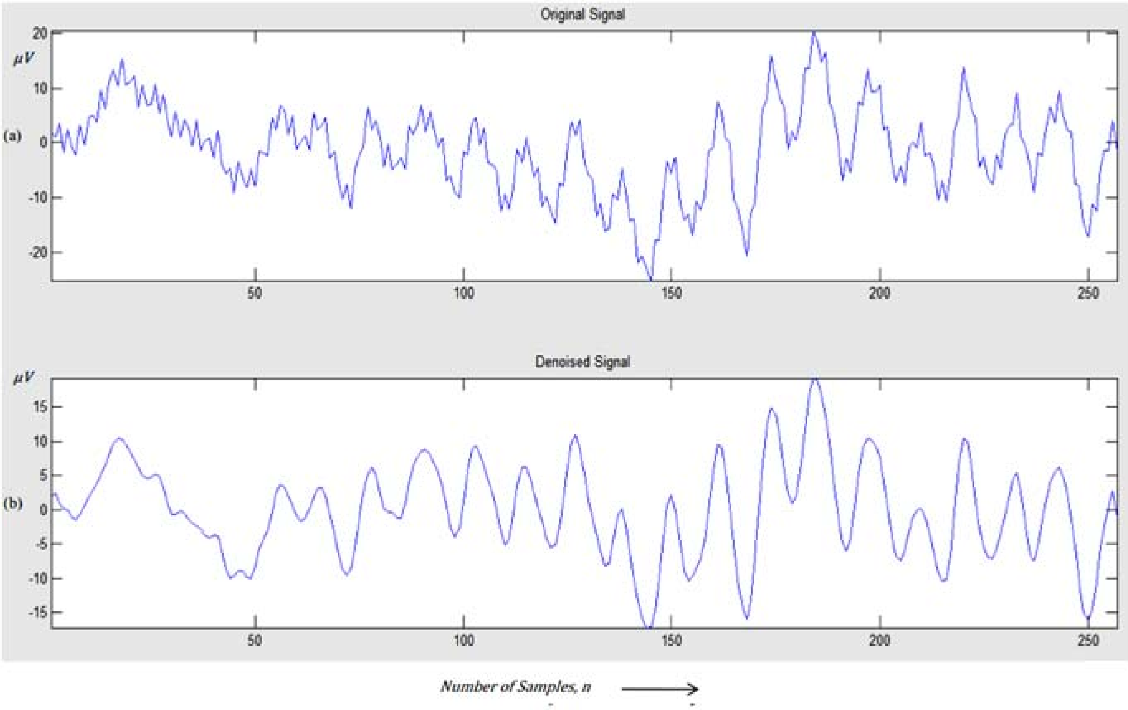

Fig. 2. Denoising of EEG signal during the reading task in the channel F3. (a) Original signal; (b) Denoised EEG signal after wavelet denoising.

The waveform of a dmey wavelet function is shown in Fig. 3 [25]. It shows resemblance to the EEG signal and provided better results in denoising EEG signals. Out of four thresholding methods, Rigrsure threshold selection rule was more effective in denoising as indicated in Table II. Hard thresholding achieved better performance compared to soft thresholding.

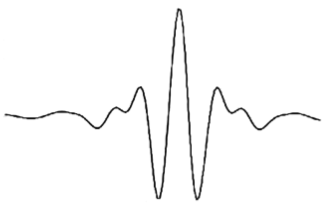

Fig. 3. Discrete Meyer Wavelet function

Peak Signal to Noise Ratio (PSNR) of different wavelet functions for denoising EEG signals during the reading task and mental arithmetic task are provided in Table III. Effects of hard thresholding and soft thresholding are also included in the table. The wavelet function Discrete Meyer- 'dmey' achieved the highest PSNR in both groups. Along with 'dmey', wavelet functions sym20, sym19, db20, db19, and db18 provided good PSNR as illustrated in Table III.

TABLE II. PERFORMANCE COMPARISON OF DIFFERENT THRESHOLDING SELECTION RULES IN DENOISING EEG SIGNALS DURING THE READING TASK FOR THE REPRESENTATIVE SUBJECT (CHANNEL FP1)

Threshold Selection Rule	Wavelet Function	PSNR	RMSE	PRD	CC
Rigrsure-hard	dmey	52.756	0.01927	0.708	0.9999
Rigrsure-soft	dmey	47.927	0.03361	1.236	0.9999
Heursure-hard	dmey	43.398	0.05661	2.082	0.9997
Heursure-soft	dmey	43.073	0.05876	2.161	0.9997
Minimaxi-hard	dmey	44.886	0.04769	1.754	0.9998
Minimaxi-soft	dmey	37.486	0.11181	4.112	0.9992
Sqtwolog-hard	dmey	41.559	0.06996	2.573	0.9996
Sqtwolog-soft	dmey	33.629	0.17432	6.411	0.9981

Relative band power for each EEG rhythmic activity- delta, theta, alpha, beta, and gamma has been computed. Fig. 4 shows the variations in band power of EEG signal containing artifacts, before and after wavelet denoising. The highest variation occurred in the delta band after denoising. Relative band power for the delta band in the denoised signal was decreased by 13.82% from that of original signal, as an indication of removal of artifacts in the range of delta band. Consequently, an increase of relative band power has been found in theta (7.01%), alpha (4.55%), beta (2.19%) and gamma (0.07%) of the denoised EEG signal.

TABLE III. PERFORMANCE COMPARISON OF DIFFERENT WAVELET FUNCTIONS IN DENOISING EEG SIGNALS FOR THE READING TASK GROUP AND MENTAL ARTIMETIC TASK GROUP. MEAN VALUE OF PSNR IS PROVIDED IN THE TABLE.

Wavelet Function	**Reading Task**		**Mental Arithmetic Task**	
	PSNR- Hard Thresholding	***PSNR- Soft Thresholding***	***PSNR- Hard Thresholding***	***PSNR- Soft Thresholding***
dmey	45.985	43.371	46.414	43.045
sym20	43.819	40.994	44.942	40.786
sym19	44.567	42.230	44.829	40.524
db19	44.148	41.216	44.343	40.508
db20	43.420	41.617	45.312	41.777
db16	43.722	40.483	44.993	41.994
db15	42.989	41.105	45.243	40.916
db18	43.789	40.865	44.587	41.711
sym16	43.940	40.753	44.749	40.613
sym13	43.848	41.352	45.208	41.067
sym17	43.413	40.894	45.007	41.417
sym18	43.251	40.881	44.287	41.315
db12	43.017	38.949	44.169	40.258
db11	42.669	39.798	44.588	39.905

Significant difference in EEG rhythmic activity between the original EEG signal and its denoised form was examined using the statistical analysis. It has been observed that there exists a significant difference due to wavelet denoising in delta ($P = 0.001$), theta ($P = 0.020$), alpha ($P = 0.003$), beta ($P = 0.001$) and gamma ($P=0.001$) rhythms. The results indicate that wavelet denoising is an effective technique for removing noise components of different frequencies embedded in the EEG signal.

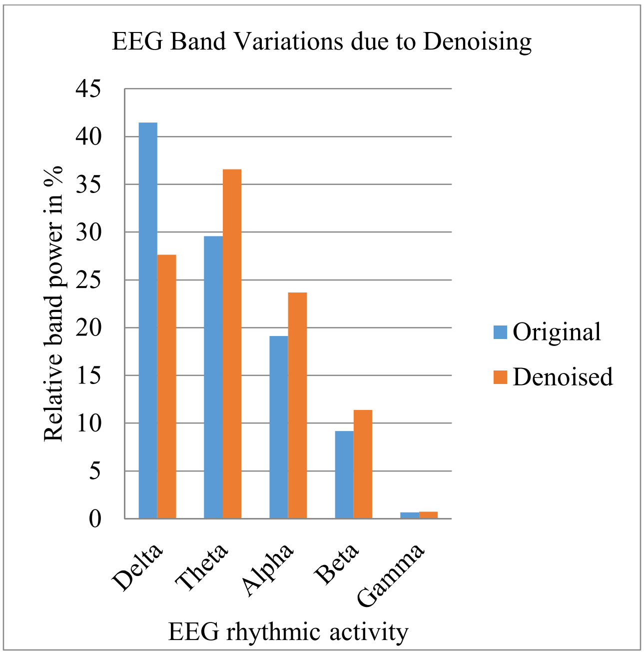

Fig.4. Relative band power of EEG signals due to wavelet denoising for the representative subject in the channel Fp1. Mean values are shown.

IV. DISCUSSION

The present study investigated the effectiveness of 46 wavelet functions and four thresholding methods in denoising EEG signal during the reading task and mental arithmetic task. Rigrsure thresholding was observed as the best thresholding selection rule in this study, which is consistent with the results of previous experiments [20, 26]. Hard thresholding achieved better results than soft thresholding in terms of PSNR and RMSE, in similar to the findings of Rupjyoti et al. [26] and Alyasseri et al. [9]. Out of 46 wavelet functions, the wavelet function Discrete Meyer (dmey) provided the highest performance for denoising EEG signals during the reading task and the mental arithmetic task. It has been reported that Discrete Meyer wavelet function has been the best performing wavelet function for denoising EEG of epileptic and Parkinson's disease patients [21, 26]. The present study demonstrates wavelet denoising as an effective technique for removing artifacts from EEG signals during cognitive tasks like reading and arithmetic tasks.

Most EEG artifacts including ocular and muscular artifacts lie in the frequency range of EEG signal (0.1-60Hz) [27- 29]. Ocular artifacts include eyeball movement and eye blinks which are characterized by high amplitude and low frequency (0- 16 Hz) [11,30]. EMG artifacts mainly affect the high frequency band of the EEG signal and are characterized by larger intensity and frequencies higher than 20Hz [27- 29]. The current study observed a significant difference in each rhythmic activity between the original EEG signal and the denoised signal during reading and mental arithmetic tasks. The variations in EEG frequency bands indicate that artifact components lying in different frequency ranges can be removed using wavelet denoising technique. All these together illustrate that wavelet denoising is an efficient technique for denoising EEG signals during reading and mental arithmetic tasks.

V. CONCLUSION

The findings of the current study depict that wavelet denoising is an effective method for reducing artifacts of different frequencies contaminated with the EEG signals during cognitive tasks. The study focused on EEGs of healthy subjects during reading and mental arithmetic tasks, while the previous studies have demonstrated the effectiveness of wavelet denoising for clinical EEG data sets such as epilepsy, Parkinson's disease, etc. The effectiveness of various wavelet denoising techniques was evaluated based on the performance metrics Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE), Percentage Root Mean Square Difference (PRD) and the cross- correlation coefficient (CC). The discrete Meyer (dmey) wavelet function with Rigrsure hard thresholding achieved the best results for both reading and mental arithmetic tasks. Consequently, a significant difference in each EEG rhythmic activity ($P<0.05$) has been found due to wavelet denoising. The findings provide the optimal wavelet denoising method for eliminating artifacts from EEG signals during reading and mental arithmetic task.

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