Relative Wavelet Energy as a tool to select suitable wavelet for artifact removal in EEG

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Abstract—We proposed a novel approach to select a wavelet for artifact removal in electroencephalogram (EEG) by comparing their relative wavelet energies before and after thresholding. Relative wavelet energy (RWE) gives information about the relative energy associated with different frequency bands and can be considered as a time-scale density. RWE can be used as a tool to detect and characterize a specific phenomenon in time and frequency planes. We used Lifting Wavelet Transform to remove the common artifacts exist in EEG i.e. blink and eye movements. Three basic steps involved are to transform the EEG, hard thresholding the wavelet coefficients and the corrected EEG is obtained by inverse transform these threshold coefficients. It is of paramount important to select a suitable wavelet and threshold to accomplish this task. From this study, we concluded that cdf4.4 outperformed db4 and haar wavelets by removing the artifacts at the correct times and frequency bands.

Index Terms—EEG, lifting wavelet transform, ocular artifacts, relative wavelet energy

I.

INTRODUCTION

Electroencephalogram (EEG) signal is used to control a brain-computer interface (BCI) system. Thus it is very important to ensure a true EEG signal is generated from the brain, however this is not possible as there exist artifacts that suppresses the EEG signals. These artifacts are generated by non-neural sources like muscle movements, heart beat, eye movements and perspiration [1]-[6]. However EEG is dominantly affected by eye movement such as blinking and eyeball movements [1]-[6]. These movements elicit voltage potential known as electrooculogram (EOG) that spread across the scalp to contaminate the EEG and is referred as ocular artifact (OA) [1]-[6].

Therefore, we will present in this paper an investigation of OA removal using Lifting Wavelet Transform (LWT) since wavelet transform do not rely on visual inspection and reference EOG channel [7]. Wavelet transform has emerged as one of the superior technique in analyzing non-stationary signals like EEG. Its capability in transforming a time domain signal into time and frequency localization helps to understand more the behavior of a signal. For instance, the occurrence of OA in the EEG signal can be clearly recognized when this signal is decomposed into few levels with different scales. LWT is known as second generation wavelets that do not shift

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and translate as in the first classical multiresolution-based wavelets. LWT had simplified the computation mechanism and it is suitable for real-time applications [8]–[11].

Wavelet denoising technique introduced by Donoho and Johnstone [11]-[13] has been employed in this study. To get a satisfactory result of OA removal, it is of paramount important to use a suitable wavelet and threshold value. We use a tool namely relative wavelet energy, RWE to compare the effectiveness of the wavelets used. RWE is considered as time-scale density that can be used to detect a specific phenomenon in time and frequency planes [14]-[15].

The concept of LWT and RWE will be presented after some explanation on ocular artifact is highlighted. Then, analysis on simulation offline results will be presented before some discussion is finally made at the end of the paper.

II. OCULAR ARTIFACTS

Ocular artifact is due to voltage potentials elicited when the eye blinks and moves (round, horizontal and vertical movements). Cornea in human eye is having a positive charge while retina with negative charge [1]-[6] produces a potential difference of about 100mV between them [1], [3]. Thus eye movements and blinking can easily generate the voltage potential known as EOG. Consequently, this EOG spread across the scalp to contaminate the neural potentials, EEG. Many researchers had reported that ocular activity occur in low frequency bands, below 5 Hz [1]-[2], but in the same study made by the researchers [2], suggested that although largest effect is in delta and theta band, there is also some considerable OA effect in alpha and beta bands. Hence there is a basis of not ignoring the upper frequency band i.e. in alpha and beta bands when analysis on OA is done [1]-[2].

They [2] also mentioned that all regions on the scalp were affected by OA in delta and theta bands with the anterior regions have higher power density than the posterior regions. However, for alpha band, the OAs are affected mainly in frontopolar (Fp1,Fp2), lateral frontal (F7,F8) and medial frontal (F3, F4) regions, whereas in beta band OAs are seen affected mostly in lateral frontal, medial frontal and occipital (O1,O2) regions [2]. The electrode sites configuration is as shown in Fig. 5.

Blinking generates spike-like shapes [1]-[6] with their peaks can reach up to 800 uV and occur in a very short period, 200 –

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400 ms [2]. Eye movements produce square-like waves with smaller magnitude and longer duration [1]-[6].

It has been accepted clinically that eyeball make a momentary upward rotation when the eyelid blink, hence the potential change produced is augmented by the effect of eyelid movement [1], [3], [5]-[6]. Evinger *et al* [3] had reported that a slight downward rotation of the eyes also accompanied by blinks. This finding allow us to eliminate OAs in the EEG by considering only one threshold value for a frequency band as proposed in this paper.



Fig. 1 Ocular Artifacts from most affected channels FP1, FP2, F7 and F8

III. LIFTING WAVELET TRANSFORM

Lifting scheme was introduced by Sweldens in 1995 had simplified the mechanism in constructing wavelets and this approach becomes more practical to be realized for real-time applications [8]–[11]. The scheme does not require the information in Fourier transform because the wavelet transform can be implemented in spatial or time domain [8]-[11]. The basic steps in lifting operations [8]-[11] are:

- *I)* Split: The original signal of length n where $n = 2^{j}$ is separated into two disjoint sets of even and odd samples.
- 2) Predict: The predict step replaces the odd element with this difference as in Eqn.(1) and can be considered as high frequency or detail components. Therefore the predict step can be viewed as high-pass filter. This is done by the following equation:

$$d_{j-1}[n] = x_o[n] - P(x_e[n])$$
(1)

where P is the predict operator.

3) Update: This step replaces the even element with an approximation that is the signal becomes smoother

compare to the previous scale. Hence this operation is viewed as low-pass filtering since the smoother signal contains fewer high frequency components. The update equation is as follows:

$$a_{i-1}[n] = x_e[n] + U(d_{i-1}[n])$$
(2)

where U is the update operator.

 Normalization: The approximation and details coefficients must be normalized in the final step of the transformation.

The lifting step is depicted in Fig. 2 for the decomposition or analysis of the forward wavelet transform. The update and predict stages can become a pair but sometimes they may not be together in a lifting step.



Fig. 2 One step forward lifting operation

To obtain the signal back, the operations can be undone by just reversing them and change the signs as shown in Fig. 3. The operation is working backwards from the forward lifting operation.



Fig. 3 Inverse lifting step

In the inverse step, the update step is followed by predict step and finally the odd and even components are merged which interleaves the odd and even elements back into one data stream. The equation for the inverse lifting steps are given by:

$$x_{e}[n] = a_{j-1}[n] - U(d_{j-1}[n])$$
(3)

$$x_0[n] = d_{j-1}[n] + P(x_e[n])$$
(4)

If more steps are required, they can be added singly. The first generation wavelets can be converted into lifting steps by factoring its h-coefficients as shown in many texts [8]-[11]. In this study we used few wavelets that had be factorized into lifting steps and their lifting coefficients are as follow:

'p' : -1 and 'u': 0.5,

- normalization: [1.414, 0.707].
- 2) Cohen,Daubechies,Feauveau, cdf4.4 'u': [-0.25 -0.25] 'p': [-1 -1]

'u': [-0.039 0.226 0.226 -0.039] normalization: [2.828, 0.3535]
3) Daubechies, db4
'p': [-0.322]
'u': [-1.117 -0.300]
'p': [-0.018 0.117]
'u': [2.131 0.636]
'p': [-0.469 0.140 -0.024] normalization: [0.734, 1.362]
(Note: 'p' is predict and 'u' is update)

These wavelets are shown in Fig. 4 (a-c) for analysis and synthesis transformation.



Fig. 4 Wavelets (a) Haar, (b) cdf4.4 and (c) db4

IV. WAVELET DENOISING

Donoho and Johnstone proposes an algorithm to suppress noise in a signal known as wavelet denoising [11]-[13]. The three steps [11]-[13] in wavelet denoising procedure are as follows :

1) Decompose the signal.

 Apply a threshold function to the detail coefficients by comparing with a threshold value, i.e. coefficients greater than the threshold will be eliminated (set to zero). 3) The corrected signal is obtained by inverse transformed of the threshold coefficients.

We employ an adaptive wavelet denoising since the threshold value is determined separately for every level of decomposition. The threshold is based upon the statistical properties of the wavelet coefficients i.e. mean and standard deviation values.

V. RELATIVE WAVELET ENERGY

It is inherently difficult to evaluate the successful of OA correction using different type of wavelets. Croft and Barry [4] had reported that since there is no correlation between EOG and uncontaminated EEG, then correlation between low EOG and corrected EEG can be used as a criteria to assess the effectiveness of the method used, but it is still not a refined measure of validation. They [4] also suggested the most useful form of validation is corrected EEG should be reasonably visualized. Thus we use a tool, relative wavelet energy to assist us to choose an effective wavelet in our technique. RWE gives information about relative energy with associated frequency bands and can detect the degree of similarity between segments of a signal [14]-[15]. For this study we determine relative energies for every band before and after thresholding to compare the similarities and effectiveness of each wavelet used to remove the artifacts. RWE is defined as follows:

$$RWE = \frac{E_j}{E_{tat}} \tag{5}$$

with the energy of the detail signal at each resolution level, j is

$$E_{j} = \sum_{j=1}^{J} \left| D_{j}(k) \right|^{2}$$
(6)

and the total energy for all levels is given by:

$$E_{tot} = \sum_{j} \sum_{k} \left| D_{j}(k) \right|^{2} = \sum_{j} E_{j}$$
(7)

VI. METHODOLOGY

1) To determine the threshold

The EEG signals from FP1, Fp2, F8 and F8 channels were decomposed to seven levels of interest that can be considered as beta, alpha, theta and delta frequency bands. According to Nyquist criterion, the maximum frequency in a signal is half of the sampling frequency (in this case, Fs= 256 Hz), thus the beta band occupies in 16 - 32 Hz, alpha band in 8 - 16 Hz, theta band in 4 - 8 Hz, delta 1 band in 2 - 4 Hz, and delta 2 band associates with 0 - 2 Hz of frequency ranges after the decomposition.

We used a clean signal (no presence of blinking and eye movements) from the same channel of another recording trial to determine the threshold. The signal was decomposed for every one second epoch, hence we obtained 10 segments since the EEG signals were recorded for ten seconds. There were ten segments with different values of mean and standard deviation for bands 3 to 7. Finally the threshold for each band, k of concern was determined by taking the mean and standard deviation of maximum absolute value, M_k of detail coefficients from all segments:

$$T_{k} = mean(M_{k}) + 2 * std(M_{k})$$
(8)

The threshold chosen must remove the OAs at the correct times and frequency bands of the particular signal.

2) EEG recording

The EEG was recorded according to this controlled environment. Subject was seated comfortably on a recliner chair in a dim, acoustic laboratory with air-condition switched off, and scalp electrodes according to standard 10-20 configuration (Fig. 5) from Electro-Cap International, Inc connected to two electrically linked mastoids at A1 and A2. All electrode impedances were measured below 1 k Ω and they were connected to MindSet24 for EEG acquisition. The subject was asked to perform a mental task with eyes opened and were repeated for five times. During the recording, the subject was asked to focus his eyes on the computer monitor and follow the instructions given by a stimulus program. Data was sampled at 256 Hz and the recording was done for 10s for the task, thus there are 2560 data samples for the channel.



VII. RESULTS AND DISCUSSIONS

From Fig.1, there are OAs exist in the signals for all channels for all segments except segment 5 can be considered free of all artifacts. As there is not enough space here, we will only show waveforms from a signal, channel Fp1. Fig. 6 depicts the thresholding occurred in segment 1 (0 to 1 second). It can be concluded that the waveforms appear reasonable and corrections had been made at the right frequency and space localization for all wavelets since blinking and eye movement present in this segment. We can see that most contamination is in delta and theta ranges, with some of OA effect in alpha and beta bands for Fp1 channel. These results are consistent with the findings reported by the Hagemann and Neumann [2]. From Fig. 5, we present the graphical output of relative wavelet energy, RWE versus all ten segments of the same signal. However when looking at the relative wavelet energy, it appears that haar and db4 had wrongly corrected the signal in segment 5 which is not contaminated. This is because the values before and after thresholding are different contrary to the fixed RWE value produced when cdf4.4 is used. For all segments in all frequency bands, cdf4.4 had threshold the signal correctly compared to other wavelets.

From our experiments, we can conclude that cdf4.4 wavelet can be used in LWT for OAs correction for this application. When comparing the lifting operations involve in these wavelets, haar and db4 wavelets start their lifting scheme by predicting the odd element unlike cdf4.4 wavelet, it starts with updating the even elements, probably this help to detect the artifacts present furthermore, the shape of the cdf4.4 wavelet as shown in Fig. 4(b) resembles the artifact of interest.

VIII. CONCLUSION

Relative wavelet energy is a useful tool in evaluating the effectiveness of selecting a wavelet and threshold in this application. Future works will investigate the use of this technique for other channels of interest.

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(a) Original signal of FP1 from 0 – 1 sec (segment1 of the signal FP1 in Fig. 1) (b) Haar (c) cdf4.4 (d) db4



Fig. 6 Corrections made for every frequency bands for segment 1 with each wavelet used (a) haar, (b) cdf4.4 and (c) db4.





825 82

(ii)



(b)

I

1.00



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(i)



(ii)



(iii)



(ii)



seg5

Tim

(iv)







0.



et al idan et al



Fig. 7 Relative wavelet energy, RWE for channel FP1 for all frequency bands obtained by different wavelets (a) Haar, (b) cdf4.4 and (c) db4

seg8

seg9