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A Fully Automatic Method for Ocular Artifact Suppression from EEG Data Using Wavelet Transform and Independent Component Analysis

Hosna Ghandeharion and Abbas Erfanian

Abstract—**Contamination of electroencephalographic (EEG) recordings with different kinds of artifacts is the main obstacle to the analysis of EEG data. Independent component analysis (ICA) is a general accepted tool for isolating artifactual components. One major challenge to artifact removal using ICA is the automatic identification of the artifactual components. However there is still little consensus on criteria for automatic rejection of undesired components. In this paper we present a new identification procedure based on an efficient combination of statistical and wavelet-based measures for ocular artifact suppression. The results on 420 4-s EEG epochs indicate that the artifact components can be identified correctly with 96.4%.**

I. Introduction

Ocular artifacts can be orders of magnitude larger than the brain-generated electrical potentials; hence they clearly hinder the interpretation of EEG recordings. A classic approach to derive parameters characterizing the appearance and spread of electrooculographic (EOG) artifacts in EEG signals is regression in time or frequency domain [1], performed on parallel EEG and EOG recordings. However due to the bidirectional mixture of ocular and cerebral activities, regression methods inevitably involve subtracting some relevant EEG data. The well-known method of principal component analysis (PCA) presents acceptable results for elimination of eye artifacts, but it cannot completely separate ocular artifacts from brain signals especially when they have comparable amplitudes [2]. Adaptive noise canceller which is a special approach to adaptive filtering has been used in ocular artifacts cancellation [3]-[5].

Recently, a more effective method has been introduced for removing a wide variety of artifacts from multi-channel EEG signals based on blind source separation by Independent Component Analysis (ICA) [2]. The result on EEG data collected from normal and autistic subjects shows that ICA can effectively detect, separate, and remove a wide variety of artifacts (including ocular artifacts, muscle artifacts, and line noise power) from contaminated EEG recordings [2].

An important point to note is that all of the methods discussed above require visual inspection of ICA components and manual classification of the interference components. This can be time-consuming and is not desirable for real-time artifact suppression.

A. Erfanian and H. Ghandeharion are with the Department of Biomedical Engineering, Faculty of Electrical Engineering, Iran University of Science and Technology, Tehran, IRAN (phone:98-21-73913553; fax: 98-21-77240490; e-mail: erfanian@iust.ac.ir).

To overcome this problem, James, *et al*. [6] used constrained ICA (cICA) to extract a single independent component that is constrained to be similar to some reference signal. The method was employed for eye blink suppression in multi-channel recordings of EEG and MEG recordings. Delorme, *et al*. [7] developed a graphical method to semi-automatically assist experimenter in rejection of independent components and noisy single data trials based on their statistical properties. They used three high-order statistical measures for each component obtained by ICA: the entropy of the activity of component, the kurtosis of the component's activity, and the kurtosis of the spatial projection of the component. By setting an adequate rejection threshold, the artifactual components semi-automatically were detected and rejected.

An automatic eye blink suppression based on ICA was proposed by Delsanto, *et al*. [8]. They used mean square difference between the FFT of the eye blink waveform model and each segment of the Fp1 raw data channel. It was found different distance distribution for eye blink and non-eyeblink. By defining an appropriate threshold distance, the eye blink on the raw data is detected. Then the eye blink component obtained by ICA is identified based on the spatial topographic criteria.

II. Independent Component Analysis

ICA is a statistical technique in which observed random data are linearly transformed into components that are maximally independent from each other. Let us assume that an array of sensors provides a vector of N observed signals

$$\mathbf{x}(k) = \left[x_1(k), x_2(k), ..., x_N(k)\right]$$

that are linear mixtures of N unobservable sources,

$$\mathbf{s}(k) = \left[s_1(k), s_2(k), ..., s_N(k)\right].$$

The sources are real-valued, non-Gaussian distributed, and mutually statistically independent for each sample value k. The aim in ICA is to estimate the separating matrix, $\mathbf{W}$, such that

$$\mathbf{s} = \mathbf{W}\mathbf{x}.$$

The matrix $\mathbf{W}$ defining the transformation is obtained so that the mutual information of the transformed components s_i, *i.e.* independent components, is minimized. Several algorithms have been developed to find such a linear transformation. A survey and compilation of the progress in this field is contained in [9].

III. Wavelet Analysis of EEG Contaminated by EOG

Wavelet transform is well-suited to analyze the irregular structures and transient phenomena in signals. By decomposing the signals into elementary building blocks that are localized both in space and frequency, the wavelet transform can characterize the local regularity of the signal. This feature can be used to distinguish EOG waves from the EEG activity.

Figs. 1 (c), (d), (g) and (h) show the scalogram of a portion of the EEG signal and the corresponding independent components using biorthogonal 4.4 as the mother wavelet. It is clearly observed that the ocular artifacts can be detected and tracked by the continuous wavelet transform of the independent components of the EEG signals.

The discrete wavelet transform of the independent components of the EEG signal contaminated by the ocular artifacts is shown in Figs. 1 (e), (f), (i) and (j). Again, the biorthogonal 4.4 mother wavelet is used in this analysis. It is observed that the coarse and detail waveforms at the levels 4 and 5 are capable of enhancing, detecting and locating the ocular artifacts' waveforms.

IV. Method for Artifactual Component Detection

The method is based on the statistical properties of the independent components and wavelet transform of the EEG signals. We applied different measures for identifying the artifactual components: kurtosis of independent sources, kurtosis of the coarse and detail waveforms, correlation coefficient between sources and EOG signals, the relative strength of each component at the vertical and horizontal EOG.

To measure peaky activity distribution, the kurtosis was used. Kurtosis is fourth-order cumulant of a random variable. The kurtosis of s , denoted by $kurt(s)$, is defined by

$$kurt(s) = E(s^4) - 3[E(s^2)]^2 \quad (1)$$

where E is the statistical expectation. Kurtosis is zero for a Gaussian random variable, positive for super-Gaussian, and negative for sub-Gaussian [9]. Thus, if the kurtosis is highly positive, the activity distribution is highly peaked.

The correlation criterion reveals the similarity between the recorded EOG signals and the independent components. The similarity of independent components with the vertical and horizontal EOG is quantified by means of correlation coefficient.

The elements of each row of the inverse matrix W^{-1} give the strength of a component at each of the scalp sensors. To compute the relative strength of the j^{th} source at the vertical and horizontal EOG, the j^{th} element of the corresponding row vector of $A=W^{-1}$ is divided by its Frobenius norm as follows:

$$c_{ij} = \frac{a_{ij}}{\sqrt{\sum_k a_{ik}^2}} \times 100 \quad (2)$$

where c_{ij} is the strength percentage of source j to the i^{th} scalp sensor and a_{ij} is the element of the inverse matrix W^{-1}.

Decision Rule: Nine measures were exploited for automatic artifactual component identification: kurtosis of sources, the relative strength of the components at the two EOG reference channels (c_v and c_H), correlation coefficient between sources and EOG reference channels (r_v and r_H) and finally kurtoses of the coarse and detail waveforms of sources at the levels 4 and 5 (A_4, A_5, D_4 and D_5). Therefore, there are nine measures for each source. To identify the artifactual components, the sources related to the maximum value for each measure are marked. It is found experimentally that the components with at least four measures with maximum value can be identified as the artifactual components.

V. Results

The EEG data of three healthy volunteer subjects were recorded at a sampling rate of 256 by Ag/AgCl scalp electrodes from positions F_3, F_4, Fz, Pz, C_3, Cz, and Fp1 defined by 10-20 system. The horizontal eye movement artifacts were recorded by placing an electrode at the left temple. All recording channels were referenced to the right earlobe. The signals continuously were collected and processed while the subject is free to blink and to move his eyes.

Table I reports the measures of a 4-s EEG epoch contaminated by eye movement and eye blink artifacts. It is observed that the source 1, 2, and 3 are identified as the artifact components. Fig. 2 shows the result of artifact correction using extended Infomax algorithm [10]. The results on 420 4-s EEG epochs indicate that the artifact components can be identified correctly with 96.4%.

VI. Conclusion

In this paper, we have presented a fully automatic method for ocular artifact suppression employing wavelet transform and independent component analysis. The identification method is based on maximum values of computed measures for all independent components rather than a thresholding scheme. The results show that the method could separate ocular artifacts with accuracy of 96.4% over 420 4-s EEG epochs.

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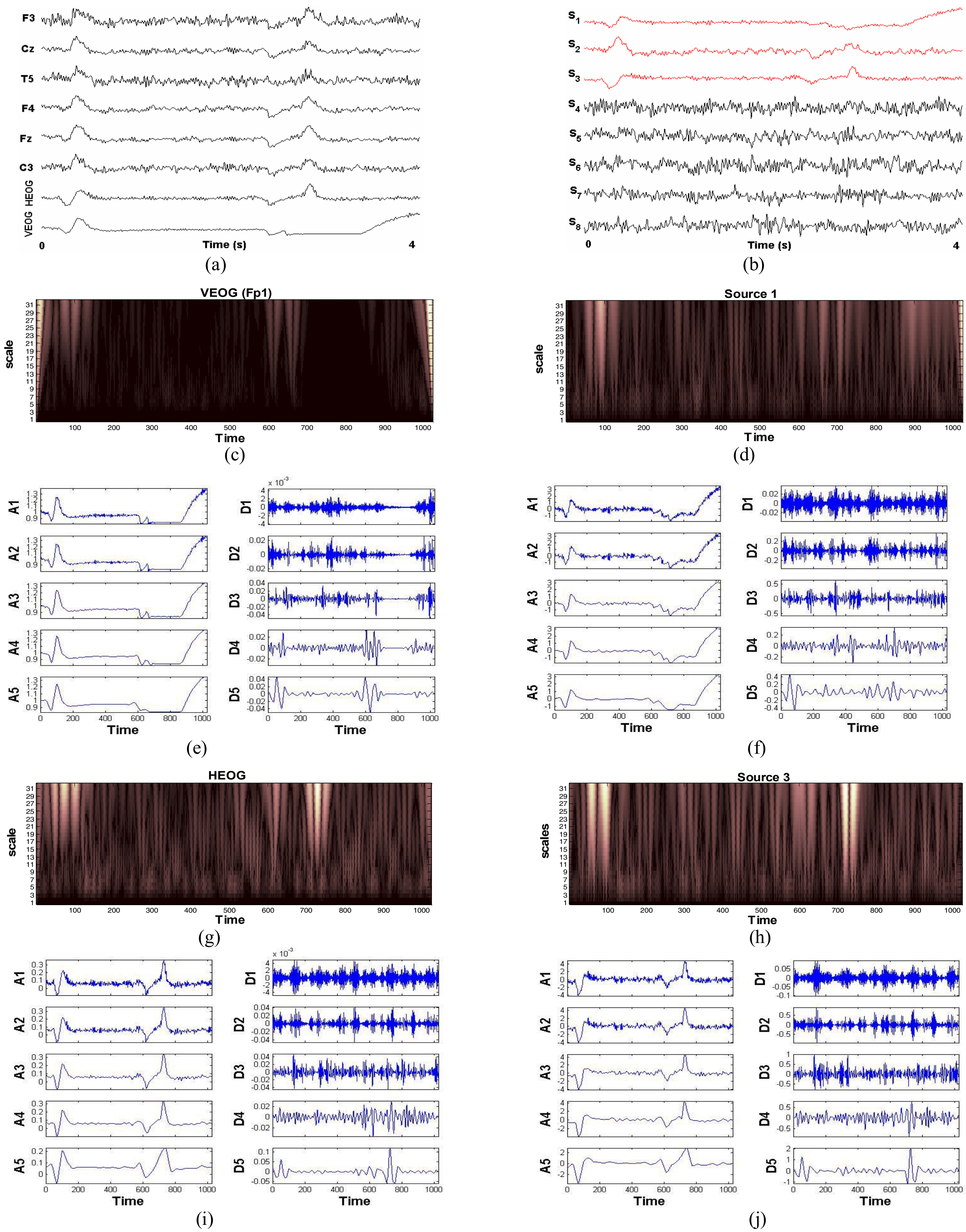

Fig. 1. (a) Recorded EEG, (b) Independent sources extracted by extended Infomax algorithm. (c) Scalogram of VEOG. (d) Scalogram of source 1. (e) Discrete wavelet transform of VEOG. (f) Discrete wavelet transform of source 1. (g) Scalogram of HEOG. (h) Scalogram of source 3. (i) Discrete wavelet transform of HEOG. (j) Discrete wavelet transform of source 3.

TABLE I

THE MEASURES OF A 4-S EEG EPOCH CONTAMINATED BY EYE MOVEMENT AND EYE BLINK ARTIFACTS INCLUDING KURTOSIS OF SOURCES, THE RELATIVE STRENGTH OF THE COMPONENTS AT THE TWO EOG CHANNELS (c_v AND c_H), CORRELATION COEFFICIENT BETWEEN SOURCES AND EOG REFERENCE CHANNELS (r_v AND r_H) AND KURTOSES OF THE COARSE AND DETAIL WAVEFORMS OF SOURCES AT THE LEVELS 4 AND 5.

Sources	Kurtosis	r_V	r_H	c_V	c_H	Kurtosis of A_4	Kurtosis. of A_5	Kurtosis of D_4	Kurtosis of D_5
S_1	2.48	0.954596	0.000561	96.193	1.6519	2.58141	2.5927	3.43809	4.1781
S_2	4.39526	0.246878	0.462938	25.157	46.892	4.72823	4.99101	0.92918	0.60834
S_3	7.2593	-0.01872	0.853149	0.8449	85.083	8.22433	5.34038	1.92107	9.31507
S_4	-0.3300	0.144577	0.091772	7.9573	4.2027	-0.4052	-0.8974	0.05282	0.36144
S_5	0.07657	-0.04851	-0.20169	4.98596	20.347	1.57805	0.81785	0.61608	0.5890
S_6	-0.5056	-0.04791	0.120806	2.16919	5.5036	-0.5112	0.0165	1.84604	0.09749
S_7	0.855196	0.046864	0.10239	4.27473	9.8104	0.49068	-0.4418	0.453	1.22125
S_8	0.221346	-0.01392	-0.00876	1.49735	1.0529	-0.0305	-0.613	3.14775	0.0118

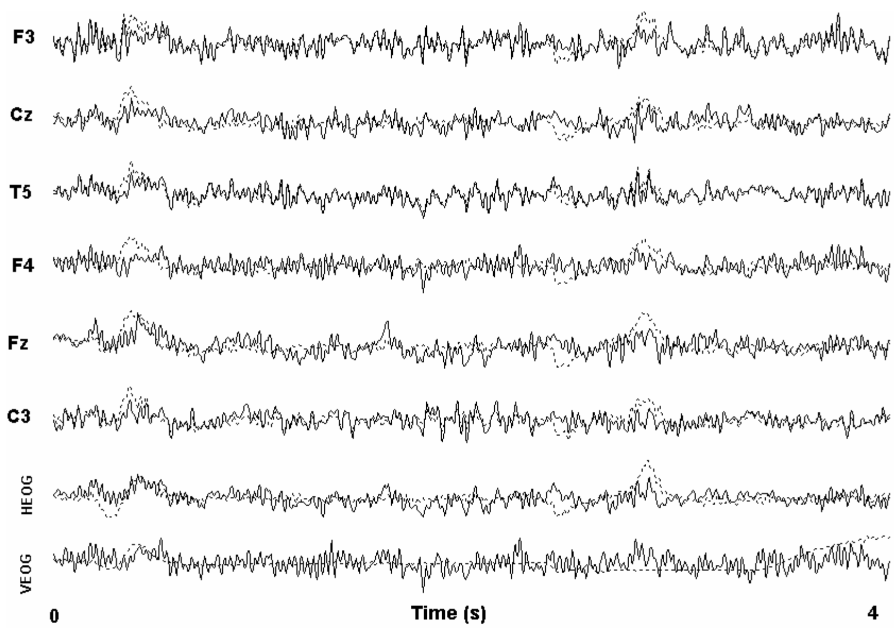

Fig. 2.The result of automatic artifact suppression by applying the proposed identification method on the sources obtained by extended Infomax algorithm: recorded EEG (dotted line), artifact-free EEG (solid line).

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