Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

Real-Time Ocular Artifacts Suppression from EEG Signals Using an Unsupervised Adaptive Blind Source Separation

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Abstract— **Independent component analysis (ICA) has been shown to be a powerful tool for artifactual suppression from electroencephalogram (EEG) recordings. However, the real-time application of this method for artifact rejection has not been considered so far. This article presents a method based on an unsupervised, self-normalizing, adaptive learning algorithm for on-line blind source separation. Simulation results are provided to show the validity and effectiveness of the technique with different distributions. The results from real-data demonstrate that the proposed scheme removes perfectly eye blink and eye movement artifacts from the EEG signals and is suitable for use during on-line EEG monitoring such as EEG-based brain computer interface.**

I. Introduction

The EEG signals are contaminated by noise from sources such as eye blink and eye movement. The traditional method of the eye blink suppression is the removal of the segment of EEG data in which eye blinks occur. This scheme is rigid and does not lend itself to adaptation. Moreover, a great amount of data is lost. Several methods based on regression in the time domain [1] or frequency domain have been proposed for removing eye blink artifacts. However, all these methods require off-line analysis which is not suitable for real-time application. To overcome these problems and to shorten the experimental session, the customary practice is to invoke the use of adaptive noise canceller (ANC). Sadasivan and Dutt [2] adopted a nonlinear ANC which is based on second-order Volterra function for reducing the EOG in electroencephalography measurements.

HE *et al.* [3] employed two separate ANCs for off-line ocular artifacts canceling. Recorded vertical EOG and horizontal EOG were used as two separate reference inputs. Each reference is first processed by an adaptive filter and then subtracted from the recorded EEG. Erfanian and Mahmoudi [4] proposed a method based on adaptive noise canceller using a recurrent artificial neural network for real-time removal of ocular artifacts from the EEG signals. The results demonstrate that the proposed scheme removes ocular artifacts from the contaminated EEG signals and is suitable for real-time and short-time EEG recordings

Recently, a more effective method has been introduced for removing a wide variety of artifacts from EEG and electromagnetic brain signals based on blind source separation by Independent Component Analysis (ICA) [5].

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However, the real-time artifacts suppression was not considered in these works.

Various ICA methods with adaptive learning algorithm have been developed [6]-[9]. Cichocki and Unbehauen [6] developed unsupervised, self-normalizing, adaptive learning algorithm for on-line blind separation of independent sources. Choi *et al.* [7] developed an on-line learning algorithm with flexible nonlinearity, so named flexible ICA that is able to separate instantaneous mixtures of sub- and super-Gaussian. A class of neural networks with multilayer feedforward structures was also proposed for performing complete ICA [8].

In this work, we proposed a method based on adaptive independent component analysis for real-time ocular artifact suppression.

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

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

that are linear mixtures of *N* unobservable sources

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

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 demixing matrix, **W**, such that

$$\mathbf{s} = \mathbf{W}\mathbf{x}\,. \qquad (1)$$

The matrix **W** defining the transformation is obtained so that the nongausssianity of the transformed components s_i, i.e. independent component, is maximized. 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. Method

The procedure of on-line artifact suppression using ICA consisted of three steps as follows:

A. Whitening

The first step in many ICA algorithms is to whiten the observed data. In this work, we used the following adaptive whitening as follows [8]:

$$\mathbf{V}_{t+1} = \mathbf{V}_t - \mu_t(\mathbf{v}_t\mathbf{v}_t^T - \mathbf{I})\mathbf{V}_t$$
$$\mathbf{v}_t = \mathbf{V}_t\mathbf{x}_t, \tag{2}$$

where $\mathbf{V}_t$ is the estimated whitening matrix, $\mathbf{x}_t$ is the observed data and $\mathbf{v}_t$ is the new data which is white. However, this stochastic approximation algorithm suffers from stability problems [8]. The initial value of $\mathbf{V}_t$ is set to be $\mathbf{ED}^{-1}\mathbf{E}^{\mathrm{T}}$, where $\mathbf{E}$ is the orthogonal matrix of eigenvectors of $E\{\mathbf{xx}^T\}$ and $\mathbf{D}$ is the diagonal matrix of its eigenvalues. Initial whitening matrix, $\mathbf{V}_0 = \mathbf{ED}^{-1}\mathbf{E}^{\mathrm{T}}$, is defined by a portion of data and then used for on-line whitening.

B. Adaptive Learning Algorithm for on-line Blind Source Separation

Cichocki and Unbehauen [6] proposed an unsupervised, self-normalizing, adaptive learning algorithm for on-line blind source separation. Consider a single layer feedforward neural network with *n* linear neurons described by

$$\mathbf{y}_t = \hat{\mathbf{W}}_t\mathbf{x}_t \tag{3}$$

where $\hat{\mathbf{W}}_t$ is the matrix of adaptively synaptic weights, $\mathbf{x}_t$ is the vector of the observed signals, and $\mathbf{y}_t$ is vector of the output signals which after learning phase must be an estimate of the source signals. For the above model Cichocki and Unbehauen [6] proposed the following on-line learning algorithm

$$\hat{\mathbf{W}}(k+1) = \hat{\mathbf{W}}(k) + \eta(k)[\mathbf{\Lambda} - \mathrm{f}[\mathbf{y}(k)]\mathrm{g}^{\mathrm{T}}[\mathbf{y}(k)]]\hat{\mathbf{W}}(k)$$
$$k = (0,1,2,...) \quad \textit{with} \quad \hat{\mathbf{W}}(0) \neq \mathbf{0} \quad \textit{and} \quad \det\hat{\mathbf{W}}(0) \neq 0 \tag{4}$$

where $\eta(t)$ is the learning step, $\mathbf{\Lambda}$ is a diagonal matrix with the amplitude scaling factors, $\boldsymbol{f}(\mathbf{y})$ and $\boldsymbol{g}(\mathbf{y})$ are nonlinear different odd activation functions as follows:

$$f_i(y_i) = \begin{cases} y_i^p\, sign(y_i) & p: even \\ y_i^p & p: odd \end{cases} \tag{5}$$
$$g_j(y_j) = \tanh(\beta_i y_j) \qquad \forall i, j$$

The performance of this leaning algorithm strongly depends on the shape of the activation function $f_i(y_i)$ and $g_i(y_i)$. The optimal selection of these functions requires the knowledge of the probability distributions of the sources. If the measured signals contain mixtures of both sub-Gaussian and super-Gaussian sources [7], then the learning algorithm in (4) with activation function in (5) may fail to separate these signals. Since probability distributions of sources are not known in advance, a more flexible activation function was used [10] as follows:

$$f_i(y_i) = \begin{cases} \tanh(\beta_i y_i) & \kappa_4(y_i) > \delta \\ \mathrm{sign}(y_i)|y_i|^{p_i} & otherwise \end{cases}. \tag{6}$$
$$g_i(y_i) = \begin{cases} \mathrm{sign}(y_i)|y_i|^{p_i} & \kappa_4(y_i) > -\delta \\ \tanh(\beta_i y_i) & otherwise \end{cases}.$$

Where $\kappa_4(y_i) = E(y_i^4)/E^2(y_i^2) - 3$ is the normalized value of kurtosis and $\delta \geq 0$ is a small threshold.

The most interesting feature of the learning algorithm is that it allows separating the source signals with an extremely wide range of amplitudes. Moreover, the mixing matrix can be very ill-conditioned. These features make it quite suitable for ocular artifacts suppression from EEG signals.

C. Adaptive Learning Algorithm of Mixing matrix

For artifact suppression using ICA, the artifactual components should be set to zero. Artifact-free EEG signals can then be derived as $\hat{\mathbf{x}}_{\mathbf{t}} = \hat{\mathbf{w}}_t^{-1}\hat{\mathbf{y}}_t$, where $\hat{\mathbf{y}}_t$ is the matrix, $\mathbf{y}_t$, of independent components with rows representing artifactual components set to zero. To estimate $\mathbf{A}_t = \hat{\mathbf{W}}_t^{-1}$, the mean-squared error, $E\{\|\mathbf{x} - \mathbf{A}_t\mathbf{y}\|^2\}$, can be minimized by using the stochastic gradient algorithm which yields the following iterative learning rule:

$$\mathbf{A}_{t+1} = \mathbf{A}_t + \mu_t(\mathbf{x}_t - \mathbf{A}_t)\mathbf{y}_t)\mathbf{y}_t^T \tag{7}$$

IV. Simulation Study

Extensive simulation studies were carried out to test the capabilities of the adaptive learning algorithm for on-line source extraction. In this work, we illustrate the performance by one example consisted of sub-Gaussian and super-Gaussian. Consider a ramp, a sinusoid, a saw-tooth, and a Gaussian white noise (Fig. 1 (a)). These sources were mixed linearly using a 4×4 randomly chosen matrix (Fig. 1(b)).

The ICA network is trained with the first 200 samples of the signals with learning step 0.00001. The results of source separation using the adaptive learning algorithm (4) with activation functions in (5) and (6) are shown in Fig.1 (c) and (d), respectively. It is observed that the algorithm with activation functions in (5) fails to separate the sources, but the algorithm with activation functions in (6) could perfectly extract the original sources.

V. Real-Time Ocular Artifacts Suppression

The EEG data of 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.

For on-line artifact suppression, we trained the ICA network with a portion of the EEG signals including eye blinks and eye movements and then used for source separation and artifacts suppression. During on-line separation and artifact suppression, the learning process never stops and continuously adapts the free parameters of the network to variations in the incoming signals.

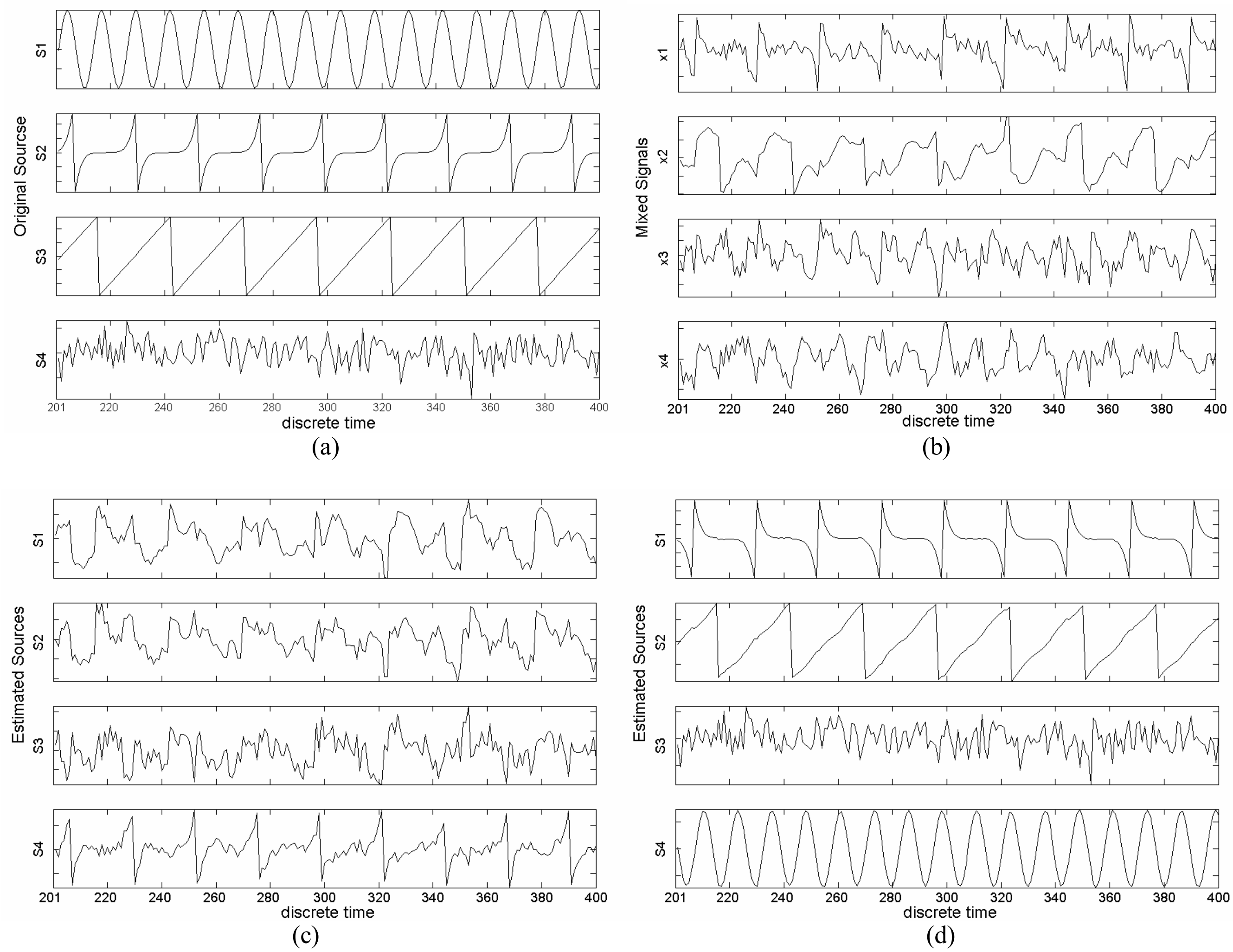

Fig. 1. Results of computer simulation for on-line source separation (a) Original source waveforms. (b) Linear mixture of four sources. (c) Extracted sources using activation functions in (5). (d) Extracted sources using activation functions in (6).

VI. Results

Fig. 2 shows the results of real-time eye movement artifacts suppression by using on-line source separation for some portion of the EEG data. The EVD whitening matrix, the ICA network and mixing matrix were trained by the first 12 s of the recorded EEG signals. It should be noted that the learning process never stops and continuously adapts the demixing and mixing matrices. The results on different trial experiments on different subjects show that that the ocular artifacts can be perfectly removed by the proposed algorithm. For comparison, the result of artifact correction using FastICA [9] is shown in Fig. 2(d).

The results of on-line source separation and artifact removing using extended Infomax [11] is shown in Fig. [3]. It is observed that this algorithm could not successfully suppress the ocular artifacts.

VII. Conclusion

In this paper, we have presented a method based on an adaptive blind source separation for on-line ocular artifact suppression. The results of this work indicate that the ocular artifact can be removed from EEG signals during on-line EEG recordings. It is observed that the algorithm could separate ocular artifacts with different ranges of amplitudes.

Acknowledgment

This work was supported by Iran Telecommunication Research Center, Tehran , IRAN.

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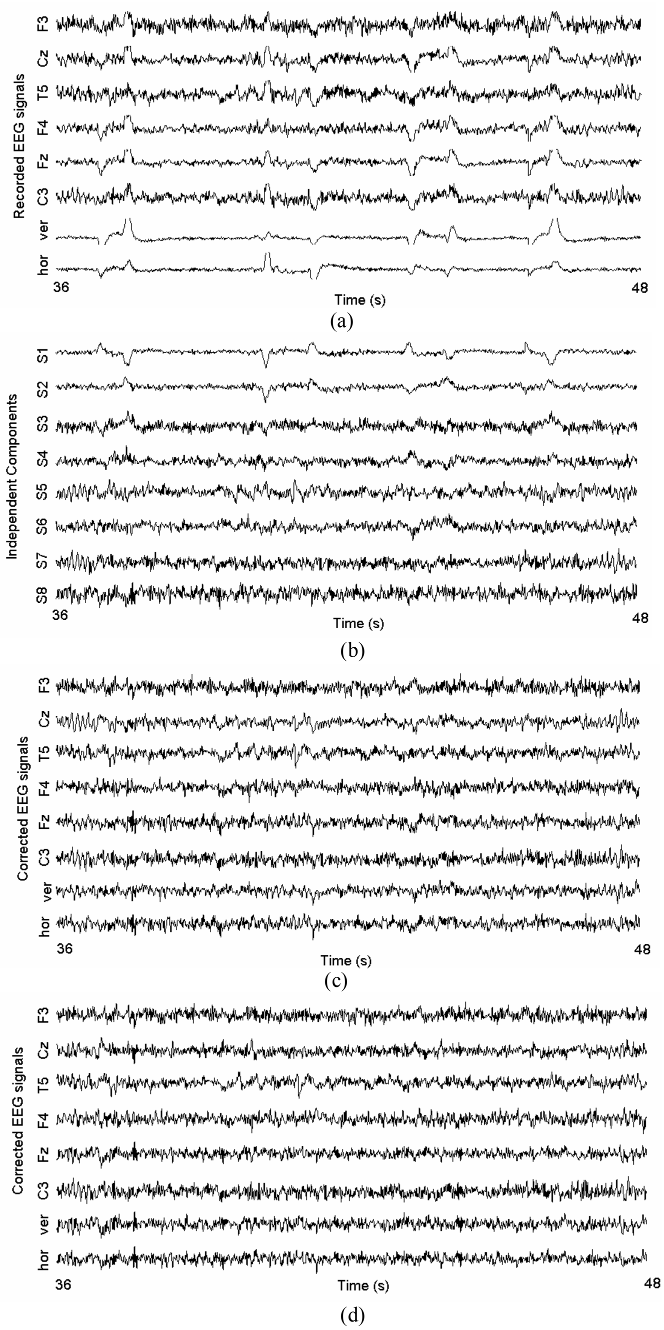

Fig. 2. (a) Portion of measured EEG signals. (b) Extracted independent components using on-line blind source separation. (c) Artifact-free EEG using adaptive leaning algorithm. (d) Artifact-free EEG signals using FastICA.

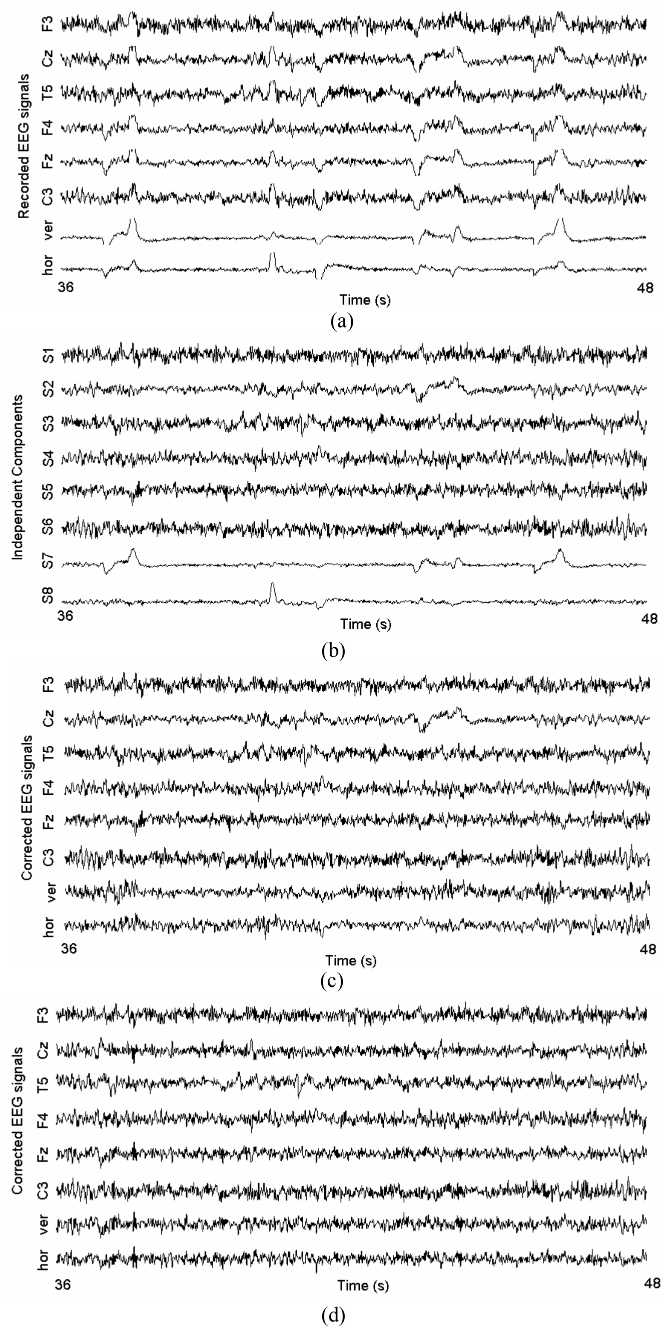

Fig. 3. (a) Portion of measured EEG signals. (b) Extracted independent components using on-line extended Infomax. (c) Artifact-free EEG using extended Infomax. (d) Artifact-free EEG signals using FastICA.