Removal of Artifacts from Electroencephalography Signal using Multiwavelet Transform

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Abstract: The signal from the brain can be recorded using Electroencephalography (EEG). The proposed work summarizes a unique method which is used for the removal of mixed artifacts presented in the electroencephalography signal during the acquisition process. Artifacts comprises of various bio-potential unit such as electrooculogram, electrocardiogram, and electromyogram. These artifacts are referred as a noise sources which is responsible for the complexity of the EEG signal. The artifacts obtained from the EEG signal leads towards improper diagnosis of pathological conditions. The EEG signal which is obtained from the brain is the multi-dimensional signal with the various statistical properties. Time consumption of the EEG signal is not reproducible due to the biological properties of the signal. The information of the EEG signal consists of the data of the neuron levels which is collected for every millisecond with the temporal resolution scale. In account of special cases, EEG signal contains noise and artifacts where information is collected using the extraction of signals. To obtain the information of the artifacts the proposed technique is used to maintain higher accuracy in the extraction process. The proposed technique consists of multiwavelet transform to remove the artifacts from the input EEG signal. In the proposed multiwavelet transform, the signal which consists of noisy features can be decomposed using GHM and thresholding technique. This experimental analysis shows the removal of artifacts from the EEG signals. The pathological conditions are removed which leads to the increase in the accuracy of the system. Also, this research findings shows that the proposed multiwavelet transform based approach outperforms significantly with respect to conventional approaches. The reconstructed EEG signal has the lesser reliability range which is measured in-terms of signal to noise ratio and power spectral density.

Keywords: Electroencephalography, Artifacts, GHM and thresholding, signal to noise ratio and power spectral density.

1. INTRODUCTION

EEG signal acquisition process consists of recordings of the brain activity which is used for the clinical and biomedical diagnosis. This signal is affected by the various types of artifacts parameters which occurred due to the patient as well as disturbances caused by the medical devices. This artifact which is also referred as the noise is originated through the power grid, EEG signals has acquisition during eye blinks, eye movements, heartbeat and movements in muscle activities. In case of eye blink detection voltage changes with higher magnitude varies from endogenous brain activity of the human.
In similar case data acquired need to be neglected and removed from the source.

The data acquired as artefacts are combined with EEG signals are neglected the affected part of EEG signals. The fixed length portion removed and one second data measurement is artefact is detected. In artefacts generated by eye movements and blink are commonly diagnosed by a sharp increase in voltage higher than 100 μV in EOG channel. Other than filtered signals are neglected and manually noticed by physician. By eliminating these EEG signals can paths data for analysis and subsequent pathological diagnosis. The multiple methods has been discussed to eliminate are following in below sections.

2 LITERATURE REVIEW

2.1 Review on Principal Component Analysis (PCA)
PCA is a Principal Component analysis method of singular value decomposition (SVD) is used for temporal study of an epoch in multichannel electroencephalogram which is classified into linearly independent, temporally and spatially uncorrelated components. The original epoch signal can built components with linear combination. The time series waveform of SVD gives amount and quantity of components used for EEG channels. In elimination of non-significant waveform in linear combination, and it can be rebuilt by appropriate ways of original EEG signals. By removing the remainder of EEG signals improvisation of proper removal such as interracial discharge. In this research here to adopt new technique with primary factors of reconstructed with modified EEG signal which formed in matrix structure. Without reputation of time consuming scheme in SVD new EEG signals are manipulated continuously. And its matrix structure acts as spatial filtering functions. These scheme used for removal of electrocardiographic artefacts and ocular movements. Myogenic artefacts are lesser since there is a significant improvement and in ability in visualization and underlying properties EEG signals. The limitations in method of inability to complete discrimination with artefacts with cerebel activity with same range of amplitudes and spatial filter function neglect the distribution activates in which artefacts with overlapped are removed. The main limitations for PCA is in required conditions artefacts are uncorrelated with measure EEG signals. The major requirement than the independency requirement of ICU. PCA cannot be used for separation of eye movement, EMG, ECG have distinct amplitude levels with EEG signal particularly. In proceedings PCA need not to be decomposed are similar of EEG and its applicable to epochs. The major impact is difficulty in interpretation of PCA and its not working with original components.

2.2 Feature Extraction Using Independent Component Analysis (ICA) Technique
There are various feature extraction technique exist which is used to extract the features of the signal. One of the techniques used in the proposed work is the Independent Component Analysis (ICA) technique. This technique is used because of the blind source separation in the multiwavelet domain with the medium of linear functions. Delay with the signal is affordable due to the feature extraction process. The temporal function of the EEG signal is independent and the sources within the function depend upon the number of sensors used. The sensor count is represented as N. In the separate sources N represents the number of sensors used in the ICA algorithm [4]. On the account of EEG signal, the multichannel recordings were undergone with the combination of both the brain activity and the artifact signal. The proposed algorithm consists of ICA algorithm which includes the complex blind source. The complex blind source has the problem of separation which is used to recover the independent sources. The input source signal is represented as the \{s_1(t), \ldots, s_n(t)\}. The value of the matrix is obtained from the derived source signal. The square matrix of the derived input signal is represented as the W that has subjected towards the spatial filters. In the EEG signal, the row of the matrix is represented as the x which is obtained from the different position of electrodes. The output of this row matrix is obtained is represented as U=Wx with the time dependent. In this ICA analysis, the column obtained from the inverse matrix is indicated as W^{-1} which has the higher strength due to the individual element of the electrode parameters. The topography consist of various information which is depends upon the position of the input signal. The denoising signal which is expressed in the
form of $x'' = W u''$ where the $u''$ is the matrix implementation which has the rows and columns that set towards zero. The ranking of the EEG signal depends upon the denoising and noising signal. The proposed ICA technique of the EEG signal involves various limitations. The proposed ICA implementation brings out better accuracy in the EEG signal analysis but also various limitations undergone based on the filter. This ICA method is used for testing the limited amount of data because of its statistical value [5]. The testing data which is available is subjected towards the spatial filtering which removes the spreaded artifacts within the signal. The main reason for the development of artifacts within the signal is due to the cerebral activities which are analyzed in the spatial domain and the sources of the noise within the required time. The noise dependency should be lesser than that of data channels. In the general consideration, the artifacts are originated from the noise disturbance due to the cerebral activity and the timing difference of the source signal. The limitation of the proposed work is that the artifacts removal process needs the ICA components which is to be determined from the components which is to be removed from the signal. This method is applicable for the real time artifact removal in the clinical diagnosis of the EEG signal.

2.3. Proposed Canonical Correlation Analysis

The multivariate noises are originated from analysis of cocktail party problem. This problem requires the Canonical Correlation Analysis method (CCA) to remove the noises from the signal. This technique is used to overcome the limitations of Independent Component Analysis (ICA). This technique includes the Blind Source Separation (BSS) technique which removes the artifacts in the EEG signal. The auto-correlation characteristics are the major process used in the CSS technique and it is indicated as the contrast function. When the two multidimensional signal is considered, the linear relationship of the signal depends upon the correlation analysis. This method is mainly used for the lesser amount of error factor within the signal and it can also be implemented within the real time environment.

2.4 Analysis of Wavelet Transform

The wavelet transform technique is emerged recently and implemented in various signal processing applications which can be used to represent real-time non stationary signals efficiently with time specific parameters. In specific, the wavelet transform is a benchmark technique and certainly it is an alternative tool for traditional time-frequency representation transforms such as the discrete Fourier transform, discrete sine transform, discrete cosine transform and its other variants. The wavelet transform has been used widely in various applications such as transient signal analysis, computer vision, image/video compression, numerical analysis of real time signals and also many other audio-video applications because of its multi-resolution representation capability. This kind of transform domain is mostly required to be implemented in applications such as consumer electronics and it results a single chip hardware implementation which is more appropriate than a implementation of multi-chip based parallel system.

The wavelet transform is a transform domain analysis which is similar to the conventional Fourier transform or particularly more specific to the windowed Fourier transform and it has entirely distinct merit function. The major difference is that the Fourier transform basically decomposes the signal into sinusoidal and cosine components, i.e. the trigonometric functions are localized in Fourier space in contrast to the wavelet transform which uses the functions that are specified and localized in both the time domain and Fourier domain. Generally, the wavelet transform can be defined by the following expression:

$$F(a, b) = \int_{-\infty}^{\infty} f(x) \psi^*(a, b)(x) \, dx$$

(1)

Where the symbol * represents the complex conjugate and the symbol $\psi$ represents the sum function. Generally, this functional parameters can be specified arbitrarily provided that it adheres some defined rules.
As it is perceived that the wavelet transform contain an infinite set of distinct transforms primarily based on the merit functional characteristics which are used for its effective computational aspects. This is the primary reason, that we are use the term “wavelets transform” in very distinct situations and several applications. In addition, there are different ways and means to sort the variants of the wavelet transforms. In this research, we summarize the division based on the orthogonal properties of wavelets. We can use the orthogonal properties for the discrete wavelet transform development and non-orthogonal properties for continuous wavelet transform development. The properties of the two transforms are mentioned below:

1. The discrete wavelet transform gives a output data vector of the same size as the applied input. Generally, in this output vector most of the data are non-significant and it is represented as zero. This is mainly related to the fact of transform domain that the coefficients are decomposed into a subset of wavelet functions which are orthogonal in to its scaling and translations. Hence, we can able to decompose the signal in to an equal or lower the number of the wavelet coefficient of spectrum as contained in the number of signal data points. This kind of wavelet spectrum is very useful for the signal analysis and compression applications because of the absence of redundant information.

2. In contrary, the continuous wavelet transforms gives an array of one dimensional data which is larger than the applied input data. For instance, a 1D data obtained from an image in its time and frequency plane. This can be easily interpreted that the signal frequencies originated during the period of the particular signal and can be compared its spectrum with respect to other spectra of signals. When we used the type of non-orthogonal set of wavelets in which the data are highly correlated thus it lead to large redundancy of information.

2.5 Denoising Using Multiwavelet Transform

Denoising is defined as the technique of removing the noise from the input signal which is from the unknown sources. The noise removal from the input signal is initiated from the Donoho and Johnstone (1995). There are various procedures involved in the noise removal process. The procedure is initiated is as follows.

Initially, the wavelet with the order N and the original input source signal is subjected towards the N factor using the Discrete Wavelet Transform (DWT) which gives subjected to produce the co-efficient due to the different scaling factors with the various magnitude functions.

Noise removal in this method is based on each and every level, N level of noise is removed from the detail basis functions using one of the two processes mentioned below:

- In wavelet transforms maxima in which noise is totally eliminated and enhances the information of the original signal. The computational process is however non-stable and the amount of calculation is great.
- Wavelet thresholding technique which was proposed by Donoho is implemented in our work.
- When threshold is applied, the coefficients are categorized based on its magnitude levels. Generally, noisy signals produces coefficients with smaller magnitudes than those of the natural signal and also according to Donoho and Johnstone, the denoising using basic wavelets is performed by considering the WT of the signal, s[t] contaminated with noise and then centering out the detail coefficients of the signal that fall below a certain noise threshold. Subsequently, the other coefficients which are larger magnitude levels are usually caused by the desired signal.
  - Keep (hard-thresholding) or
  - Shrunk (soft-thresholding)[7]

Finally, denoised signals are firmly reconstructed from the wavelet coefficients using an reverse wavelet transform which is applied to the signal with appropriate threshold in order to yield an estimate for the true signal stated as the following equation,
\[ X[t] = D(s[t]) = W^{-1}(A(W(s[t]))) \]

Where, \( ^st \) is the diagonal thresholding operator that zeroes out wavelet coefficients less than the threshold, \( t \).

### 3. PROPOSED METHODOLOGY

Multiwavelets can be well-defined with the distinct number of wavelets along with many scaling functions (Geronimo, J., D. Hardin, & P. R. Massopust, 1994). Multiwavelets offer good number of advantages with respect to scalar wavelet (Strang, G. & V. Strela, 1995). This kind of wavelets support diverse features such as compact support, symmetric, high order approximation, orthogonal and are play a vital role in signal and image processing applications, but a scalar wavelet does not support all these characteristics features simultaneously (Strang, G. & T. Nguyen, 1995). Fortunately, multiwavelet system have a significance to support for perfect reconstruction of the signal while preserving inherent features such as length with its orthogonal property, greater performance particularly at the edges through the property of linear-phase symmetry, and also have a higher order of approximation.

Thus multiwavelet provides a high degree of freedom specifically in image analysis and processing applications with the possibility of greater performance in comparison with the scalar wavelets. In a multiwavelet functions, \( r \) representing scaling functions and when it comprises \( r \) wavelet functions then it is said to be multiplicity of \( r \). If \( r = 1 \), it means that it has only one scaling function and one wavelet function subsequently [8]-[10] then the multiwavelet system lead to the scalar wavelet system. Multiwavelets contain two or multiple scaling functions and wavelet functions. The set of scaling functions can be represented by vector notation and it is shown as follows,

\[
\Phi(t) = [\phi_1(t), \phi_2(t), \ldots, \phi_r(t)]^T
\]  

where, \( \Phi(t) \) represents the multiple scaling function. Similarly, the multiwavelet function can be defined from the set of individual wavelet functions and are expressed as follows,

\[
\psi(t) = [\psi_1(t), \psi_2(t), \ldots, \psi_r(t)]^T
\]  

\( r=1, \psi(t) \) which is represented as a scalar wavelet is indicated as a wavelet of the source EEG signal. Multiwavelets which is different from the scalar wavelet system consists of various input signal that is subjected towards the multiwavelet filter bank. This multiwavelet waveform is considered with the vector cases which have the lesser noise signal. By the presence of scalar wavelet with the original EEG signal, the Multi Resolution Analysis (MRA) is carried out as the major principle. The main differences which is gathered from the original denoised signal and the noised signal is the inheritance scaling factor and basic function of the wavelet domain is expressed as the following with the \( V_0 \) and \( V_1 \) with the \( N \) scaling factors.

\[
\Phi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} H_k \phi(t-k)
\]

Subsequently, the multiple scaling functions and the multiwavelet function would satisfies the matrix dilation as expressed in the following equations,
\[
\psi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} G_k \phi(2t-k)
\]

Figure 1. Flow chart for various steps of artifacts removal

The figure 1 clearly explains the various steps of our proposed method of artifacts removal. The above equation includes the filter coefficients which includes the representation of \( H_k \) and \( G_k \) are \( N \times N \) transform functions. As the matrix is formed using the derived function using the filter bank. The matrix which is formed using the derived values consists of \( N \times N \) matrix. This derived matrix has the „Taps‟ which consists of \( N \) number of Rows and \( N \) number of Columns. This matrix is indicated as the variable „C‟. With the unitary filter bank consideration, four matrices with \( N \times N \) rows and columns which is represented as \( D \). The designing consists of low pass filter bank system with the input data as \( N \). The \( N \) is the input data which depends upon the rows and columns. The Figure 2 shows the input source streams with the down sampled factor by 2.

Each rows within the filter bank is represented as the \( N \) number of filtering bank which consists of various input data streams. Various considerations were taken to consider multiwavelet transform. The reasons are listed as the following.

1. Multiwavelet is considered in the proposed work due to the inherent properties which reduces the filter constraint properties.
2. Symmetric signal always required symmetrical filter which is the major consideration of using the multiwavelet.
3. Orthogonality property enables the transform domain which is easy to design and implement the customized applications.
4. Multiwavelets generally possess all these significant properties simultaneously in contrast to the constraints in the scalar wavelets, [11].

Also, the major required feature of any transform domain used for the implementation of image compression applications is the energy compaction property and it is supported by multiwavelet system. The energy compaction properties of a filter system can easily decorrelates uniformly distributed source signal into a various number of micro particles called scaling coefficients which contains maximum energy distribution along with a large number of sparse representation of wavelet coefficients factor [12]. This characteristics are very important during the process of quantization, because the wavelet coefficients are significantly represented with a fewer bits than the scaling coefficients. The performance improvement is done using the wavelet co-efficient. This value is centered with the zero with the variation in the variance of the signal[13]-[15]. Due to this, the quantization of the signal due to the noise is lesser. Hence, multiwavelets exhibit the great potential to provide an appropriate reconstructive quality maintaining with the equal bit rate.

4. VARIOUS DENOISING TECHNIQUE USING MULTIWAVELET

Consider that an EEG signal is acquired in which an external noise is embedded on it. This EEG signal is the true signal represented as, $S(t)$ and the external noise is represented as $\varepsilon(t)$, So that the acquired signal can be expressed in the form stated as follows,

$$X(t) = S(t) + \varepsilon(t)$$  \hspace{1cm} (7)

The only presumption required that the parameters $S(t)$ and $\varepsilon(t)$ are considered as uncorrelated and stationary processes and it can be written as in equation (7). Thresholding is a method used for signal and image denoising applications. When the decomposition process is carried out in the original signal, the wavelet transform is the major technique carried out with the wavelet co-efficient of higher frequencies. They have the correlation towards the higher frequency in the sub bands. The sub bands comprises of details of the input dataset. The dataset can be affected when there is any loss of features in the signal [16]-[18]. The de-noising of the EEG signal is carried out using the threshold values with the different combinations of parameters of thresholding and window size consideration.

The thresholding value which is obtained using the denoising procedure is the complex structure. This process is the difficult step which removes the various artifacts from the original signal. The major disadvantage of this procedure is the loss of information in the test data. The proposed work represents the statistical analysis equation, that can be applied for calculating the thresholding values and the limits. The improvement within the signal is done using the derived formula. Threshold based on Statistics of the signal

Threshold Value

$$T_k = \frac{N}{\sqrt{\frac{\mean^2}{x^2} + \sigma^2}}$$ \hspace{1cm} (8)

Window Length=10 Seconds

Where, $N$ represents the positive integer ranges from 100 to 150
$x$ represents the mean value of all samples
$\sigma$ represents the standard deviation of all samples

5. RESULTS AND DISCUSSION

The source EEG signal is collected from the database link of
http://www.sccn.ucsd.edu/~arno/famzdata/publicly_available_EEG_data.html for the analysis of the proposed work. The artifacts which are present within the frontal channels and frontal–polar channels of Fp1, Fp2, F7, F8 of EEG signal has the primary dominating factors. Therefore, the proposed work can be tested with the higher accuracy range. In the Multiwavelet transform, denoising of EEG signal is done using the threshold value obtained from the thresholding method with the consideration of different types of window size. By the consideration of thresholding limit and the thresholding functional value the artifacts within the signal can be removed. With the removal of artifacts within the signal, the Error within the signal can be removed without removal of required information of the EEG signal [20], [21]. The Figure 3, Shows the Original EEG and Figure. 4 is Known as Noisy EEG. The Figure 5 is noise removed signal using multiwavelet transform. Denoised signal using Multiwavelet transform and original EEG is same.

![Original EEG](image1)

**Figure 3.** Original EEG

![Noisy EEG Signal](image2)

**Figure 4.** Noisy EEG Signal

![Denoised Signal Using Multiwavelet](image3)

**Figure 5.** Denoised Signal Using Multiwavelet Transform
Figure 6 represents the power spectral analysis of both denoised EEG signal and the noise affected EEG signal. The figure implements that the power spectral components of the proposed method is lesser as compared with the noisy signal.

The figure 7 shows the power spectra plot for original EEG, Noisy signal and Denoised signal using multiwavelet transform. The performance of the EEG signal is analyzed using the performance metric parameters such as Signal to Noise Ratio (SNR) which is shown in the Table 1. The Tabulation implements that if the error within the EEG signal is high, the SNR value will be high due to the noise within the signal. The denoised signal will have the lesser SNR value as compared with the noised signal [22]

| Table 1. Signal to Noise ratio values |
|--------------------------------------|
| Noisy Signal                        | Denoised Signal (Using Multiwavelet Transform) |
| 5.006                                | 11.7763                                      |

The proposed cross correlation technique within the source EEG signal and the noise affected EEG signal EEG is shown in the table 2. This analysis was made with the consideration of shape parameter in both the signals.

| Table 2. Correlation factor values |
|-----------------------------------|
| Correlation factor for Noisy Signal | Denoised Signal (Using Multiwavelet Transform) |
| 0.3966                             | 0.9692                                        |
6. CONCLUSION

The implemented work consists of various validation parameters which detect the several artifacts within the several signals. In this proposed work, adaptive thresholding is carried out to avoid the effect of ocular artifacts within the signal with the help developed thresholding formula. This developed work gives the better results than the various conventional methods with the source file as the EEG signal. The performance of the proposed work can be analyzed with the help of parameters such as power spectral density, Signal to Noise Ratio (SNR), correlation parameters. These experimental results shows that the multiwavelet decomposition have the lesser complexity as compared with the other techniques and produced the better results with the removal of various artifacts within the signal. By the removal of artifacts within the signal, the quality of the signal increases with the elimination of various error parameters within the signal.

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