Removal of ECG Artifact from EEG data using Independent Component Analysis and S-Transform

N.Narendra Kumar and Dr.A.Guruva Reddy

***Abstract*— The electroencephalogram (EEG) is a noninvasive method to study normal and abnormal brain activities. Sometimes the EEG recordings are contaminated by electrical potential produced by cardiac activity, resulting in spiky activities that are referred to as electrocardiogram (ECG) artifact. These artifacts are similar to epileptic spikes. While examine the epilepsy patient, it is great importance to remove those artifacts. To remove electrocardiograhic (ECG) artifacts in electroencephalogram (EEG) signal a method is being proposed which uses the combination of independent component analysis (ICA) and Stockwell transform**

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***Index Terms*— Electrocardiographic (ECG) artifact, electroencephalogram (EEG), independentcomponent analysis(ICA), stockwell transform (S-Transform).**

I.INTRODUCTION

The need for ambulatory electroencephalographic monitoring has increased in both clinical practice and research, in areas such as sleep/wake state or epilepsy monitoring .However, long-term recordings are vulnerable to various artifacts .In particular, cardiac activity may have pronounced effects on the electroencephalogram (EEG) because of its relatively high electrical energy, especially upon the noncephalic reference recordings of EEG.

Algorithms have been proposed to eliminate electrocardiogram (ECG) artifacts from the EEG. Nakamura and Shibasaki proposed an ECG artifact elimination algorithm, which we call the ensemble average subtraction (EAS) method, whereby ECG-contaminated EEG series are synchronously segmented with respect to the timing of consecutive ECG R-peaks. By subtracting the ensemble average across EEG segments from the contaminated EEG, the algorithm eliminates ECG artifacts. EAS is based on the strict assumptions of homogeneity across segments and Gaussian property of the EEG

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Using a different concept, the independent component analysis (ICA) method was also applied to eliminate ECG artifacts using multichannel signals . Previously, we adopted adaptive noise canceling theory to eliminate such ECG artifacts using a reference ECG channel. It should be noted that these algorithms use consecutive R-waves in a separate ECG channel as a reference, and therefore, cannot be applied when an ECG channel is not available. Several ambulatory monitoring systems used for studying sleep/wake states do not record ECG waveforms. Ambulatory sleep/wake recordings use a reduced number of essential channels, compared with the laboratory polysomnographic units. The electro- encephalogram (EEG), electrooculogram (EOG), and chin electromyogram (EMG) are necessary to assess the brain state, and nasal airflow, respiratory effort, oxygen saturation, and heart rate to monitor respiration and circulation. Recording heart rate is frequently preferred to recording the ECG waveform in order to reduce the data size when the ECG waveform is not a main concern. Therefore, a new method of eliminating ECG artifacts from the EEG is required when an ECG channel is unavailable. In this paper, we propose a method for removing ECG artifacts from EEG data,

II. DESIGN METHODOLOGY

In this project a component-based automatic algorithm for detection and removal of ECG artifact is presented that uses only measures that are specific to this artifact, i.e., being spiky, quasi-periodic and having a specific distribution on the scalp. The method applies a stockwell transformation (S-Transformation) to the ICs to detect any existing peaks and checks if they occur (quasi-)periodically. The component that satisfies these criteria and has the highest correlation to a pre computed scalp distribution is marked as being related to ECG and is rejected. Since the proposed algorithm is entirely specific to ECG artifact. To the best of our knowledge, stockwell transformation has not been used for detecting artifactual ICs, although stockwell transformation has been applied to enhance the performance of ICA.

The following block diagram shows the working of the proposed algorithm

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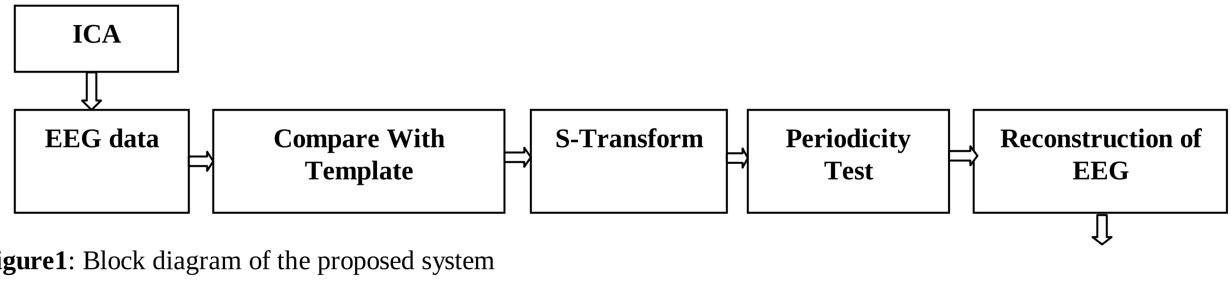

Figure1: Block diagram of the proposed system

Applying of ICA on EEG data: ICA is a higher order statistical technique that attempts to recover linearly independent components of an observed signal source by reducing statistical dependence of an observed collection of signals.ICA has been mainly used in feature extraction, and blind source separation with emphasis on physiological signals. ICA is a popular method for source separation with application in many different fields including de-mixing EEG data. The method works based on the assumption that the recorded channels are a linear mixture of independent non-Gaussian sources. One way to estimate these sources is to search for a linear combination of the recorded data that maximizes non-Gaussianity. The rational for this approach is that the sum of independent random variables usually has a distribution that is closer to a Gaussian than the original variables. To rigorously define ICA we can use a statistical latent variables model. Assume that we observe n linear mixtures $x_1,\ldots, x_n$ of n independent components

$$\mathbf{x_j = a_{j1}s_1 + a_{j2}s_2 + \ldots + a_{jn}s_n; \text{ for all } j.}$$

We have now dropped the time index t in the ICA model we assume that each mixture x_j as well as each independent component s_k is a random variable instead of a proper time signal. The observed values $x_j(t)$,e.g., the microphone signals in the cocktail party problem are then a sample of this random variable. Without loss of generality we can assume that both the mixture variables and the independent components have zero mean. If this is not true then the observable variables x_i can always be centered by subtracting the sample mean which makes the model zero mean.

It is convenient to use vector matrix notation instead of the sums like in the previous equation. Let us denote by x the random vector whose elements are the mixtures $x_1 \ldots\ldots x_n$ and likewise by s the random vector with elements $s_1 \ldots\ldots s_n$ Let us denote by A the matrix with elements a_{ij} Generally bold lower case letters indicate vectors and bold upper case letters denote matrices. All vectors are understood as column vectors thus x^T or the transpose of x is a row vector Using this vector matrix notation the above mixing model is written as

$$x = As$$

Sometimes we need the columns of matrix 'A' denoting them by 'a_j' the model can also be written as

$$x = \sum_{j=1}^{n} a_j s_j$$

The statistical model is called independent component analysis or ICA model. The ICA model is a generative model which means that it describes how the observed data are generated by a process of mixing the components s_i The independent components are latent variables meaning that they cannot be directly observed. Also the mixing matrix is assumed to be unknown. All we observe is the random vector x and we must estimate both A and s using it.This must be done under as general assumptions as possible. The starting point for ICA is the very simple assumption that the components s_i are statistically independent. It will be seen below that we must also assume that the independent component must have non-Gaussian distributions However in the basic model we do not assume these distributions known if they are known the problem is considerably simplified For simplicity we are also assuming that the unknown mixing matrix is square but this assumption can be sometimes relaxed as explained in Section Then after estimating the matrix A we can compute its inverse say W and obtain the independent component simply by

$$\mathbf{s = Wx}$$

ICA is very closely related to the method called blind source separation BSS or blind signal separation. A source means here an original signal .i.e. independent component like the speaker in a cocktail party problem. Blind means that we no very little if anything on the mixing matrix and make little assumptions on the source signals.ICA is one method perhaps the most widely used for performing blind source separation. In many applications it would be more realistic to assume that there is some noise in the measurements see e.g., which would mean adding a noise term in the model .For simplicity we omit any noise terms since the estimation of the noise free model is difficult enough in itself and seems to be sufficient for many applications

Detection of ECG related IC: Each column of the mixing matrix, as defined above, represents the scalp distribution of the corresponding IC.ECG artifact is known to have a recognizable pattern on the scalp, although the pattern is somewhat dependent on the position of the head and other parameters. In our method, after applying ICA, the ICs whose spatial distributions on the head were similar (absolute value of correlation coefficients larger than 0.6) to that of a template (see below for details on how the template is computed) were selected for further analysis. The ECG related independent component is spiky and periodic. A peak detection algorithm could be used check the whether or not a given Independent component has period peaks. This will be referred as the "periodicity test". Such peak detection algorithm, however would work much better on Stockwell transforms of independent components

Principle of S-Transform: The S-Transform was proposed in 1996 by Stockwell.It provides frequency-dependent resolution while maintaining a direct relationship with the

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Fourier spectrum. The ST originates from two advanced signal processing tools, the short time Fourier transform (STFT) and the wavelet transform (WT). It can be viewed as a frequency dependant STFT or a phase corrected wavelet transform. This transform provides a good time and frequency resolution. In addition, it allows us access to any frequency component in the time–frequency domain without requiring to any digital filter.

Derived from the STFT, the standard ST of a time varying signal $x(t)$ is given by

$$S(\tau,f)=\int_{-\infty}^{\infty} x(t)w(t-\tau)e^{-i2\pi ft}dt$$

where w(t) is a time window centered in $t = 0$ and used to extract a segment of $x(t)$. The S-Transform can be found by defining a particular window function w(t), a normalized gaussian

$$W(t)=\frac{1}{\sigma\sqrt{2\pi}}\, e^{(-t^2)/(2\sigma^2)}$$

where 'σ'characterizes the width of the gaussian window. Note that the gaussian window was chosen since it is the most compact in time and frequency. We allow w(t) a translation 'τ' and a dilatation (a variable width σ). A constraint is added to restrict the window width 'σ'to be a function of the frequency $\sigma(f)=1/|f|$,then w(t-τ)can be written as

$$W(t-\tau)=\frac{|f|}{\sqrt{2\pi}}\, e^{(-(t-\tau)^2f^2)/2}$$

The function S-Transform is then rephrased as

$$S(\tau,f)=\frac{|f|}{\sqrt{2\pi}}\int_{-\infty}^{\infty} x(t)\, e^{(-(t-\tau)^2f^2)/2}e^{-i2\pi ft}dt$$

where τ and f denote respectively the time of the spectral localization and Fourier frequency. The window width σ varying inversely with frequency makes S-Transform performing a multi-resolution analysis on the signal. At each instant t_0, the one dimensional function of the frequency variable f defined by $S(t_0, f)$ is a local spectrum. The one dimensional function of the time variable τ and a fixed frequency f_0 defined by $S(\tau, fo)$ is called a voice.The S-Transform can be seen as a continuous wavelet transform $W(\tau, d)$ with a specific mother wavelet and a phase factor correction

$$S(\tau, f)=W(\tau, d)e^{-i\pi 2ft}$$

Periodicity test: To determine if a given IC is periodic (has multiple quasi-periodic peaks), for any two consecutive detected peaks the quantity f = 1/T was calculated, where T is the elapsed time between the two peaks. In other words, for an IC with n detected peaks, a set of n − 1 frequencies and also their median, denoted by F, were computed. For an ECG IC, F would be very close to the average frequency of the heartbeat over that epoch of data being analyzed. An IC was considered periodic, and so a candidate for being related to ECG, if F satisfied all of the following: 1) $F \geq 2/3$ Hz (minimum heart rate); 2) $F \leq 3$ Hz (maximum heart rate); and 3) $N \geq [CFt]$, where N is the number of f s that are between $F(1 - D)$ and $F(1 + D)$ with $D = 0.25$, t is the length (in seconds) of the data being analyzed, [x] denotes the largest integer not greater than x, and C = 0.8. If F is the average heart rate, Ft will be the expected number of time intervals between consecutive peaks in the ECG-related IC. In other words, the third criterion guarantees that most members of {fi} are close to F, and that at least 80% of the expected time intervals have been detected.

III.ALGORITHM

Algorithm: Removal of ECG Artifact from EEG data using Independent Component Analysis and S-Transform

Input: Raw EEG data

Output: Artifact-free EEG

Steps:

- Apply Independent Component Analysis(ICA) on Raw EEG data. Then we get independent components(ICs)
- Compare these Independent components(ICs) with pre-computed ECG pattern. ICs whose scalp distribution have large correlation coefficients with pre-computed pattern of ECG are considered for further analysis.
- A Stockwell Transform is performed on those ICs
- Apply periodicity test on after performing of Stockwell Transform on those ICs. Reject the peaks occurred periodically.
- Reconstruct the EEG data

IV.DESIGN FLOW

The design flow diagram for "Removal of ECG Artifact from EEG data using Independent Component Analysis and S-Transform" is shown in below figure.

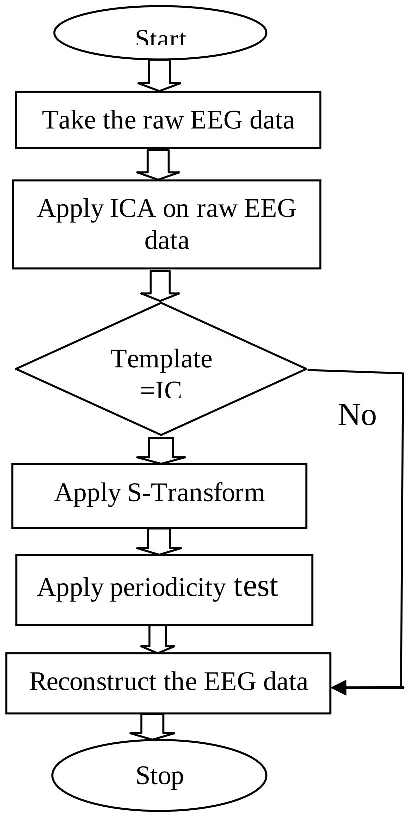

Figure2: Design flow of proposed system

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V. RESULTS SUMMARY

In this section, the results of electrocardiograhic (ECG) artifact removal from EEG data using independent component analysis (ICA) and S-transform are discussed. The performance of "Electrocardiographic (ECG) artifact removal from EEG data using independent component analysis(ICA) and S-transform is compared with Electrocardiographic (ECG) artifact removal from EEG data using independent component analysis(ICA) and continuous wavelet transform (CWT). In this project Output Signal To Noise Ratio (OSNR), Mean Square Error (MSE) and Entropy (H) are calculated to evaluate the performance of algorithm.

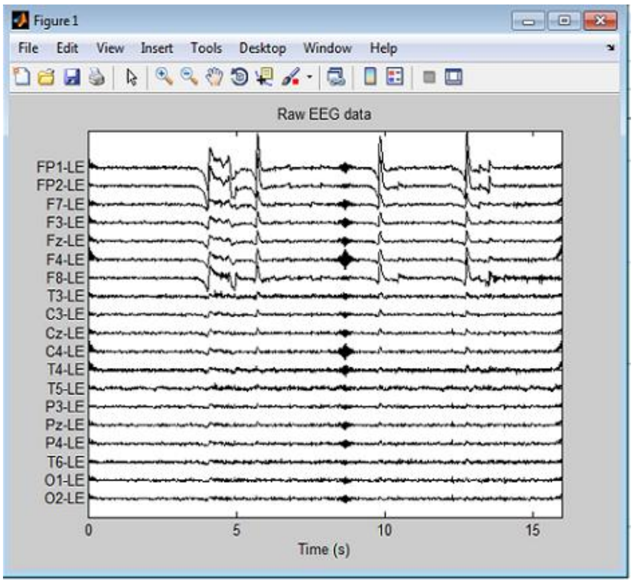

Figure3: EEG signal corrupted with ECG artifact

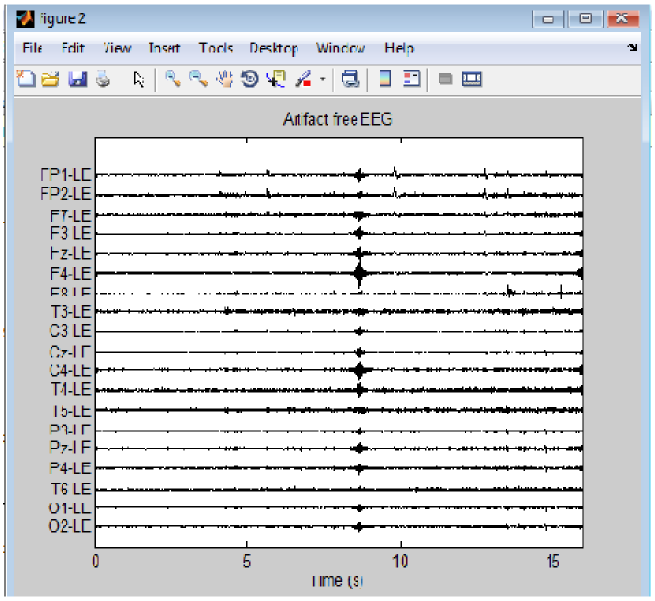

Figure4: Artifact-free EEG signal

TABLE I

Comparison of metrics for different methods

Metric / Method	OSNR	MSE	Entropy
Extraction of EEG using ICA+CWT	35.94	16.67	2.53
Extraction of EEG using ICA+S-Transform	36.24	15.54	3.16

VI.CONCLUSION

The use of Independent Component Analysis (ICA) and Stockwell transform was successfully used in the removal of ECG artifact from the EEG data. In this project we exhibit the use of the proposed algorithm for minimization of ECG artifact from contaminated EEG signal. The proposed algorithm is compared with "removal of ECG artifact from EEG data using ICA and CWT to evaluate its relative performance. We have evaluated the performance of the algorithm using simulated results. Output SNR and Entropy improvement and minimum MSE are used as the performance measures for comparison. Results obtained shows that removal of ECG artifact from EEG data using ICA and S-transform technique outperforms the removal of ECG artifact from EEG data using ICA and CWT.

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