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Blinking Artifact Removal in Cognitive EEG Data Using ICA

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Abstract—**Eye blinking artifacts present serious problems for electroencephalographic (EEG) interpretation and analysis. In this study, we apply independent component analysis (ICA) to eye blinking artifact removal from cognitive EEG recordings. Due to the specific design of the experiment, the eye blinks almost always co-occur with the event-related potentials (ERP), which creates problems for ICA. We introduced another data set of spontaneous blink and combined it with single-trial ERP data. Our results show that ICA on the combined data set gives separation that makes more sense and makes it easier for EEG interpretation and analysis.**

I. INTRODUCTION

Electroencephalographic (EEG) recordings are usually contaminated by eye movements, eye blinks, muscle activity and line noise. These artifacts can be orders of magnitude larger than the signals of interest and may propagate across much of the scalp. This poses a big problem if some properties (amplitude, latency, etc.) of the signals are to be analyzed, which is common for event-related potentials (ERP) analysis. Thus it is desirable to remove the artifacts as completely as possible without distorting the underlying brain signals.

A common approach is to reject the EEG epochs containing artifacts with some pre-selected voltage threshold. However, the rejected amount of data may become unacceptable when blinks and muscle movements occur too frequently in some subjects [1]. Several methods have been proposed particularly for removing ocular artifacts, which are based on regression either in time domain or frequency domain [2]-[3]. One of the main drawbacks for all regression methods is that the reference channels, typically electro-oculogram (EOG), contain both eye activity and brain activity and can result in a considerable distortion of relevant brain signals [4]-[5].

Principal component analysis (PCA) as a decomposition method has been proposed to remove eye artifacts in EEG recordings [6]. An inherent constraint by PCA is that the projections of the data components are orthogonal, which dose not necessarily hold for artifacts and brain signals. Another method that combines source modeling, PCA and artifact averaging [7] provides an improvement on the above individual methods but requires a prior modeling of event-related brain activity as well as a large amount of calibration data.

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More recently, independent component analysis (ICA) has emerged as an effective approach to the blind source separation (BSS) problem. Makeig and Vigario et al. have demonstrated independently that ICA can be used to separate brain activity from muscle and blink artifacts in EEG and (magnetoencephalographic) MEG data, respectively [8]-[9]. Jung et al. applied the extended Infomax ICA algorithm to spontaneous EEG data and effectively removed a wide variety of artifacts, such as eye blinks, muscle noise, heart signals and line noise [5]. Artifact removal based on ICA has since become a promising field for analysis of EEG data.

II. ICA

ICA is a statistical method that aims to find a linear transformation of the data that will make the outputs as independent as possible. It is a very useful method for blind source separation (BSS) in cases where the sources can be assumed to be statistically independent. The basic linear instantaneous ICA model is:

$$\mathbf{x} = \mathbf{A}\mathbf{s} \tag{1}$$

where $\mathbf{x} = (x_1, x_2, ..., x_m)^T$ is the observed m-dimensional random vector; $\mathbf{s} = (s_1, s_2, ..., s_m)^T$ is an unknown random vector with independent components representing the sources; $\mathbf{A}$ is an unknown $m \times m$ constant mixing matrix.

The solution to the basic ICA problem can be expressed as the form:

$$\mathbf{y} = \mathbf{W}\mathbf{x} \tag{2}$$

where, $\mathbf{W}$ is the $m \times m$ demixing matrix.

There are a multitude of algorithms that have been proposed to estimate the demixing matrix $\mathbf{W}$, among which, Informax, FastICA, JADE, SOBI are probably the most widely used [10]–[13]. We briefly describe here the extended Infomax [14], which is an extension of the Infomax algorithm. The extended Infomax is able to separate sources with both sub-Gaussian and super-Gaussian distributions based on the information maximization principle. The extended Infomax introduces a learning rule that switches between the two types of distributions:

$$\Delta\mathbf{W} \propto \left[\mathbf{I} - \mathbf{K}\tanh(\mathbf{y})\mathbf{y}^T - \mathbf{y}\mathbf{y}^T\right]\mathbf{W} \qquad \begin{cases} k_i = 1, \text{supergaussian} \\ k_i = -1, \text{subgaussian} \end{cases} \tag{3}$$

The elements of the diagonal matrix $\mathbf{K}$ are obtained according to:

$$k_i = \mathrm{sign}\left\{E[\mathrm{sech}^2(u_i)]E[u_i^{\,2}] - E[\tanh(u_i)u_i]\right\} \qquad (4)$$

The separation is achieved by maximization of network entropy, which is equivalent to the maximum likelihood approach under certain conditions. Maximizing the likelihood of independent identically distributed (*iid*) data is well known to be minimizing the mutual information between the data. So sources that are independent can be separated using the extended Infomax algorithm.

III. Applying ICA to EEG and Artifact Removal

The application of ICA to the above setting requires the following conditions be satisfied: the existence of statistically independent sources, their linear instantaneous mixing at the sensors and the stationarity of the mixing process. It has been suggested that these are reasonable assumptions at EEG frequencies [15].

When ICA is applied to EEG data, very often several independent components (IC) will exhibit characteristics that resemble artifacts. One way to distinguish artifacts from brain activities is to look at the time course of the component. For instance, eye blinks usually have brief large monopolar peaks. Another important factor is the relative projection strengths of the component at each of the scalp sensor, which is given by the corresponding column of $\mathbf{W}^{-1}$. These coefficients give the scalp topography of each component and thus provide evidence for the component's physiological origin [5]. For instance, eye blinks should project most strongly to far frontal sites on the scalp. Once a certain independent component is identified as artifact, artifact removal can be achieved by simply projecting the IC back to each scalp sensor and subtracting them from the original EEG recordings.

IV. The Cognitive EEG Data and Some Practical Issues

EEG data were recorded from one normal subject at 128 scalp electrodes according to 128-channel Geodesic Sensor Nets placements. All 128 channels were referred to Cz and were digitally sampled for analysis at 100Hz. A bandpass filter between 0.1Hz to 60Hz was applied to all channels, which were then converted to average reference. We selected 33 out of 129 channels (including Cz) according to the standard International 10-20 Electrode Placement System for final analysis.

The experiment was designed such that an acoustic startle stimulus (a 50 ms, 95 dB burst of white noise with instantaneous rise time) was presented while the subjects were viewing some pictures with certain valence [16]. The single-trial ERP data set we used consisted of 122 trials, where each trial lasted for 1000 ms with 250 ms before the startle stimulus.

Because of the way the experiment was designed, each time the startle stimulus was presented, the subject would blink once. Thus the eye blink is time-locked to the stimulus onset and becomes 'event-related'. This means that blinks and ERP (specificly N100 wave) are synchronized by the stimulus and both have similar monopolar shapes with peaks occurring at around the same time. This poses a problem for ICA because the independence assumption is weakened by the fact stated above. In fact, it has been pointed out that when separate topographically distinguishable sources nearly always co-occur in the data, ICA may derive single components accounting for the co-occurring phenomena [17].

There have been, if any, very few previous studies that deal with removal of eye blinks from ERP that are time-locked to the same stimulus using ICA.. In order to tackle this problem, we combined another data set composed of 159 trials of spontaneous blinks (with no stimulus presented) with the original single-trial ERP data and fed the combined data set to ICA. In the next section, we will compare the results of artifact removal for the combined data set and single-trial ERP data set using ICA.

V. Results

In this section the results of ICA on the combined data set and single-trial ERP data set are illustrated. Here, we only consider the removal of eye blink artifacts since they have dominant effects on the analysis of ERP. The ICA computation was realized using the software package EEGLAB[18], which is a useful tool for the analysis of single-trial EEG recordings.

It is well known that eye blink activities project most strongly to far frontal sites on the scalp and exhibit large brief monopolar potentials in time. After the ICA decomposition was done, we carefully examined the scalp topographies and waveforms of all the 33 independent components and manually picked up the component which resembled the characteristics of the blink artifact.

Fig. 1 and 2(a) show the characteristics of IC1 obtained from single-trial ERP data set and combined data set,

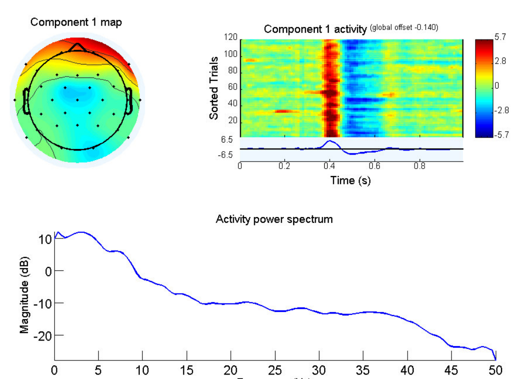

Fig. 1. independent component 1 obtained from single-trial ERP data. Upper left, scalp topography. Upper right, ERP image and average waveform. Bottom, average power spectrum.

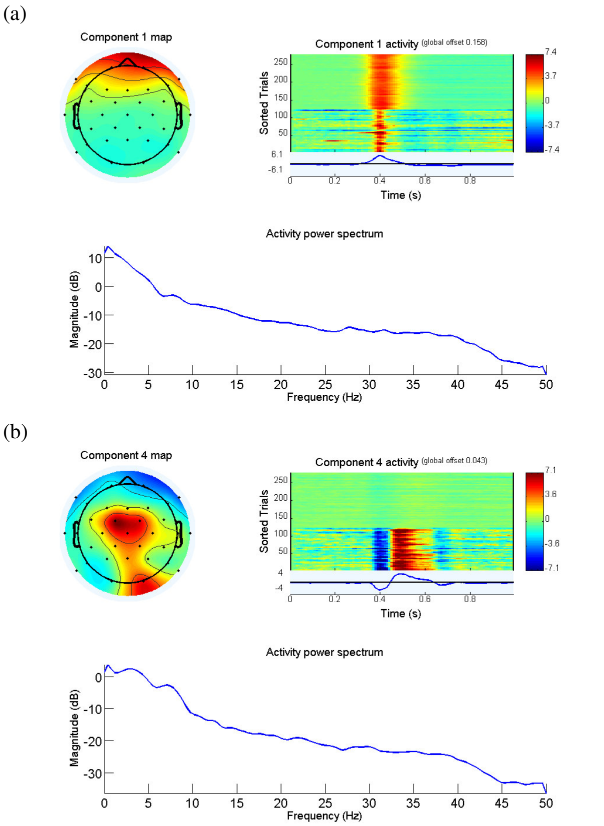

Fig. 2. independent components obtained from combined data set. (a), IC1; (b), IC4

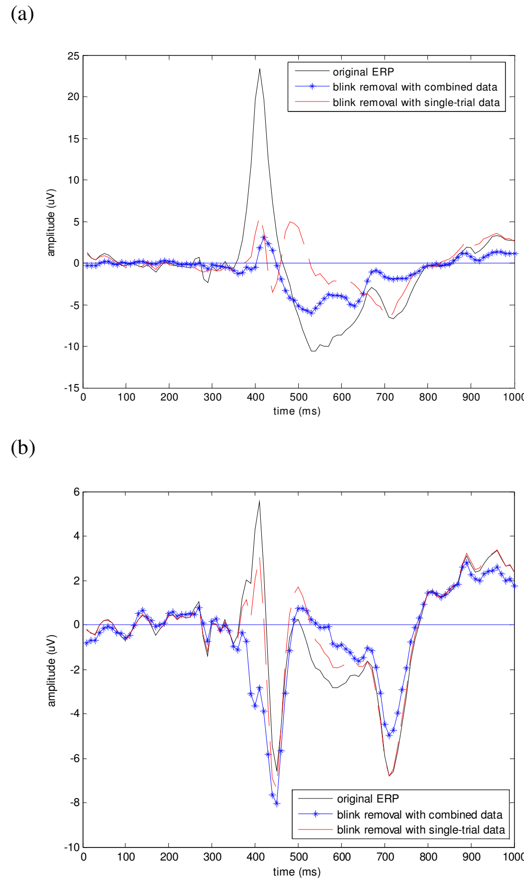

Fig. 3. average ERP before and after blink removal at, (a), Fp1. (b), Fz. Solid line: original ERP. Starred line: blink removal with combined data; dashed line: blink removal with single-trial data

respectively. They were both identified as blink artifacts. For all the repeated runs, these two independent components were consistently extracted as IC1 by the extended Infomax algorithm for the two data sets. Beside the original 122-trial ERP data, the ERP image in Fig. 2(a) also contains 159 trials of EEG data which resemble the spontaneous blinks. This confirms our previous identification of IC1 as blink artifacts.

Interestingly, when ICA was applied to the combined data set, the ERP itself could be identified as a single IC, which is shown in Fig. 2(b). The scalp topography of IC4 agrees with the fact that startle ERP project most strongly to central part of the scalp and the two peaks in the waveform correspond to N100 and P300 wave, respectively. But we have to be careful when dealing with IC4 because there might be other IC's which extract some ERP, though insignificantly.

Next, we compare the performance of blink removal of ICA for the two different data sets. Fig. 3 and 4 show the average ERP before and after blink removal at Fp1, Fz, and Cz, Pz, respectively. It can be immediately seen that the blink removal using only the single-trial ERP data failed because while eye blinks were removed from the data, most ERP were also taken away. This can be expected since the IC1 obtained from the single-trial ERP data is really the co-activation of both blinks and ERP (notice the negative projection on the central part of the scalp). This again shows that ICA cannot successfully separate sources that are almost always co-occurring in the data. On the other hand, ICA using the combined data set gave results that make more sense. The N100 and P300 waves were recovered at Cz, Pz and even at Fp1, where eye blinks have large projections (note the negative projection of the ERP at Fp1). While it seems that the blinks were removed at Fz, it is still difficult to analyze. It may be that the baseline was improperly shifted for this particular channel.

VI. Discussion

The above analysis represents our initial efforts to separate the eye blink artifacts from ERP. We could have applied ICA on the continuous EEG recordings. But that would require an enormous amount of time to prune the EEG data and ICA may give results that are very difficult to interpret. Combining single-trial ERP data with blink data takes in the least information ICA needs to separate the two sources and no more.

We think that the synchronization of the blinks and ERP by the same stimulus introduces some form of 'ill-conditioning' to ICA and creates problem when we try to separate the two sources. Our reasoning is this, if we consider the demixing matrix $\mathbf{W}$ as a set of spatial filters, each row of $\mathbf{W}$ represents a vector in a space spanned by all the spatial filters. When two sources are slowly co-varying in time, then the

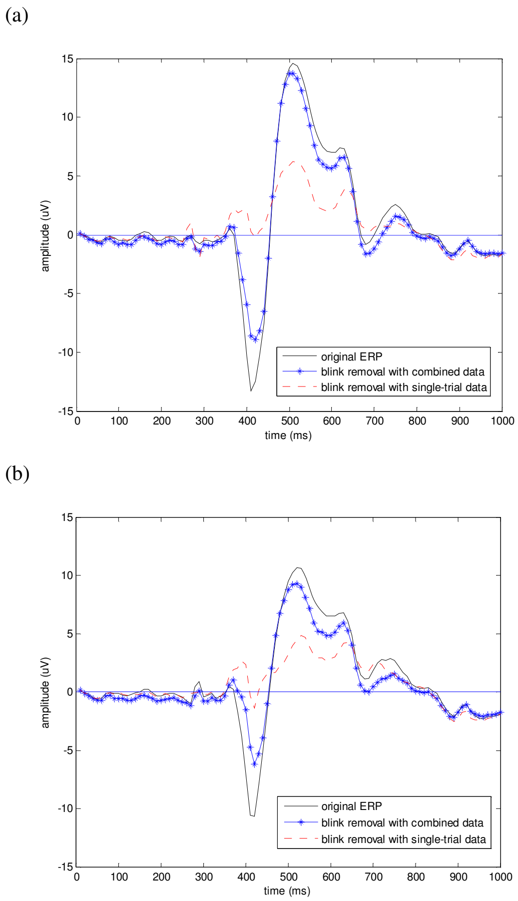

Fig. 4. average ERP before and after blink removal at, (a), Cz. (b), Pz.

corresponding two rows of $\mathbf{W}$ will point in the directions so close in the space of spatial filters, that the estimation of $\mathbf{W}$ becomes ill-conditioned and eventually ICA will merge the two spatial filters and identify the two sources as a single IC.

However, when we furnish the spontaneous blink data to ICA algorithms, this new information which is not contained in the original single-trial ERP data will attract the 'attention' of ICA and thus make the separation problem 'better-conditioned'. If we look at the component maps of IC1 and IC4 obtained from the combined data set (see Fig. 2), they do have very different scalp topographies although they are temporally correlated. It is these distinct spatial projections of the blinks and ERP that ICA seeks and therefore it is possible to separate the two sources.

We have to point out that the above approach to the separation problem still utilizes the fundamental assumption of independence. It is not guaranteed that the separation is optimal because for the single-trial ERP data, the blinks and ERP become essentially dependent due to the same stimulus. One possible way to solve this is to work in the framework of conditional independence. In graphical models, the stimulus is a common parent node to both blinks and ERP since there are causal relationships between the stimulus and the two responses. So the blink and the ERP become conditionally independent given the same stimulus. A recent TCA model proposed by Bach [19] may be suitable for this problem. Another way is to take into account the special temporal structure of the blinks and use temporally constrained ICA to tackle the problem.

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