A Wavelet based Statistical Method for De-Noising of Ocular Artifacts in EEG Signals

P. Senthil Kumar [1], R. Arumuganathan [1], K. Sivakumar [2], C. Vimal [3]

[1] Dept. of Mathematics & Computer Applications, [2] Dept. of Electronics and Communication Engg.,
[3] Dept. of Bio-Medical Engineering
PSG College of Technology, Coimbatore, India.

Summary
This paper presents a new empirical method for de-noising of ocular artifacts in the electroencephalogram (EEG) records. In many biomedical signal processing approach, source signals are noisy and some have kurtosis close to zero. These noise sources increase the difficulty in analyzing the EEG and obtaining the clinical information. To remove this artifacts a method based on Donoho's de-noising method is used. Recently Stationary Wavelet Transform (SWT) has been used to de-noise the corrupted EEG signals. In this paper, statistical empirical method for removing ocular artifacts from EEG recordings through SWT is suggested.

Key words:
EEG, de-noising, ocular artifacts, 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, the noise removal is of the prime necessity to make easier data interpretation and representation and to recover the signal that matches perfectly a brain functioning. 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 lead 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.

Current Independent Component Analysis (ICA) methods of artifact removal require a tedious visual classification of the components. P. LeVan [1] proposed a method which automates this process and removes simultaneously multiple types of artifacts. 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. 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).

There has been a tremendous amount of activity and interest in the applications of wavelet analysis to signals, in particular methods of wavelet thresholding and shrinkage [8,13] for the removal of additive noise from corrupted biomedical signals and images. 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. V. Krishnaveni [9,10] 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 fundamental motivation behind these approaches is that the statistics of many real world signals, when wavelet transformed are substantially simplified.

Wavelet transforms are used to analyze time varying, non-stationary signals, and EEG fall into these category of signals. The ability of wavelet transform is to accurately resolve EEG into specific time and frequency components lead to several analysis applications and one among them is de-noising. The wavelet transform of the noisy signal generates the wavelet coefficients which denote the correlation coefficients between the noisy EEG and the wavelet function. Depending on the choice of mother

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wavelet function, larger coefficients will be generated corresponding to the noise affected zones. The larger coefficients will be an estimate of noise
Tatjana Zikov [12] proposed a wavelet based de-noising of the EEG signal to correct for the presence of the ocular artifact. In this paper, we proposed a simple statistical empirical de-noising formula for removing artifacts in the EEG signals without using any reference signals. This formula very much reduces the complexity and time factor.

2. Wavelets for analyzing EEG signals

In statistical settings we are more usually concerned with discretely sampled, rather than continuous functions. It is then the wavelet analogy to the Discrete Wavelet Transform (DWT) which is of primary interest . Wavelet transform [6] has emerged as one of the superior technique in analyzing non-stationary signals like EEG [3,7]. Its capability in transforming a time domain signal into time and frequency localization helps to understand more the behavior of a signal.

The DWT means choosing subsets of the scales ‘a’ and positions ‘b’ of the mother wavelet $\psi(t)$.

$$\Psi_{(a,b)}(t) = 2^{\frac{a}{2}} \psi(2^a t - b) \quad (1)$$

Choosing scales and positions are based on powers of two, which are called dyadic scales and positions { $a_j = 2^{-j}$; $b_{j,k} = 2^{-j} k$ } (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 Stationary Wavelet Transform (SWT) [14] 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 level to another.

This decomposition scheme is shown in the figure 1.

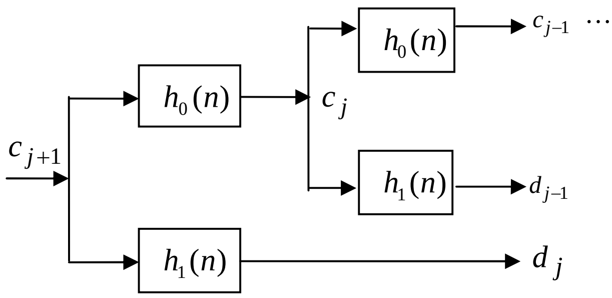


Fig. 1 Wavelet Decomposition Scheme

3. A Simple De-Noising Technique

Suppose one has to measure a signal on which an external noise is superimposed. We call this EEG signal the true signal S(t) and the external noise $\varepsilon(t)$, so that the measured signal can be written in the form

$$x(t) = S(t) + \varepsilon(t) \quad (2)$$

The only assumptions needed are that S(t) and $\varepsilon(t)$ are uncorrelated and are stationary processes, and can be written as equation (2). Thresholding is a technique used for signal and image de-noising. When we decompose a signal using the wavelet transform, we are left with a set of wavelet coefficients that correlates to the high frequency subbands. These high frequency subbands consist of the details in the data set. If these details are small enough, they might be omitted without substantially affecting the main features of the data set.
The de-noising of EEG signal is carried out by using different combinations of threshold limit, thresholding function and window sizes. Choice of threshold limit and thresholding function is a crucial step in the denoising procedure, as it should not remove the original signal coefficients leading to loss of critical information in the analyzed data

In this paper, the following thresholding (statistical empirical) formula is used for calculating the thresholding limits. This formula produces better de-noised results than [11], which is applied to the entire length of the signal.

Threshold based on Statistics of the signal

Threshold value

$$T_k = N \times \left(\frac{\bar{x} - \sigma}{\bar{x} + \sigma} \right) \qquad (3)$$

Window length - 10 seconds

where N is a positive integer , ranging from 100 to 150

$\bar{x}$ - mean of all samples

σ - standard deviation of all samples

The thresholding 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

4. Methodology

The general goal of this study is to removal of artifacts from EEG signals. Towards this, we propose the following method. To estimate the signal x(t), we propose the following method :

(i) The Stationary Wavelet Transform (SWT) to the contaminated EEG signal with Symlet (sym3) as a basis function and decomposes upto eight levels
(ii) To calculate statistical measures , mean and standard deviation for the entire length of the signal.
(iii) To apply equation (3) to fix the suitable threshold value.
(iv) To apply threshold function to fix the wavelet coefficients in a new position.
(v) To apply wavelet reconstruction procedure to reconstruct the EEG signal.

5. 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 method. The data is sampled at a rate of 128 samples per second. The effect of ocular artifacts is dominant in the Frontal and Fronto-polar channels like FP1, FP2, F7 and F8. Hence it is sufficient to apply the method to these channels. Consider the 10 second EOG contaminated EEG epoch (sampled at a rate of 128 samples/second) shown in Fig.2

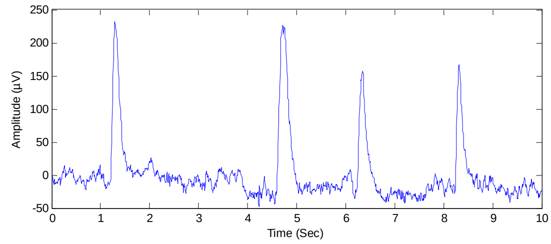


Fig.2 EOG Contaminated EEG

The de-noising of EEG signal is carried out by using threshold limit, threshold function and window size. Choice of threshold limit and thresholding 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. Figure 3 shows a 10 second epoch of EOG contaminated EEG with its corrected version using our proposed method.

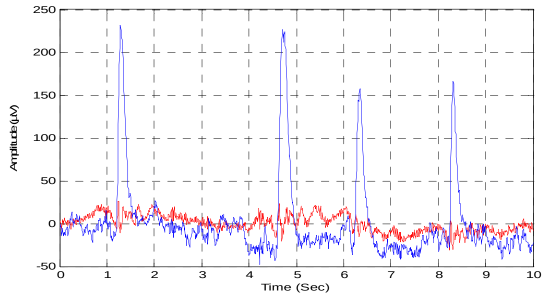


Fig.3 Contaminated EEG and Corrected EEG

Figure 4 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 fully retained. The cross correlation between the noisy EEG and EOG is shown in figure 5. This shows how close both the signals are in terms of the shape.

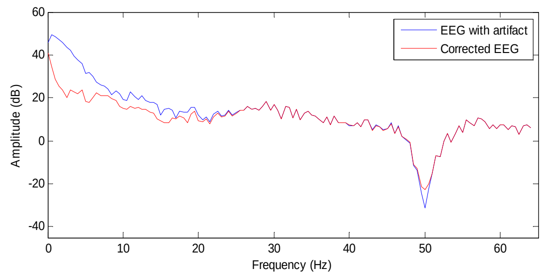


Fig. 4 Power Spectra Plot

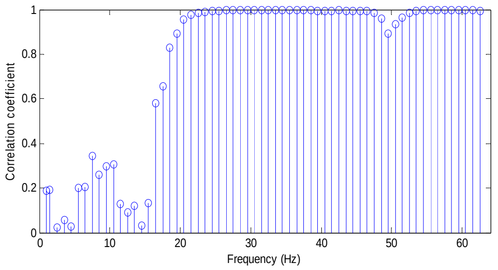


Fig. 5 Correlation Plot

The results obtained has been compared with the existing methods. Figure 6 and 7 shows the artifact removal using [11,12]. The proposed method shows a better result when compared with [11] which is depicted in figure 8,9 and 10. One can observed that the artifacts in EEG signals are considerably reduced using the proposed method and shown in figure 9 and 10.

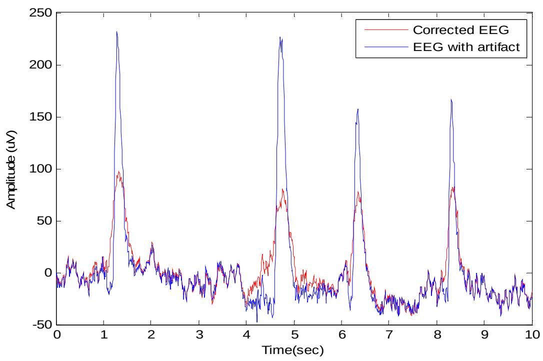


Fig.6 Modified Threshold function (mean + 2*standard deviation)

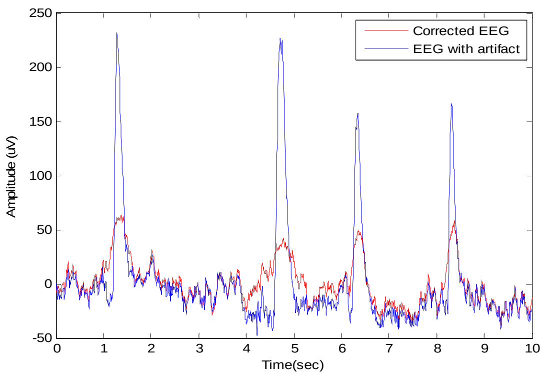


Fig. 7 Threshold function (1.5*standard deviation)

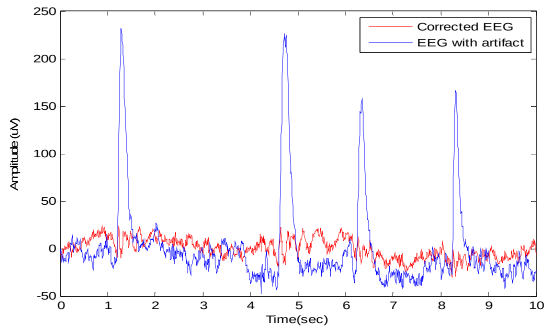
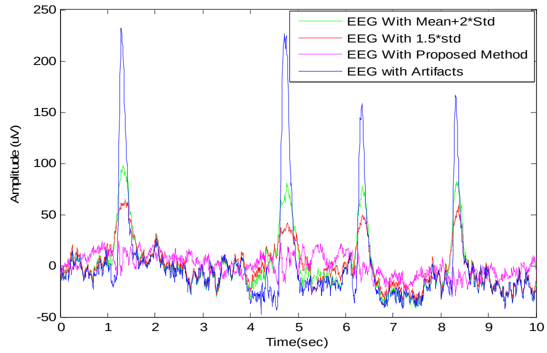
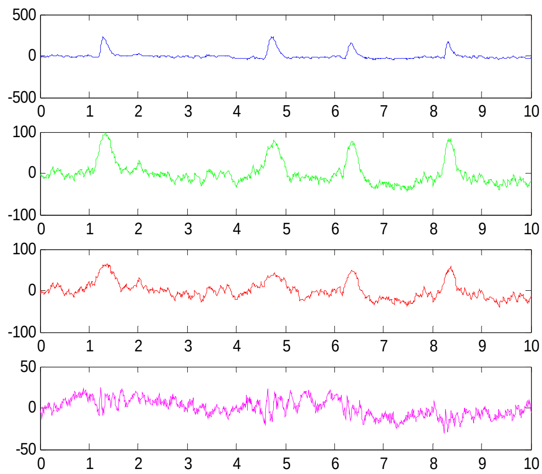


Fig. 8 Proposed method



(a)



(b) (i) EEG with artifacts
(ii) Modified Threshold function
(iii) Threshold function
(iv) Proposed method

Fig. 9 (a), (b) Comparison results

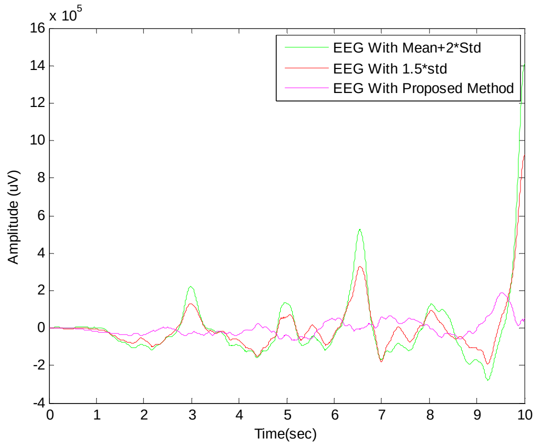


Fig. 10 Cross Correlation Plot

6. Conclusion

The accuracy of the technique has been checked on several artifical signals. In this paper, a method to remove ocular artifacts using a new threshold formula and threshold function is given. Our method gives a better result without any complexity and also retains the original information contained in the EEG signal. Power Spectral Density plot and Correlation plot are used as performance metrics. We conclude that our proposed statistical method gives lesser complexity and easier to remove the artifacts with the help of wavelet decomposition. It is an efficient technique for improving the quality of EEG signals in biomedical analysis.

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P. Senthil Kumar received the M.Sc.,and M.Phil degrees in Mathematics from Bharathiar Univ. India in 1987 and 2001 respectively. He is working as a Senior Lecturer in Department. of Mathematics and Computer Applications, PSG College of Technology, Coimbatore. India. He is pursuing his Ph.D. under the guidance of Prof. R. Arumuganathan. His research interests include wavelet transforms and linear algebra. He is a life member of ISTE.

Dr. R.Arumuganathan received the M.Sc., M.Phil., degrees in Mathematics from Madurai Kamaraj Univ., India. He received Doctoral degree from Bharathiar Univ. India in 1998. Now he is working as a Professor in the Dept. of Mathematics and Computer Applications., PSG College of Technology, Coimbatore, India. His research interests include queueing theory and wavelet transforms.

K. Sivakumar received the B.E and M.E. degrees in Electronics and Communication Engineering from Anna Univ. India in 2003 and 200 respectively. His area of interests are digital signal processing and bio-medical signal processing.

C. Vimal is a student of dept. of Bio-Medical Engineering, PSG College of Technology, Coimbatore. India. His area of interests are bio-medical signal processing and medical imaging.