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Artifact Removal from EEG using Kurtosis Based Blind Source Extraction and Spatially Constrained Independent Component Analysis followed by Wavelet Denoising

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Abstract— **this paper presents a novel technique for removing the artifacts from the Electro-Encephalo-Gram (EEG) signals. EEG signals are influenced by different characteristics, like line interference, EOG (Electro-Oculogram) and ECG (Electrocardiogram). The elimination of artifact from scalp EEGs is of substantial significance for both the automated and visual examination of underlying brainwave actions. These noise sources increase the difficulty in analyzing the EEG and obtaining clinical information related to pathology. Hence it is crucial to design a procedure to decrease such artifacts in EEG records. This paper uses an online blind extraction algorithm, suitable for the generality of complex-valued sources, both complex circular and noncircular, is introduced. This is achieved based on higher order statistics of latent sources, and using the deflation approach SpatiallyConstrained Independent Component Analysis (SCICA) to separate the Independent Components (ICs) from the initial EEG signal. As the next step, Wavelet Denoising (WD) is applied to extract the brain activity from purged artifacts, and finally the artifacts are projected back and subtracted from EEG signals to get clean EEG data. Here, thresholding plays an important role in delineating the artifacts and hence a better thresholding technique called Otsu's, thresholding is applied. Experimental results show that the proposed technique results in better removal of artifacts.**

Keywords— **Electro-Encephalo-Gram (EEG), EOG (Electro-Oculogram), ECG (Electrocardiogram), SpatiallyConstrained Independent Component Analysis (SCICA)**
Wavelet Denoising (WD)

I. INTRODUCTION

Human brain possesses rich spatiotemporal dynamics because of its complicated nature. Electroencephalography (EEG) provides a direct determination of cortical behavior

Electroencephalogram (EEG) is multivariate time series data measured using multiple sensors positioned on scalp that imitates electrical potential produced by behaviours of brain and is a record of the electrical potentials created by the cerebral cortex nerve cells. There are two categories of EEG, based on where the signal is obtained in the head: scalp or intracranial. Scalp EEG being the main focus of the research, uses small metal discs, also called as electrodes, which are kept on the scalp with good mechanical and electrical touch. Intracranial EEG is obtained by special electrodes placed in the brain during a surgery. The electrodes should be of low impedance, in order to record the exact voltage of the brain neuron. The variations in the voltage difference among electrodes are sensed and amplified before being transmitted to a computer program.

EEG offers a continuous graphic display of varying voltage with time.

However, the captured EEG [4-7] includes artifacts in the waveforms. Several researches have been conducted to remove the artifacts in the EEG signal and various techniques are resulted due to this research. This paper proposes a new technique for removing the artifacts [8, 9] from the EEG signal which uses kurtosis based on difference of Gaussian and Super-Gaussian signal and Spatially-Constrained ICA (SCICA) [12, 13] and wavelet denoising techniques. Threshold plays an important role in separating the artifacts from the non artifact EEG [17]. Otsu's Threshold is been adopted as the thresholding method in this paper. This method assumes that EEG contains two classes namely, artifact and non artifact signal and then it calculates the optimum threshold separating those two classes.

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with millisecond temporal resolution when compared to other techniques.

II. Related Work

Shao et al., [1, 2] proposed an automatic EEG Artifact removal which uses a Weighted Support Vector Machine approach with error correction. An automatic electroencephalogram (EEG) [15- 16] artifact removal method is presented in this paper. Compared to past methods, it has two unique features:

1) A weighted version of support vector machine formulation that handles the inherent unbalanced nature of component classification and

2) The ability to accommodate structural information typically found in component classification.

The advantages of the proposed method are demonstrated on real-life EEG recordings with comparisons made to several benchmark methods. Results show that the proposed method is preferable than the other methods in the context of artifact removal by achieving a better tradeoff between removing artifacts and preserving inherent brain activities. Qualitative evaluation of the reconstructed EEG epochs also demonstrates that after artifact removal inherent brain activities are largely preserved.

Kavitha et al., [3] suggested a modified ocular artifact removal technique from EEG [10, 11] by adaptive filtering. Electroencephalogram (EEG) is the reflection of brain activity and is widely used in clinical diagnoses and biomedical researches.

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EEG signals recorded from the scalp contain many artifacts that make its interpretation and analysis very difficult. One major source of artifacts is from eye movements that generate the Electrooculogram (EOG). Many applications of EEG such as Brain Computer Interface (BCI) need real time processing of EEG [14]. Adaptive filtering is one of the most efficient methods for removal of ocular artifacts which can be applied in real time. In conventional adaptive filtering, the primary input is the measured EEG and the reference inputs are vertical EOG (VEOG) and horizontal EOG (HEOG) signals. In this paper, an adaptive filtering approach is proposed which includes radial EOG (REOG) signal as a third reference input. The analysis based on the performance of adaptive algorithms using two reference inputs i.e. VEOG and HEOG and that with three reference inputs i.e. VEOG, HEOG and REOG , it is found that the proposed 3 reference method gives more accurate results than the existing two reference method.

III. METHODOLOGY

The architecture of the proposed method for pre-processing of EEG data is presented in figure 1.
As represented, EEG data implicated is generated based on ICA model as:

$$\mathbf{x(t)\ As(t)\ v(t)} \qquad \mathbf{(1)}$$

where x(t) = [x1(t), x2(t), · · · , xM(t)]T, which is a linear mixture of N sources s(t) = [s1(t), s2(t), · · · , sN(t)]T, A is M×N mixing matrix, and v(t) = [v1(t), v2(t), · · · , vM(t)]T is nothing but the additive noise at the EEG sensors. Here the number of sources is represented as N and the waveforms are represented as si(t), and mixing matrix A are all unknown. In order to make the problem simple, the square mixing problem is considered, i.e., M = N. The source signals si(t) can be regarded as being created from various brain regions and artifacts. These artifacts mask the brain activity data, and are dangerous for further examination and processing. Thus it is especially vital to process EEG data x (t) so that contribution of artifacts is separated, without damaging the brain-activity data, and is the key focus of the technique provided by the author. As represented in figure 1, the proposed technique consists of following key process:

- *Pre-processing with the help of existing filtering uses kurtosis based on difference of Gaussian and Super-Gaussian signal.*
- *Use SCICA to obtain SC-ICs representing artifacts in EEG data.*
- *Use Wavelet Denoising (WD) to separate any brain activity leaked to these artifact ICs.*
- *The extracted artifact-only signals are projected back, and subtracted from, EEG data to get clean EEG for further examination and processing.*

The purpose of conventional filtering is to process raw EEG data x(t) to eliminate 50 Hz line noise, baseline values, artifacts which dwell in very low frequencies and high frequency sensor noise v(t), and this phase may include mixture of different existing notch, low-pass, and/or high pass filters.

Complex statistics: Kurtosis

Kurtosis, is a well understood concept in statistics of realvalued random variables, and has been used to design contrast functions in BSS, such as in the FastICA [30], and BSE algorithms [13]. It is common to use the normalised kurtosis KR(.) instead of the standard kurtosis kurtR(.) as it allows for the comparison of the Gaussianity of random variables, irrespective of the range of amplitudes. In [31], the extension and relevance of this concept to the complex domain, as well as the relation between the kurtosis of the real and imaginary components of a complex random variable, kurtR(zr) and kurtR(zi), and the kurtosis of the complex random variable kurtc(z) has been discussed. The real-valued normalised kurtosis of a complex random variable can be defined in several forms, where

$$K_c(z) = \frac{\mathrm{kurt}_c(z)}{(E\{|z|^2\})^2} = \frac{E\{|z|^4\}}{(E\{|z|^2\})^2} - \frac{|E\{z^2\}|^2}{(E\{|z|^2\})^2} - 2$$

$$\mathrm{kurt}_c(z) = E\{|z|^4\} - |E\{z^2\}|^2 - 2(E\{|z|^2\})^2$$

The first term in above equation is the normalised fourth order moment whereas the second term is the square of the circularity coefficient, and $\mathrm{kurt}_c(z)$ in above equation is the real-valued kurtosis of the complex random variable z. Similar to the kurtosis of a real-valued Gaussian random variable, the value of Kc is zero for both circular and noncircular complex Gaussian random variables. Furthermore, in this measure, kurtosis values of a subGaussian complex random variable are negative and that of a super-Gaussian complex random

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variable is positive, irrespective of the circularity/non-circularity of the random variable.

Spatially-Constrained ICA (SCICA)

The main process in the proposed technique is the application of SCICA to obtain artifact ICs from filtered and baseline corrected EEG data y (t). Description of SCICA is portrayed in detail. The key intention is to depict a Spatial Constraint (SC) on the mixing matrix A to symbolize specific prior knowledge or prior assumptions concerning the spatial topography of some source sensor projections, i.e., the SC operates on chosen columns of A and is enforced with reference to a set of predetermined constraint sensor projections, represented by Ac. Thus, the spatially constrained mixing matrix consists of two kinds of
columns

$$A = [Ac, Au] \qquad (2)$$

Where A~Ac, are columns which are regarded as constraint, and Au otherwise regarded as Unconstrained columns. Based on the usage, the predetermined sensor projections could be gathered by manual choice of sources extracted from a previous information segment with the help of existing ICA technique or derived from the predictions of some mathematical model of the signal obtaining procedure under examination.

Based upon the confidence level regarding the accuracy of the constraint topographies Ac, and the level to which constrained columns may diverge from reference Ac, there are three kinds of constraints:

1) Hard constraints representing fixed column, 2) Soft constraints permitting divergence within a small angular threshold α, and

3)Weak constraints that only afford an initial approximation for otherwise unconstrained assessment. The spatially-constrained-FastICA (SCFastICA) technique is the one categorized under soft SCs.

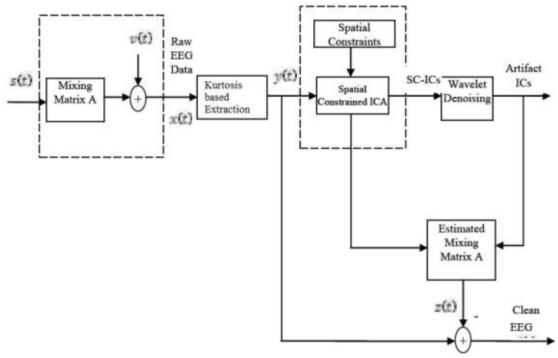

Figure1: overall process of artifact removal

The SCFastICA technique aims to maximize the statistical independence of the unconstrained sources and at the same time reducing the divergence among the spatially constrained source sensor projections and their corresponding reference topographies. A deflationary technique is implemented to take out only desired components, and therefore the output of the SCFastICA technique is SC-ICs (which are artifact signals in our case), and an estimate of corresponding mixing matrix. This results in fast computational time, as compared with if all ICs are extracted.

Wavelet Denoising (WD) of SC-ICs

It is significant mentioning that SC-ICs determined by SCFastICA are expected to correspond to artifacts only; on the other hand, some brain action might escape to these gathered signals. The purpose of conventional filtering is to process raw EEG data x(t) to eliminate 50 Hz line noise, baseline values, artifacts inhabiting very low frequencies and high frequency sensor noise v(t), and this phase may include mixture of different existing notch, low-pass, and/or high-pass filters. As artifacts have a frequency overlap with the brain signals, conventional filtering technique cannot be utilized, and therefore this paper focuses on using Wavelet Denoising to take away any brain activity from gathered SC-ICs.

The Discrete Wavelet Transform (DWT) examines a finite length time domain signal by breaking up the initial domain in two phases: the detail and approximation data. The approximation domain is sequentially decomposed into detail and approximation domains. The basic principle is that the decomposition of a noisy signal on a wavelet basis (by DWT) has the property to “concentrate” the informative signal in few wavelet coefficients having large absolute values without altering the noise random distribution. After performing these

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operations, the noise coefficients have minimum values, inversely to the informative signal (normal or pathologic neural activity and artifacts). Consequently, denoising can be attained by thresholding the wavelet coefficients using Otsu's thresholding method. The Implementation is as follows:

- Choosing the value of the threshold using Otsu's Thresholding Method
- Then DWT is performed to the SC-IC signal to obtain details and approximations
- Threshold the detailed components obtained in the previous step
- Finally inverse DWT is utilized to obtain only the artifact signal

Otsu's Thresholding Method

In computer vision and image processing, Otsu's method is used to automatically perform histogram shapebased image thresholding, or the reduction of a gray-level image to a binary image. The algorithm assumes that the image to be thresholded contains two classes of pixels or bi-modal histogram (e.g. foreground and background) then calculates the optimum threshold separating those two classes so that their combined spread (intra-class variance) is minimal. The extension of the original method to multilevel thresholding is referred to as the Multi Otsu method. Otsu's method is named after Nobuyuki Otsu.

IV. EXPERIMENTAL RESULTS

This section presents the evaluation of the proposed artifact removal technique. Initially, EEG signals are captured with occurrence of artifacts. The captured EEG signal is shown in figure 2. The results obtained are depicted in figure 3 and figure 4.

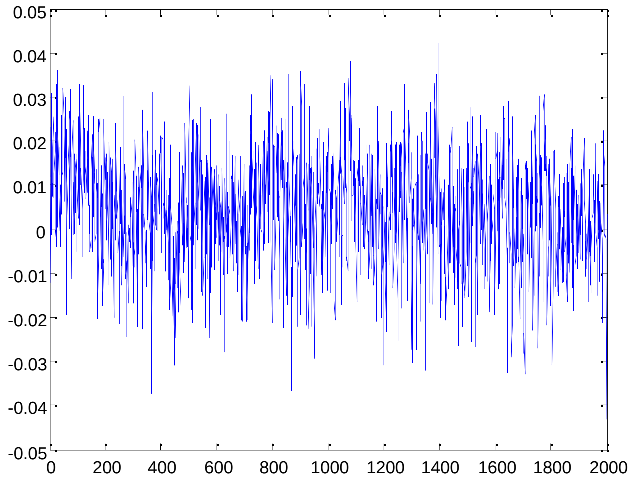

Figure2: Original Electroencephalogram Signals

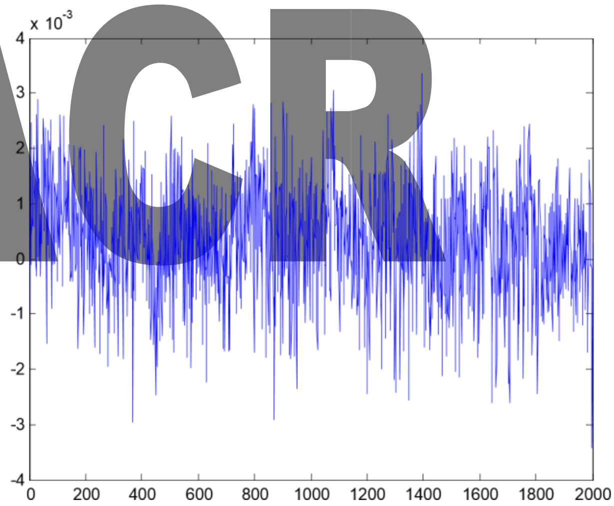

Figure3: Kurtosis Based Blind Source Extraction of Complex Noncircular input Signals

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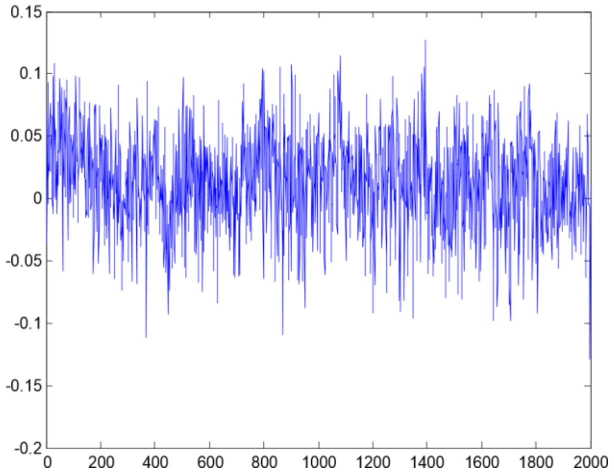

Figure4: Spatially Constrained Independent Component Analysis on Conventionally Filtered transformation matrix

The signal resulted after the usage of wavelet Kurtosis Based Blind Source Extraction and Spatially-Constrained ICA is shown in figure 2(b) and 3(b). Final signal obtained by using the otsu's thresholding technique is shown in figure 2(c) and 3(c). From the figures, it can be observed that the proposed artifact removal technique results in better removal of artifacts when compared to the existing technique. This will help in improving the performance of the further processing with this obtained EEG signal.

V. CONCLUSIONS

This paper focuses on removing the artifacts from Electroencephalogram (EEG) signals. Artifact removal is an important process before analyzing the EEG signal for prediction of any Pathological diseases. Various researchers have focused on this process and developed their own Technique for artifact removal. This paper intends on developing a new technique to remove the artifact from EEG.

The proposed approach uses Kurtosis Based Blind Source Extraction and Spatially-Constrained Independent Component Analysis (SCICA) to separate the exact Independent Components (ICs) from the initial EEG signal. Then, Wavelet Denoising is applied to extract the brain activities from purged artifacts, and finally project back the artifacts to be subtracted from EEG signals to get clean EEG data. The thresholding technique used in this paper is otsu's thresholding. Experimental evaluation suggests that the proposed approach results in better removal of artifact when compared to the existing techniques.

ACKNOWLEDGMENT

The heading of the Acknowledgment section and the References section must not be numbered.

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