Removal of Blink Artifacts from EEG: Performance Comparison of Wavelet Transform and Empirical Mode Decomposition

Almaria Joseph
PG Scholar, Communication Engineering
Amal Jyothi College of Engineering
Kanjirappally, India

Geevarghese Titus
Assistant Professor
Amal Jyothi College of Engineering
Kanjirappally, India

***Abstract*— Due to the day to day advancements in biomedical signal processing, Electroencephalography (EEG) signals are widely used in the diagnosis of brain diseases and in the field of Brain Computer Interface (BCI). (EEG) signals which obtained by placing multiple electrodes on the scalp can be contaminated with several electrophysiological signal sources. Among the wide variety of noise sources which contaminates the recorded EEG signal, those associated with eye-blink requires significant attention. This work focuses on the removal of Electro-occulogram signals or blink artifacts that strongly appears in frontal electrodes of EEG. OA removal based on the conventional wavelet de-noising is implemented and is compared with an algorithm based on recently developed technique called Empirical Mode Decomposition (EMD). Contrary to most of the previous methods, this decomposition method is adaptive and highly efficient. Experimental results show that both wavelet de-noising and empirical mode decomposition has its own inherent advantages and limitations. The efficiency of wavelet transform and EMD is compared by the use of several metrics such as Time consumption, Signal to Artefact ratio, Power spectral density etc.**

Keywords*— *EEG signal, ocular artifacts, wavelet transform, empirical mode decomposition, wavelet de-noising.

I. INTRODUCTION

Electroencephalogram (EEG) is a biological signal which represents the brain activity of a person and is measured by placing multiple electrodes on the scalp at specific points [1]. It contain several useful information related to the different state of the brain and is widely used by physicians for the identification and diagnostics of different pathological phenomena. But it is very common that the recorded EEG signal is usually affected by different contaminants which change the nature of the signal. Being an electronic system, in addition to contamination caused by the patient related factors, the EEG recording system will be surely influenced by various interferences associated with the equipments used for measurement. The different sources of artifacts associated with EEG signal includes, those related to heart activity, muscle potentials, eye blinks etc.

The electrical signal resulting from eye movements and blinks often contaminates the EEG signal and is called as Electro occulogram (EOG). The shape of the EOG waveform is determined by the direction of eye movement. Vertical eye movements (eyes moving up and down) produce a square-like EOG waveform whereas blinks cause a spike-shaped waveform [1]. A fraction of the EOG spreads across the scalp and it gets superimposed on the recorded EEG. But in order to make use of EEG signal for clinical applications, it is essential that OAs must be removed (filtered) from the EEG signal.

Various methods for the removal of artifacts associated with the EEG signal have been reported in the literature. In the early days of the literature Got man (1976) discussed about the removal of blink artifacts from the EEG signal by the subtraction of EOG signal. But this will result in loss of some of the useful information in the signal. The work of J. C. Woestenburg et.al [2] mentioned about the use of regression based techniques which employed frequency domain regession for EOG artifact removal. But the requirement of an EOG regression channel made the technique little complex. In 1994, Berg and Scherg proposed a method based on the use of adaptive filters for artifact removal [3]. The main limitation with that method was the requirement of a consistent EOG reference signal. In 1997 Lagerlund et al. [4] used Principal Component Analysis (PCA) to remove the artifacts from EEG. The drawback was that PCA cannot completely separate OA from EEG, when both the signal and artifact has nearly same voltage magnitude.

In 1998 Tzyy Ping et.al [5] proposed a method for removal of artifacts from EEG signals based on the well known technique called Independent Component Analysis (ICA). Compared to the regression techniques developed earlier, the main advantage of this technique is that it doesn't require any reference channels for the corresponding artifact [6]. But the limitation is that the component to be corrected is to be selected manually [7].

Among the various techniques developed for OA removal, the one based on wavelet transform has got significant importance. An algorithm based on Haar wavelet for decomposing the contaminated EEG was developed in [8] in which the position of eye blink was detected. The work by V. Krishnaveni et.al [9] focused on the automatic identification and removal of blink artifacts based on wavelet decomposition. The main advantage of that work was that once the OA zones are identified, the algorithm applies adaptive thresholding only to the OA zones thereby the removal of background information can be avoided. A wavelet based algorithm which employs the use of stationary wavelet transform (SWT) is proposed in 2008[10].

In this work the performance of wavelet transform in the removal of OA is evaluated and also it is compared with an algorithm based on the recently developed technique called Empirical Mode Decomposition.

Organization of the rest of the paper is as follows: Section II describes about the theoretical concepts regarding wavelet decomposition and wavelet de-noising. Section III focuses on Empirical Mode Decomposition. Proposed Methodology of artifact removal is described in section IV. Finally section V describes about the Results and Analysis of the work.

II. WAVELET TRANSFORM

A. Wavelet Transform for Signal Decomposition

Wavelet transform is one of the most popular techniques used for time-frequency transformation. Fourier transform based spectral analysis is the dominant analytical tool for frequency domain analysis. Fourier transform assumes the signal is stationary, but most of the bio signals are always non-stationary. Contrary to Fourier Transform which is localized in frequency only, the main advantage of wavelet transform is that, it is localized both in time and frequency and this transform utilizes a wavelet function for signal decomposition. A wavelet is a wave-like oscillation of limited duration which has amplitude starting from zero, increases and finally reaches to zero. Some of the common applications of Wavelet Transform includes Data compression, De- noising, Pattern Recognition etc. By the end of 1990's wavelet analysis has become widely used in different fields of research.

Among the various existing wavelet approaches discrete wavelet transform is used in this work because of its inherent advantages like fast calculation, good temporal localization properties etc. DWT is simply calculated by passing the input signal through successive high pass and low pass filters producing the detailed and approximate coefficients respectively. To be more precise DWT is recursive (D levels) decomposition of the output of the low pass filter resulting in the generation of D details and one approximation [13]. The approximate coefficients obtained in the 1st level can be further decomposed into details and approximates and this process is called as multilevel decomposition.

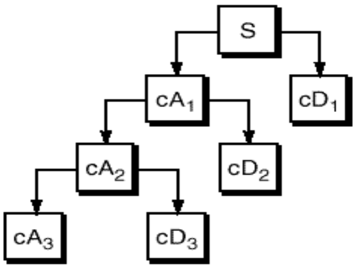

Fig.1. Multilevel wavelet decomposition tree

B. Wavelet De-noising

De-noising is a process by which original information content in the signal is recovered from a noisy signal. Steps involved in wavelet de-noising are shown in Fig. 2.

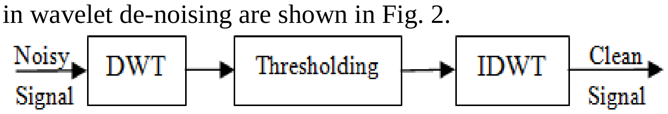

Fig. 2. Wavelet de-noising procedure

Two types of thresholding methods are commonly used in wavelet decomposition, namely soft and hard thresholding. The use of soft or hard thresholding is based on the application for which wavelet de-noising is applied. The advantage of soft thresholding is that it provides smoother results than hard thresholding. However, hard thresholding provides better edge preservation. Reconstruction of the signal is achieved by performing the Inverse Discrete transform (IDWT) of the threshold signal.

III. EMPIRICAL MODE DECOMPOSITION

Empirical mode decomposition is an algorithm which was designed and developed by Huang (1998) and is used for the time frequency analysis of any real world data.

A. Computation of EMD: Sifting Algorithm

The main concept behind EMD technique is that every signal can be regarded as the superposition of fast oscillations and small oscillations [14] and this locally adaptive method decomposes the input signal into the set of constituent oscillatory modes. Each of the oscillatory modes extracted is amplitude- frequency modulated and is commonly referred to as an Intrinsic Mode Function (IMF). The IMFs can be obtained directly from the data without any priori assumptions regarding the structure of the data. This makes EMD suitable for the analysis of nonlinear and non stationary signals [15].

Steps of sifting algorithm are described below.

1. Identify the local maxima and minima (extrema) associated with the signal x (t).
2. Generate the upper and lower envelopes e_{max} (t) and e_{min} (t) by the use of cubic spline interpolation over the maxima and minima.
3. Compute the local mean of the signal which is given as:

   $$m_1(t) = \{e_{max}(t) + e_{min}(t)\} / 2$$

4. Extract the first component h1 (t), by subtracting the local mean from the original input signal.

   $$h_1(t) = x(t) - m_1(t)$$

5. Repeat the steps till the last IMF is obtained.

An IMF needs to satisfy two conditions which commonly called as the stoppage criteria and are described below:

1. In the whole dataset, the number of extrema and the number of zero crossings should be equal or differ at most by one.
2. At any point of IMF the mean value of the envelope defined by the local maxima and the envelope defined by the local minima should be zero.

In short the equation for EMD decomposition can be represented as follows;

$$x(t) = \sum_{k=1}^{n} imf_k(t) + r(t)$$

where r(t) is the residual obtained after decomposition.

B. Comparison with DWT

Just like wavelet transform, EMD method can be used for the analysis of EEG signal as it gives information about temporal resolution. In DWT approach, the wavelet coefficients can be regarded as the sum of approximations and details and these are separated based on a priori dyadic filtering technique.

Similarly in the case of EMD, signal is considered to be the sum of fast and slow oscillations and IMF's are obtained by successive iteration. Therefore the similarity of wavelet transform and EMD is that both of them splits the signal to be analysed into "fluctuations" and "trend" whereas the difference is that scales are pre-determined for DWT and are adaptive (data-driven) for EMD.

IV. PROPOSED SYSTEM

The first step in the experimental procedure is the acquisition of EEG signal with significant amount of ocular artifacts. The EEG signal used for the work was collected from EEGLAB. Since the effect of eye blink artifact on EEG channels depends on the distance of the electrodes placed on scalp to the eyes, the electrodes placed on the frontal lobe are the most affected by the eye blinks artifacts and hence the EEG signal recorded by the frontal electrodes Fp1 and Fp2 was considered for the study. A segment of EEG signal with significant content of ocular artifact is used for the work.

A. Artifact Removal based on Wavelet Decomposition

Wavelet decomposition was performed on the EEG signal collected from EEGLAB using the Daubechieus mother wavelet (order 4) as the basis function. The choice of the mother wavelet depends on the similarity of the analysed signal with the mother wavelet. A 3 level decomposition was performed over the signal so as to obtain the wavelet coefficients (approximates and details).

Initially wavelet decomposition is performed over the noisy input signal. After decomposing the signal into different wavelet coefficients, an appropriate threshold value and thresholding method is selected. Among the various algorithms available for thresholding, the Stein's Unbiased Risk Estimate (SURE) shrinkage rule and a soft thresholding strategy was used in the experimental procedure. Thresholding is applied on the detailed coefficients using global positive thresholding. The threshold value was automatically generated by the Matlab inbuilt function 'wdencmp'. The threshold value used was 20.376.

B. Artifact Removal based on Empirical Mode Decomposition

As mentioned earlier, when compared with wavelet transform empirical mode decomposition doesn't require a basis function for decomposition. Considering this fact, after collecting sufficient literatures, we have implemented empirical mode decomposition and utilizing it an algorithm is developed.

Steps involved in the algorithm are:

1. Collection of EEG signals with significant amount of blink artifacts.
2. Perform Empirical Mode Decomposition over the data to obtain the set of intrinsic mode functions (IMF's).
3. Calculate the Shannon entropy value of each of the IMF.
4. Identify the different levels of IMF in which the entropy value increases rapidly from a small value.
5. Reconstruct the signal by the avoidance of those IMF's to get the corrected signal.

V. RESULTS AND DISCUSSION

The Fp1 input signal used for the work and the corresponding wavelet coefficients obtained by the 3 level wavelet decomposition is shown the Fig. 3 and Fig. 4 respectively.

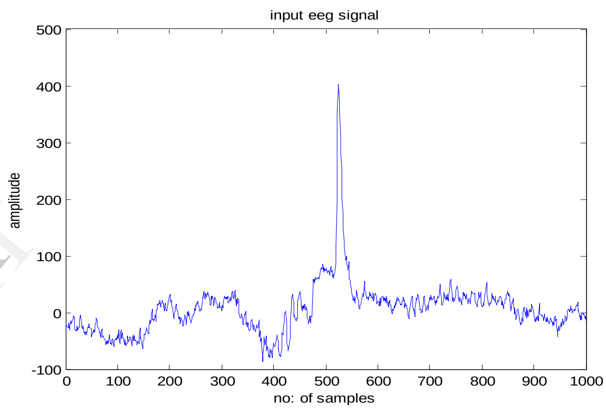

Fig. 3. Contaminated EEG from Fp1channel

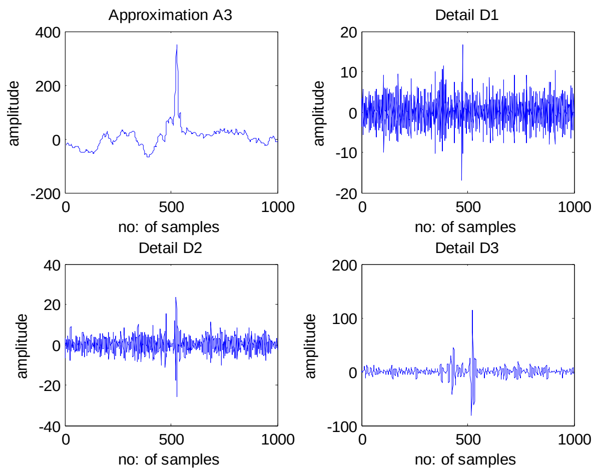

Fig. 4. Wavelet coefficients of Fp1channel

The original signal and the de-noised signal obtained as the result of wavelet de-noising is shown in the Fig. 5 The power spectral density of the corrected signal based on wavelet de-noising is shown in Fig. 6.

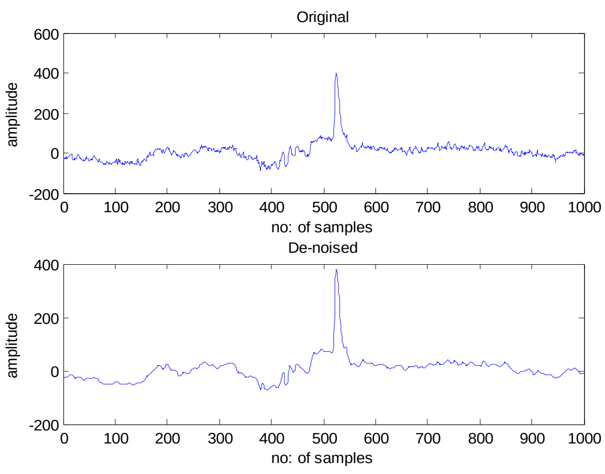

Fig. 5. Input signal and Corrected Signal

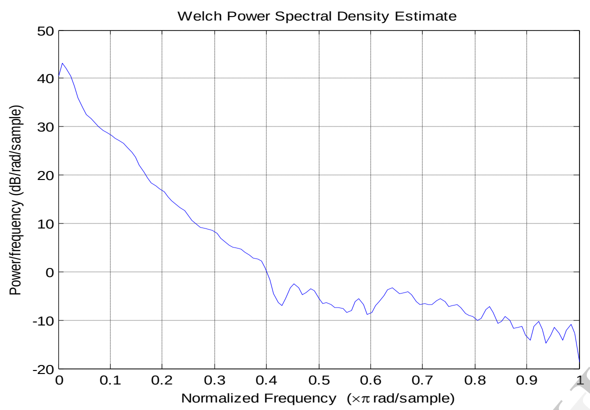

Fig.6. PSD of corrected signal based on Wavelet De- noising

The results obtained from EMD based algorithm are shown in following figures. The application of Empirical mode decomposition onto the Fp1 signal decomposed it into 9 IMF's. These are further processed by calculating the entropy value of each IMF. Shannon entropy was used as the entropy type.

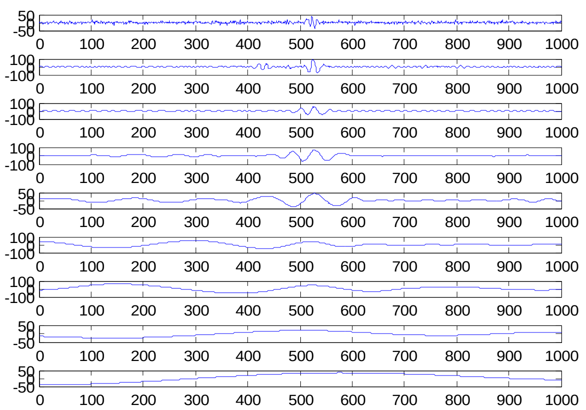

Fig 7. EMD decomposition of Fp1 channel

The original EEG signal and the corrected EEG signal based on EMD is shown in Fig. 8 and the PSD is shown in Fig. 9.

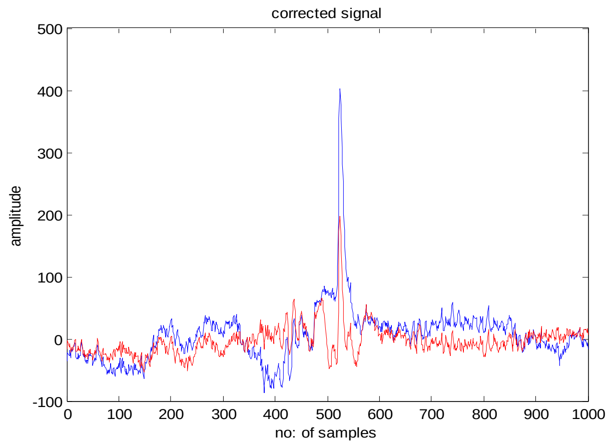

Fig. 8. Corrected signal based on EMD

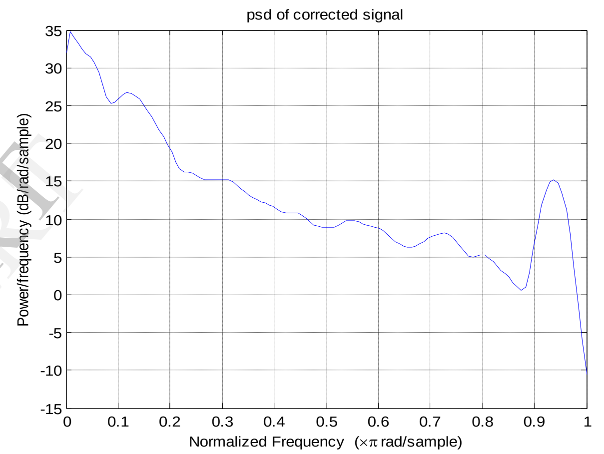

Fig. 9. PSD of corrected signal based on EMD

Performance of both algorithms was evaluated by calculating the Signal to artifact ratio (SAR), time taken for the whole process of artifact removal etc. The results obtained for various channels of EEG are shown in the following table.

TABLE 1. EXPERIMENTAL RESULT OF WAVELET DE-NOSING

EEG channel	SAR ratio	Time consumption(seconds)
Fp1	1.2257	.4149
Fp2	2.1385	.4159
F3	4.0504	.4294
F4	0.6888	.4331
F7	2.9380	.4193
F8	2.5027	.4090

TABLE 2. EXPERIMENTAL RESULT OF EMD BASED ALGORITHM

EEG channel	SAR ratio	Time consumption(seconds)
Fp1	19.3664	.3186
Fp2	15.2459	.3275
F3	15.0080	.3618
F4	16.5447	.4717
F7	14.9989	.3230
F8	13.2526	.3212

On analyzing the performance of both algorithms based on the above tabular results, it is clear that the SAR ratio is high for the wavelet based algorithm than that of EMD based algorithm. It is well understood from the plots of corrected EEG signal that in wavelet de-noising the overall shape of the signal is maintained as such, and hence most of the signal power is retained and this resulted in the higher value of SAR ratio. But in case of EMD based algorithm the corrected signal has much variation from the original input signal.

Considering the time taken for the process, even though both the algorithm has taken almost same time for the work, time taken by the wavelet based algorithm is slightly high compared to the other one. Even though the no: of steps involved is more in EMD when compared with wavelet de-noising both algorithm has taken nearly same time for the whole process of artifact removal. This result validates the performance of EMD and hence it can be used for signal decomposition in various signal processing applications.

CONCLUSION

Electroencephalogram is a key diagnostic tool for many of the pathological conditions. One of the main challenges faced by EEG recordings is the contamination by various sources. Empirical mode decomposition is a newly developed tool in the field of EEG de-noising. This work mainly concentrates on the removal of blink artifacts from the recorded EEG. The performance of wavelet transform and empirical mode decomposition in the removal of ocular artifacts from EEG is evaluated in this work. One main advantage of EMD is that unlike the stochastic approaches like ICA, CCA etc. it doesn’t require the availability of multichannel data for processing.

The experimental results show that both wavelet de-noising and empirical mode decomposition has its own inherent advantages and limitations. EMD performs well in the artifact removal process in certain respects.

REFERENCES

[1] James N. Knight,”Signal Fraction Analysis and Artifact Removal in EEG”, Master of Science thesis, Department of Computer Science, Colorado State University, Fort Collins, Colorado Fall, 2003.

[2] J. C. Woestenburg, M. N. Verbaten, and J. L. Slangen, “The removal of the eye-movement artifact from the EEG by regression analysis in the frequency domain,” Biol. Psychol., vol. 16, pp. 127–147, 1983.

[3] Berg P and Scherg M. Dipole models of eye activity and its application to the removal of eye artifacts from the EEG ad MEG, CZin. Physiol. Meas., 12(Supplement A):49-54, 1991.

[4] T. D. Lagerlund, F. W. Sharbrough, N. E. Busacker, “Spatial filtering of multichannel electroencephalographic recordings through principal component analysis by singular value decomposition”, Clinical Neurophysiology,1997.

[5] Tzyy- Ping Jung, Colin Humphries , ``Removing Electroencephalographic Artifacts: Comparison between ICA and PCA", Article from the office of Naval Research, 1998 IEEE.

[6] Vigario R, J. Sarela, V. Jousmaki, M. Hamalainen, E. Oja, “Independent Component Approach to the Analysis of EEG and MEG Recordings”, IEEE Transactions on Biomedical Engineering, Vol 47, No.5, pp. 589- 593, 2000.

[7] A. Delorme, S. Makeig, T. Sejnowski , “Automatic artifact rejection for EEG data using high-order statistics and independent component analysis”, Proceedings of the Third International ICA Conference, pp. 9- 12, 2001

[8] S. V. Ramanan, N. V. Kalpakam, J. S. Sahambi, “A Novel Wavelet Based Technique for Detection and De-Noising of Ocular Artifact in Normal and Epileptic Electroencephalogram”, International Conference of IEEE on Volume 2, Issue , pp. 27-29 June 2004.

[9] V.Krishnaveni , S.Jayaraman , S.Aravind , V.Hariharasudhan , K.Ramadoss, “Automatic Identification and Removal of Ocular Artifacts from EEG using Wavelet Transform”, Measurement Science Review, vol. 6, sec. 2, no. 4, 2006.

[10] Majid Kiamini, Shahpour Alirezaee, “A Wavelet Based Algorithm for Ocular Artifact Detection In The EEG Signals”, Proceedings of the 12th IEEE International Multitopic Conference, December 23-24, 2008

[11] Mohammad Shahbakhti, Vahidreza Khalili, “Removal of Blink from EEG by Empirical Mode Decomposition (EMD)”, The Biomedical Engineering International Conference (BMEiCON), 2012

[12] P. Senthil Kumar, R. Arumuganathan, “Removal of Ocular Artifacts in the EEG through Wavelet Transform without using an EOG Reference Channel”, Int. J. Open Problems Compt. Math., Vol. 1, No. 3, December 2008

[13] Robi Polikar, “The Wavelet Tutorial Second Edition ".

[14] G. Rilling, P. Flandrin, ‘On Empirical Mode Decomposition and its Algorithms’, IEEE-EURASIP Workshop on Nonlinear Signal and Image Processing, Grado, June 9-11, 2003

[15] N. E. Huang and Z. Wu, “A Review on Hilbert-Huang Transform: Method and its Applications to Geophysical Studies,” Rev. Geophys., vol. 46, 2008.