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Comparative Study of Wavelet-Based Unsupervised Ocular Artifact Removal Techniques for Single-Channel EEG Data

SALEHA KHATUN, (Student Member, IEEE), RUHI MAHAJAN, (Student Member, IEEE), AND BASHIR I. MORSHED, (Member, IEEE)

Department of Electrical and Computer Engineering, The University of Memphis, Memphis, TN 38152, USA

CORRESPONDING AUTHOR: B. I. MORSHED (bmorshed@memphis.edu)

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ABSTRACT Electroencephalogram (EEG) is a technique for recording the asynchronous activation of neuronal firing inside the brain with non-invasive scalp electrodes. Artifacts, such as eye blink activities, can corrupt these neuronal signals. While ocular artifact (OA) removal is well investigated for multiple channel EEG systems, in alignment with the recent momentum toward minimalistic EEG systems for use in natural environments, we investigate unsupervised and effective removal of OA from single-channel streaming raw EEG data. In this paper, the unsupervised wavelet transform (WT) decomposition technique was systematically evaluated for the effectiveness of OA removal for a single-channel EEG system. A set of seven raw EEG data set was analyzed. Two commonly used WT methods, Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT), were applied. Four WT basis functions, namely, haar, coif3, sym3, and bior4.4, were considered for OA removal with universal threshold and statistical threshold (ST). To quantify OA removal efficacy from single-channel EEG, five performance metrics were utilized: correlation coefficients, mutual information, signal-to-artifact ratio, normalized mean square error, and time-frequency analysis. The temporal and spectral analysis shows that the optimal combination could be DWT with ST with coif3 or bior4.4 to remove OA among 16 combinations. This paper demonstrates that the WT can be an effective tool for unsupervised OA removal from single-channel EEG data for real-time applications.

INDEX TERMS Artifact removal, electroencephalogram (EEG), ocular artifact, wavelet transform, single channel EEG.

I. INTRODUCTION

Electroencephalogram (EEG) is the recording of the brain's spontaneous electrical activity captured non-invasively by placing electrodes on the scalp [1]. EEG has been utilized in many medical diagnosis, prognosis and therapies including epilepsy, sleep disorder, coma, encephalopathy and brain deaths [2]. EEG signals are often corrupted by two sources of artifacts: physiologic such as eye, muscle, and cardiac activities, and extraphysiologic such as line interference and electrode noise. Extraphysiologic artifact can often be removed using appropriate filtering techniques as there is spectral separation. However physiologic artifact removal requires careful attention as they can be within the same frequency range of the EEG signal and are aperiodic. Ocular artifacts (OA) due to eye movement and eye blinks are dominant over other contaminating physiologic artifacts [3]. As EEG signal can be used for analyzing different diseases [4]–[6], monitoring brain engagement [7], [8], different techniques have been proposed for the removal of OA from EEG to make it more reliable for different purposes. The widely used methods for removing OAs are based on regression in time domain [9] and frequency domain [10]. But these methods need the recording of Electrooculogram (EOG), and can also result in the elimination of neural activities [11]. Statistical techniques like Principal Component Analysis (PCA) [12], Kurtosis [13], Independent Component Analysis (ICA) [14] and Multiscale sample entropy [15] are also shown to be effective to remove OA, but they rely on multiple channel data. One of the robust and promising ocular artifact removal techniques for single channel EEG data is Wavelet Transform (WT) [11], [18].

Zikov *et al.* discussed applying stationary wavelet transform with *coif3* wavelet filters to denoise the EEG signal [8]. In their proposed study, 60-second baseline EEG was recorded to calculate threshold required for denoising. Use of *haar* wavelet is explored in detecting changes in the state of the eye (eye-blinks and eyeball movements) [17]. Stationary wavelet transform with *coif3* as a basis function with various non-adaptive thresholding methods have also been demonstrated [18]. Another wavelet-based approach of removing ocular artifact was to use stationary wavelet transform with *sym3* as a basis function and to use the coefficient of variation to detect and denoise the artifact [19].

With the advent of ambulatory and miniaturist body-worn EEG systems with few channels for routine monitoring [20]–[22], there is a growing need to develop effective OA removal technique that can operate on few channel EEG data. For real-time applications like mental state classification, comfort sensing, emotion sensing, movement prediction etc., algorithms should perform reasonably with short epoch of streaming EEG data. Many brain-computer interfacing (BCI) systems are utilized for routine and continuous monitoring of brain activities for epilepsy [23], autistic spectrum disorder (ASD) [24], and Alzheimer's patients [25]. Hence, removal of artifacts in real-time with the access of few channel (especially single channel) is of research interest. Though there is a vast amount of literature available on using wavelet transform for ocular artifact removal from EEG data [20]–[22], a little have investigated the effects of using various possible forms of WT for single channel OA removal. The evaluation of existing WT techniques is critical in order to find the efficient, reliable and unsupervised way of denoising OA for real time BCI applications.

This paper compares different combinations of wavelet decomposition techniques, thresholds and mother wavelets. Specifically, we present a comparative study of discrete and stationary wavelet transform using four basis functions: *haar*, *coif3*, *sym3*, and *bior4.4* with Universal and Statistical Thresholding for OA removal from single channel EEG data. These combinations are carefully selected as they are commonly used for OA removal [19]–[22], [25]. Furthermore, we present objective performance metrics using multiple statistical measures in time domain and frequency domain.

II. WAVELET TRANSFORM AND PERFORMANCE METRICS

A. WAVELET TRANSFORM (WT) DECOMPOSITION

WT can be applied to any single channel EEG data to remove OAs without information from any other EEG or EOG channels. WT decomposes a time-varying signal into its set of basis functions known as wavelets. These basis functions known as wavelets are obtained by performing dilations and shifting of the mother wavelet:

$$\Psi_{\mathrm{a,b}}(\mathrm{t}) = \Psi(\frac{t-b}{\mathrm{a}}) \tag{1}$$

where a is the scaling parameter and b is the shifting parameter [13]. In this study, we have implemented multi-level wavelet decomposition in order to get precise information about the wavelet coefficients. In addition to ocular artifact removal, WT is proven to be a robust tool in several applications like machine condition monitoring [27], hologram analysis [28], pitch detection of speech signals [29], multimodality medical image fusion [30], fault detection in a spur gear [31], power quality analysis [32], signal processing in white-light interferometry [33].

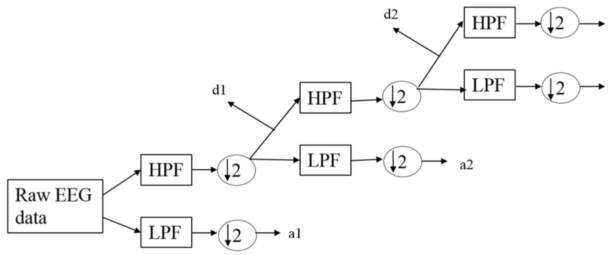

FIGURE 1. Graphical representation of DWT decomposition. (HPF: High pass filter, LPF: Low pass filter.)

1) DISCRETE WAVELET TRANSFORM (DWT)

DWT is considered non-redundant and highly efficient wavelet transform to obtain discrete wavelet representation of signals [34], [35]. In DWT, the input signal is passed through a low pass and high pass filter to get approximate coefficients (ak) and detail coefficients (dk), respectively, where k represents the level of decomposition (Figure 1). This process is repeated until the desired frequency range is obtained. At each stage, the filter output is down-sampled by 2, later up-sampled to reconstruct the signal. In this study, we have used in-built *wavedec* function in Matlab (MathWorks, Natick, MA) to implement DWT in the denoising algorithm.

2) STATIONARY WAVELET TRANSFORM (SWT)

The major drawback of DWT is its time-variance, which is particularly important in statistical signal processing applications such as EEG [36]. SWT overcomes this translation-invariance drawback of DWT, but has redundant information and is relatively slow [37]. The design difference between DWT and SWT is the filter at each stage [38]. The approximate and detail sequences at each level of decomposition are of the same length as the original sequence. After obtaining the coefficients at j^{th} level, the algorithm up samples the filter coefficients by a factor of 2^{j-1}. It has been implemented by the *swt* function of MATLAB in this study.

3) WAVELET BASIS FUNCTIONS

WT of the EEG signals yields the wavelet coefficients which represents the correlation between EEG signal and the wavelet basis functions. Figure 2 represents some commonly used WT basis functions utilized in the literature for OA removal. For eye-blink removal, these wavelets

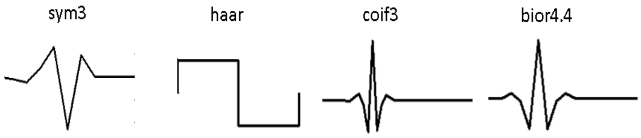

FIGURE 2. Examples of common wavelet basis functions that can be applied for artifact removal from EEG data. (Plotted using Matlab built-in functions.)

perform well as they resemble the characteristics of these eye blinks [16], [18], [19]. In this paper, we have compared the performance of widely used symlet (sym3), haar (haar), coiflet (coif3), and biorthogonal (bior4.4) wavelets.

4) WAVELET THRESHOLDING FOR DENOISING

The approximate and detail coefficients of the decomposed EEG needs to be denoised to separate the artifactual coefficients from neural signal coefficients. For thresholding the wavelet coefficients, two commonly used metrics: Universal Threshold (UT) and Statistical Threshold (ST) are evaluated in this paper. UT is implemented as:

$$K = \sqrt{2\log N}\sigma \tag{2}$$

$$\sigma^2 = \text{median}(\frac{|C_a|}{0.6745}) \tag{3}$$

where, K is the estimation of neuronal wide band signal magnitude using UT, N is the length of data to be processed, C_a is the wavelet coefficients at a^{th} level of decomposition that undergoes thresholding, and 0.6745 is the constant value for Gaussian noise [15].

We also implemented ST (proposed by Krishnaveni *et al.* in [18]) in our study which is based on the statistics of the signal. As discussed in [19], the proposed threshold produces better de-noised results than the other conventional thresholds. Mathematically, the proposed ST is formulated as:

$$T = 1.5^* std(H_k) \tag{4}$$

where T is the estimation of neuronal wide band signal magnitude using ST, $std(Hk)$ employs standard deviation of wavelet coefficients at k^{th} level. In both cases, hard thresholding is applied, where wavelet coefficient is removed if the absolute value of wavelet coefficient is greater than the threshold.

B. PERFORMANCE METRICS

Different statistical performance metrics have been used to objectively compare various combinations of OA removal in time and frequency domain. For time domain comparison, correlation coefficient, mutual information, signal to artifact ratio and normalized mean square error have been evaluated. For frequency domain comparison, time frequency analysis has been utilized.

Correlation Coefficient (CC) is a statistical method that shows the degree of association between two variables. Suppose C(t1, t2) is the auto-covariance of a process x(t), or in another way, *C (t1, t2)* is the covariance of the random variables *x (t1)* and *x (t2),* then correlation coefficient of the process $x(t)$ is [39]:

$$\mathrm{r\,(t1, t2)} = \frac{\mathrm{C\,(t1, t2)}}{\sqrt{\mathrm{C\,(t1, t1)\,C\,(t2, t2)}}} \tag{5}$$

Mutual Information (MI) is used statistically to measure how much information one random variable contains about the other random variable. If U and V are two partitions of sample space S, then information about U contained in V or information about V contained in U is:

$$\mathrm{I\,(U, V) = H\,(U) + H\,(V) - H(U.V)} \tag{6}$$

I (U, V) represents mutual information [39].

Signal to Artifact Ratio (SAR) is a quantification method to measure the amount of artifact removal in a specific signal after processing with an algorithm [40]. If z is the EEG signal containing artifact and $\hat{z}$ is the signal obtained after running an artifact free algorithm. Hence,

$$SAR = 10\log(\frac{std\ (z)}{\mathrm{std}\left(\mathrm{z} - \hat{\mathrm{z}}\right)}) \tag{7}$$

Normalized Mean Square Error (NMSE) approximates the difference between the ideal and actual data [11]. NMSE is computed in dB using the equation:

$$NMSE = 20logE\{\frac{\sum [x1\ (i) - x2\ (i)]^2}{\sum [x1\ (i)]^2}\} \tag{8}$$

Time and frequency components can be analyzed simultaneously using the wavelet decomposition tool of EEGLAB toolbox (Matlab, CA, US). This allows qualitative comparison of the signals before and after artifact denoising.

III. EXPERIMENTAL METHOD

For EEG acquisition, a 14-channel referential montage EPOC headset (Emotiv, Eveleigh, NSW, Australia) at a sampling rate of 128 sps was used in the lab setting. Before data acquisition, the skin of the subject was cleaned using Nuprep skin preparing gel (Weaver and Company, Aurora, CO) and mild abrasive strips to remove the dead skin and thereby moisten the skin. Data was collected from four subjects (two males, two females) at AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, and O2 channel locations in a closed room for 1 min 45 s. During the recording, subjects were instructed to blink 9 times with a 5 s hiatus. As OAs are prominent in the frontal lobe, only AF3 channel data was used for analysis in this study. Out of two sessions/subject data recording, 7 datasets were used for this study using an approved Institutional Review Board protocol (University of Memphis IRB# 2289).

As OAs are prominent in the frontal lobe, most of the comparison plots in this study are from AF3 channel. However, as discussed in the literature, WT can be applied to denoise any channel location, as depicted in Figure 3. OAs occur due to eye movement and eye-blinks and have frequency ranges of 0-7 Hz and 8-13 Hz, respectively [16]. To accurately

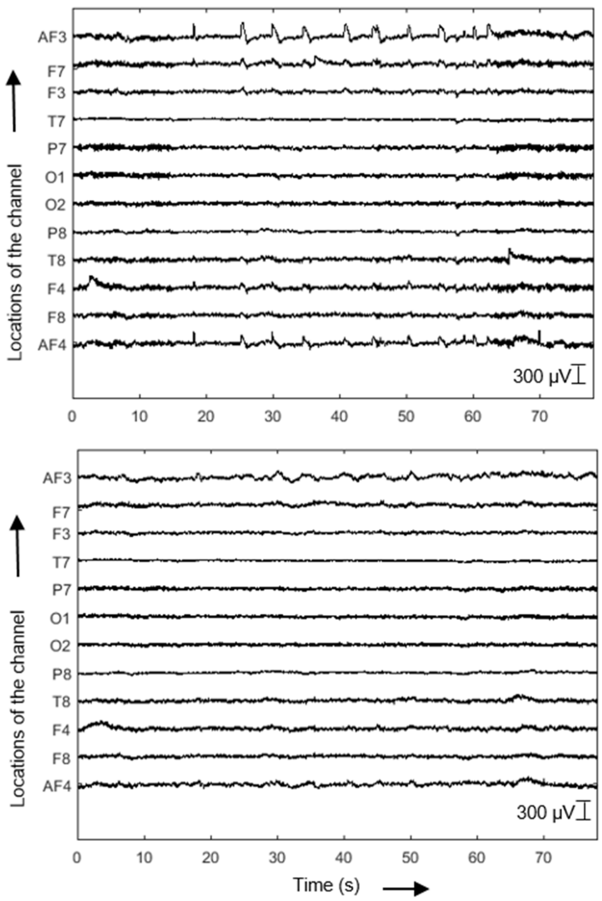

FIGURE 3. 12-channel EEG data from the Dataset 4 (Top) Raw (Below) OA artifact-free. X-axis is time in seconds and Y-axis is amplitude in microvolts.

identify artifact related wavelet coefficients, we have implemented multi-level wavelet decomposition using SWT or DWT. The decomposition was done up to level 8 (level 8: 0.25-0.5 Hz, level 7: 0.5-1 Hz, level 6: 1-2 Hz, level 5: 2-4 Hz, level 4: 4-8 Hz, level 3: 8-16 Hz, level 2: 16-32 Hz and level 1: 32-64 Hz) to obtain the frequency range of interest. For denoising the wavelet coefficients, thresholding has been done over the detail coefficients from level 8 up to level 3. As the sampling rate of the dataset is 128 sps, decomposing up to level 3 gives us the required ocular related wavelet coefficients for denoising. Either UT or ST is implemented for thresholding and *sym3*, *haar*, *coif3* or *bior4.4* have been used as mother wavelet. With two wavelet decomposition techniques (DWT/SWT), two thresholds (UT/ST) and four mother wavelets (*sym3*/*haar*/*coif3*/*bior4.4*), 16 combinations or methods are possible to remove OA from EEG. The outputs of these combinations are quantified and compared using different performance metrics.

IV. RESULTS AND ANALYSIS

Figure 4 compares raw and OA-artifact free EEG data using *coif3* wavelet basis function with statistical threshold to denoise single channel EEG data using SWT and DWT techniques. Careful observation indicates that SWT produced cleaner processed signals, however, DWT is a faster method, which is an important aspect of real time data processing (e.g. streaming data). Most OA removal algorithms affected neuronal signals where there is no blink artifact (non-blink regions). To the distinguish performance of an algorithm to remove OA, while preserving neuronal signals, we have segregated the raw EEG data into "Blink regions" and "Non-blink regions."

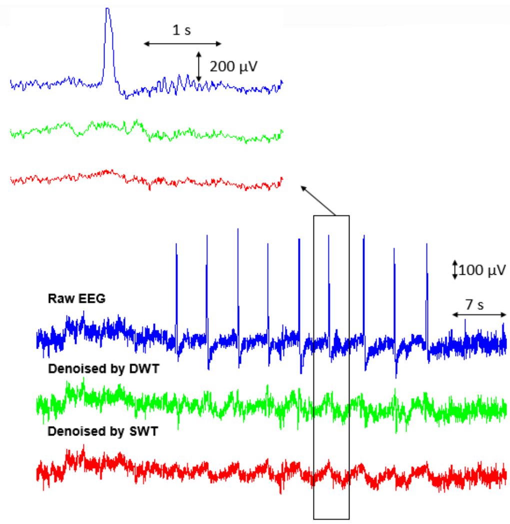

FIGURE 4. Comparison of a section of EEG data from AF3 channel (Dataset 1) before and after denoising using SWT and DWT decomposition techniques with *coif3* wavelet.

CC and MI have been calculated between raw and reconstructed signals for blink and non-blink regions of the entire EEG data. The ideal eye blink removal algorithm would produce high CC and MI values in the non-blink region, while low CC and MI values in the blink region [41], [42]. Figure 5 and Figure 6 show the statistical analysis of the CC and MI metrics (averaged over 7 datasets) for both blink and non-blink regions of AF3 channel EEG data.

In both cases, DWT with UT performs better in an eye-blink region than all other WT threshold combinations. Among them, *DWT+UT+sym3* gives the lowest value of CC, while *DWT+UT+haar* gives the lowest value of MI. However, the efficacy of DWT with UT to preserve neuronal information in a non-blink region is poor. This might be due to spectral shift introduced by DWT technique. Similarly, among all cases, the SWT with ST generates higher values of CC and MI than all other WT threshold combinations for non-blink regions. Among these, *SWT+ST+haar* provides the highest values of CC and MI in non-blink regions. Based on CC and MI metric, SWT with UT reveals that neuronal signals retention is poor, but removes or changes the blink zone in a greater amount. SWT with ST retains neuronal signals based on both CC and MI metrics, even though OA removal performance based on CC and MI is not as good as other methods. Applying DWT with UT doesn't show the power of preserving neural information based on CC and MI metric. DWT with ST is excellent to retain neuronal

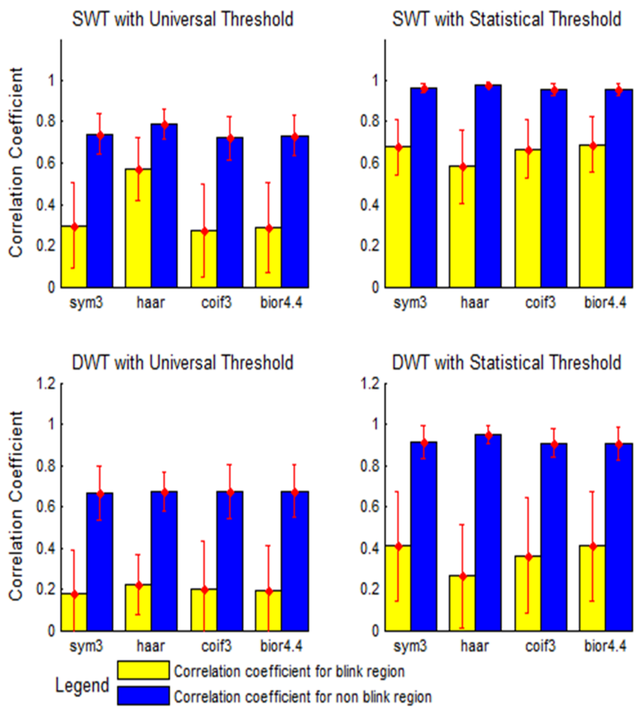

FIGURE 5. **Correlation coefficient comparison (N=7) for blink and non-blink EEG data using UT and ST thresholds with SWT and DWT methods.**

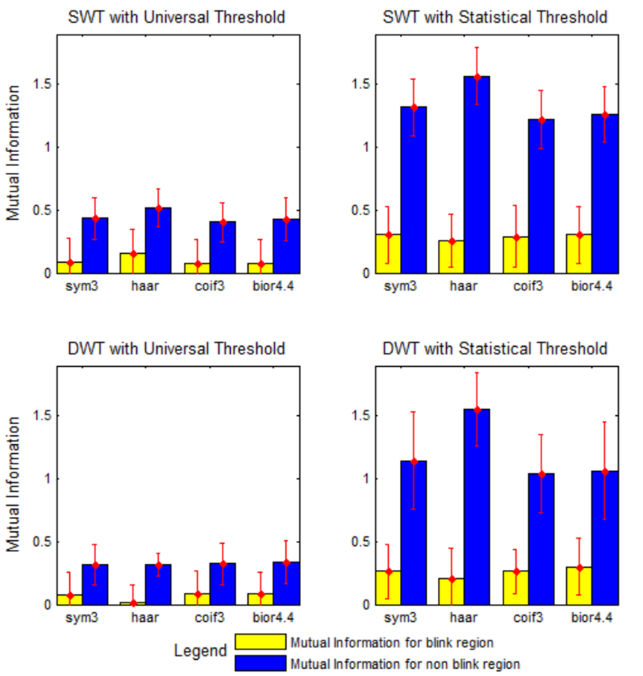

FIGURE 6. **Mutual Information comparison (N=7) for blink and non-blink EEG data using UT and ST thresholds with SWT and DWT methods.**

information based on CC metric for all wavelets, but performance is dependent on wavelet types based on MI metric, where *haar* wavelet outperforms other basis functions.

According to the definitions, the technique that produces the higher value in the SAR and the lower value in the NMSE is considered to be more effective. Table 1 depicts the values of SAR for different methods. Based on SAR, *SWT+ST* combination performs superior to others. It is noted from Table 1 that, in general, SAR values are higher when ST is used with any types of wavelet, indicating ST is aggressive in eliminating probable artifacts, while UT is conservative. *DWT+ST* performs better after *SWT+ST* combination.

TABLE 1. **SAR on EEG datasets using UT and ST thresholds with SWT and DWT methods.**

WT+Thresh.	sym3	haar	coif3	bior4.4
SWT + UT	1.42±0.61	1.48±0.58	1.40±0.61	1.42±0.61
SWT + ST	**2.33±0.86**	2.18±0.79	*2.32±0.85*	2.28±0.85
DWT + UT	1.28±0.63	1.13±0.49	1.31±0.63	1.3±0.62
DWT + ST	1.93±0.82	1.68±0.65	1.89±0.80	1.89±0.78

TABLE 2. **NMSE on EEG datasets using UT and ST thresholds with SWT and DWT methods.**

WT+Thresh.	sym3	haar	coif3	bior4.4
SWT + UT	-5.88±2.37	-6.11±2.23	-5.79±2.36	-5.85±2.37
SWT + ST	**-8.92±3.25**	-8.47±2.96	*-8.84±3.2*	-8.77±3.21
DWT + UT	-5.31±2.5	-4.7±1.94	-5.43±2.49	-5.39±2.45
DWT + ST	-7.97±3.18	-6.9±2.49	-7.8±3.1	-7.82±3.02

Table 2 depicts the values of NMSE for different methods. Based on Table 2, *SWT+ST* again outperforms other methods, while *DWT+ST* is the second best, compared to other WT threshold combinations. As the lower NMSE indicates better technique, both SWT and DWT show superior performance with ST for any type of wavelet basis functions. NMSE values are lower when ST is applied with both SWT and DWT using any type of wavelet basis functions.

Time-frequency analysis results are shown along with the raw signal (Dataset 1, AF3 channel location) in Figure 7. Few DWT methods are observed to have introduced new artifactual noise in the processed data during the OA removal throughout the spectrum (e.g. *DWT+UT+haar*, *DWT+ST+haar*). DWT with UT is also noted to decrease the overall magnitudes of neuronal signals. Within DWT results, ST with *coif3* and *bior4.4* seems to retain neuronal signals effectively while minimizing OA. Further, in order to analyze over frequency domain, magnitude squared coherence measure is calculated between the raw and OA-artifact free EEG data and is plotted for these two combinations in Figure 8. Magnitude squared spectral coherence estimate between 0 and 1 corresponds to how well the two-signals, *a* and *b*, relates at various frequencies and is mathematically

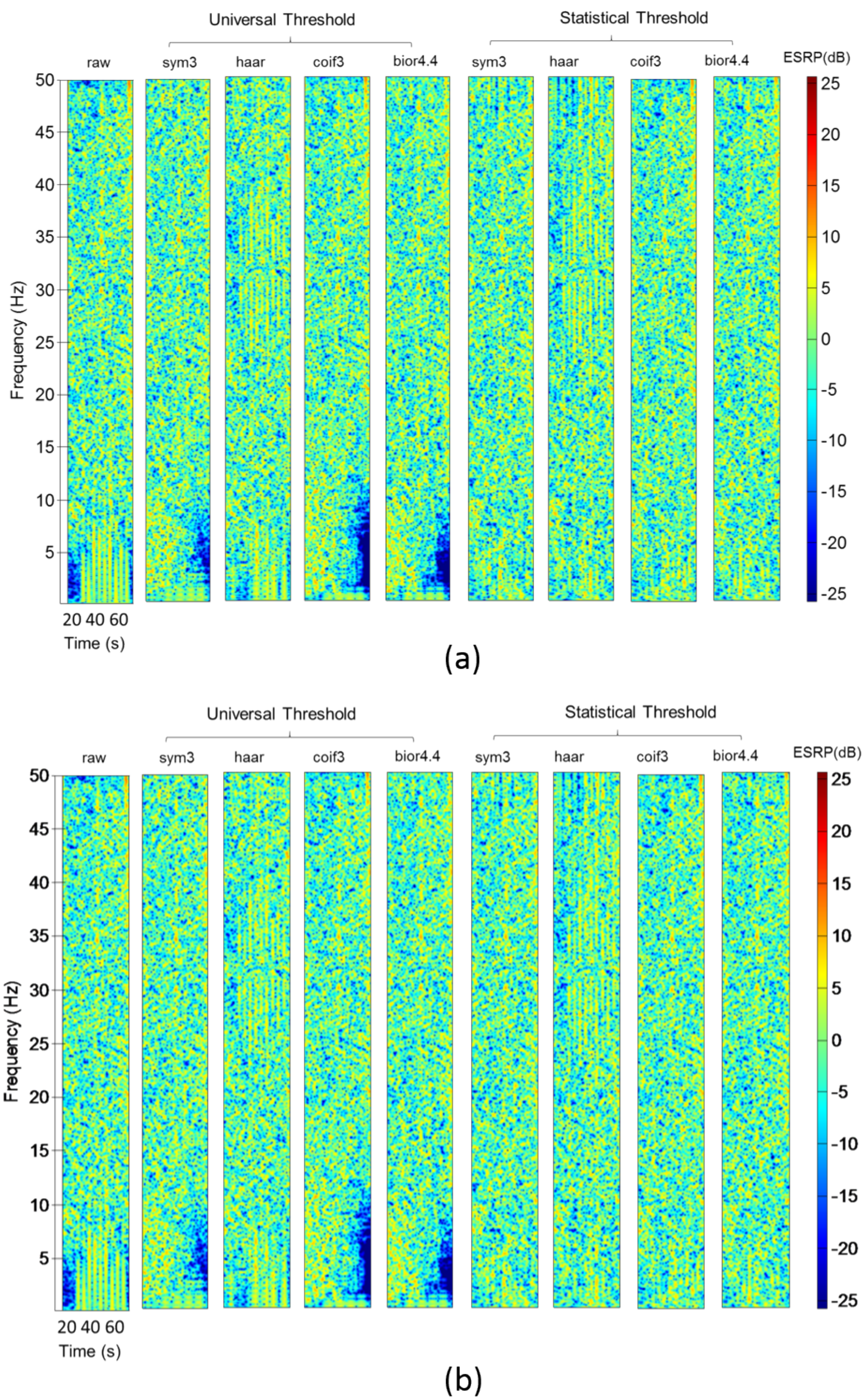

FIGURE 7. **Time-Frequency comparison plots of various wavelets and thresholds for OA artifact denoising technique using (a) SWT (b) DWT. Raw EEG signal is from prefrontal AF3 channel location of Dataset 1.**

calculated as:

$$C_{ab}(\mathrm{f}) = \frac{P_{ab}(f)^2}{P_{aa}(f)P_{bb}(f)} \tag{9}$$

where $P_{ab}(f)$ is the cross power spectral densities of the signal, $P_{aa}(f)$ is power spectral density of raw EEG signal and $P_{bb}(f)$ is power spectral density of OA-artifact free EEG

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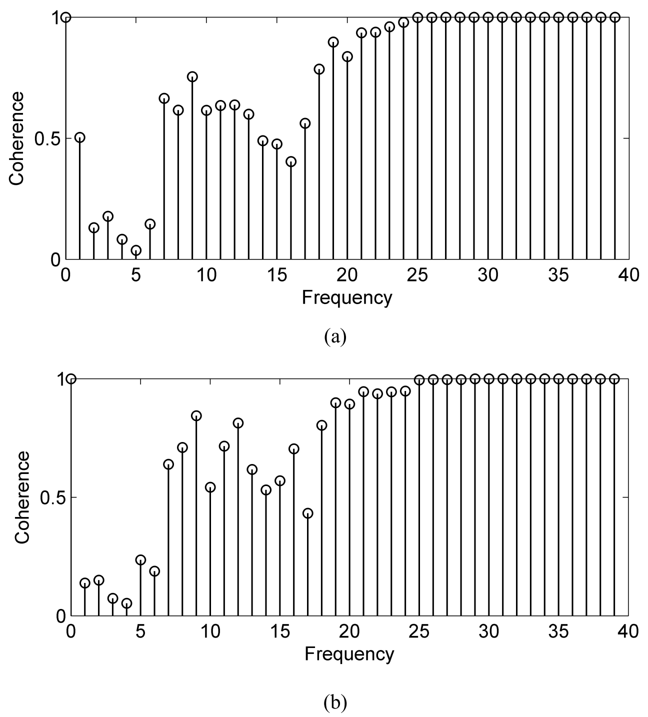

FIGURE 8. Magnitude squared coherence measure plot for one subject from AF3 location after denoising with (a) *DWT+ST+coif3* (b) *DWT+ST+bior4.4* combination.

signal. It has been implemented in this study using *mscohere* function of Matlab. It has been observed that all of the SWT combinations show efficacy in preserving neuronal signals and do not introduce new artifacts like some of the DWT combinations.

V. DISCUSSION AND CONCLUSIONS

Brain monitoring using a few EEG sensors in non-clinical settings has drawn a lot of attention lately. These real time BCI applications like cognitive load assessment, diagnosis of brain disorders, fatigue prediction, and cognitive biometrics, need fast and efficient pre-processing algorithms in order to process and analyze raw brain signals reliably in real time. The most common artifact in the EEG signal is due to the ocular activity. This study, therefore, focusses on comparing the effectiveness of commonly used wavelet based techniques for ocular artifact removal in a single channel EEG system. This will allow us to determine the optimal wavelet decomposition technique and corresponding threshold to denoise EEG signal effectively.

In this paper, data from AF3 channel has been presented as a representative of EEG signal contaminated with artifacts to compare several WT based methods. However, the algorithm is not specific to the channel and is applicable to EEG recordings from any channel. Based on CC and MI metrics, DWT with ST using *haar* wavelet is found to be more effective than *DWT+ST+coif3* or *DWT+ST+bior4.4*, but time-frequency analysis shows higher distortion in the processed data using this combination. As these metrics analyze different performances of the algorithm, so none of the combinations was superior based on all metrics. Based on these results, DWT with ST using *coif3* and *bior4.4* wavelet basis functions have performed well for OA removal while preserving neuronal signals in the non-blink regions based on CC, MI, SAR, NMSE and time-frequency analysis.

As fast algorithms are required for real-time systems, a trade-off must be considered for an efficacious method with low distortion. It is known that DWT is a faster technique requires less computational resources than SWT for real-time analysis [43]. According to the results presented in this paper, *DWT+ST+coif3* or *DWT+ST+bior4.4* could be an optimum choice. For the applications, where computation time is not critical, SWT with *haar* wavelet can be used with the statistical threshold. Instead of applying OA removal algorithm over the whole dataset as outlined in this paper, another approach is to identify blink regions and apply OA removal algorithm only to these OA regions to develop a faster OA removal technique, which we have reported previously [44]. Our future research directions include hardware implementation and optimization of efficacious OA removal technique for a single channel EEG system, real-time OA removal, feature extraction, and cognitive load classification to monitor brain engagement in natural environment within a wearable embedded system.

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SALEHA KHATUN (S'14) received the B.Sc. degree in electrical and electronics engineering from the Bangladesh University of Engineering and Technology, Dhaka, Bangladesh, in 2011. She is currently pursuing the Ph.D. degree with the Electrical and Computer Engineering Department, The University of Memphis. She received the prestigious Herff Fellowship from Herff Engineering College in 2015.

RUHI MAHAJAN (S'15) received the M.S. degree in instrumentation and control engineering from the National Institute of Technology, Jalandhar, India, in 2009. She is currently pursuing the Ph.D. degree with the Electrical and Computer Engineering Department, The University of Memphis. Her research interests are wearable EEG, embedded electronics, DSP, and BCI.

BASHIR I. MORSHED (M'12) received the B.Sc. degree in electrical and electronics engineering from the Bangladesh University of Engineering and Technology, in 2001, the M.Sc. degree in electrical and computer engineering from the University of Windsor, in 2004, and the Ph.D. degree in electrical and computer engineering from Carleton University, in 2010. Since 2011, he has been an Assistant Professor with the Electrical and Computer Engineering Department, The University of Memphis. He received the prestigious Canadian Commonwealth Scholarship in 2002.