Automatic Identification and Removal of Ocular Artifacts from EEG using Wavelet Transform

V.Krishnaveni[1], S.Jayaraman[1] , S.Aravind[1], V.Hariharasudhan[1], K.Ramadoss[2]

[1]Department of Electronics & Communication Engineering, PSG College of Technology, Coimbatore – 641 004 India, venimurthy@hotmail.com
[2] PSG Institute of Medical Sciences and Research, Coimbatore – 641 004 India

Abstract: *The Electroencephalogram (EEG) is a biological signal that represents the electrical activity of the brain. Eye-blinks and movement of the eyeballs produce electrical signals that are collectively known as Ocular Artifacts (OA). These are of the order of milli-volts and they contaminate the EEG signals which are of the order of micro-volts. The frequency range of EEG signal is 0 to 64 Hz and the OA occur within the range of 0 to 16 Hz. If the wavelet based EOG correction algorithm is applied to the entire length of the EEG signal, it results in thresholding of both low frequency and high frequency components even in the non-OA zones. This leads to considerable loss of valuable background EEG activity. Though the detection of OA zones can be done by visual inspection, the OA time zones need to be given as input to the EOG correction procedure, which is a laborious process. Hence there is a need for automatic detection of artifact zones. This paper discusses a method to automatically identify slow varying OA zones and applying wavelet based adaptive thresholding algorithm only to the identified OA zones, which avoids the removal of background EEG information. Adaptive thresholding applied only to the OA zone does not affect the low frequency components in the non-OA zones and also preserves the shape (waveform) of the EEG signal in non-artifact zones which is of very much importance in clinical diagnosis.*

Keywords: *EEG, EOG, OA, Adaptive Thresholding*

1. Introduction

Electroencephalogram is a recording of electric fields of signals emerging from neural currents within the brain and is measured by placing electrodes on the scalp. The electrical dipoles of eyes change by eye movements and blinks, producing a signal known as electrooculogram (EOG). A fraction of EOGs contaminate the electrical activity of the brain and these contaminating potentials are commonly referred to as ocular artifacts (OA). In current data acquisition, these OA are often dominant over other electrophysiological contaminating signals (e.g. heart and muscle activity, head and body movements), as well as external interferences due to power sources. Hence, devising a method for successful removal of OA from EEG recordings is still is a major challenge. Fig 1 shows a segment of EEG signals corrupted with ocular artifacts. Since ocular artifacts decrease rapidly with the distance from the eyes, the most severe interference occurs in the electrodes placed on the patient's forehead. Notice the large dips on frontal channels FP1-F3, FP2-F4, FP1-FP7 and FP2-F8. Blink artifacts are so prominent on these channels because they are located nearest to the eyes.

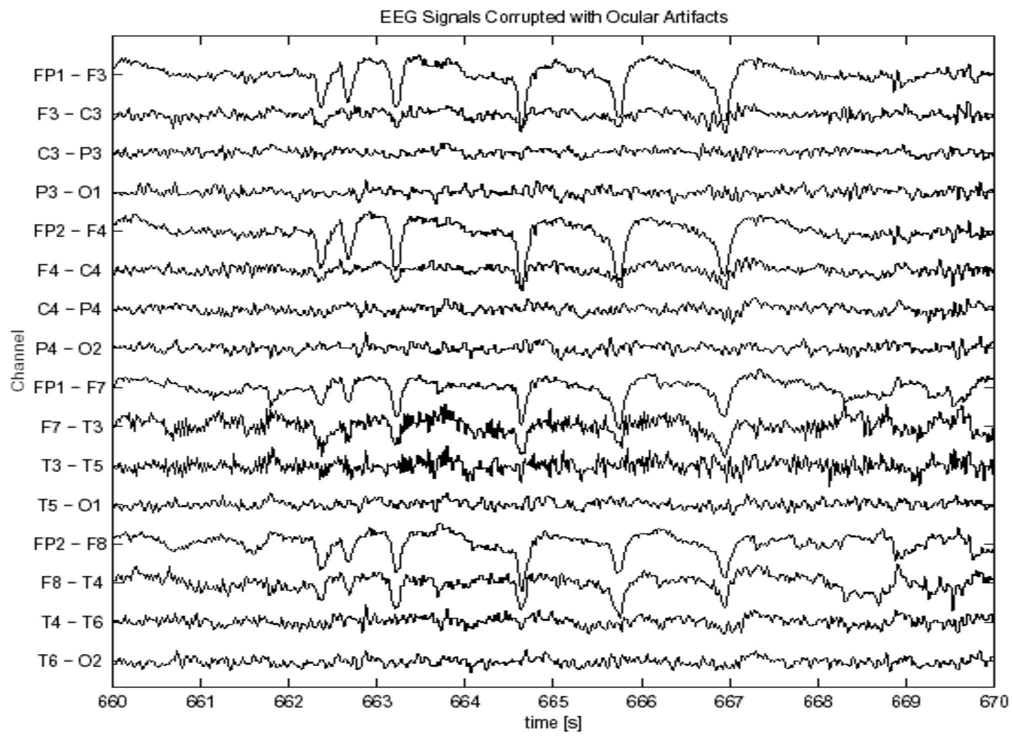

Fig 1. EEG recording corrupted by ocular-artifacts

A variety of methods have been proposed for correcting ocular artifacts and are reviewed in [1,2]. One common strategy is artifact rejection. The rejection of epochs contaminated with OA is very laborious and time consuming and often result in considerable loss in the amount of data available for analysis. Eye fixation method in which the subject is asked to close their eyes or fix it on a target is often unrealistic. Widely used methods for removing OAs are based on regression in time domain [3] or frequency domain [4] techniques. All regression methods, whether in time or frequency domain depend on having one or more regressing (EOG) channels. Also both these methods share an inherent weakness, that spread of excitation from eye movements and EEG signal is bidirectional. Therefore regression based artifact removal eliminates the neural potentials common to reference electrodes and to other frontal electrodes.

Another class of methods is based on a linear decomposition of the EEG and EOG leads into source components, identifying artifactual components, and then reconstructing the EEG without the artifactual components. Lagerlund et.al [5] used Principal Component Analysis (PCA) [6] to remove the artifacts from EEG. It outperformed the regression based methods. However, PCA cannot completely separate OA from EEG, when both the waveforms have similar voltage magnitudes. PCA decomposes the leads into uncorrelated, but not necessarily independent components that are spatially orthogonal and thus it cannot deal with higher-order statistical dependencies.

An alternative approach is to use independent components analysis (ICA), which was developed in the context of blind source separation problems to obtain components that are approximately independent [7]. ICA has been used to correct for ocular artifacts, as well as artifacts generated by other sources [8,9,10]. ICA is an extension of PCA which not only decorrelates but can also deal with higher order statistical dependencies. However, the ICA components lack the important variance maximization property possessed by the PCA components. ICA algorithms are superior to PCA, in removing a wide variety of artifacts from the EEG, even in the case of comparable amplitudes. The component based procedures used for artifact removal [5, 8, 9, 10] are not automated, and require visual inspection to select the artifactual components to decide their removal. An ICA based method for removing artifacts semi automatically was presented by Delorme et.al [11]. It is automated to flag trials as potentially contaminated, but these trials are still examined and rejected manually via a graphical interface. Carrie Joyce et.al [12] used SOBI algorithm along with correlation metrics and Nicolaou et.al [13] used TDSEP along with Support Vector Machine (SVM) for automatic removal of artifacts. The results of these studies does not imply that SOBI/TDSEP is the overall best approach for decomposing EEG sensor data into meaningful components, and has not been completely validated by the authors. The estimated source signals (obtained from any ICA algorithm) should be as independent as possible (or least dependent on each other) for better removal of artifacts from EEG. Since, either by visual inspection, or by automated procedure, only the estimated sources are classified as EEG or artifacts. But, the actual independence of the components (estimated sources) obtained from ICA/BSS algorithms used in [8,9,10,11,12,13] are not tested for their independence and uniqueness.

Tatjana Zikov et.al [14] proposed a wavelet based denoising technique for removal of ocular artifacts in EEG. This method neither relies upon the reference EOG nor visual inspection. However, the threshold limit was estimated from the uncontaminated baseline EEG, which is recorded from the same subject. Krishnaveni et.al [15] proposed various non-adaptive thresholding methods using different threshold limit and thresholding function for ocular artifact correction. They reported an appropriate threshold limit calculated from the statistical averages of the contaminated EEG signal and thresholding function for OA removal. This shows that the algorithm is data independent. However, the threshold limit is empirically selected and is non-adaptive, and is context sensitive and needs further investigation. In [16] a nonlinear time-scale adaptive denoising system based on wavelet shrinkage scheme has been used for removing OAs from EEG. The time-scale adaptive algorithm is based on Stein’s Unbiased Risk Estimate (SURE), and soft-like thresholding function is used which searches for optimal thresholds using gradient based adaptive algorithms. Denoising EEG using this algorithm yields better results, in terms of ocular artifact reduction and the retainment of the background EEG activity compared to non-adaptive thresholding methods. Since, the wavelet based EOG correction algorithm proposed in [16] is applied to the entire length of the EEG signal, it results in thresholding of both low frequency and high frequency components even in the non-OA zones. This paper discusses a method to automatically identify slow varying OA zones and applying wavelet based adaptive thresholding algorithm proposed in [16] only to the identified OA zones, which avoids the removal of background EEG information. Adaptive thresholding applied only to the OA zone does not affect the low frequency components in the non-OA zones and also preserves the shape (waveform) of the EEG signal in non-artifact zones which is of very much importance in clinical diagnosis.

2 Methodology

The EEG recordings are contaminated by EOG signal. The EOG signal is a non-cortical activity. The eye and brain activities have physiologically separate sources, so the recorded EEG is a superposition of the true EEG and some portion of the EOG signal [1]. It can be represented as

$$EEG_{rec}(t) = EEG_{true}(t) + k.EOG(t) \tag{1}$$

where,

$EEG_{rec}(t)$ - Recorded contaminated EEG,

$EEG_{true}(t)$ - EEG due to the cortical activity (i.e., Brain activity)

$k.EOG(t)$ - Propagated ocular artifact from eye to the recording site.

$EEG_{true}(t)$ is to be estimated from $EEG_{rec}(t)$ by efficiently removing the $k.EOG(t)$ at the same time retaining the EEG activity.

The Algorithm proposed in this paper involves the following steps:

i) Apply Discrete Wavelet Transform to the contaminated EEG with Haar wavelet as the basis function to detect the Ocular Artifact zone [17].

ii) Apply Stationary Wavelet Transform with Coif 3 as the basis function to the contaminated EEG with OA zones identified for removing Ocular Artifacts.

iii) For each identified OA zone, select optimal threshold limit at each level of decomposition based on minimum Risk value and apply that to the soft-like thresholding function [16] which best removes noise.

iv) Apply inverse stationary wavelet transform to the thresholded wavelet coefficients to obtain the de-noised EEG signal.

2.1 Automatic Identification of OA Zones Using Haar Wavelet

By analyzing the frequency spread of the EEG data that contained the Ocular Artifacts, researchers found that the difference in the frequency of the spikes caused due to rapid eye blink and the EEG signal could be used along with a simultaneous recording of the EOG to detect and remove these artifacts. But correlation of the EEG and EOG is futile, especially because of the inherent corruption of EEG data by the restraint on the user's eye movements and blinks. The accurate detection of these artifacts by singular observation of the time or frequency domains fails and hence wavelet transform can be used to study the time-frequency maps of the EOG contaminated EEG. In [17] Haar wavelet is used to decompose the recorded EEG Signal to detect the exact moment when the state of the eye changes from open to closed and vice versa. Decomposition of the EEG data with the Haar wavelet results in a step function with a falling edge for a change in the state of the eyes from open to close and a step function with a rising edge for a change in state of the eyes from close to open. The same technique is used to detect the ocular artifacts zones in the contaminated EEG.

Consider the 4 second EOG contaminated EEG epoch (sampled at a rate of 128 samples/second) shown in Fig 2, where there are blink artifacts between 0.5s and 1s and between 2s and 2.5s. On decomposing this with a Haar Wavelet (up to 6 levels), the final approximation yielded the Step function with rising edges at 0.5s and 2s and falling edges at 1s and 2.5s as shown in Fig 3.

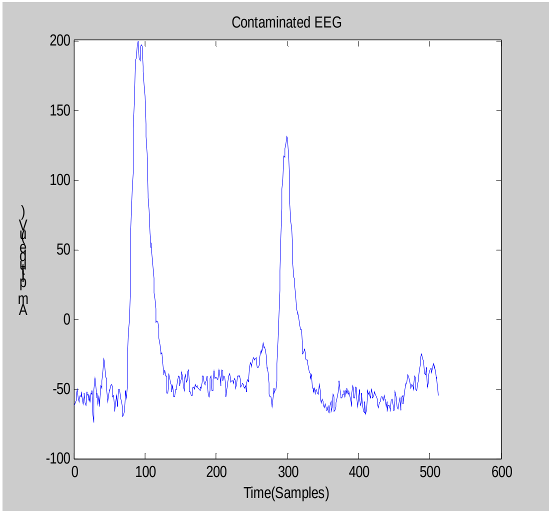

Fig 2. EOG contaminated EEG epoch of 4 seconds

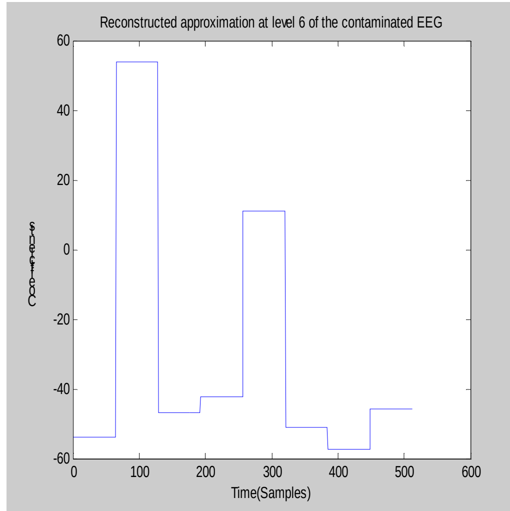

Fig 3. Reconstructed approximation at level 6

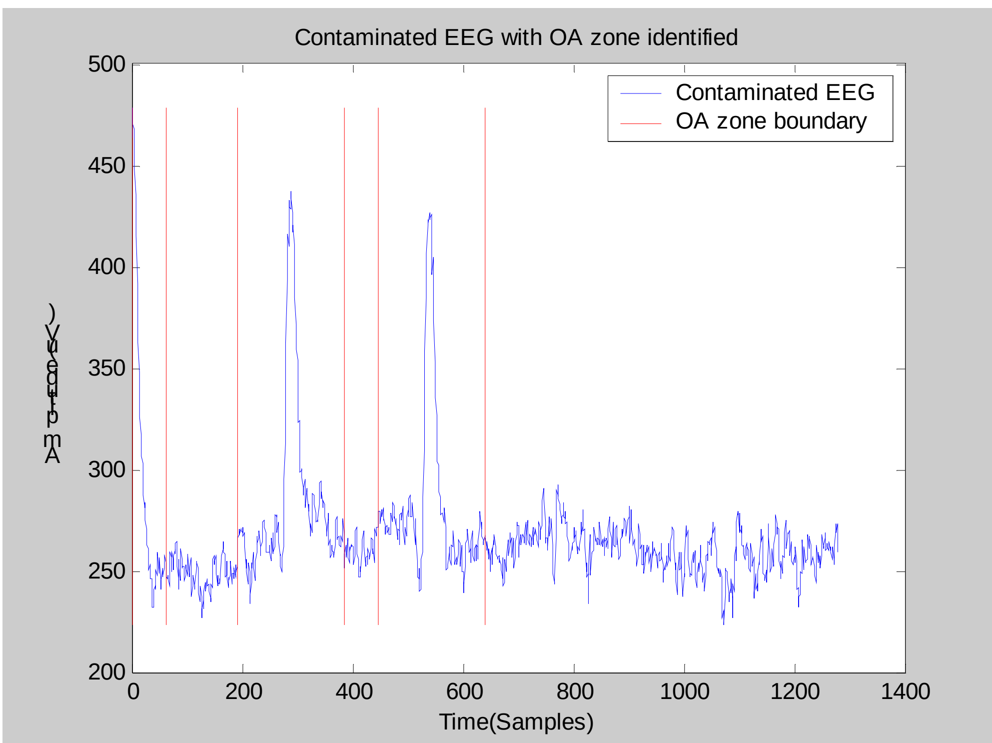

Fig 4. EOG contaminated EEG signal with Ocular Artifact zones identified

The EOG contaminated EEG is decomposed up to 6 levels using Haar wavelet. The approximation coefficients at level 6 are reconstructed. The maximum of the rising and falling edges are found. The reconstructed signal samples are compared with its successive samples to identify the edges. The edges are classified into Artifact Rising Edge (ARE), Artifact Falling Edge (AFE), Rising Edge (RE) and Falling Edge (FE) depending on whether the edges correspond to eye blinks and those that do not correspond to eye blinks, based on their relative amplitude. The identified edges ARE, AFE, RE and FE are scaled using four integers 3, 2, 1 and 5 respectively and summed up so as to get the edges information in a single array. After scaling, the values of ARE, AFE, RE and FE are 4, 7, 1 and 5 respectively. The edges and the instants at which they occur are stored in separate arrays. The array containing the edges are traversed sequentially to identify unique patterns which correspond to the OA zones. For example, 47 (which is nothing but a OA rising edge followed by OA falling edge) corresponds to OA zone. Once the patterns are identified, the time instants at which the artifacts occur can be obtained and the OA zone can be identified. Fig 4 shows the EOG contaminated EEG signal with Ocular Artifact zones identified and Fig 5 shows the flowchart for identification of ocular artifacts zones from EEG.

EOG Correction Using Adaptive Thresholding of Wavelet Coefficients

A nonlinear time-scale adaptive denoising system proposed in [16] is based on wavelet shrinkage scheme and has been used in this paper for removing the identified OAs from EEG. The time-scale adaptive algorithm shown in Fig 6 is based on Stein's Unbiased Risk Estimate (SURE), and soft-like thresholding function is used which searches for optimal thresholds using gradient based adaptive algorithms.

3. Results and Discussion

EEG data with ocular artifacts are taken from http://www.sccn.ucsd.edu/~arno/famzdata/ publicly_available_EEG_data.html for testing the proposed algorithm. The data is sampled at a rate of 128 samples/second. The effect of Ocular Artifacts will be dominant in the Frontal and Frontopolar channels. Hence it is sufficient to apply the algorithms to these channels. The results obtained using the proposed method is compared with adaptive thresholding method proposed in [16], which is applied to the entire length of the signal. Fig 7 shows a 10 second epoch of EOG contaminated EEG with its corrected version using adaptive algorithm proposed in [16] and the modified adaptive algorithm proposed in this paper. The PSD plot for Fig 7 is shown in Fig 8. By visually comparing the time domain plots shown in Fig 7, it is clear that the proposed modified adaptive algorithm reduces the amplitude of the ocular artifact while preserving the background EEG. Yet another performance metric for validating the noisy data and denoised data is correlation in the frequency domain. The frequency correlation between two signals x and y can be calculated using the formula given below [18]:

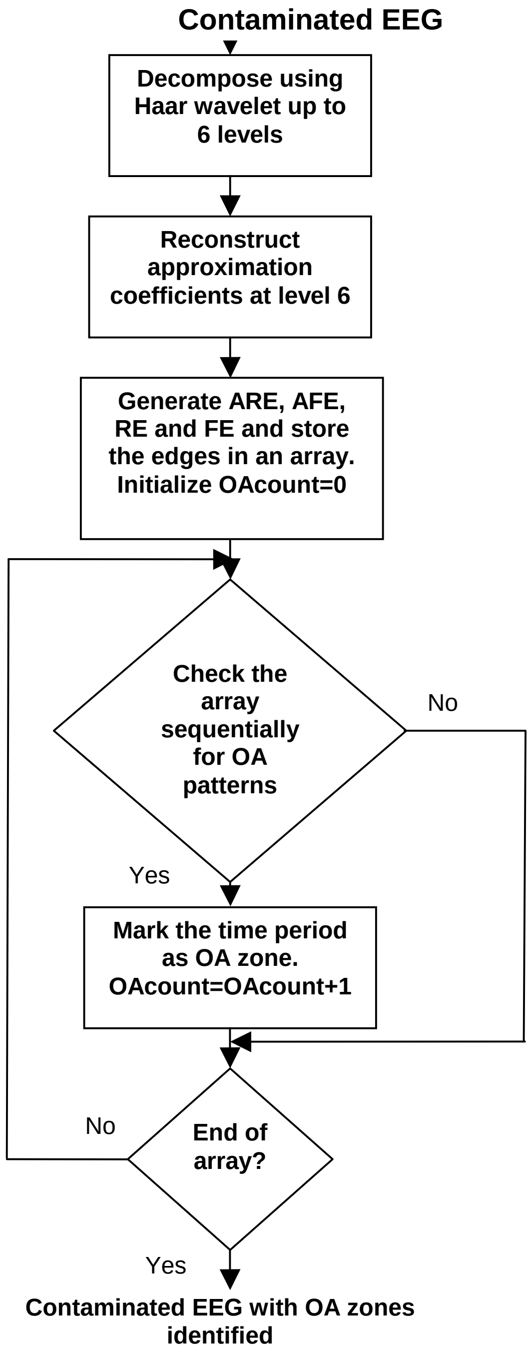

Fig 5. Flow chart for identification of Ocular Artifact zones

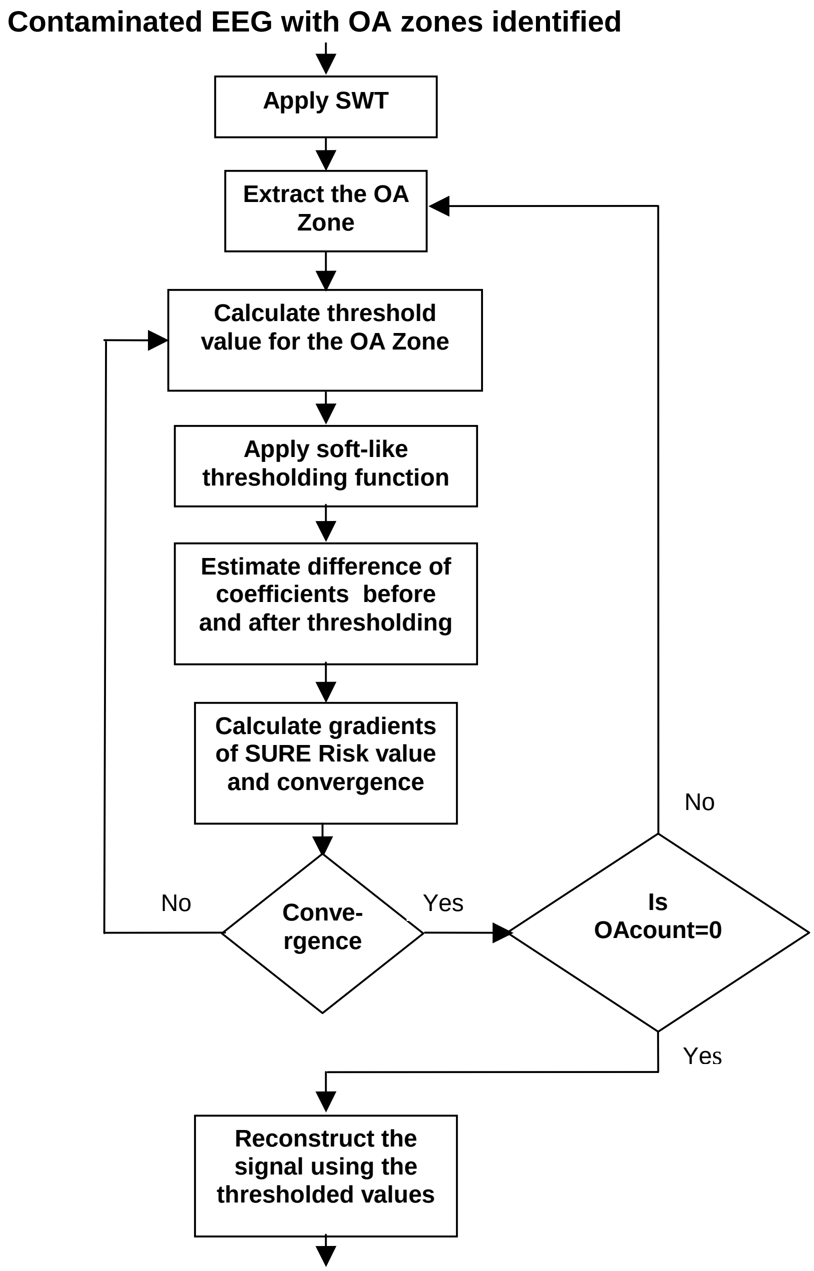

Fig 6 Time-scale adaptive de-noising method [16]

$$c_{x,y} = \frac{.5 * \sum_{w1}^{w2} \tilde{x}^{*}\tilde{y} + \tilde{x}\tilde{y}^{*}}{\sqrt{\sum_{w1}^{w2} \tilde{x}\tilde{x}^{*} * \sum_{w1}^{w2} \tilde{y}\tilde{y}^{*}}} \qquad (2)$$

where,
w1 and w2 are the window limits
$\tilde{x}$ and $\tilde{y}$ are the Fourier coefficients of x and y.
$\tilde{x}^{*}$ and $\tilde{y}^{*}$ are the complex conjugate of $\tilde{x}$ and $\tilde{y}$

Here x and y are noisy EEG and denoised EEG signals respectively. It turns out, that the definition of the correlation of frequency filtered time series is equivalent to calculating the correlation between the (complex) fourier coefficients in the corresponding frequency window. Here the window is chosen with 3 Hz that covers 25 fourier transform coefficients. The 3Hz window is then moved through the entire spectrum of 64 HZ and correlation coefficient at the corresponding centre frequencies (1.5, 2.5…62.5) are found. Above mentioned formula calculates 125% correlation coefficient assuming the mean of the two signals as zero. So the mean of EEG signal is made zero by subtracting the mean of the entire signal with each value of the signal. The frequency correlation between noisy data and the denoised data shown in Fig 7 obtained using modified adaptive algorithm and adaptive algorithm is shown in Fig 9 and Fig 10 respectively. The PSD plot and the Frequency correlation plots for both the techniques have shown considerable decrease in the power of low frequency components while retaining the power of higher frequency components. However, from Fig 10 it is clear that adaptive thresholding applied to the entire length of the signal removes the low frequency components to a greater extent ie the low frequency components which corresponds to EEG may also be removed. As illustrated in Fig 9 adaptive thresholding applied only to the OA zone does not affect the low frequency components in the non-OA zones and also retains the high frequency components i.e. preserves the shape of the EEG signal in non-artifact zones which is of very much importance in clinical diagnosis.
Hence from the time domain plots, PSD’s and frequency correlation plots, it is clear that the proposed modified adaptive thresholding method applied to the identified ocular artifact zones, minimizes the amplitude of the ocular artifact, and retains the background EEG, much better compared to the adaptive thresholding method proposed in [16].

4. Conclusion

In this paper, a method to automatically identify slow varying OA zones is proposed and a time-scale adaptive algorithm based on Stein’s Unbiased Risk Estimate (SURE) along with soft-like thresholding function is applied to the OA zone. Adaptive thresholding applied only to the OA zone does not affect the low frequency components in the non-

OA zones and also preserves the shape (waveform) of the EEG signal in non-artifact zones which is of very much importance in clinical diagnosis. The proposed method minimizes the amplitude of the ocular artifact, while preserving the magnitude and phase of the high frequency background EEG activity compared to the method proposed in [16]. Efforts should be directed towards designing Haar and other similar discontinuous wavelets for highly artifact selective detection and de-noising. Power Spectral Density plots and Frequency correlation plots are used as performance metrics in this paper. But it gives only an estimate in providing an inference relating to the relative superiority of the algorithms used for removing ocular artifacts from EEG. Further it is our considered opinion that a suitable performance metric for validating the de-noised EEG signals should be devised for quantitatively comparing the algorithms for OA removal.

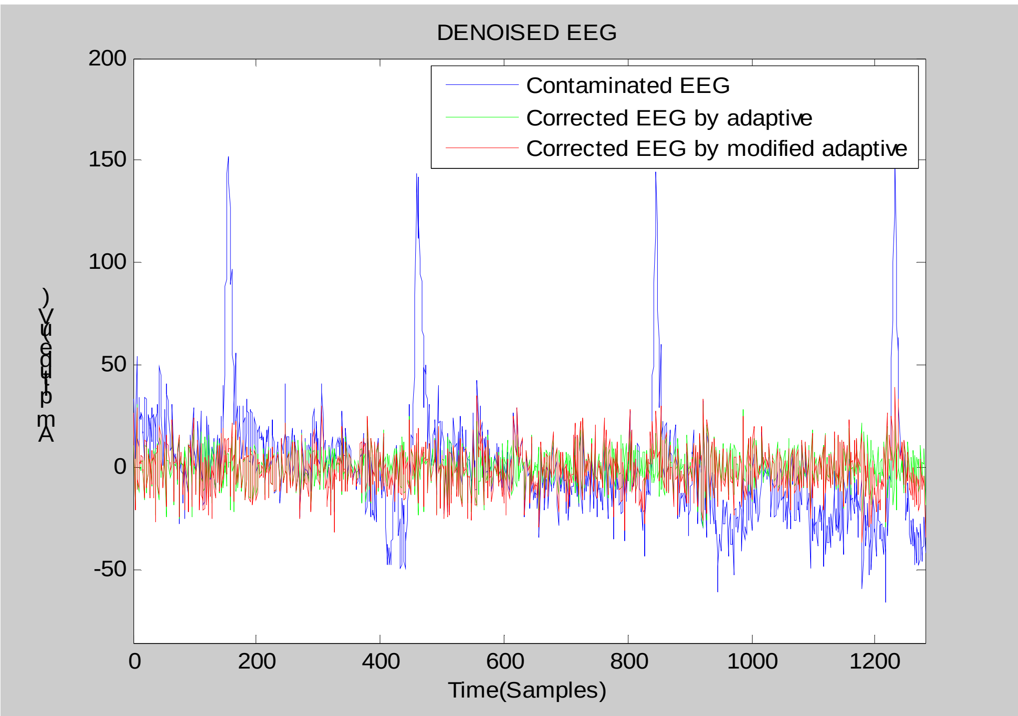

Fig 7. Contaminated EEG and Corrected EEG

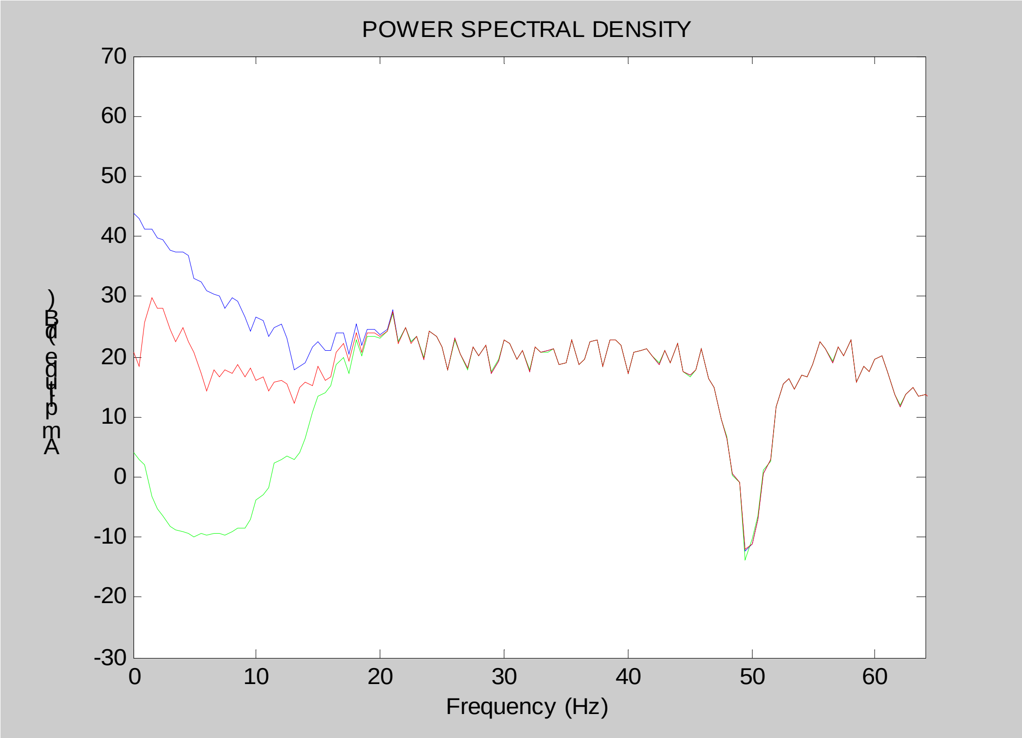

Fig 8. PSD of noisy and denoised data shown in Fig 7

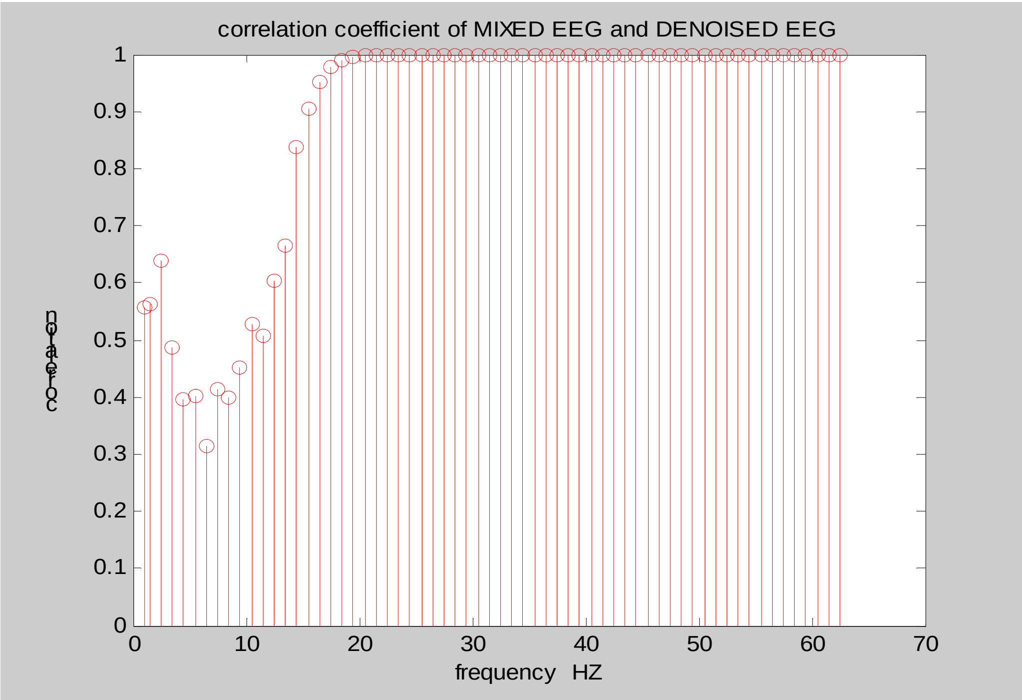

Fig 9. Frequency correlation between noisy data and denoised data
(obtained using modified adaptive algorithm) shown in Fig 7

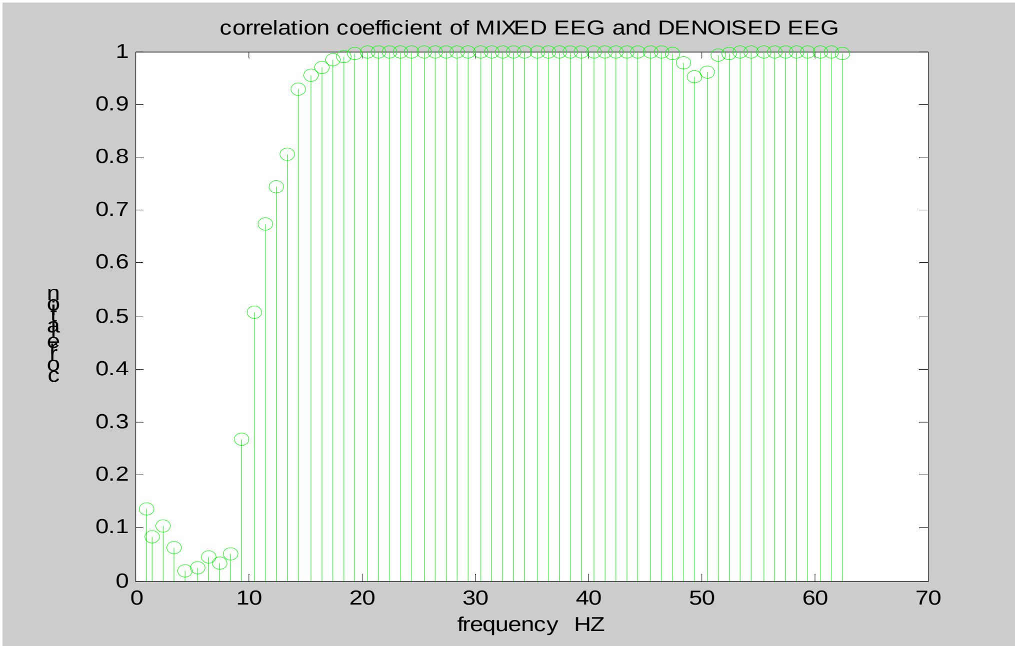

Fig 10. Frequency correlation between noisy data and denoised data
(obtained using adaptive algorithm [16]) shown in Fig 7

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