Comparative Analysis of Wavelet Based Approaches for Reliable Removal of Ocular Artifacts from Single Channel EEG

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***Abstract*—For biomedical and scientific fields, Electroencephalography (EEG) has turned out to be an important tool to understand, study, and utilize brain functionalities. To fully utilize EEG signals in real-life closed-loop applications, artifacts such as ocular must be removed. Wavelet transform is one of the powerful methods to remove ocular artifacts from single channel EEG devices. In this study, both stationary and discrete wavelet transforms (SWT and DWT, respectively) have been compared with various wavelet basis functions, such as sym3, haar, coif3, and bior4.4 using either universal threshold (UT) or statistical threshold (ST). Different combinations of wavelet transform techniques, mother wavelets, and thresholds are compared to identify an optimum combination for ocular artifact removal. Performance metrics like Correlation Coefficient (CC), Normalized Mean Square Error (NMSE), Time Frequency Analysis, and execution time have been calculated for measuring the effectiveness of each combination. According to CC, DWT+UT combination turned out to be a good option for the ocular artifact removal. However, according to NMSE and time frequency analysis, SWT+ST has generated better performance in keeping neural segments of EEG unaffected. According to the measurement of execution times, DWT+ST is faster compared to other combinations. The study shows that wavelet transform is suitable in artifact removal from single channel EEG data to implement in ambulatory real-time EEG systems.**

***Index Terms*—Electroencephalogram, Wavelet Transform, Ocular Artifact, Artifact Removal.**

I. INTRODUCTION

Neuro-physiological signals like EEG, MEG, and ECG have been utilized in medical diagnosis, therapies, cognitive load studies, etc. [1-3]. EEG signal is vastly used in different scientific research projects. According to international 10-20 system, EEG has been obtained from different locations of the brain like frontopolar, frontal, temporal, occipital, central and parietal locations [1]. The locations near to the eyes are prone to get contaminated with the ocular artifacts (eye movements and eye blinks) [4]. Ocular artifacts are dominant over other physiological artifacts because they generally have larger amplitudes [5]. To obtain clean EEG, different artifact removal methods have been used like Regression in time domain [6] and frequency domain [7], Principal Component Analysis (PCA) [8], Independent Component Analysis (ICA) [9], and Wavelet Transform (WT) [4, 10]. Most of these methods require multiple channels of EEG data or recording of Electrooculography (EOG) signal except WT technique. Hence, WT has a potential to be a suitable technique for denoising single channel EEG systems.

T. Zikov *et al.,* in their study, applied stationary wavelet transform (SWT) with coiflet 3 mother wavelet filter to EEG and denoised the ocular artifacts using threshold calculated from 60-second baseline EEG [4]. Furthermore, different combinations of wavelet transform techniques, thresholds, and mother wavelets have been studied for denoising ocular artifacts from EEG. SWT with coif3 was implemented in [11] with different non-adaptive thresholds for denoising, such as universal threshold, statistical threshold, etc. The results in the study [11] concluded that the statistical threshold (1.5*standard deviation of detail coefficients) performs better. In [12], adaptive thresholding mechanism was explored with SWT and coif3 for the purpose of removing ocular artifact. To avoid the complexity of adaptive thresholding technique, coefficient of variation with soft thresholding approach was used with SWT and sym3 for denoising EEG in [13].

Usage and applications of single channel portable EEG capturing devices are increasing day by day. Wearable EEG acquiring systems are helpful in continuous monitoring of patients, brain computer interface (BCI) applications, etc. As inferred from the literature, Wavelet transform is a robust technique in ocular artifact removal of EEG in single channel system. In this study, a comparative analysis has been performed using the combinations of different WT techniques (i.e. SWT and DWT), different thresholds (Universal and Statistical), and different mother wavelet functions (sym3, coif3, haar, and bior4.4) to identify the suitable combination to effectively clean ocular artifacts. This paper presents an objective comparative study of various combinations of wavelet transformations, basis functions and threshold techniques to remove eye-blink artifacts from a single channel EEG data.

II. DEFINITIONS

In this section, some important terms used in this study are defined.

A. Wavelets

Wavelets are the functions with large varying amplitudes within a restricted time and limited range of frequencies [14]. Popular wavelets used in biomedical signal analysis are sym3, coif3, haar, bior4.4, and db4 as shown in Fig. 1.

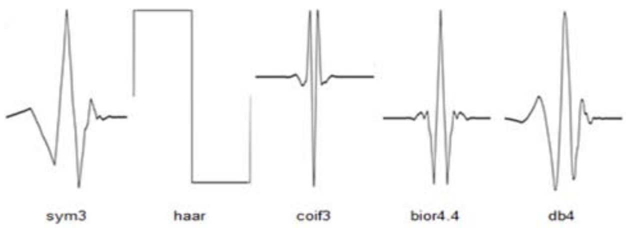

Fig. 1. Examples of common wavelet basis functions.

B. Wavelet Transform

Wavelet transform (WT) breaks down a waveform into the set of time-scaled and time-translated versions of the same basic wavelet [14]. The idea of WT is to pass a signal into a high pass filter and a low pass filter which thereby generates detail and approximate coefficients, respectively. There are two wavelet decomposition methods - Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT). In DWT, the input signal is down sampled, i.e. if the input signal has *n* coefficients, output from each filter (high pass and low pass) would have *n/2* coefficients. In SWT, the output from each filter would have *n* coefficients provided that the input signal has *n* number of samples.

C. Threshold

For denoising the EEG signal, two thresholds have been evaluated in the analysis as explained below.

1) *Universal Threshold (UT):* Let us assume that at a certain level of wavelet decomposition, the number of wavelet coefficient is *N*. Then the universal threshold Tj would be,

$$T\text{j} = \sigma\sqrt{2logN} \quad (1)$$

where, σ^2 = median (|Cj|/0.6745), C_j is the wavelet detail coefficients at j^{th} level and constant 0.6745 accounts for the Gaussian noise [15].

2) *Statistical Threshold:* According to [11], the effective statistical threshold T_j would be,

$$Tj = 1.5 * std(Cj) \quad (2)$$

Where, C_j is detail coefficients at the j^{th} level.

D. Performance Metrics

For measuring the effectiveness of the algorithms, different performance metrics have been implemented in this study like Correlation Coefficient (CC), Normalized Mean Square Error (NMSE), and Time Frequency Analysis, etc. If CC is represented by *r(t1,t2)*, then *r(t1,t2)* is represented by [16]:

$$r(t1, t2) = \frac{C(t1,t2)}{\sqrt{C(t1,t1)C(t2,t2)}} \quad (3)$$

Where, *C (t1, t2)* is the auto-covariance of a process *x (t)* or in other way, *C (t1, t2)* is the covariance of the random variables *x (t1)* and *x (t2)*. CC gives high value if two random variables have high similarity and low value if they are different. NMSE is used to measure the difference between the neural part of the raw and reconstructed signal [17]. To compute the NMSE in dB, the equation is given below:

$$\text{NMSE} = 20\text{logE}\{\frac{\sum[x1(i)-x2(i)]^2}{\sum[\text{x1(i)}]^2} \quad (4)$$

For the time frequency analysis, the wavelet decomposition tool of EEGLAB toolbox (MATLAB Toolbox, California, US) has been used.

III. METHODOLOGY

Using 14-channel referential montage EPOC headset (Emotive, Eveleigh, NSW, Australia), EEG data was acquired at the sample rate of 128 sps using an IRB approved protocol (University of Memphis IRB# 2289). Data was recorded for 1 minute 45 seconds from four subjects. Seven datasets were collected for the analysis in an instructed protocol with subjects in rest and blinking state.

EEG signal of interest generally lies from (0.1-100) Hz (Delta: 0.1Hz to 3Hz, Theta: 4Hz to 7Hz, Alpha: 8Hz to 12Hz, Low Beta: 12Hz to 15Hz, Midrange Beta: 16Hz to 20Hz, High Beta: 21Hz to 30Hz, Gamma: 30Hz to 100Hz). Generally ocular artifacts (OA) lie in low frequency bands [4]. So in this study, the captured EEG signals are decomposed up to Level 8 for both wavelet decompositions (SWT or DWT). The frequency bands in each level are L1: (64-128) Hz, L2: (32-64) Hz, L3 : (16-32) Hz , L4: (8-16) Hz , L5: (4-8) Hz, L6: (2-4) Hz, L7: (1-2) Hz, and L8: (0.5-1) Hz. Thresholding is done for the detail coefficients from level 8 up to level 3. The wavelet decomposition, thresholding and reconstruction are performed using MATLAB (MathWorks, California, US) and EEGLAB toolbox.

IV. RESULTS

Wavelet decomposition methods (SWT or DWT) have been applied to each of the EEG datasets for removing blinks with mother wavelets (sym3, haar, coif3, and bior4.4 etc.) using specific thresholds (UT or ST). In section II, the types of mother wavelets and thresholds that have been used in this analysis are discussed. For understanding of the efficacy of a particular combination of wavelet transform (WT), mother wavelet (MW), threshold (T), we have segregated our datasets into blink and non-blink zones. The result of average correlation coefficient (CC) between raw and reconstructed EEG signal for blink and non-blink zone for a particular combination (WT+MW+T) is given in Table I. For effective OA removal algorithm, the correlation coefficient values for the blink zone are expected to be very low (ideally zero) and the correlation coefficient values for the non-blink zone are expected to be very high (ideally one). In Table I, it is seen that DWT is dominant over SWT in cleaning OA in the OA zone, but it affects the artifact-free zone more, especially for DWT with UT, compared to DWT with ST. So, according to the CC performance metric, combination of DWT+ST would be a good choice for cleaning OA. Fig.2 gives a time domain representation of raw and denoised EEG signal with the DWT+ST+coif3 wavelet combination. In Fig. 2, the time frequency representations of SWT technique with different mother wavelets and different thresholds along with the raw EEG signal have been shown. If each combination of MW+T is compared with the raw EEG signal, then haar with SWT appeared to be the worst wavelet in cleaning artifacts. In Fig. 3, different combinations of (MW+T) with DWT have been displayed. It is to be noted that DWT is introducing extra artifacts while applying them to the EEG signal with the usage of universal threshold. Considering the artifact removal and effect upon neural part, DWT+UT+coif3, DWT+UT+bior4.4, and DWT+ST+coif3 performs better than other combinations. In Fig. 4, NMSE results of different combinations have been presented. As mentioned in section II, the more negative the NMSE, the better it is. From Fig. 4, it can also be concluded that both SWT and DWT make less errors while using with ST than while using with UT. In other words, it can be said that while using ST, the neural part of the EEG signal is less affected.

The algorithms were executed on a Windows 7 OS computer system with (processor Intel® Core™ i5 and speed 3.33 GHz), 4 GB of RAM using Matlab codes. Average processing time for the four WT+T combinations are calculated for the same data length and the results are tabulated in Table II. The table clearly depicts that DWT+ST combination is the fastest among all the combinations. So for implementing the EEG artifact removal algorithm in real-time, DWT+ST might be a suitable choice.

V. CONCLUSIONS

In this paper, different combinations of existing wavelet transform techniques, different thresholds, and different mother wavelets have been applied to the EEG signal for finding the best option to remove ocular artifact from EEG, while keeping the neural part unaffected. The reason for choosing wavelet transform technique is because it is applicable for denoising single channel EEG system and is comparatively faster than many conventional methods. Considering both the artifact cleaning efficacy and the effect upon neural part, DWT+ST is a good combination from the performance metric analysis based on Correlation Coefficient metric. In this study, Normalized Mean Square Error is also used to compute the reconstruction error in the neural part of the EEG signal. Among all the combinations, SWT+ST performs better in keeping the neural part less affected. In time frequency analysis, most of the SWT combinations give satisfactory results while very few DWT combinations perform satisfactorily. According to the average processing time results, DWT+ST is the fastest, which might be a good choice for single channel hardware implementation. Our future research direction includes implementation of these algorithms in a single channel EEG hardware platform for performance evaluation.

TABLE I

CC OF 7 EEG DATASETS USING UT AND ST THRESHOLDS WITH SWT AND DWT METHODS

	Zone	sym3	haar	coif3	bior4.4
SWT +UT	Blink	0.40±0.16	0.69±0.12	0.35±0.17	0.38±0.17
	Non-Blink	0.81±0.08	0.83±0.08	0.80±0.08	0.81±0.08
SWT + ST	Blink	0.69±0.13	0.74±0.12	0.65±0.15	0.67±0.14
	Non-Blink	0.99±0.01	0.99±0.01	0.99±0.01	0.99±0.01
DWT + UT	Blink	0.28±0.18	0.37±0.16	0.32±0.23	0.33±0.22
	Non-Blink	0.75±0.10	0.75±0.10	0.78±0.10	0.77±0.10
DWT +ST	Blink	0.48±0.25	0.41±0.21	0.43±0.27	0.48±0.24
	Non-Blink	0.95±0.08	0.97±0.04	0.96±0.06	0.95±0.08

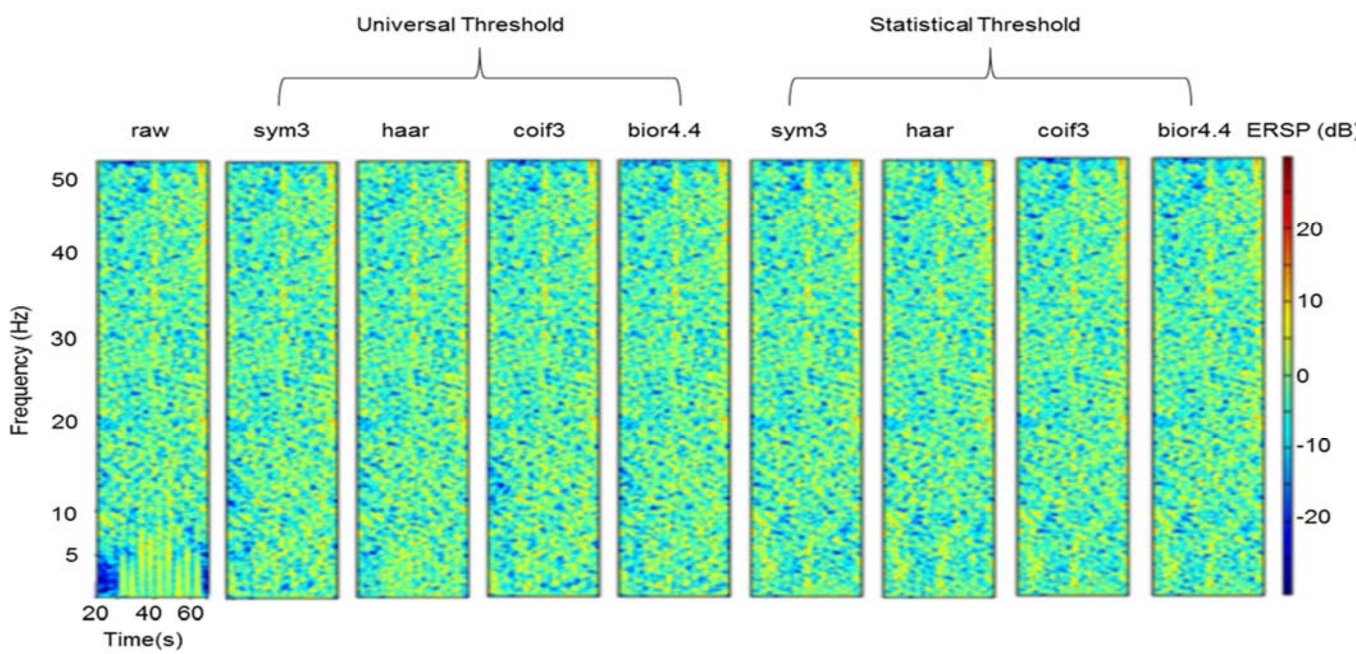

Fig.2. Time-Frequency spectrogram of SWT techniques with different wavelet basis functions and thresholds for FP1 channel EEG data.

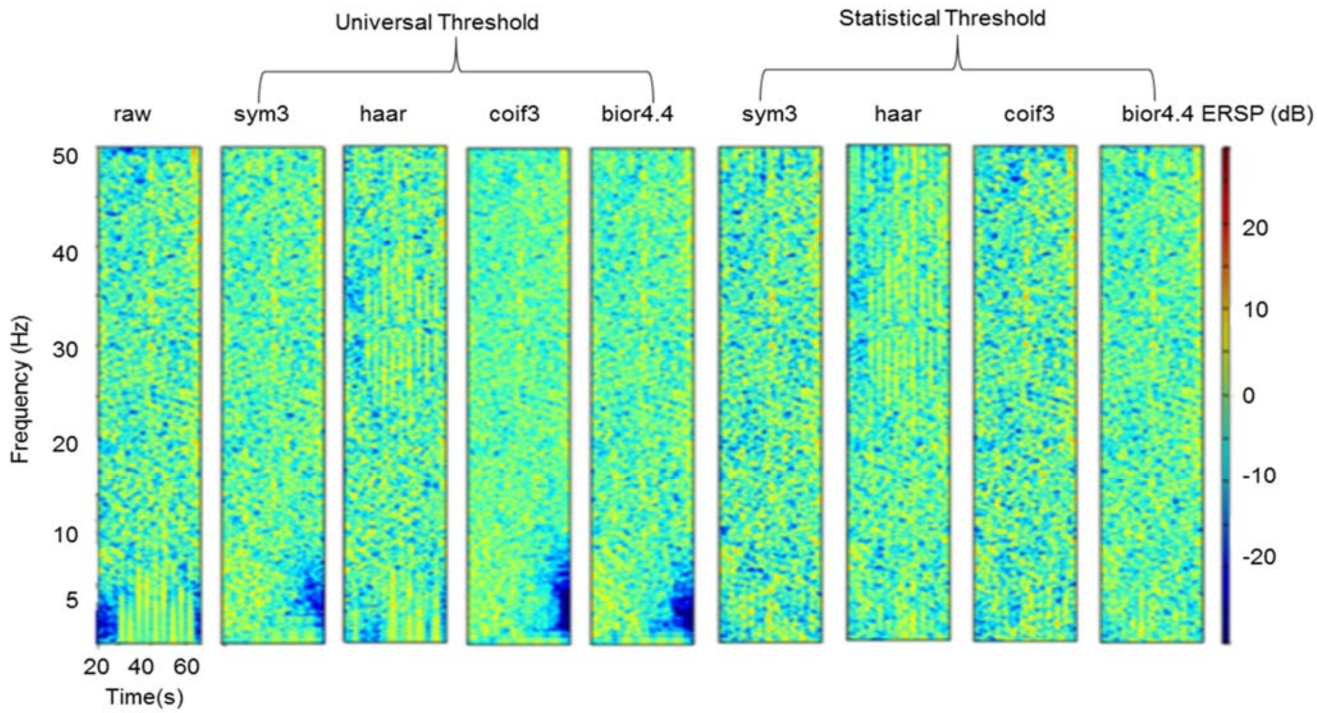

Fig. 3. Time-Frequency spectrogram of DWT techniques with different wavelet basis functions and thresholds for FP1 channel EEG data

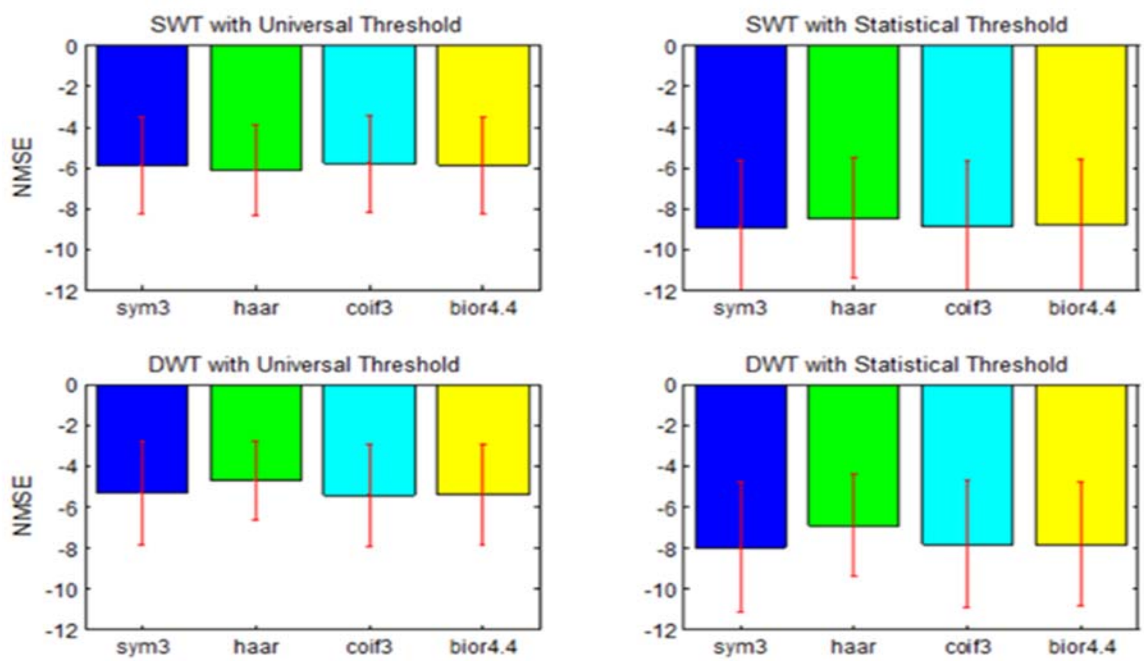

Fig. 4. NMSE comparison among different SWT and DWT techniques.

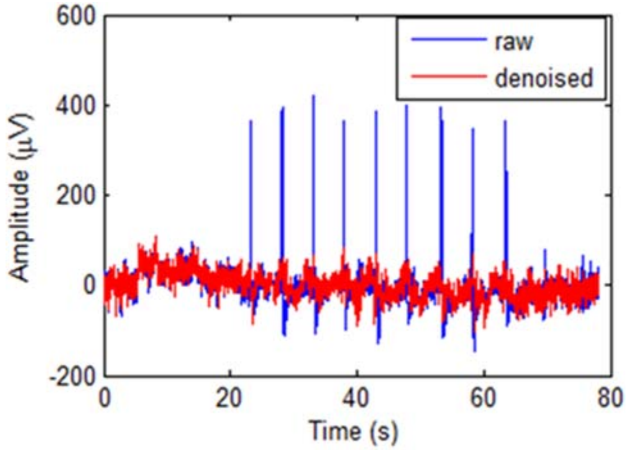

Fig. 5. Raw and the reconstructed EEG signal using DWT+ST+coif3 approach

TABLE II

EXECUTION TIME COMPARISON BETWEEN 4 COMBINATIONS

Method	Average Execution Time (s)
SWT+UT	0.18
SWT+ST	0.17
DWT+UT	0.18
DWT+ST	0.03

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