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Short communication

Automatic removal of eye movement artifacts from the EEG using ICA and the dipole model

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Abstract

In this study, we proposed and evaluated the use of Independent Component Analysis (ICA) combining the EEG dipole model to automatically remove eye movement artifacts from the EEG without needing EOG as a reference. We separated the EEG data into independent components using the ICA method, and determined the source localization of these independent components with a single dipole model. The EEG signal was reconstructed by automatically excluding those components localized within a preset eye model. EEGs from 12 patients were analyzed. The experimental results indicate that ICA with the dipole model is very efficient at automatically subtracting the eye movement artifacts, while retaining the EEG slow waves and making their interpretation easier.

Keywords: Independent Component Analysis (ICA); Dipole model; Artifact; EEG

1. Introduction

Eye movements and blink artifacts can cause pervasive problems in electroencephalogram (EEG) analysis and research. Epochs contaminated by ocular artifacts can be manually excised, but at the cost of intensive human labor and substantial data loss. The electric potentials created during saccades and blinks can be orders of magnitude larger than the EEG and can propagate across much of the scalp, masking and distorting brain signals.

The Intracarotid Amobarbital Procedure (IAP) used for the lateralization of language function and for assessing the potential for memory loss when considering surgical removal of epileptic brain tissue [1] usually results in an abrupt appearance of large amplitude slow waves in the scalp EEG, mostly ipsilateral to injection, but with some spread to the contralateral side. It is often difficult to assess the presence of slow waves caused by the amobarbital because there are very frequent eye blinks and eye movements. The difficulty originates from the fact that slow waves and eye movement artifacts both predominate in the frontal regions, and eye movements are frequent and vigorous as the patient is constantly stimulated visually by showing various objects and asking the patient to perform motor tasks.

Eye movement activity can be measured more directly with the electrooculargram (EOG), using electrodes placed above and around the eyes. Unfortunately, these measurements are contaminated with EEG signals of interest because electrodes around the eye are necessarily close to the brain. Simple subtraction of the EOG is, therefore, not a removal option [2]. Regression methods for removal of eye artifacts in either the time or frequency domain depend on having a good reference EOG channel. They have the same inherent weakness as subtraction because of the lack of independence between EOG and EEG signals [2,3].

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The use of Principal Component Analysis (PCA) cannot completely separate eye movement artifacts from the EEG signal, especially when they have comparable amplitudes [4]. PCA finds components that are spatially orthogonal. In general, it is unreasonable that the EEG source and artifacts will be spatially orthogonal to one another. Therefore, PCA cannot effectively separate signals into brain activities and artifact components [2,5]. A method based on source modeling and PCA provides an improvement for artifact correction [6,7], but the accuracy of this method depends on the availability of accurate inverse source solutions for EEG and EOG, and also requires a substantial amount of calibration data.

Independent Component Analysis (ICA) is able to separate superimposed signals into components having different statistical characteristics [8–10]. ICA has been applied to many different types of signals. It has been used to separate epileptic spikes from the EEG background [11] and to remove artifacts, such as eye blinks [12]. In this last study, only normal EEGs were illustrated, a situation in which eye blinks and normal EEG patterns have very different frequency and spatial characteristics. Eye blinks and eye movement artifacts could also be eliminated with ICA in the presence of large amplitude slow waves having a relatively similar spatial distribution [13].

Automated methods are preferable because they eliminate the subjectivity associated with non-automated correction; they are significantly more time and resource efficient. A semiautomated ICA-based method is presented by Delorme et al. [14]. Automated eye artifacts removal based on blind component separation was also introduced with the aid of extra EOG electrodes [15].

The aim of this study was to investigate an automated method for eliminating ocular contamination from EEG signals using ICA and the dipole model without needing EOG as a reference, and to obtain good quality EEG for further evaluation.

2. Materials and methods

2.1. EEG data collection

The EEGs from 12 patients were included in this study. Patients were selected consecutively, starting in April, 2003. The IAP was performed as part of the presurgical evaluation of patients with medical refractory epilepsy. EEG data were digitally recorded at a rate of 200 samples/s with a 12-bit resolution using the Harmonie system (Stellate, Montreal, Canada) at the Montreal Neurological Hospital. Electrodes were placed according to the 10–20 system, at the following 16 locations: Fp1, F3, C3, P3, O1, F7, T3, T5, Fp2, F4, C4, P4, O2, F8, T4 and T6 with a reference at FCz. EEGs were examined and analyzed after having

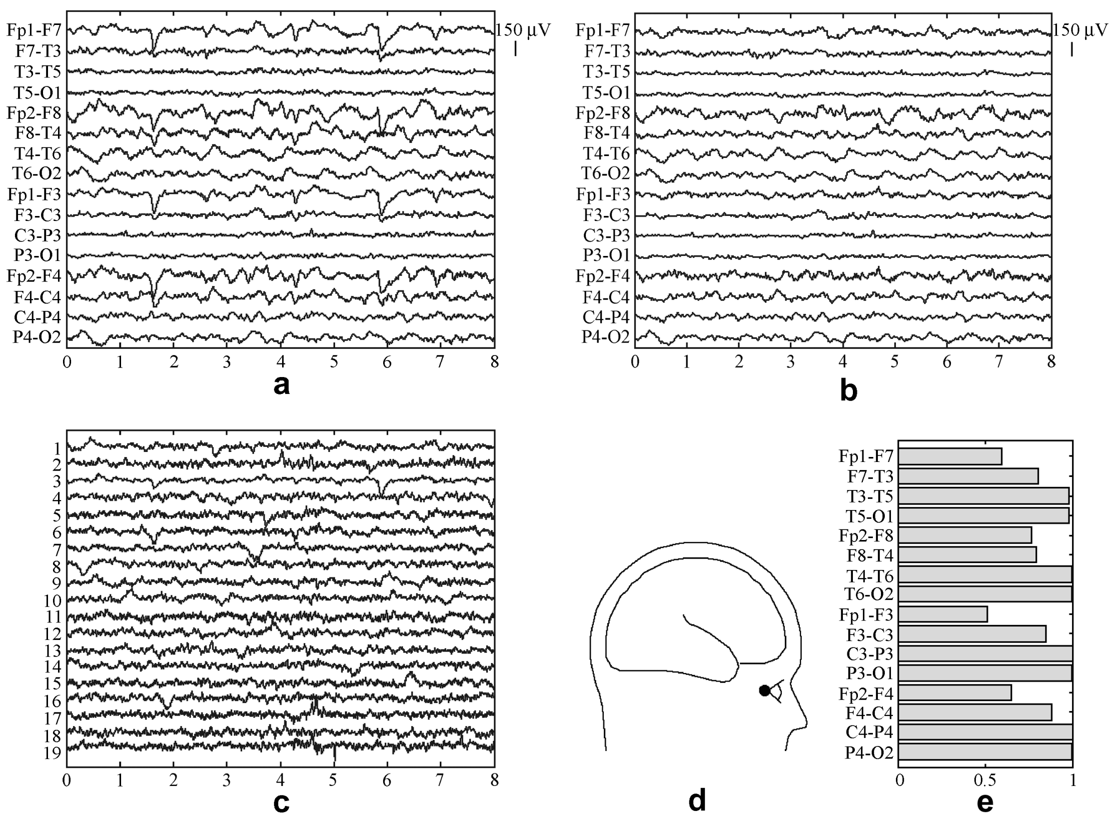

Fig. 1. Removal of eye blinks and movements in EEG during IAP (Patient 1). Time scale of (a–c) in seconds. (a) 8-s page of EEG recording during IAP. (b) The EEG during IAP after eye artifact removal. (c) Separated components by ICA. Components 3 and 6 are automatically chosen as eye artifacts with the proposed approach. (d) The dipole location of IC6. (e) Correlation between original channels and reconstructed channels.

been reformatted to a bipolar "double banana" antero-posterior montage.

The EEG was recorded at least 2 min prior to injection and for at least 10 min after the injection. We examined sections taken in the 2 or 3 min following injection, a time at which the slow waves are the most prominent. We selected sections in each patient at which there were clear slow waves, as well as clear eye movement artifacts.

2.2. Independent Component Analysis

ICA is performed by optimizing an objective function that approximates measures of independence between components. The ICA model of a linear instantaneous mixture can be formulated as $\boldsymbol{x} = \boldsymbol{A}\boldsymbol{s}$, where $\boldsymbol{s} = [s_1, \ldots, s_m]^{\mathrm{T}}$ is a vector of independent sources. These independent sources are mixed through a linear system (a mixing matrix) $\boldsymbol{A}$. The signals that can be measured are the mixed signals and we call them $\boldsymbol{x} = [x_1, \ldots, x_n]^{\mathrm{T}}$. In this situation, the source $\boldsymbol{s}$ and the mixing system $\boldsymbol{A}$ are unknown. We only measure the mixed signals $\boldsymbol{x}$. Blind source separation may be undertaken by adaptively adjusting the weight matrix $\boldsymbol{W}$ (called the separating matrix) of a neural network using a particular learning algorithm and eventually make the network's output, $\boldsymbol{u} = \boldsymbol{W}\boldsymbol{x}$, composed of sources $[u_1, \ldots, u_m]^{\mathrm{T}}$ as independent as possible. $\boldsymbol{u}$ is the estimation of $\boldsymbol{s}$ with independent components and $\boldsymbol{W}$ is the estimation of $\boldsymbol{A}^{-1}$.

2.3. Applying ICA to EEG data

The use of ICA for blind source separation of EEG data is reasonable because (1) EEG data recorded at multiple scalp sensors are linear sums of temporally independent components arising from spatially fixed, distinct or overlapping brain areas and the propagation time delays are negligible; (2) the eye artifacts and EEG are independent since they have a completely different generating mechanism.

For EEG analysis, the rows of the input matrix, $\boldsymbol{x}$, are EEG signals recorded at different electrodes and the columns are measurements recorded at different time points. The rows of the output data matrix, $\boldsymbol{u} = \boldsymbol{W}\boldsymbol{x}$, are the time courses of the ICA components or sources. The inverse, $\boldsymbol{W}^{-1}$, is referred to as the mixing matrix, giving the spatial distribution of the respective components at each scalp electrode. EEGs free of ocular artifact were derived by reconstructing the EEG with selected non-artifactual ICA components: $\boldsymbol{x}_0 = \boldsymbol{W}^{-1}\boldsymbol{u}_0$, where $\boldsymbol{u}_0$ is formed by replacing the ocular artifactual components of $\boldsymbol{u}$ with zero vectors.

In this study, the ICA was performed by using the joint approximate diagonalization of eigenmatrices (JADE) algorithm [16,17], which achieves good statistical perfor-

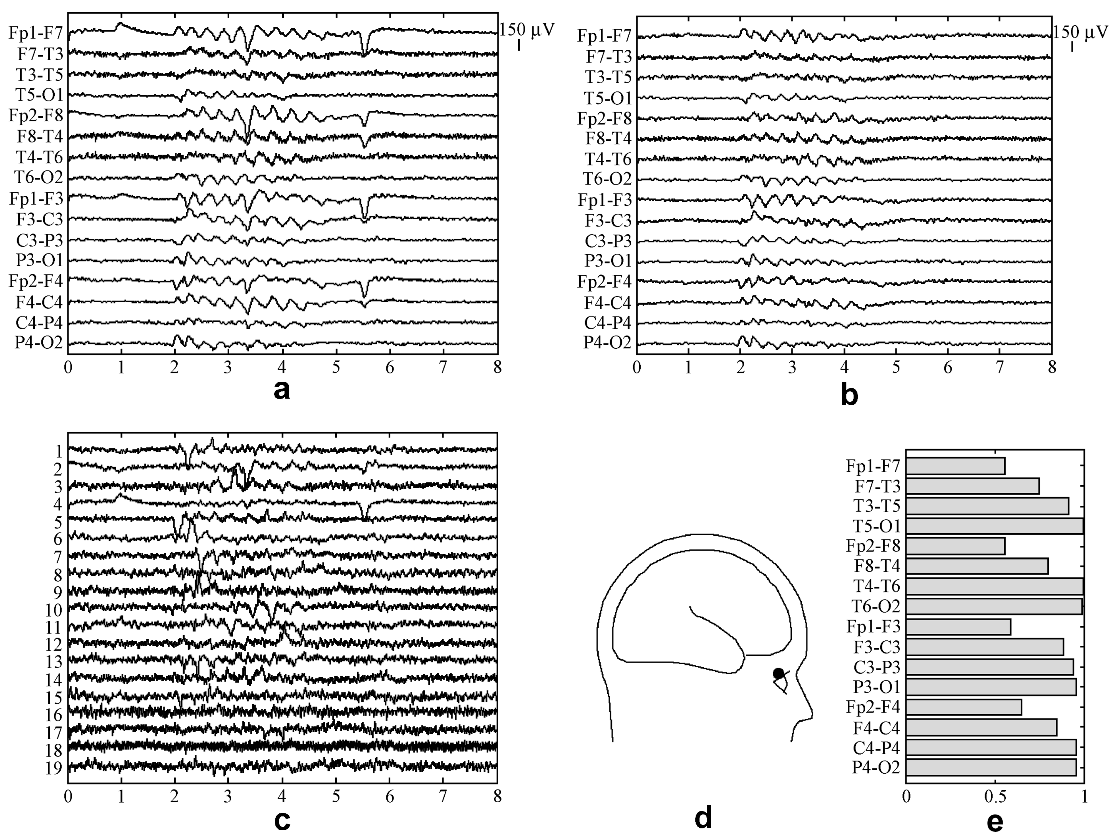

Fig. 2. Eye artifact removal from the EEG recording (Patient 6). Time scale of (a–c) in seconds. (a) A section of EEG recording during IAP. (b) The EEG during IAP after eye artifact removal. (c) Separated components by ICA. Components 2, 4 and 18 are automatically chosen as eye artifacts with the proposed approach. (d) The dipole location of IC2. (e) Correlation between original channels and reconstructed channels.

mance. JADE is an efficient batch algorithm, and has been successfully applied to the processing of real data sets, such as telephony and radar signals as well as biomedical signals. The advantage of JADE is that it works without parameter tuning. The weakest point of the current implementation is that the number of sources is limited to 40 or 50 depending on the available memory of the computer.

2.4. Dipole source localization of independent components

Localizing electrical activity within the brain based on multichannel EEGs has been important in both basic and clinical neuroscience. With the dipole model, active neurons within small regions of the brain are often modeled as current dipoles whose parameters may be computationally determined based on the observed EEG data from the scalp [18,19]. This has been an inverse problem of the EEG. In our study, each independent component is projected to the scalp, and is fitted with a single dipole model [19]. The EEG signal was reconstructed by automatically excluding those components localized within a preset eye model.

2.5. Correlation

The correlation coefficients between the original and the corrected EEG channels were calculated to measure how much the channels were altered, expecting to prove that channels not involved in eye movements should remain almost unaffected.

3. Results

Experiments were carried out with the EEG data collected during IAP from 12 patients. Fig. 1 shows the removal of eye blinks and movements in EEG during IAP for Patient 1. Fig. 1(a) is an 8-s page of EEG recording during IAP with prominent slow waves in the right hemisphere. The separated components by ICA are shown in Fig. 1(c). Components 3 and 6 are automatically chosen as eye artifacts since their dipole location is within the eye area. The dipole location of component 6 is given in Fig. 1(d). Fig. 1(b) gives the EEG during IAP with eye artifacts removed, and it can be seen that the eye blinks are largely removed, whereas the slow waves remain. The correlation between original channels and reconstructed channels shown in Fig. 1(e) was low for channels Fp1-F7, Fp1-F3 and Fp2-F4, and very high for all channels in the posterior half of the head, reflecting the fact that modifications were only made to the anterior channels.

Figs. 2–4 show the removal of eye blinks and movements in EEG during IAP of patients 6, 7 and 12 separately. The EEGs from the other eight patients are not

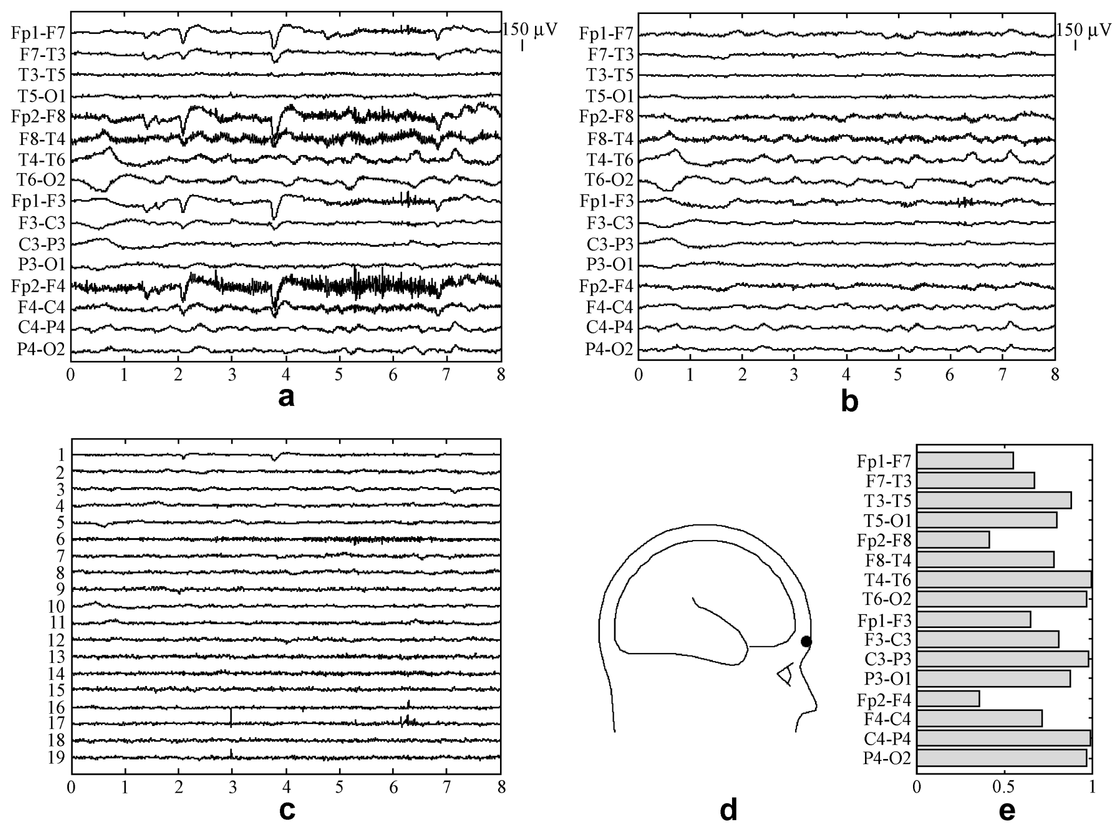

Fig. 3. Removal of eye blinks and movements in EEG during IAP (Patient 7). Time scale of (a–c) in seconds. (a) 8-s page of EEG recording during IAP. (b) The EEG with eye artifacts removed. (c) Separated components by ICA. Components 1, 2 and 6 are automatically chosen as eye artifacts. (d) The dipole location of IC2. (e) Correlation between original channels and reconstructed channels.

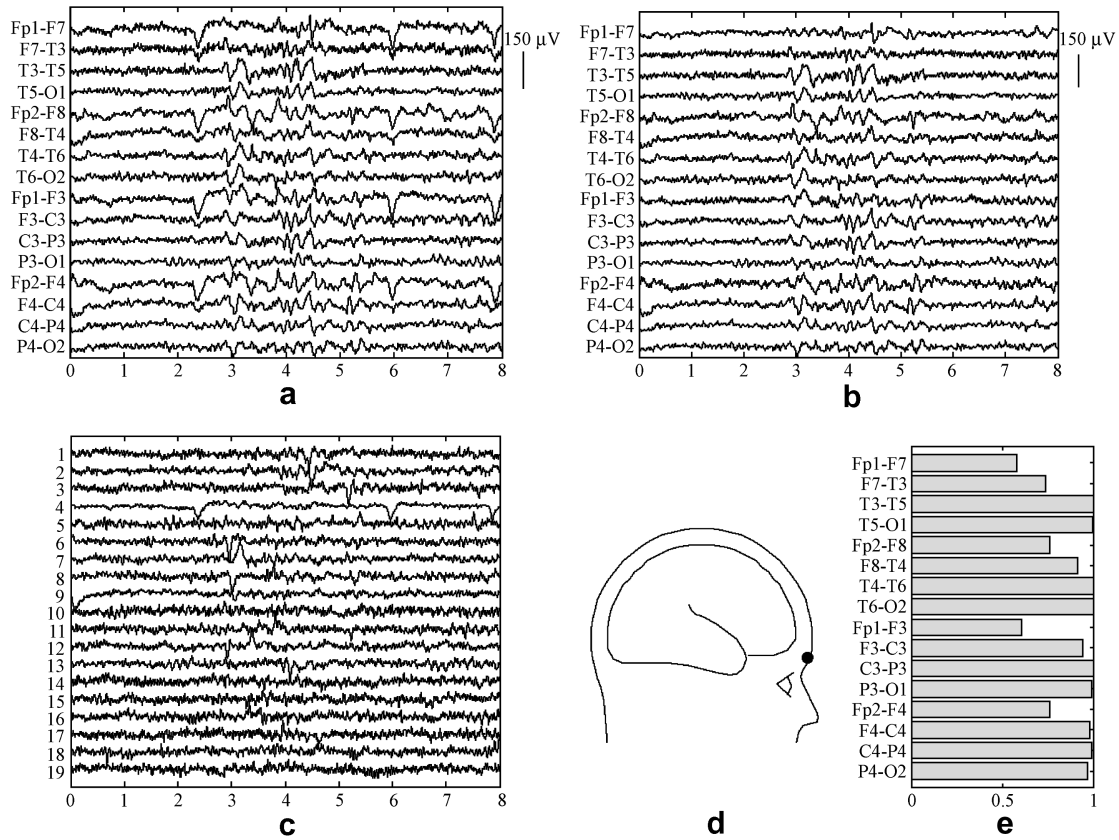

Fig. 4. Another example of removal of eye blinks and movements in the EEG (Patient 12). Time scale of (a–c) in seconds. (a) 8-s page of EEG recording during IAP. (b) The EEG with eye artifacts removed. (c) Separated components by ICA. Components 4 and 15 are automatically chosen as eye artifacts. (d) The dipole location of IC4. (e) Correlation between original channels and reconstructed channels.

illustrated here, but they showed results very similar to those illustrated, with excellent automatic removal of eye movement artifacts.

4. Discussion

The proposed use of Independent Component Analysis combining the EEG dipole model to automatically remove eye movement artifacts from the EEG without the need for extra EOG recording was investigated in this study. This approach was found to be effective to automatically remove the ocular artifacts embedded in the EEG. Other methods have been used in the past to remove eye blink and eye movement artifacts from the EEG. Early methods used a simple filtering concept, simply ignoring very low frequencies, typically below 1.5 or 2 Hz [20]. This is not practical in the context of an EEG dominated by frontal slow waves in the delta band. Other methods have proposed the recoding of horizontal and vertical EOG with electrodes around the eye, and then the subtraction of an optimal linear combination of the horizontal and vertical EOG from the various EEG channels affected by artifact [21]. Such methods would probably not perform well in the context of a large amount of frontal slow waves because EOG recording would be contaminated by this slow wave activity.

Compared with other artifact removal methods, ICA has several advantages. The ICA algorithm is computationally efficient. It can simultaneously separate the EEG and artifacts into independent components without relying on the availability of reference artifacts. This avoids the problem of mutual contamination between EEG and EOG channels that could not be solved with filters, regression and PCA. The corrected EEG can easily be derived by a combination of the components without artifacts.

While using ICA algorithms for ocular artifact correction, a crucial step is to correctly identify the artifact components among the decomposed independent components. Manually identifying the ocular artifact components is subjective, inconvenient and a time consuming process when dealing with a large amount of EEG data. This paper presents a novel, automated method for eliminating ocular contamination from EEG signals using ICA and the dipole model without needing EOG as a reference. Our method appears to be a generally applicable and effective method for automatically removing ocular artifacts from EEG recordings, although slow waves and ocular artifacts share similar frequency distributions.

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