Performance Analysis of Various Thresholds for Correction of Ocular Artifacts from Single Channel EEG in WT and EMD domains

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Abstract

Physicians use Electroencephalogram (EEG) to dissect different nervous system disorders like Alzheimer's, Parkinson's, Seizures, Epilepsy etc.. EEG signals indicate bioelectric brain activity and are usually tainted with different artifacts due to movements of eye, heart and muscles and power line interference. Among these, ocular activities create significant artifacts and make the analysis difficult. This paper a new threshold is presented for removal of Ocular Artifacts (OA) from the single channel EEG signals in Wavelet Transform (WT) and Empirical Mode Decomposition (EMD) domains. Using the EEG Motor Movement/Imagery (eegmmidb) dataset, extensive computations are carried out and compared the performance of Proposed Threshold (PT) with current thresholds i.e., Universal Threshold (UT), Minimax Threshold (MT) and Statistical Threshold (ST) using several standard performance metrics: change in Signal to Noise Ratio (ΔSNR), Artifact Rejection Ratio (ARR), Correlation Coefficient (CC), Normalized Mean Square Error (NMSE). Results of these studies reveal that the PT is able to remove the OAs from EEG signals effectively maintaining the background neural activity in non artifact zones intact in contrast with those of existing ones.

Keywords: EEG, OA, EMD, WT, Thresholding, ΔSNR, ARR, CC, and NMSE.

I. Introduction

EEG is a vital tool for physicians to diagnose certain neurophysiological states and disorders. Amplitudes of these range typically between 10 to 100µV and mostly lie below 50µV. It is difficult to analyze the EEG signals due to the presence of biological artifacts resulting from muscular movements, eye blinks, and cardiac pulses etc.. Artifacts related to ocular activity are of the order of milli-volts and distort the EEG signals as these are in the order of micro volts. The frequency range of EEG signal is 0 to 64 Hz where as that of OAs is 0 to 16 Hz. There is a considerable loss of EEG activity due to overlapping spectra if the process of removal of artifacts is not proper.

Numerous methods are in vogue for correcting ocular artifacts in EEG recordings. Widely used methods are regression in time and frequency domain techniques (adaptive filtering) and Blind Source Separation (BSS) methods: Principle Component Analysis (PCA) and Independent Component Analysis (ICA) [1]-[4].

Correction procedure in regression based method involves subtracting the approximated Electroculogram (EOG) from EEG which requires that EOG and EEG must be uncorrelated. But these are bidirectional in practice [1]. Adaptive filtering methods call for the use of reference EOG signals. Obtaining reference EOG signals require long periods and are inconvenient to the subject [2], [3]. Methods based on BSS deal with multichannel EEG data by assuming that the number of EEG channels observed is greater than the number of sources generating EEG signals. But the real number of sources is unknown [4].

One of the powerful and promising ocular artifact correction techniques for single channel EEG data is Wavelet Transform (WT). Many investigators have removed ocular artifacts from EEG signals employing various combinations of wavelet transform techniques: Discrete Wavelet Transform (DWT) and Stationary Wavelet

Transform (SWT) [5]-[6]. In WT, mother wavelets are used to identify the artifact zones and then apply thresholding in the identified zones to keep the background neural information [7]-[8]. Saleha Khatun, et.al [9] compared the performance of various combinations of discrete and stationary wavelet transforms with universal and statistical threshold functions for the removal of ocular artifacts from a single channel EEG data and concluded that the statistical threshold is the better one. Vijayasankar et.al [10] proposed a new level dependent threshold for correction of ocular artifacts from single channel EEG and compared its performance with existing thresholds (UT and ST) in terms of standard metrics: SNR and ARR, which has been enhanced in this study.

EMD has come into prominence of late to extract the signal from noisy data. EMD involves decomposing the signal into Intrinsic Mode Functions (IMF) and filtering those IMFs that correspond to artifacts for signal denoising, which may lead to loss of signal information [11]-[12]. Yannis Kopsinis et.al and Stephen McLaughlin et.al [13] have developed EMD Interval Thresholding (EMDIT) inspired by wavelet thresholding for signal denoising. Since, application of wavelet-like thresholding directly to the intrinsic mode functions (IMF) is not correct and can have catastrophic consequences for the reconstructed signal.

In recent years the hybrid approach, which is the combination of several methods, has been proposed for automatic removal of artifacts [14]-[15]. These methods may remove the artifact automatically but enhance the computational complexity. Thresholding the coefficient for correction of artifacts in WT and EMD domains is simple, effective and require less computational recourses than existing techniques. Many threshold functions are available in the literature to correct artifacts of the bio-signals, in particular Universal, Minimax, and Statistical thresholds [16], [17].

In this paper, a level dependent threshold is proposed for the removal of ocular artifacts and the performance of different thresholds are compared in WT and EMD domains. Section II provides a brief description of WT and EMD thresholding methods for artifact correction. The concepts of current and proposed threshold functions are detailed in section III. Section IV deals with various performance metrics used in this study. Results and discussions are illustrated in section V, and the conclusions drawn are presented in section VI.

II. Methods for Artifact correction

A. WT Description and Thresholding

Wavelet transforms are used to evaluate time varying, non-stationary signals like EEG; it decomposes the signal into its set of basis functions known as wavelets. There are two wavelet decomposition methods in particular- Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT). In DWT the signal $x(t)$ is allowed through a series of low-pass and high-pass filters with different cut-off frequencies, which results in a set of detail (C_d) and approximate (C_a) coefficients helping in analyzing the signal with different resolutions. It is a powerful tool for various non-stationary signal processing applications. However, it suffers from major limitations such as shift sensitivity and lack of phase information. Researchers have developed the real-valued extensions to standard DWT, i.e., Stationary Wavelet Transform (SWT) to overcome these limitations. In SWT the approximate and detail coefficients at each decomposition level are of equal in length as the original sequence. Consequently SWT is computationally complex than DWT. The complexity at level K is increased from $O(2^K)$ to $O(K2^K)$ in contrast with DWT [5].

Usually OAs lay in the low frequency bands, i.e., Theta and Alpha bands [7]. The EEG signal is decomposed into a set of approximate and detail coefficients by WT and the value of threshold at each level is estimated based on mean absolute deviation or standard deviation of the wavelet coefficients. Applied soft thresholding to the detailed wavelet coefficients (C_d) and perform inverse DWT to obtain the clean EEG signal. Removal of artifacts depends on the choice of wavelet, decomposition level and threshold estimation to a larger extent [18]. Theoretically the Maximum number of decomposition levels is

$m = \log_2 N$ for a N point sequence. In this simulations, single channel EEG segments of 10 seconds duration are taken from eegmmidb (Physionet) data base, each of which is of frame length N=1600. The level of wavelet decomposition is neither too high nor too little. It is difficult to remove the noise effectively if the level of decomposition is small; however, if the decomposition level is high, the signal to noise ratio is poor. We, therefore, selected eight levels of decomposition as a compromise. Figure 1 illustrated the detail coefficients by WT methods for the signal on electrode Fp1.

There are several possible mother wavelet functions but coif3 is morphologically more similar to the OAs [9]. Thresholding is done for the detail coefficients running from level 8 to 5. Method of soft thresholding for the detail wavelet coefficients W_i is given below.

$$W_i = \begin{cases} W_i - \lambda & W_i \geq \lambda \\ W_i + \lambda & W_i \leq -\lambda \\ 0 & |W_i| < \lambda \end{cases} \qquad -(1)$$

The wavelet decomposition, thresholding and reconstruction are carried out using MATLAB. The process of artifact correction using wavelet transform method is shown in figure 2.

(a)

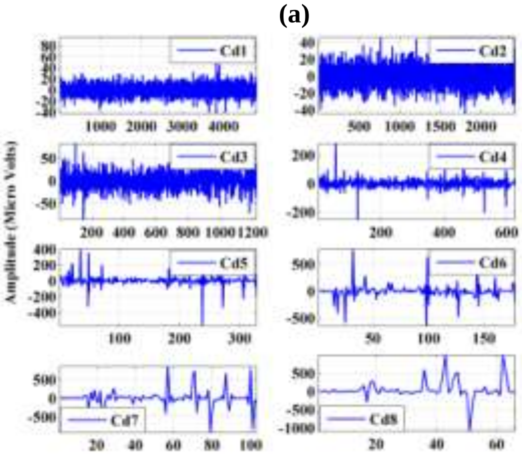

Fig.1. (a) Detail coefficients for the signal on electrode Fp1 by DWT

(b)

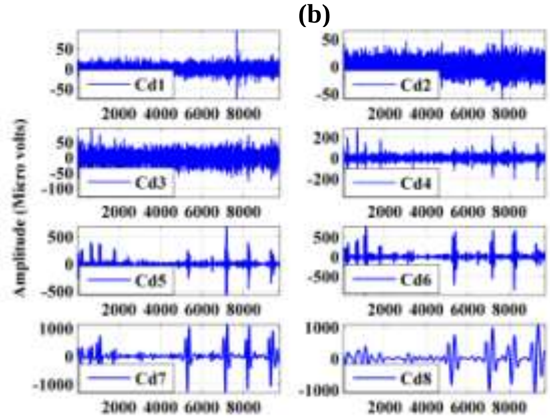

Fig.1. (b) Detail coefficients for the signal on electrode Fp1 by SWT

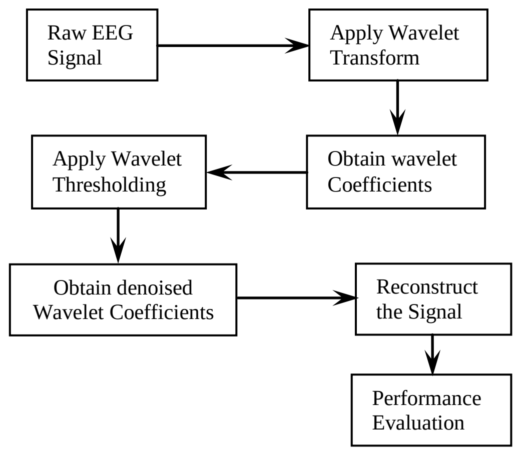

Fig 2. Denoising approach based on Wavelet Thresholding

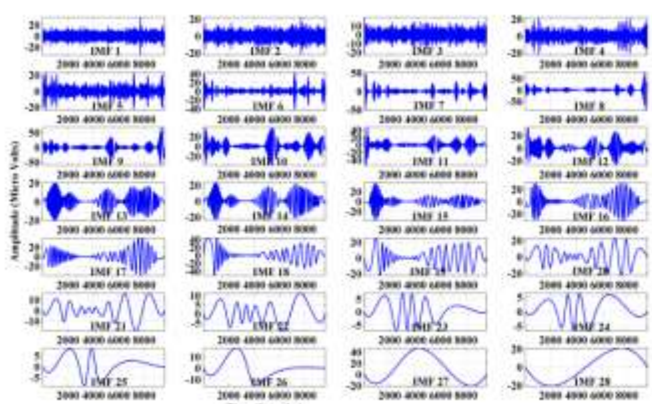

Fig 3.EMD decomposition of raw EEG signal of electrode Fp1.

B. *EMD Interval Thresholding*

EMD adaptively decompose the multi-component signal $x(t)$ into K number of IMFs [13].

$$x(t) = \sum_{i=1}^{K} h_i(t) + d(t) \qquad -(2)$$

where $d(t)$ is the residue that is a nonzero slowly varying function with few extrema. IMFs $h_i(t)$ have zero mean, the successive maxima and minima values be positive and negative respectively.

The extremas of IMF $h_i(t)$ positioned in time instances $t_j = [t_1, t_2, ..., t_M]$ and the corresponding IMF points $h_i(t_j)$, $j = 1,2,3..,M$, will alternate between maxima and minima values. That results a single zero crossing z_j between any pair of extrema $t_j = [h_i(t_j), h_i(t_{(j+1)})]$. z_j is the j^{th} zero crossing of an i^{th} intrinsic mode function. Depending on the shape of IMF, the number of zero-crossings can be either M or $M-1$. The interval of zero crossing for an i^{th} IMF is $z_{ij} = [z_j, z_{j+1}]$ and the corresponding IMF points are $h_i(z_{ij})$.

The set of IMFs for the signal on electrode Fp1 is shown in Fig 3. Higher order IMFs contain low frequency noise and lower order IMF components consist of high frequency noise, i.e., the ocular artifacts lay in the last several IMFs. Applied soft thresholding (3) to the IMF coefficients and construct the clean signal using the modified IMFs [13].

$$h_i(z_{ij}) = \begin{cases} h_i(z_{ij}) * \left[\dfrac{h_i(t_j) - \lambda_i}{h_i(t_j)}\right] & h_i(t_j) > \lambda_i \\ 0 & h_i(t_j) \le \lambda_i \end{cases} \qquad -(3)$$

for $j = 1,2,3....M$, where $h_i(z_{ij})$ indicates the samples from instants z_j to z_{j+1} [13]. The process of artifact correction using EMD interval thresholding method is shown in figure 4.

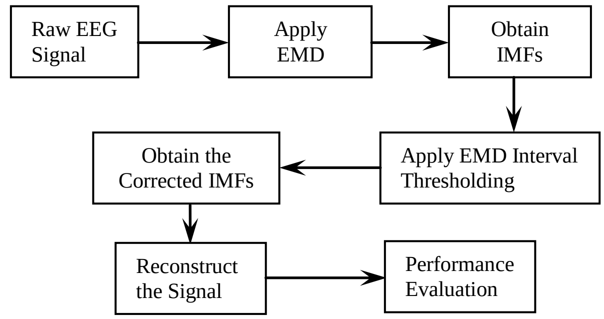

Fig 4. Denoising Approach Based on EMD-IMF Thresholding

III. Existing and Proposed Threshold Functions

Selection of threshold is a critical step in the denoising process. It should not eliminate the original signal coefficients which may lead to loss of significant information in the analyzed data. The clean signal remains noisy if the threshold is too small or as well large. So, an adaptive threshold is to be found. The decomposed EEG signal coefficients at each level must be customized by thresholding to separate the artifactual coefficients from neural signal coefficients. Threshold functions for artifact correction are described below.

A. *Universal Threshold (UT)*

Universal threshold was proposed by Donoho [16]. This is a global threshold function, Threshold values are calculated using the universal method given by

$$\lambda_i = \sigma_i \sqrt{2 \log N} \qquad (4)$$

Where N is the length of the raw EEG signal, σ_i is the mean absolute deviation and λ_i is the threshold at i^{th} decomposition level or threshold for i^{th} IMF. σ_i is expressed as

$$\sigma_i = \frac{Median\,|\,h_i\,|}{0.6745} \qquad -(5)$$

Where h_i denotes the WT/EMD coefficients at i^{th} level. The numerator is rescaled by 0.6745 in the denominator so that it will be a suitable estimator for Gaussian white noise.

B. Minimax Threshold (MT)

The effective minimax threshold λ_i is given by [17].

$$\lambda_i = \begin{cases} \sigma_i(0.3936 + 0.108\log_2 N) & N \geq 32 \\ 0 & N < 32 \end{cases} \quad -(6)$$

C. Statistical Threshold (ST)

Statistical threshold is proposed by Krishnaveni et al., which is based on the statistics of the signal [6]. The effective statistical threshold λ_i would be

$$\lambda_i = 1.5 * std(h_i) \quad -(7)$$

Where h_i denotes the WT/EMD coefficients at i^{th} level and the factor 1.5 is an estimator for standard white Gaussian noise.

D. Proposed Threshold (PT)

The proposed threshold is adaptive to different sub- band characteristics by analyzing the parameters of the IMF coefficients [19]. The new threshold function λ_{iNEW} is given by

$$\lambda_{iNEW} = P_i * std(h_i) \quad -(8)$$

$$P_i = e^{\frac{(\lambda_i - S_i)}{(\lambda_i + S_i)}} \quad -(9)$$

Where P_i is the threshold improvement factor and λ_i is the universal threshold function.

$$S_i = \frac{\sum_i |h_i|}{N} \quad -(10)$$

Where N represents the number of IMF coefficients at each level.

In case of Universal and Minimax thresholds, threshold value at each decomposition level is a function of mean absolute deviation (MAD) and the length of raw EEG signal (N), whereas in statistical threshold it is a factor of standard deviation of the coefficients. Threshold value derived from mean absolute deviation is typically smaller; shrink the coefficients that retain the noisy information. However, threshold value based on standard deviation is usually larger and shrinks the coefficients that affect the background neural activity in non artifact zones. Hence a compromise between universal and statistical thresholds is proposed in this study.

IV. Performance Metrics

The performance of the proposed threshold is compared quantitatively with respect to the other thresholds based on the following metrics: improvement in signal-to-noise-ratio (ΔSNR), Artifact rejection ratio (ARR), Correlation Coefficient (CC), and Normalized mean square error (NMSE) in dB. Change in signal to noise ratio is defined as the difference of SNR before and after removal of artifacts, often expressed in dB and was computed using equation (11).

$$\Delta SNR = 10\log_{10}\left(\frac{\sigma_x^2}{\sigma_y^2}\right) \quad -(11)$$

Whereas σ_x^2 and σ_y^2 is the variance of error signal before and after application of artifact removal technique respectively.

Artifact rejection ratio (ARR) is the ratio of the power of the removed artifacts to the power of the clean EEG signal expressed as

$$ARR = \frac{\sum_{n=1}^{N}(x[n] - y[n])^2}{\sum_{n=1}^{N} y^2[n]} \quad -(12)$$

Where $x[n]$ and $y[n]$ denote the contaminated and clean EEG signals respectively.

Correlation Coefficient (CC) is a statistical method that shows the degree of similarity or relatedness between two signals expressed as

$$CC = \frac{\sum_{n=1}^{N}(x[n] - \bar{x})(y[n] - \bar{y})}{\sqrt{\sum_{n=1}^{N}(x[n] - \bar{x})^2 \sum_{n=1}^{N}(y[n] - \bar{y})^2}} \quad -(13)$$

Normalized Mean Square Error (NMSE) approximates the difference between the raw and clean EEG data [14]. NMSE is computed in dB using the equation (14).

$$NMSE = 20\log E\left\{\frac{\frac{1}{N}\sum_n (x_1[n] - y_1[n])^2}{\frac{1}{N}\sum_n [x_1^2[n]]}\right\} \quad -(14)$$

Where x_1 and y_1 denote the samples of input and reconstructed signals respectively in originally artifact-free region, and $E\{.\}$ denotes the mathematical expectation operator.

The Power Spectral Density (PSD) function shows the energy of the signal as a function of frequency. It has been implemented in this study using power spectral density estimate via Welch's method (pwelch). Spectrum of the signal before and after processing is shown in Fig 7.

V. Results & Discussions

In this work, single channel EEG segments of 60sec duration each from five subjects are taken at polysomnographic records (https://physionet.org/cgi-bin/atm/ATM) [20]. The ocular artifacts are found dominant in the frontal and fronto-polar channels like F7, F8, Fp1 and Fp2. Hence it is reasonable to take F7, F8, Fp1 and Fp2 as contaminated / corrupted EEG signals. The raw EEG signal (Fp1) with identified artifacts is shown in Figure 5. However, the method is applicable for EEG recordings of any channel. Various thresholds (UT, MT, ST and PT) are applied to each of the EEG data sets for correction of ocular artifacts in WT and EMD methods. Figure 6 illustrates the raw and clean EEG signals by WT and EMD methods with combination of different thresholds (UT, MT, ST, and PT) for the Fp1 EEG signal.

All the methods (DWT, SWT and EMD) described in section II are efficient in correcting the artifacts, but careful perception demonstrates that, EMD inspired by wavelet thresholding correct the artifacts better compared to the WT based methods and SWT performed better than DWT method. EMD method is more appropriate to analyze non-stationary signals like EEG when compared to WT methods. ST has shown superior performance for artifact rejection in WT and EMD based methods and PT is better after ST compared to other thresholds (UT and MT).

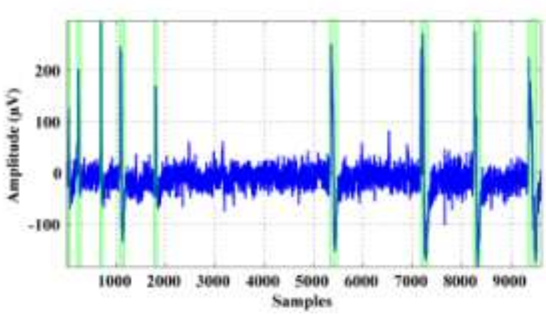

Fig 5 Raw EEG with Identified Artifacts

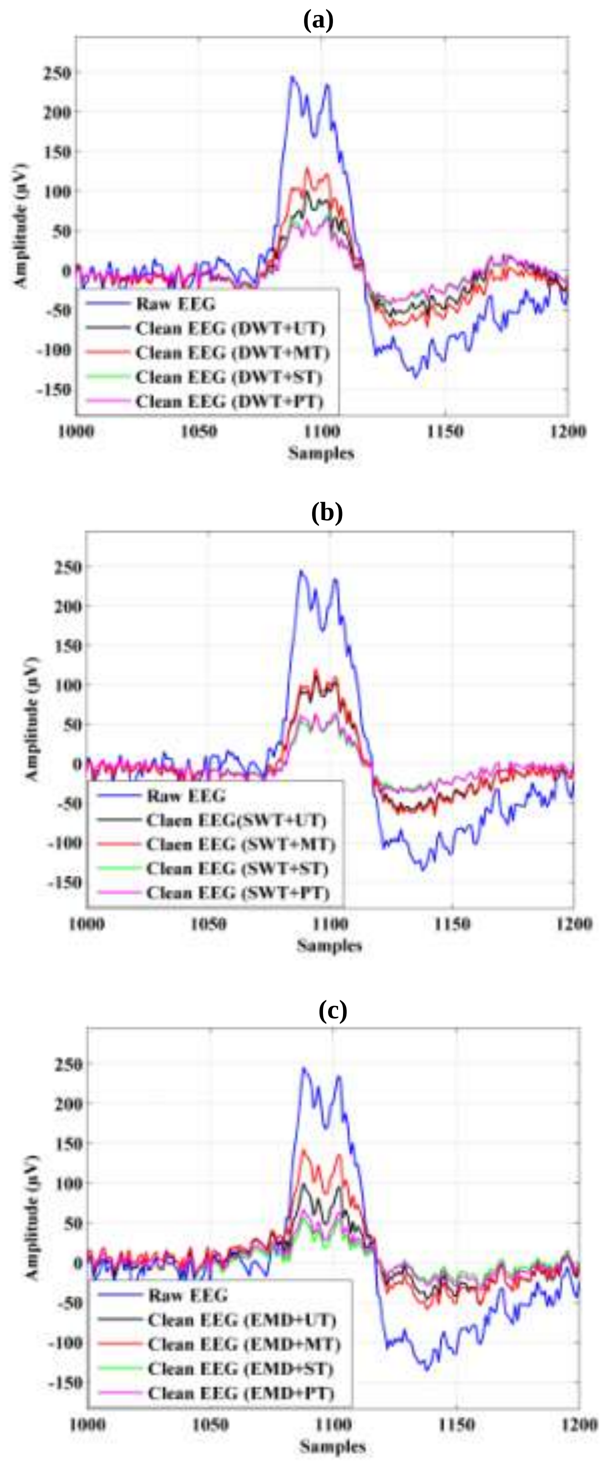

Fig 6(a), 6(b) And 6(c) Clean EEG Signals Using Different Thresholds During The Samples (1000-1200) For The Signal On Electrode Fp1 By DWT, SWT And EMD Methods Respectively.

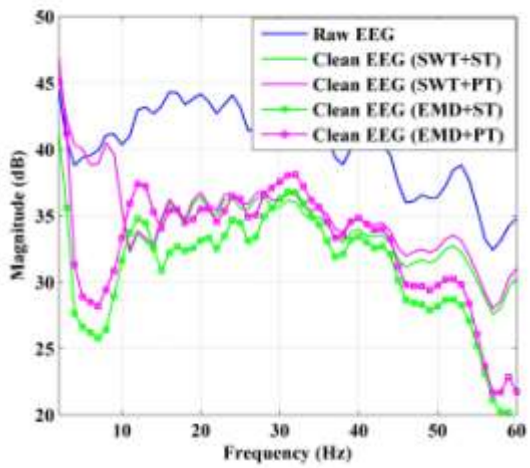

Fig 7.Spectra of clean and raw EEG signals using thresholds ST and PT in WT and EMD domains.

Figure 7 illustrate the power spectra of contaminated and clean EEG signals using statistical and proposed thresholds for WT and EMD domains. The clean EEG signals by EMD+ST method containing the less power at lower frequencies prove the effective removal of ocular artifacts in that region. EMD+PT method performed better than EMD+UT and EMD+MT methods respectively.

The ultimate artifact removal algorithm requires high SNR as well as ARR. From Table 1 these values are considerably better in EMD method when compared to WT methods, where as SWT method is better than DWT method. Based on ΔSNR and ARR once again ST has shown superior performance than other thresholds indicating that it is aggressive in removing the probable artifacts, where as PT is better after ST in both WT and EMD domains.

An efficient eye blink removal algorithm should be capable of correcting the artifacts in the blink region and preserving the background activity normal in artifact free zones. This can be accomplished by segregating the EEG signal into blink and non blink regions and evaluating the metrics CC and NMSE between raw and clean EEG signals over non-blank regions [7]. High CC and low NMSE for the non blink regions are chief requisites for an effective artifact removal algorithm. Figure 5 illustrated a raw EEG with identified artifacts. Based on Table 2, SWT is outperformed than other methods where as EMD is better after SWT. It is also observed that MT has shown better performance than other thresholds; however thresholds UT and PT are with moderate performance.

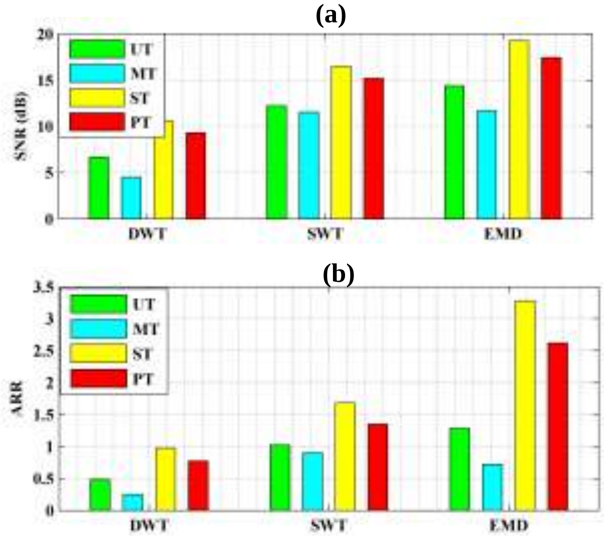

Fig. 8 (a) and (b) Performance comparison of thresholds in terms of ΔSNR and ARR respectively for Fp1 EEG signal.

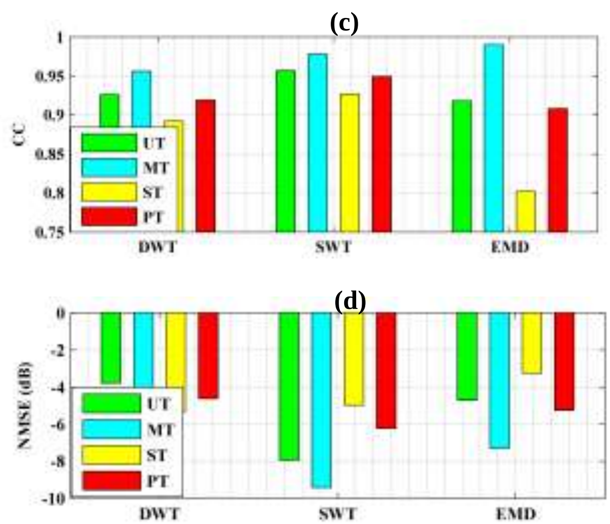

Fig. 8 (c) and (d) Performance comparison of thresholds in terms of CC and NMSE respectively for Fp1 EEG signal over non blink regions.

Comparison of different thresholds in terms of performance metrics (ΔSNR, ARR, CC and NMSE) for the signal on electrode Fp1 is shown in figure 8. An optimum artifact removal technique must have high ΔSNR, ARR, CC and low NMSE. The EMD based method is noticed with high SNR, ARR, moderate CC and NMSE, whereas SWT method is with moderate ΔSNR, ARR, high CC and low NMSE, due to inherent redundancy at each level of decomposition. However ST performed better in terms of ΔSNR and ARR but the neural activity in the nonblank regions slightly effected. Thresholds UT and MT are preserving the neural activity in non-blink regions but unable to reject the artifacts well, where as PT has shown acceptable performance in all the metrics in both WT and EMD schemes. So EMD and SWT with PT is a better choice for rejecting the artifacts from single channel EEG signals.

VI. Conclusions

This study focused on comparing the effectiveness of various thresholds for correction of ocular artifacts from single channel EEG data based on WT and EMD domains. Results of this study reveal that EMD+PT is an optimum choice for the removal of ocular artifacts from single channel EEG signal. However, the computational time for correction of artifacts from single channel EEG using EMD methods is higher than WT based methods, SWT+PT is the better choice for real time applications.

Table1. ΔSNR and ARR on EEG Datasets Using Different Thresholds by WT and EMD Methods

Channels		F7		F8		Fp1		Fp2	
Method	Metrics Threshold	ΔSNR (dB)	ARR	ΔSNR(dB)	ARR	ΔSNR(dB)	ARR	ΔSNR(dB)	ARR
DWT	UT	5.72±0.45	0.27±0.15	6.61±0.72	0.45±0.05	6.66±0.94	0.48±0.26	5.15±0.53	0.38±0.21
	MT	3.7±0.32	0.14±0.05	4.38±0.34	0.24±0.02	4.52±0.86	0.25±0.15	3.45±0.32	0.19±0.11
	ST	10.41±0.78	0.74±0.25	9.57±1.71	0.88±0.26	10.58±0.61	0.98±0.28	9.57±1.56	0.64±0.23
	PT	8.57±0.20	0.55±0.24	8.87±1.18	0.75±0.14	9.32±0.42	0.77±0.30	7.63±1.24	0.48±0.18
SWT	UT	*12.15*±0.52	1.12±0.18	12.92±0.98	1.10±0.36	12.22±0.42	1.02±0.45	11.96±0.40	1.06±0.21
	MT	*11.45*±0.48	1.06±0.16	12.25±0.84	1.00±0.31	11.53±0.37	0.90±0.28	11.26±0.38	0.94±0.24
	ST	16.31±1.75	2..03±0.28	15.86±2.57	1.53±0.28	16.47±1.59	1.68±0.62	16.42±1.47	1.93±0.63
	PT	*14.91*±1.75	1.64±0.19	14.40±2.32	1.21±0.17	15.19±1.52	1.35±0.47	15.18±1.50	1.59±0.52
EMD	UT	*14.25*±1.45	1.16±0.32	13.64±1.65	0.98±0.38	14.38±1.31	1.28±0.43	13.76±1.14	1.32±0.52
	MT	*12.25*±0.98	0.78±0.19	11.58±0.94	0.62±0.24	11.68±0.64	0.72±0.28	11.44±0.79	0.83±0.23
	ST	*18.36*±2.72	3.04±0.96	17.74±2.16	2.52±0.61	19.24±3.15	3.28±1.32	17.32±2.18	2.24±0.87
	PT	*17.24*±1.68	2.46±0.56	14.88±1.73	1.87±0.55	17.45±1.75	2.62±0.97	15.78±1.25	1.78±0.76

Table2. Average CC and NMSE Using Different Thresholds by WT and EMD Methods

Channels		F7		F8		Fp1		Fp2	
Method	Metrics Threshold	CC	NMSE(dB)	CC	NMSE(dB)	CC	NMSE(dB)	CC	NMSE(dB)
DWT	UT	0.934±0.018	-6.08±2.31	0.925±0.027	-4.92±1.78	0.926±0.032	-3.78±1.28	0.976±0.016	-7.16±2.85
	MT	0.953±0.014	-6.24±2.52	0.948±0.018	-5.11±1.86	0.956±0.020	-4.13±1.43	0.991±0.005	-7.27±2.48
	ST	0.906±0.036	-7.05±3.23	0.882±0.024	-6.14±2.15	0.892±0.044	-5.33±2.16	0.942±0.023	-7.85±3.14
	PT	0.932±0.035	-6.53±3.14	0.928±0.021	-5.22±2.01	0.919±0.038	-4.61±1.65	0.973±0.017	-7.34±2.92
SWT	UT	0.958±0.012	-7.94±2.74	0.924±0.035	-8.09±2.38	0.957±0.029	-7.94±2.64	0.968±0.019	-8.44±2.63
	MT	0.990±0.008	-9.40±3.25	0.982±0.015	-10.6±2.92	0.987±0.018	-9.40±3.37	0.990±0.004	-10.69±2.27
	ST	0.904±0.042	-4.96±1.84	0.884±0.042	-6.35±1.73	0.927±0.032	-4.96±1.43	0.925±0.036	-6.36±1.83
	PT	0.937±0.025	-6.28±2.66	0.917±0.036	-7.27±2.16	0.949±0.036	-6.22±2.69	0.959±0.026	-7.25±2.07
EMD	UT	0.922±0.052	-4.71±1.76	0.923±0.028	-6.82±2.86	0.918±0.033	-4.71±1.62	0.936±0.025	-5.18±1.84
	MT	0.992±0.002	-9.28±3.19	0.987±0.007	-9.88±3.26	0.990±0.003	-7.29±2.82	0.992±0.002	-9.13±3.08
	ST	0.821±0.062	-3.62±1.16	0.812±0.042	-4.35±1.98	0.802±0.055	-3.24±1.23	0.806±0.067	-3.48±1.29
	PT	0.915±0.032	-5.22±1.86	0.915±0.039	-6.25±2.54	0.908±0.049	-5.25±1.78	0.912±0.041	-5.16±1.98

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