Int. J. Open Problems Compt. Math., Vol. 1, No. 3, December 2008

Removal of Ocular Artifacts in the EEG through Wavelet Transform without using an EOG Reference Channel

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Abstract

This paper presents a statistical method for removing ocular artifacts in the electroencephalogram (EEG) records. Artifacts in EEG signals are caused by various factors, like line interference, EOG (electro-oculogram) and ECG (electrocardiogram). The removal of ocular artifact from scalp EEGs is of considerable importance for both the automated and visual analysis of underlying brainwave activity. These noise sources increase the difficulty in analyzing the EEG and obtaining clinical information. For this reason, it is necessary to design a procedure to decrease such artifacts in EEG records. In this paper, a statistical method for removing ocular artifacts from EEG recordings through wavelet transform without using an EOG reference channel is proposed.

Keywords: *EEG, ocular artifacts, spike detection, stationary wavelet transform*

1 Introduction

The statistical analysis of electrical recordings of the brain activity by an Electroencephalogram is a major problem in Neuroscience. Cerebral signals have several origins that lead to the complexity of their identification. Therefore, noise removal is of prime necessity to make easier data interpretation and representation and recover the signal that matches the brain which functions perfectly. Recent Independent Component Analysis (ICA) method of artifact removal requires a tedious visual classification of the components. P. LeVan [1] proposed a method which automates this process and removes multiple types of artifacts simultaneously.

A common problem faced during the clinical recording of the EEG signal, are the eye-blinks and movement of the eye balls that produce ocular artifacts. It has been known for quite some time now that the Alpha rhythm of the EEG, which is the principal resting rhythm of the brain in adults while they are awake, is directly influenced by visual stimuli. Auditory and mental arithmetic tasks with the eyes closed, leads to strong alpha waves, which are suppressed when the eyes are opened. This property of the EEG has been used, ineffectively, for a long period of time to detect eye blinks and movements. The slow response of thresholding, failure to detect fast eye blinks and the lack of an effective de-noising technique forced researchers to study the frequency characteristics of the EEG as well. R.J. Croft [2] reviews a number of methods of dealing with ocular artifact in the EEG, focusing on the relative merits of a variety of EOG correction procedures. The distinction between frequency and time domain approaches, the number of EOG channels required for adequate correction, estimating correction coefficients from raw versus averaged data, differential correction of different types of eye movement, the most suitable procedure for estimating correction coefficients, the use of calibration trials for estimation of correction coefficients, and the distinction between 'coefficient estimation'and 'correction phase' error are also discussed.

In EEG data sets, there may be some specific components or events that may help the clinicians in diagnosis. They may tend to be transient (localized in time), prominent over certain scalp regions (localized in space) and restricted to certain ranges of temporal and spatial frequencies (localized in scale). Wavelet analysis provides flexible control over the resolution with which neuro-electric components and events are localized in time, space and scale. V.J. Samar [4] describes the basic concepts of wavelet analysis and other applications. G.G. Herrero [10] presented a method for removing electro ocular artifacts in the EEG signals without using an EOG reference channel. Neuronal gamma-band synchronization is central for cognition. Respective studies in human subjects focused on a visually induced transient enhancement of broadband EEG power. Shlomit Yuval-Greenberg [14] demonstrate that this EEG response is an artifact micro-saccades, raising the question of whether gamma-band synchronization can be assessed with EEG.

In EEG signals, the presence of artifacts introduces spikes which can be confused with neurological rhythms. So, it is difficult to analyze the EEG. Thus, noise and undesirable signals must be eliminated or attenuated from the EEG to ensure a correct analysis and diagnosis. An example of an EEG mixed with EOG is illustrated in Fig. 1.

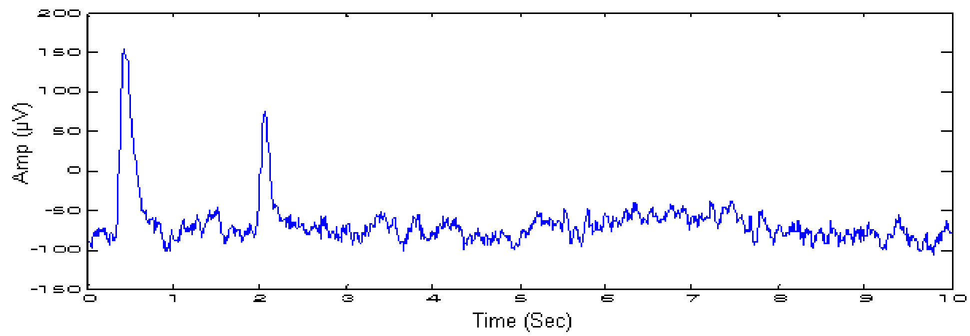

Fig 1 EEG mixed with EOG

V. Krishnaveni [11,12] has discussed a method to automatically identify slow varying ocular artifact zones and applying wavelet based adaptive thresholding algorithm only to the identified ocular artifact zones, which avoids the removal of background EEG information. The above author have used the method which consists of two stages: firstly, identification of ocular zones using Haar wavelets and secondly, removal of artifacts using stationary wavelet transform with Coif 3 as a basis function. In the second stage, finding of artifact rising and falling edges [11] is complex. Locating the zones and the calculation for finding the edges are lengthy. However, it retains all the information. To overcome this complexity, a statistical method to remove the ocular artifacts using Stationary Wavelet Transform (SWT) without the reference of EOG channel and applying a new threshold formula for removing ocular artifacts in EEG signals is presented. In the present method, the EEG signal using stationary wavelet transform with Symlet (sym3) as a basis function is directly decomposed. Using the statistical approach, viz. coefficient of variation, the artifact ocular zones are very easily identified. The new threshold formula removes entire artifacts in the zones. The comparison results are shown in section 4.

2 Wavelets for analyzing EEG signals

In statistical settings usually one is more concerned with discretely sampled, rather than continuous functions. Wavelet transform [3,6,7] has emerged as one of the superior techniques in analyzing non-stationary signals like EEG. Its capability in transforming a time domain signal into time and frequency localization helps to understand the behavior of a signal , better.

The Discrete Wavelet Transform (DWT) means, choosing subsets of the scales 'j' and positions 'k' of the mother wavelet $\psi(t)$.

$$\Psi_{j,k}(t) = 2^{\frac{j}{2}} \psi(2^j t - k) \tag{1}$$

Choosing scales and positions are based on powers of two, which are called dyadic scales and positions (j and k are integers). Equation (1) shows that, it is possible to build a wavelet for any function by dilating a function $\psi(t)$ with a coefficient 2^j, and translating the resulting function on a grid whose interval is proportional to 2^{-j}. Contracted (compressed) versions of the wavelet function match the high-frequency components, while dilated (stretched) versions match the low-frequency components. Then, by correlating the original signal with wavelet functions of different sizes, the details of the signal can be obtained at several scales. These correlations with the different wavelet functions can be arranged in a hierarchical scheme called multi-resolution decomposition. The multi-resolution decomposition algorithm [5] separates the signal into "details" at different scales and a coarser representation of the signal named "approximation ".

The basic DWT algorithm can be modified to give a SWT [9] that no longer depends on the choice of origin. As a consequence of the sub sampling operations in the pyramidal algorithm, the DWT does not preserve translation invariance. This means that, a translation of the original signal does not necessarily imply a translation of the corresponding wavelet coefficients. The SWT has been introduced in order to preserve this property. Instead of sub sampling, the SWT utilizes recursively dilated filters in order to halve the bandwidth from one level to another. This decomposition scheme is shown in fig. 2

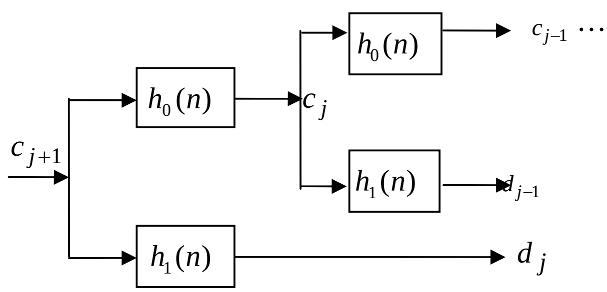

Fig. 2 Wavelet decomposition scheme

3 Methodology

3.1 Identifying Spikes

Several methods have been tried in order to identify automatically the artifact zones [8,11,12]. The spikes caused due to rapid eye blinks and movements and the EEG signal could be used along with a simultaneous recording of the EOG to detect and remove the artifacts. 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. A method for identifying the spikes which may contain artifact or not is proposed. From the number of 'detail' coefficients obtained at each level of wavelet decomposition, we select the detail coefficients in the form, $d_j > d_{j-1}, d_{j+1}$, $j = 1, 2, \ldots n$ is selected. Normally, every spike contains three coefficients. Next spike identification starts with d_{j+1} treated as d_{j-1} and checks the next two coefficients. Based on this arrangement, the spikes in the contaminated EEG have to be identified. On decomposing this with a Symlet wavelet (sym3 – up to eight levels), the final 'detail' yielded the waveform as shown in fig. 3.

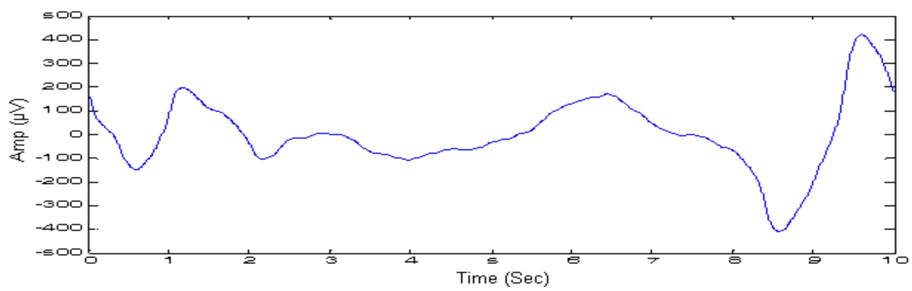

Fig. 3 Eight level wavelet decomposition (detail coeff.)

3.2 Identifying Ocular Artifact Spike Zones

After decomposing the EEG signal, at every level, the 'detail' part is considered However, one can also retain the 'approximation' part for the signal reconstruction. Using the spike zone coefficients (d_{j-1}, d_j, d_{j+1}), the coefficient of variation for every spike zone is calculated. Among the coefficient of variation values, the larger values have to be selected. since larger coefficient of variation indicates less reliable or high frequency (noise) amplitude. Consider the 10 second EOG contaminated EEG epoch (sampled at a rate of 128 samples/second) shown in fig. 4, where the EOG artifacts exist between 0.3 to 0.7 seconds and between 2.0 to 2.2 seconds.

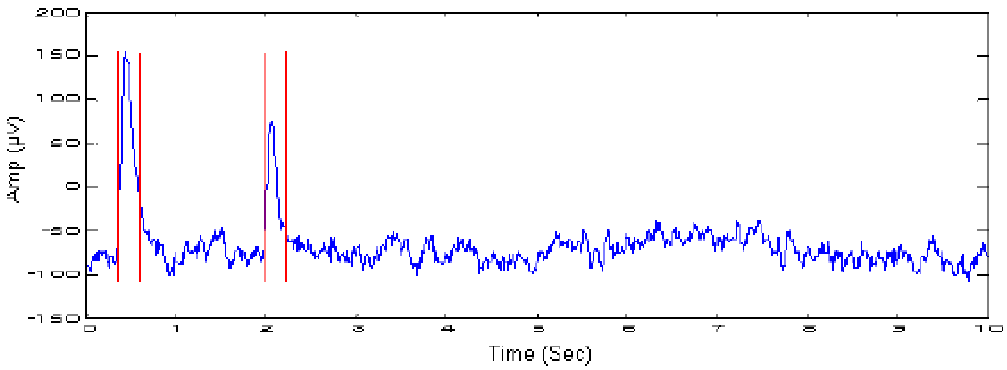

Fig. 4 Identification of artifact zones

The method proposed in this paper involves the following steps:

i. To apply stationary wavelet transform to the contaminated EEG signals and decompose it up to eight levels with Symlet (Sym3) as a basis function .
ii. To identify the spikes in the contaminated EEG at each level.
iii. To identify the ocular artifact spike zones using coefficient of variation, a statistical approach.
iv. To apply de-noising technique (equation 2) – To fix the suitable threshold value and threshold function for the artifact zones
v. To apply wavelet reconstruction procedure to reconstruct the EEG signal.

4 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 per second. The effect of ocular artifacts will be dominant in the Frontal and Fronto-polar channels like FP1, FP2, F7 and F8. Hence, it is sufficient to apply the algorithm to these channels. Fig. 5 and 6 show the 'approximation' and ' detail ' plot for the contaminated EEG signal of channel FP1.

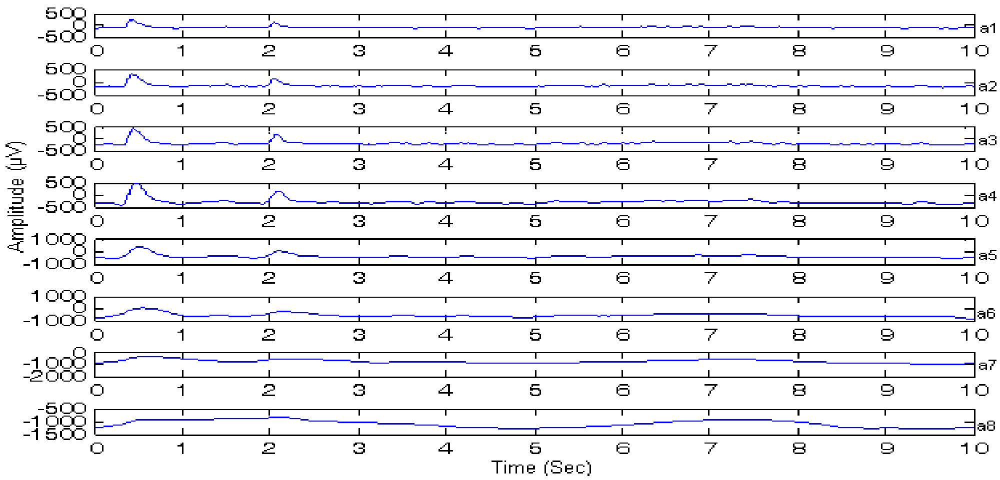

Fig. 5 ‘ Approximation’ plot

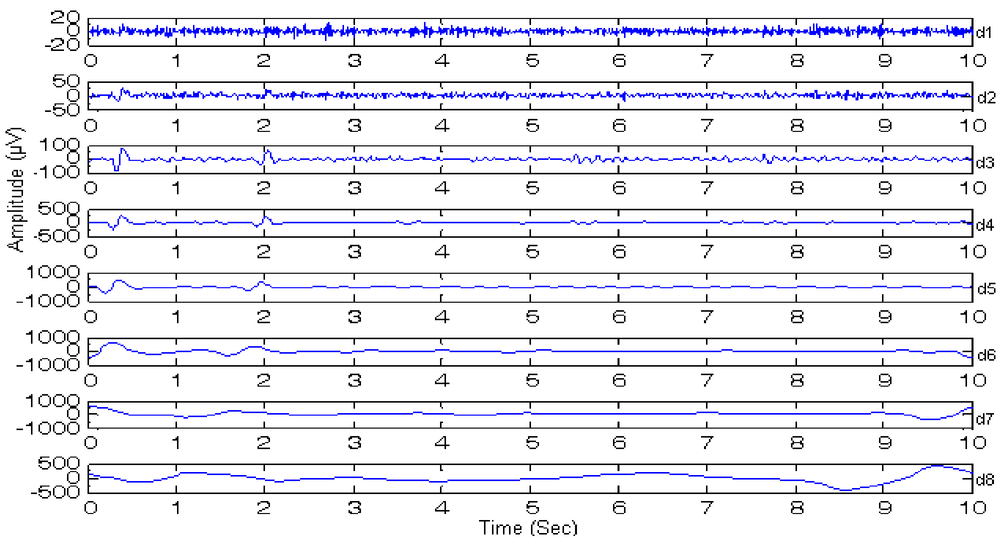

Fig. 6 ‘ Detail ‘ plot

The de-noising of EEG signal is carried out by using different combinations of threshold limit, threshold function and window sizes. Choice of threshold limit and threshold function is a crucial step in the de-noising procedure, as it should not remove the original signal coefficients leading to loss of critical information in the analyzed data. The following combination produces better de-noised results than the other methods [13] taken into consideration, which is applied to the entire length of the signal.

Threshold value = $N * \left(\frac{1}{\bar{x}+\sigma}\right)$ (2)

Threshold function - Hard

Frame length - 10 seconds

(Where $\bar{x}$ and σ denote the mean and standard deviation of artifact zones and N varying from 10 to 150)

The threshold function used in this work are as follows :

If wavelet coefficient value > threshold value

then new wavelet coefficient value = (- 0.7) * (wavelet coefficient value)

else new wavelet coefficient value = (old) wavelet coefficient value

Fig. 7 shows a 10 second epoch of EOG contaminated EEG with its corrected version using the proposed method.

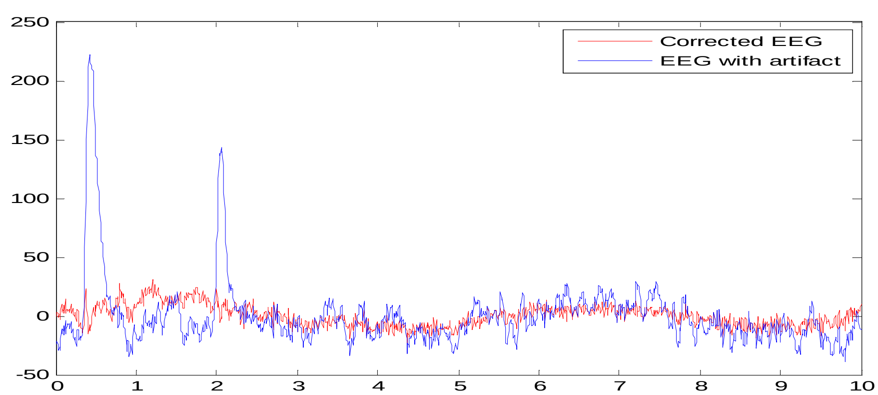

Fig. 7 EEG with artifact and Corrected EEG

The frequency correlation between the noisy EEG and Corrected EEG is shown in fig. 8. This shows how close both the signals are in terms of shape.

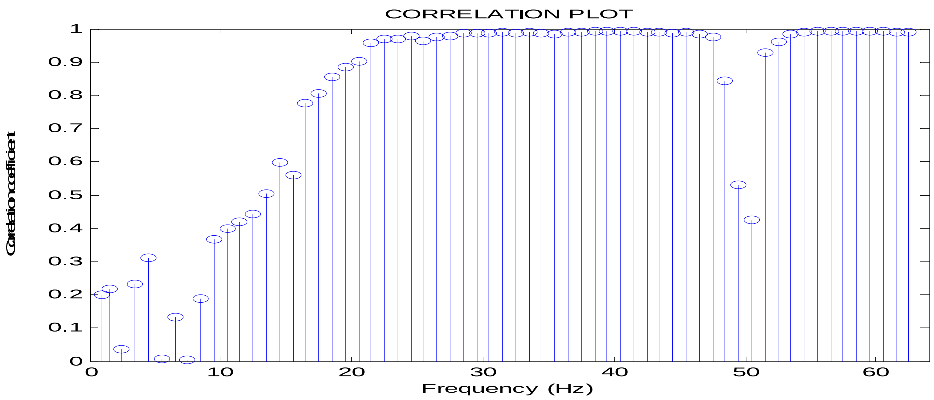

Fig. 8 Frequency correlation between noisy data and de-noised data

Fig. 9 shows the power spectra of the contaminated EEG and the corrected EEG. From this figure, it is shown that, the powers of the spectral components have been retained.

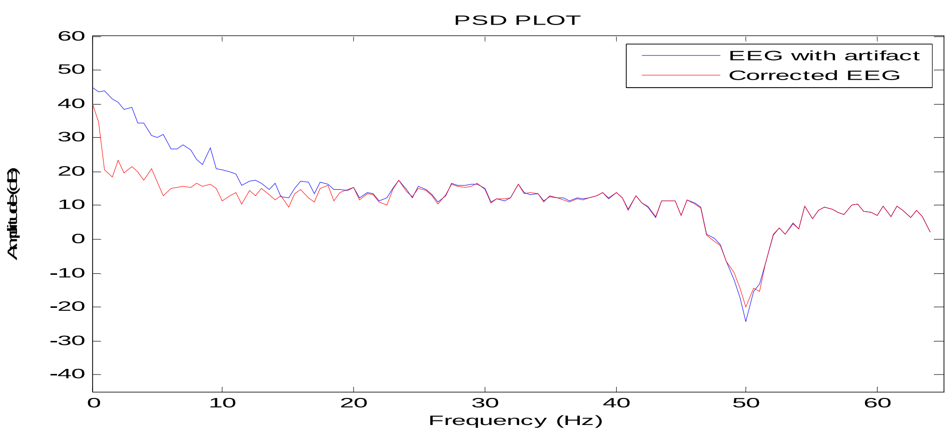

Fig. 9 Power Spectral Density Plot

The results obtained has been compared with the existing methods. Fig. 10 and 11 show the artifact removal using [13]. The proposed method shows a better result when compared with [13], which is depicted in figures 12 and 13. One can observe that the artifacts in EEG signals are considerably reduced using the proposed method.

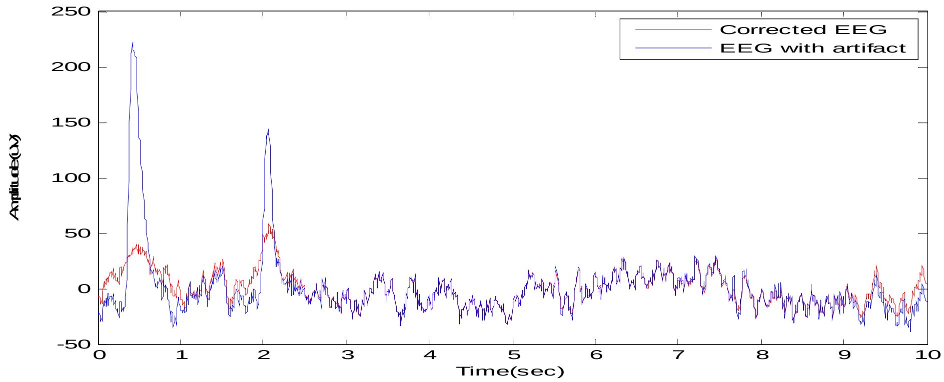

Fig. 10 Modified Threshold function
(mean + 2*standard deviation)

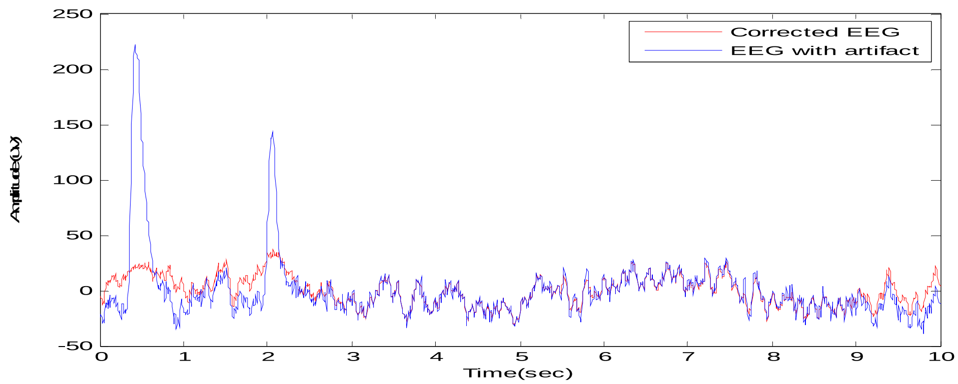

Fig. 11 Threshold function
(1.5*standard deviation)

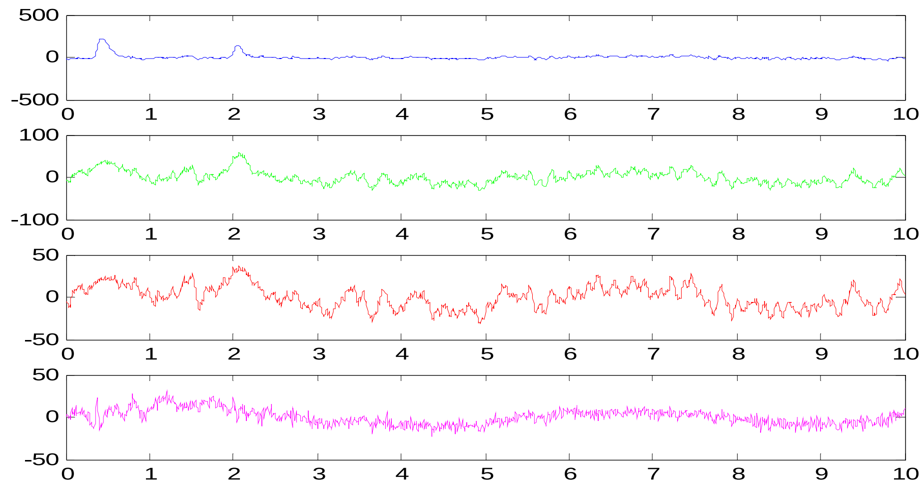

Fig. 12 (i) EEG with artifacts
(ii) Modified Threshold function
(iii) Threshold function
(iv) Proposed method

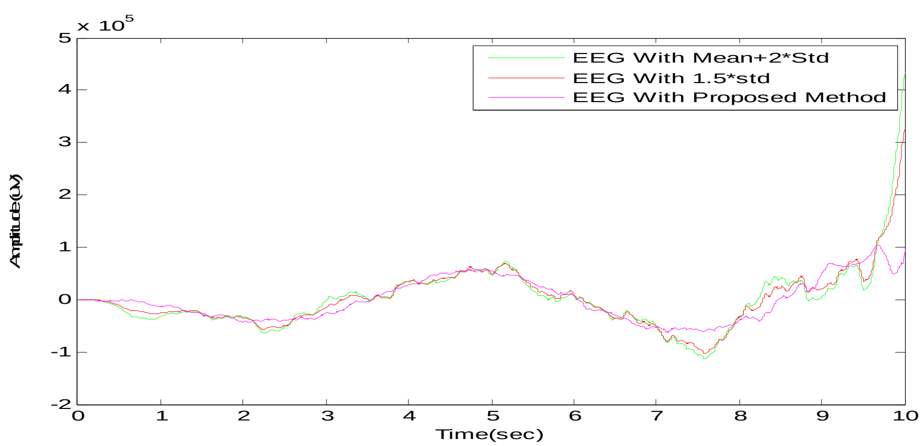

Fig. 13 Cross correlation plot

5 Conclusion

In this paper, a method to identify the ocular artifact spike zones through wavelet transform is proposed and soft-like thresholding is applied to the ocular artifact zones. Adaptive thresholding applied only to the ocular artifact zone does not affect the low frequency components and also preserves the shape of the EEG signal in the non-artifact zones which is of very much importance in clinical diagnosis. The proposed method is to minimize the complexity of the work and easily identify the artifact zones for removing the artifacts. Power Spectral Density and correlation plots are used as performance metrics in this paper. Comparing with the other methods, the suppression of ocular artifacts in dB is good. In all cases, artifacts were adequately attenuated, without removing significant and useful information. It is concluded that the proposed method gives less complexity and easier to removal of the artifacts with the help of wavelet decomposition and is an efficient technique for improving the quality of EEG signals in biomedical analysis.

Open Problem

In biomedical analysis, EEG signal consists of artifacts. A lot research work is going on in the removal of these artifacts. Even then, there is a wide scope for implementation of new techniques and methods in this area. This paper can be extended by using various adaptive filter algorithms with wavelet transform, time series analysis, etc.

ACKNOWLEDGEMENTS

The authors would like to express their deep sense of gratitude to Prof. S. Jayaraman, Head, Dept. of Electronics and Communication Engg., PSG College of Technology, Coimbatore and Dr. K. Ramadoss, PSG Institute of Medical Sciences and Research, Coimbatore for their valuable suggestions.

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