Artifact Removal from EEG using Spatially Constrained FastICA and Fuzzy Shrink Thresholding Technique

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ABSTRACT

This paper presents a novel technique for removing the artifacts from the Electroencephalogram (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 analysing 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 Spatially-Constrained Fast ICA (SC-FastICA) 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, where thresholding plays an important role in delineating the artifacts and hence a better thresholding technique called fuzzy Shrink thresholding is applied. Experimental results show that the proposed technique results in better removal of artifacts.

General Terms

Signal Processing, Neural Networks ,Soft Computing

Keywords

Artifact Removal, Electroencephalogram (EEG), Wavelet Denoising, SpatiallyConstrained-FastICA (SC-fastICA)

1. INTRODUCTION

The human brain is the most complex organ in the body, and has been a subject of intense study by many researchers from various disciplines. Among the non-invasive methods for probing human brain dynamics, Electroencephalogram (EEG) [15] offers a direct determination of cortical behaviour with millisecond temporal resolution. Electroencephalogram (EEG) is multivariate time series data measured at multiple sensors positioned on the scalp, that imitates electrical prospective produced by the 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 focus of the research, is adjunct by small metal discs, also called as electrodes, kept on the scalp with good mechanical and electrical touch. Intracranial EEG is obtained by special electrodes placed in the brain during a surgery. For the purpose of finding the exact voltage of the brain neuron, the electrodes are of low impedance. The variations in the voltage difference among electrodes are sensed and amplified before being transmitted to a computer program. Epileptic seizure [12, 13] is an abnormality in EEG gathering and is featured by short and episodic neuronal synchronous discharges with high amplitude. This anomalous synchrony may happen in the brain locally (partial seizures) that is visible only in fewer channels of the EEG signal [14], or including the entire brain (generalized seizures), that is visible in all the channels of the EEG signal.

2. RELATED WORK

Han et al., [1] proposed an EEG signal classification technique for epilepsy diagnosis based on AR model and Relevance Vector Machine (RVM). This works includes three phases: Initially, EEG characteristics are gathered from the signals according to AR models, and then these characteristics are analysed. In the next phase, based on the act ofthe characteristics, feature choice was introduced among feature extraction and classifiers. In the last phase, RVM is executed with various AR models, kernel widths, and various subsets ofthe characteristics for the purpose of getting an overview of the technique.

Sukanesh et al., [2] put forth a fuzzy technique and hierarchical aggregation functions decision trees for the classification of epilepsy risk levels from EEG signals [6, 7,

8]. Statistical spectral feature extraction for classification of epileptic EEG signals is suggested by Seong et al., [3].

Panda et al., [4] given a technique for classification of EEG signal using wavelet transform and Support Vector Machine (SVM) for epileptic seizure diction. Classification of EEG for Epilepsy Diagnosis in Wavelet Domain Using Artificial Neural Network [9] and Multi Linear Regression is suggested by Ercelebi et al., [5].

3. DATA ACQUISITION

Current EEG recording equipment is quite smaller and portable than its predecessors, which were cumbersome in nature. The Standard placement guide for electrodes used in EEG measurement is the 10-20 system of electrode placement. The term 10-20 refers to the placement of the electrodes and their relative distances with respect to each other. Each electrode has a letter and a number to identify it. The letters refer to **F**rontal, **T**emporal, **C**entral, **P**arietal and **O**ccipital lobes of the brain. Depending on usage, the number of electrodes may vary. The dataset used for this research work is acquired from Ramakrishna Medical Hospital, Coimbatore. The raw EEG signal consists of 2 sets of data for 160 patients; one corresponding to the pathology and other being normal. Each data set contains 16 channel recordings for 160 patients and the length of the recording is for 10 seconds. The data were sampled at a rate of 256 samples per second. So the total numbers of samples present in the 16 channel recordingfor a single data set are equal to 4096 samples. Therefore the numbers of samples for 160 patients under consideration are 6, 55,360 samples.

4. METHODOLOGY

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 inanalysing the EEG and obtaining clinical information related to pathology. Hence it is crucial to design aprocedure to decrease such artifacts in EEG records.

The architecture of the proposed method for removing the artifacts of EEG data is presented in figure 1.

EEG data implicated is generated based on ICA model as

$$x(t) = As(t) + v(t) \quad (1)$$

where $x(t) = [x_1(t), x_2(t), \cdots, x_M(t)]^T$ which is a linear mixture of N sources $s(t) = [s_1(t), s_2(t), \cdots, s_N(t)]^T$, A is M×N mixing matrix, and $v(t) = [v_1(t), v_2(t), \cdots, v_M(t)]^T$ 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 $s_i(t)$, and mixing matrix A are all unknown. In order to make the problem simple, the square mixing problem is considered, i.e., M = N.

4.1 Preprocessing

The purpose of conventional filtering is to process raw EEG data x(t) to eliminate 50 Hz line noise, baseline values, artifacts dwelling in very low frequencies .Here a notch filter is implemented at 50Hz to remove line noise ,which is adaptive in nature ,in order to remove noise occurring at 49Hz -51 Hz.

4.2 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). Here SCICA is described in detail. The key intention is to describe 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

$$A = \begin{bmatrix} \widehat{A}_c, A_u \end{bmatrix} \quad (2)$$

where $\widehat{A}_c \approx A_c$ are columns regarded as constraint, and Au are otherwise regarded as unconstrained columns.

The spatially-constrained ICA technique aims to maximize the statistical independence of the unconstrained sources and at the same time reduce the divergence among the spatially constrained source sensorprojections and their corresponding reference topographies. A deflationary technique is implemented to takeout only desired components, and therefore the output of the spatially-constrained ICA technique is SC-ICs. This results in fast computational time, as all ICs are extracted.

4.3 Wavelet Denoising (WD) of SC-ICs

It is significant mentioning that SC-FastICA are expected to correspond to artifacts only; on the other hand,

some brain action might escape to these gathered signals. As artifacts have a frequency overlap with the brain signals, here 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. Consequently, denoising is attained by thresholding the wavelet coefficients FuzzyShrink thresholding method. Finally inverse DWT is utilized to obtain the reconstructed clean signal.
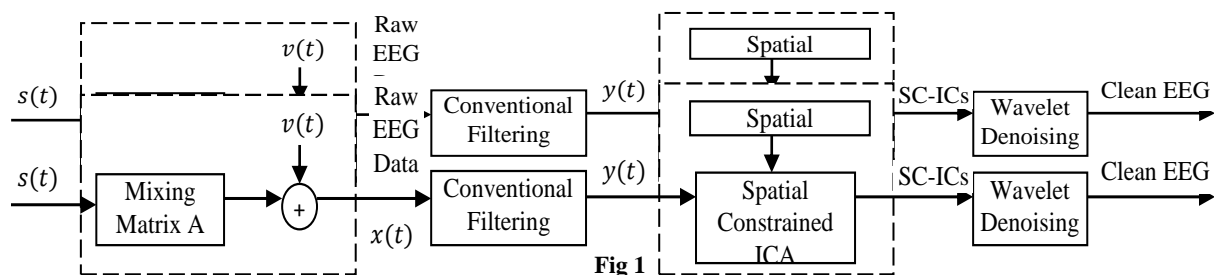
4.4 Algorithm for FastICA

1. Choose the number of Independent Components n and set p=1

2. Initialize W_i randomly

3. Perform Centering and Whitening of data

4. Finding W_i by non-gaussianity

5. Normalize W_i

6. De-correlate W_i with the existing p-1 independent components

7. Whether W_i Converges or not if not go to Step 2

8. Repeat the same for all the n components

Fig 1

4.5 Flow chart for Fuzzy Shrink Thresholding
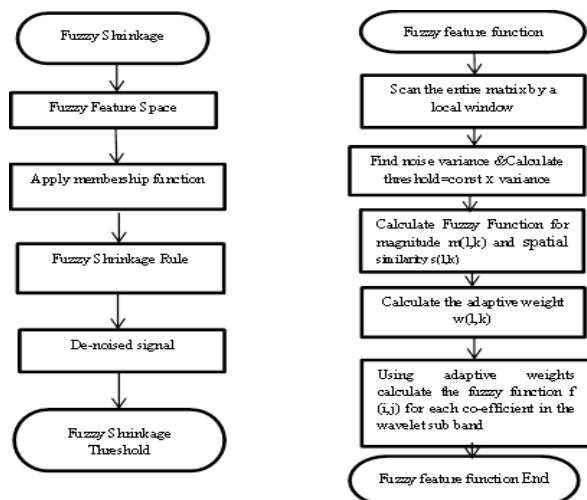
Fig 2

Performance Analysis for Electrical Artifact removal

Techniques		PSNR (dB)	MSE	Time Taken (secs)
Fast ICA		42.5436	1.0001	2.663016
Otsu		41.8702	0.9996	1.831568
Fuzzy Shrink	S shaped curve	41.9567	0.9799	3.115454
	Bsplines	57.1300	0.0322	2.760357
	Z shaped	59.7104	0.0178	3.003940
	Sigmoid	47.0331	0.3556	4.274911
	Triangular	**60.7999**	**0.0318**	**3.349184**
	Bell curve	51.0188	0.1337	4.228277
	Gaussian curve	51.5807	0.1193	5.064617

5. EXPERIMENTAL RESULTS

This section presents the evaluation of the proposed artifact removal technique

Performance Analysis for EyeBall Movement Artifact removal

Techniques		PSNR (dB)	MSE	Time Taken (secs)
Fast ICA		44.6751	1.0007	1.481553
Otsu		45.0538	1.0008	1.372437
Fuzzy Shrink	S shaped curve	44.7405	0.9931	2.581424
	Bsplines	59.9467	0.0310	2.334827
	Z shaped	67.5135	**0.0054**	**2.713516**
	Sigmoid	48.9706	0.4016	3.690825
	Triangular	**65.1513**	**0.0037**	**2.976519**
	Bell curve	55.3662	0.0900	4.035033
	Gaussian curve	57.9451	0.0492	4.074172

Performance Analysis for Eye Blink Artifact removal

Techniques		PSNR (dB)	MSE	Time Taken (secs)
Fast ICA		46.9401	1.0015	1.374718
Otsu		47.3033	1.0015	1.381986
Fuzzy Shrink	S shaped curve	47.0988	0.9699	2.566778
	Bsplines	62.2505	0.0307	2.394129
	Z shaped	62.6926	0.6277	2.795805
	Sigmoid	50.9111	0.4068	3.427329
	Triangular	**65.8221**	**0.0135**	**2.920010**
	Bell curve	56.8389	0.1095	2.719094
	Gaussian curve	57.3282	0.0979	3.244250

Performance Analysis for Spit Swallowing Artifact removal

Techniques		PSNR (dB)	MSE	Time Taken (secs)
Fast ICA		49.5212	1.0036	1.432256
Otsu		49.2044	1.0031	1.392559
Fuzzy Shrink	S shaped curve	49.3315	0.9742	2.564763
	Bsplines	62.9732	0.0436	2.404310
	Z shaped	64.3253	0.0319	2.706861
	Sigmoid	52.4775	0.4754	3.391901
	Triangular	**65.5235**	**0.0242**	**3.022603**
	Bell curve	58.7064	0.1172	3.282242
	Gaussian curve	58.6816	9.1171	2.882498

Performance Analysis for Jaw Clenching Artifact removal

Techniques		PSNR (dB)	MSE	Time Taken (secs)
Fast ICA		49.5212	1.0036	1.432256
Otsu		49.2044	1.0031	1.392559
Fuzzy Shrink	S shaped curve	49.3315	0.9742	2.564763
	Bsplines	62.9732	0.0436	2.404310
	Z shaped	64.3253	0.0319	2.706861
	Sigmoid	52.4775	0.4754	3.391901
	Triangular	**65.5235**	**0.0242**	**3.022603**
	Bell curve	58.7064	0.1172	3.282242
	Gaussian curve	58.6816	9.1171	2.882498

For all the five types of Artifact considered the Fuzzy Shrink thresholding performs better than otsu. Above all triangular membership performs well when compared to the other six membership function Subsections

5. CONCLUSION

This paper focuses on removing the artifacts from Electroencephalogram (EEG) signals. Artifact removal is an important process before analysing 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 Spatially Constrained Fast ICA (FastICA) 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. The thresholding technique used in this paper is Fuzzy Shrink thresholding which is compared with Otsu thresholding.

6. ACKNOWLEDGMENTS

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