Denoising EEG using mMSE, Kurtosis and Wavelet-ICA

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***Abstract*—Electroencephalogram (EEG) is electrical signal recorded from the scalp which represents the neural activity of human brain. EEG is often contaminated by the ocular artifacts viz. saccades, voluntarily or involuntarily eye movement and eye blink. Various methods have been proposed both in signal processing field as well as in neuroscience for identification and correction of ocular artifacts. Among many methods based on wavelet transform, adaptive filters, independent component analysis have shown promising results in removal of such artifacts. In this paper unsupervised robust and computationally fast algorithm using multi scale sample entropy (mMSE) and Kurtosis is used to automatically identify independent artifactual components and then denoising these components using wavelet decomposition. Results have shown improved reconstructed EEG signals. The proposed algorithm does not need manual identification of artifactual components.**

Keywords— Electroencephalography (EEG), ocular Artifact (OAs), discrete wavelet transform (DWT), Kurtosis, modified multi-scale sample entropy (mMSE)

I. INTRODUCTION

EEG is recording of electrical signal generated due to neural activity in the brain and it is used to diagnose different abnormalities viz. sleep disorders, brain death, coma, tumors, epilepsy, trauma, stroke etc. The signal is recorded either by placing electrodes on scalp or by recording local field potential from prefrontal cortex. A signal generated in the absence of any stimulus is termed as spontaneous EEG whereas signal generated with an external stimulus is known as Event Related Potential (ERP). For a normal person, EEG amplitude ranges from $10-100\mu V$ having following frequency components:

$$Delta(0.1-4Hz), Theta(4-8Hz), Alpha(8-13Hz), Beta(13-30Hz), Gamma(above\ 30Hz).$$

The recorded EEG signal is often contaminated by spurious signals from other unwanted sources. This kind of contamination in medical terminology is named as artifact. An erroneous potential difference appears at the electrodes due to presence of these artifacts in the EEG signal. Among these artifacts, most of them are Electro-oculogram (EOG) due to eye blink or eye movement; muscle activity and Electrocardiogram (ECG) due to electrical activity of heart [1]. An optimized way to correct for an EEG contaminated with EOG signal is to first detect the EOG signal and then to clean the corresponding EEG signal instead of cleaning the whole EEG signal. This method is not only computationally efficient but is also cost effective.

The EEG data set used in this work is created by BIH Sleep Laboratory. The dataset can be downloaded from Physio-Net ATM [2]. The dataset consists of 7 recorded channels, each having 2500 samples with sampling rate of 250 Hz, and existing MATLAB code [3] is used for FastICA.

From the dataset, we took an EEG signal and an EOG signal and then mixed these two signals to form a two channel corrupted EEG signal. This corrupted EEG signal is utilized for the examination of mMSE based algorithm for artifact removal.

In this work, Section 1 describes dataset used for this work. Section 2 gives related work for artifacts removal from EEG. Section 3 demonstrates the mMSE based algorithm used for the detection and correction of the EEG signal. Performance measurements and quantitative analysis is given in Section 4. Results, discussion and conclusion are presented in Section 5.

II. RELATED WORK

In recent years, research community both in medical science and in engineering has examined the various artifacts present in EEG. Among these artifacts, ocular artifacts are shown to cause a significant deterioration of EEG signal. Several methods to remove ocular artifacts have been proposed from decades.

V. Krishnaveni et al. [4] attempted to deal with such artifacts using wavelet based adaptive thresholding algorithm only to the identified OA zones. Adaptive thresholding applied only to OA zones preserves the shape of EEG signal in non artifact zones. The method has been shown to give promising results in removal of ocular artifacts in their method. Power spectral density plots and frequency correlation plots are used, which gives only an estimate in providing an interference relating to relative superiority of algorithm used for removing ocular artifact removal from EEG. In the algorithm, finding of artifact rising and falling edges are complex, locating the OA zones and calculating the edges is lengthy. Further, performance indices based on power

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density spectrum have only been evaluated keeping a blind eye on SNR.

R. Coifman et al. [5] used translation-invariant de-noising of EEG. The method work using the concept of cycle spinning added to wavelets. The rigorous mathematics behind Cycle Spinning and wavelets makes the detection and hence the removal of arti-facts viable, however the work does not specifically deal with ocular artifacts. There for the special features of ocular artifacts have not been exploited fully in the denoising procedure. This not only is prone of false detection results, but also gives poor precision to recall characteristics.

P. S. Kumar et al. [6] also attempted to identify and correct ocular artifacts in EEG. There method is based on SWT with Symlet (sym3) as basis function is decom-posed and the authors have claimed the filtered EEG signal with no ocular artifacts. However it lacks a strong quantitative analysis to justify the acceptable SNR level in the output signal. Furthermore the soft threshold used in the method is not always recommended from wide range of artifacts present in EEG.

M. A. Klados et al [7,8] compared three artifact removal methods automated regression filtering based on LMS adaptive filtering algorithm and two methods based on blind source separation (BSS) techniques.

P. S. Kumar et al. [9] used wavelet with adaptive filter. H. Ghandeharion et al. [10] used ICA. R. Mahajan et al. [11] used wavelet enhanced ICA.

This paper proposes an unsupervised fully automatic statistical threshold based eye blink artifact removal method using mMSE and Kurtosis to identify the artifactual blink components and multi-resolution wavelet analysis to denoise these components.

III. ARTIFACTS REMOVAL USING MMSE

This section describes automatic artifacts removal algorithm. Block diagram of the algorithm is shown in Fig. 1.

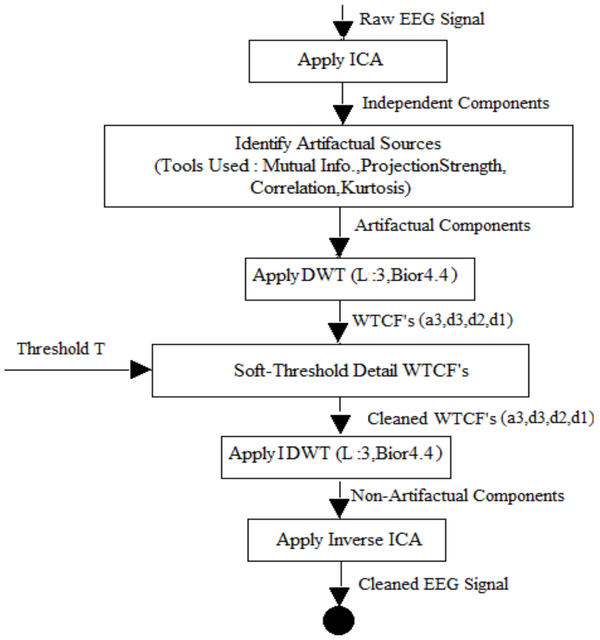

Fig.1: Block diagram of automatic artifacts removal algorithm using mMSE, Kurtosis and Wavelet-ICA.

Method proposed in is named as Wavelet-enhanced Independent Component Analysis modified multiscale sample entropy (WeICA-mMSE). The principal of operation of the method is 1) Apply ICA to the input, 2) Artifactual source Identification, 3) Replace artifactual component by its noise part 4) Apply inverse ICA to the non-artifactual sources.

In this method shown in Fig. 1, welICA independent components of input raw EEG signal are calculated using the tool InfoMAX. These independent components are normalized with respect to zero mean and unit standard deviation. To identify the Artifactual Components from the independent components, the following statistical tools are used 1) Kurtosis (Krt) of independent components, and 2) Modified Multiscale Sample Entropy (mMSE) of the normalized independent components. In this work, EEG signal is used with number of channel (N) = 12, therefore two sided 90% confidence interval of the mean for Student's t-distribution is used to detect the ocular artifacts. All the independent components with their mMSE values higher than the threshold are cerebral signals and other are marked as artifactual components. The threshold value is calculated using the following expression.

$$T_{mMSE} = \bar{x} - \frac{s}{\sqrt{N}} \times t_{N-1} \qquad (1)$$

where $\bar{x}$ is the sample mean, s is sample standard deviation, *(N-1)* is the degrees of freedom, $t_{(N-1)}$=6.3138 for two-tailed test with 1 degree of freedom.

To obtain higher accuracy, Kurtosis is also used for the identification of the ocular artifact. All the independent components with the Kurtosis values higher than threshold are marked as artifactual components and other are marked as cerebral activities.sed eye blink artifact removal method using mMSE and Kurtosis to identify the artifactual blink components and multi-resolution wavelet analysis to denoise these components.

$$T_{Krt} = \bar{x} + \frac{s}{\sqrt{N}} \times t_{N-1} \qquad (2)$$

Where $\bar{x}$ is the sample mean, s is sample standard deviation, (N-1) is the degrees of freedom, $t_{(N-1)}$= 6.3138 for two-tailed test with 1 degree of freedom.

Computation of the artifactual source identification is done using the above mentioned tools. Noise part (which is the high frequency part that corresponds to the neural activity) estimation of the artifactual components is done. The artifactual components are decomposed using the Discrete Wavelet Transform (DWT) using the Bi-orthogonal mother wavelet at the Level 4. Soft threshold is selected (as wavelet coefficients possess good continuity and are easy to process) and applied it to the wavelet coefficient at each level. The threshold value proposed in [4] is used. The threshold expression is given in equation 1. Wavelet reconstruction (Fig. 2) to the new wavelet coefficients is used and then the Inverse Independent Component Analysis is applied to obtain the clean EEG signal.

IV. PERFORMANCE MEASUREMENT

For the comparative evaluation of above mentioned six methods, two aspects are chosen.

A. Visual Inspection

It is done by plotting the 2 second epoch (each of 500 samples) of the detected EEG signal i.e. recovered EEG signal from the mixed EEG and EOG signals, and pure EEG signal.

B. Quantitative Inspection using Signal to Noise Ratio (SNR)

It is a measure that compares the level of desired signal to the level of background noise. It is the ratio of the signal power to noise power. The SNR value can be calculated using the following equation.

$$SNR = 20 \times \log_{10} \frac{RMS(Signal)}{RMS(Noise)} \qquad (3)$$

V. RESULTS AND CONCLUSIONS

Investigation on the artifacts removal using mMSE based algorithm is being explained in the following two subsections: Visual inspection and Quantative analysis using SNR.

A. Visual Inspection

Plot of amplitude vs. samples for this method is shown in Fig.2 Detected and Pure EEG for welICA algorithm (using tools Kurtosis and mMSE).

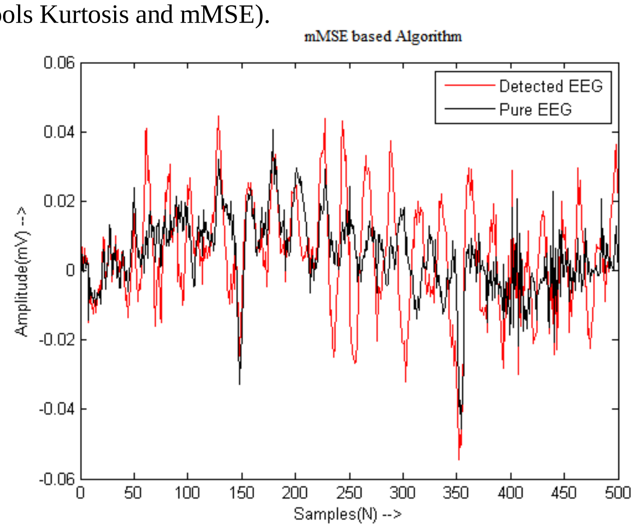

Fig.2: Amplitude vs. sample plot for automatic artifacts removal algorithm using mMSE, Kurtosis and Wavelet ICA

On the visual comparison of plots, it is evident that this Algorithm gives good overlapping between detected EEG and Pure EEG.

B. Quantitative Inspection using Signal to Noise Ratio

The signal to noise ratio as defined in equation no 3 has been calculated for the method. The found SNR for the various cases has been listed in Table 1.

First and second rows of Table 1 corresponds to SNR values of two channels A and B using Wavelet Enhanced (with tools Kurtosis and modified multiscale sample entropy (mMSE) [11] using Fast ICA algorithm [12] using existing MATLAB code [3] for FastICA.

This study recommends the algorithm should be used for ocular artifacts removal from EEG.

Table-1: SNR comparison

S. No.	SNR Comparison		
	Channel number	SNR of Raw EEG (dB)	SNR of detected EEG (dB)
1	A	0.047023	2.1853
2	B	0.026891	0.76003

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