A SIMPLE AND FAST ALGORITHM FOR AUTOMATIC SUPPRESSION OF HIGH-AMPLITUDE ARTIFACTS IN EEG DATA

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ABSTRACT

In this paper we present a simple and fast technique for correcting high amplitude artifacts that contaminate EEG signals. Examples of such artifacts are ocular movement, eye blinks, head movement, etc. Since the measured EEG data can be modeled as a linear combination of brain sources and artifacts, the proposed technique is based on multiplying the observed data matrix by a blocking matrix that has the effect of blocking high amplitude artifacts, while linearly transforming the other sources without any distortion. The advantages of using this technique are 1) it is relatively fast, so it can be applied in real time, 2) it is completely automatic, and 3) can be successfully applied to signals which fail with ICA-based algorithms.

Indexing Terms: Electroencephalogram (EEG), artifact removal.

I. INTRODUCTION

The electroencephalogram (EEG) is a noninvasive measure of brain electrical activity. These measured signals can be used as a clinical tool for studying the nervous system, monitoring of sleep stages, and diagnosing diseases such as epilepsy. Unfortunately, artifacts such as head movements, electromyogram (EMG) and electrocardiogram (ECG) signals contaminate the EEG signal. As a result, it is usually difficult to relate EEG measurements to the underlying brain process or to localize the sources of the EEG signals. Therefore, artifacts must be removed from the EEG signals before analysis. This is typically done manually, and as such is a very time consuming and tedious process. Thus, there is a need for this process to be automated.

Mathematically, the measured data at instant t can be related to their original sources through the following linear relation [4]:

$$\mathbf{x}_t = \mathbf{A}\mathbf{s}_t + \mathbf{v}_t, \quad t = 1, \ldots, T \qquad (1)$$

where $\mathbf{x}_t$ is the measured data vector of dimension M at time t where M is the number of electrodes, $\mathbf{s}_t$ is the vector whose elements are the N sources sampled at time t, $\mathbf{A}$ is a $M \times N$ mixing matrix, $\mathbf{v}_t$ is additive Gaussian noise, and T is the total number of samples. In addition to brain sources, the vector $\mathbf{s}_t$ contains artifacts, which wish to remove. Over the past decade, there has been a lot of research effort directed towards removing these artifacts. Most of the proposed methods are based on applying either principal component analysis (PCA)[5], or independent component analysis (ICA) [4].

In this paper we concentrate only on automatic removal of high-amplitude artifacts. Although PCA- and ICA-based algorithms can be used to handle this problem, they suffer from the following limitations; 1) they assume that $M \geq N$, which may not be the case when a small number of electrodes are used. In addition, generally, the number of sources are unknown; 2) they cannot be applied to remove artifacts automatically, 3) the sources must meet certain assumptions such as statistical independence, which may apply for artifacts but is questionable for brain sources, and 4) they cannot be applied in real time because of the delay involved in separation, identification, and then restoration. In addition to the above mentioned limitations, there are some situations where both PCA- and ICA-based algorithms fail, e.g, example 2 in Section IV.

The rest of the paper is organized as follows: in Section II an overview of some automatic artifact rejection and correction algorithms based on ICA and PCA is presented. The proposed algorithm is presented in Section III, and two examples are presented in Section IV in order to demonstrate the efficiency of the proposed algorithm in separating high-amplitude artifacts. Finally we conclude our work in Section V.

II. AUTOMATIC ARTIFACT REJECTION AND CORRECTION

Recently, techniques have been developed to automate the process of artifact removal [1], rejection [3], or correction [5]. In [1] a technique for automatic rejection of artifacts was proposed. The proposed technique was based on dividing the whole data set into contiguous windows, then statistical tests on each window were applied. If the artifact was detected at any channel in any window, all data in this window is marked for rejection. Although this technique works efficiently in identifying artifacts, rejection of the whole data inside the marked window has drawbacks because some useful data in the uncontaminated channels within this marked window are lost.

In [3] the authors proposed using ICA with a reference signal. This technique is based on extracting sources that are statistically independent and are constrained to be similar to the given reference signal. Although this technique was applied successfully in rejecting ocular artifacts, it is not on–line, and the original signals have to be examined first in order to select a suitable reference signal. These limitations make this technique unsuitable for real time automatic rejection and correction of ocular artifacts.

In [5] PCA was applied to separate the EEG signals into uncorrelated components. Then for each separated component, tests were applied in order to identify whether this component is an artifact or not. If the separated component is marked as artifact, the whole component is set equal to zero, then the corrected EEG signals are restored by multiplying these corrected sources by the inverse of the separating matrix. Although this technique may work faster than the previous one, the rejected component, which corresponds to the artifact, may contain some EEG signal at instants where the artifact does not occur. This means that the restored artifact-free EEG signal is distorted.

From the above discussion it is clear that each of these techniques has its own limitation which prevents it from being suitable for real time automatic correction of high amplitude artifacts. In the next section we present a simple and efficient technique that can be applied in real time to automatically correct artifacts with large amplitude.

III. THE ARTIFACT-BLOCKING ALGORITHM

The proposed algorithm corrects the measured EEG data on–line, rather than separating it first into its individual components as in PCA and ICA, as mentioned in the previous sections. In the light of the mixing model described by (1), let us assume that the i-th source is a high-amplitude artifact while the others are brain sources in addition to low-amplitude artifacts. Then (1) can be written as:

$$\mathbf{x}_t = \mathbf{a}_i s_i + \sum_{\substack{j=1 \\ j \neq i}}^{N} \mathbf{a}_j s_j, \quad t = 1, \ldots, T \tag{2}$$

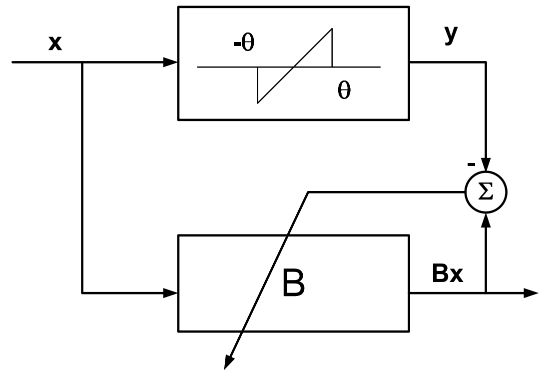

Fig. 1. The blocking matrix $\mathbf{B}$ can be calculated by minimizing $\|\mathbf{y} - \mathbf{Bx}\|$.

where $\mathbf{a}_i$ is the i-th column of the mixing matrix $\mathbf{A}$ and s_i is the i-th source. If $\mathbf{x}_t$ is multiplied by a matrix $\mathbf{B}$ such that $\mathbf{Ba}_i = \mathbf{0}$, i.e. $\mathbf{B}$ is constructed so that $\mathbf{a}_i$ is in the nullspace of $\mathbf{B}$, then we will get a new mixture $\tilde{\mathbf{x}}_t$ that is a linear function of the brain and low-amplitude artifact sources only, that is:

$$\tilde{\mathbf{x}}_t = \sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\mathbf{a}}_j s_j, \quad t = 1, \ldots, T \tag{3}$$

where $\tilde{\mathbf{a}}_j = \mathbf{Ba}_j$. To calculate $\mathbf{B}$ we consider the block diagram shown in Fig. 1. In this figure, the threshold function is defined as

$$\mathbf{y} = \begin{cases} \mathbf{x}, |\mathbf{x}| \leq \theta \\ \mathbf{0}, \text{otherwise}, \end{cases} \tag{4}$$

where $\mathbf{y}$ is the threshold function output and θ is a threshold. θ is adjusted such that it is larger than the nominal brain signal's amplitude but less than the artifact amplitude. The output of this threshold function will not contain any information about any high-amplitude artifacts in the signal. The optimal value of $\mathbf{B}$, denoted as $\mathbf{B}_{\text{opt}}$ is given as the solution to the following optimization problem:

$$\boldsymbol{B}_{\text{opt}} = \arg\min_{\boldsymbol{B}} E\|\mathbf{Bx}_t - \mathbf{y}_t\|_2^2 \tag{5}$$

where E is the expectation operator. The $\mathbf{B}$ satisfying (5) ensures that large signals exceeding the threshold (i.e., artifacts) are blocked, since the corresponding $\mathbf{y}$ is mostly zero in these intervals. However, for small signals, for which $\mathbf{y} = \mathbf{x}$, the output is an undistorted version of the input. Moreover, since the artifact occurs over a small duration of time, the minimization of (5) can be calculated over small windows rather than over the whole data set. The whole data length T is divided into contiguous windows each with length T_w, and we assume that there is only one high-amplitude artifact that can occur in each window.

Since (5) is a linear least–squares problem, the solution is straightforward and is given in closed form by

$$\mathbf{B}_{\text{opt}j} = \mathbf{R}_{yxj}\mathbf{R}_{xxj}^{-1}, \quad j = 1, \ldots, N_w \tag{6}$$

where $\mathbf{B}_{\text{opt}j}$ is the blocking matrix in the j-th window, $\mathbf{R}_{yxj}$ is the cross correlation function between $\mathbf{y}$ and $\mathbf{x}$ in the j-th window, $\mathbf{R}_{xxj}$ is the autocorrelation function of the input data $\mathbf{x}$ in the j-th window, and N_w is the total number of windows. In the j-th window, $\mathbf{R}_{yxj}$ and $\mathbf{R}_{xxj}$ can be calculated as:

$$\mathbf{R}_{yxj} = \frac{1}{T_w} \sum_{t=1+(j-1)T_w}^{jT_w} \mathbf{y}(t)\mathbf{x}^T(t), \tag{7}$$

$$\mathbf{R}_{xxj} = \frac{1}{T_w} \sum_{t=1+(j-1)T_w}^{jT_w} \mathbf{x}(t)\mathbf{x}^T(t). \tag{8}$$

As a comparison between the proposed algorithm and ICA-based algorithms used for removing ocular artifacts, for instance, it was stated in [6] that ocular artifact correction using ICA distorts the power in the recovered signal between 5 and 20 Hz . The reason for this distortion is that, by using ICA, the separated component that corresponds to the ocular artifact contains leakage brain signals at the instants where the artifact does not occur, which means that removing this component will not only remove the ocular artifact but also remove some brain signals. On the other hand, from (6) we note for those windows that do not have artifacts, we have $\mathbf{R}_{yx} = \mathbf{R}_{xx}$ which means that the blocking matrix $\mathbf{B}_{\text{opt}j}$ over these windows equals the identity matrix. As a result, the blocking matrix will affect the data only if the j-th window is contaminated with the artifact.

IV. SIMULATION RESULTS

In this section we present two examples to demonstrate the efficiency of the proposed technique in removing artifacts that have high amplitude. The EEG data were collected using 20 electrodes placed according to the International 10-20 System. The sampling frequency was 205 Hz, and an average reference was used. In these examples the threshold θ was set to $50\mu v$.

Example 1: In this example we set $T_w = 100$ samples. This example is presented to demonstrate the efficiency of the proposed technique in removing ocular artifacts. Fig. 2a shows 5 sec. of EEG data contaminated with an ocular artifact between the 7-th and 8-th second. The corrected data are shown in Fig. 2b. Clearly the ocular artifact has been successfully removed without any distortion to the data outside the windows at which the artifact occurs.

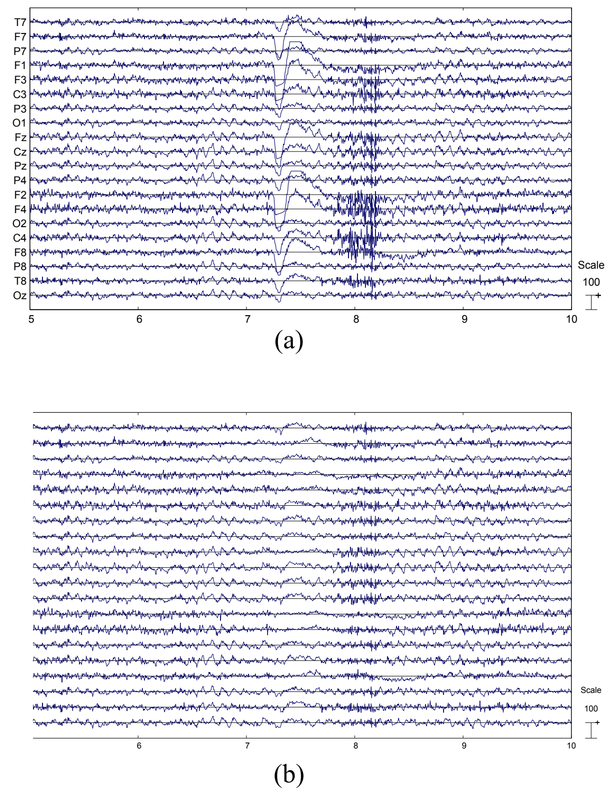

Fig. 2. (a) 5 seconds of EEG signals contaminated with ocular artifact, (b) The corrected EEG signals using AB algorithm

Example 2: In this example we set T_w= 1 sec. = 205 samples. This example is presented to show how the proposed algorithm deals with artifacts that ICA algorithms have difficulty with. The EEG signals shown in Fig. 3a contains high-amplitude artifacts that drive the amplifier into saturation on some channels. The usual way to deal with this kind of artifact is to chop it out, but this is not the best choice because there are brain signals on some channels that may still be useful. In this example we compare the recovered signals using the proposed artifact-blocking (AB) algorithm with those obtained using ICA. The ICA algorithm used here is fastICA algorithm [2]. Fig. 3b shows the separated components using fastICA. As we can see in this figure, artifacts appear in many components, mainly components 2, 3, 4, 7, 8, 10, and 11, rather than in one component as desired. In addition, these components still have brain signals outside the interval at which the artifacts occur, so a lot of data will be lost after rejecting these components. After removing these components, the corrected signals are shown in Fig. 3c. On the other hand, Fig. 3d shows the corrected signals using AB algorithm. As we can see in this figure, in the region where the artifact occurred, the algorithm has approximately similar performance as fastICA. However, unlike fastICA, it may

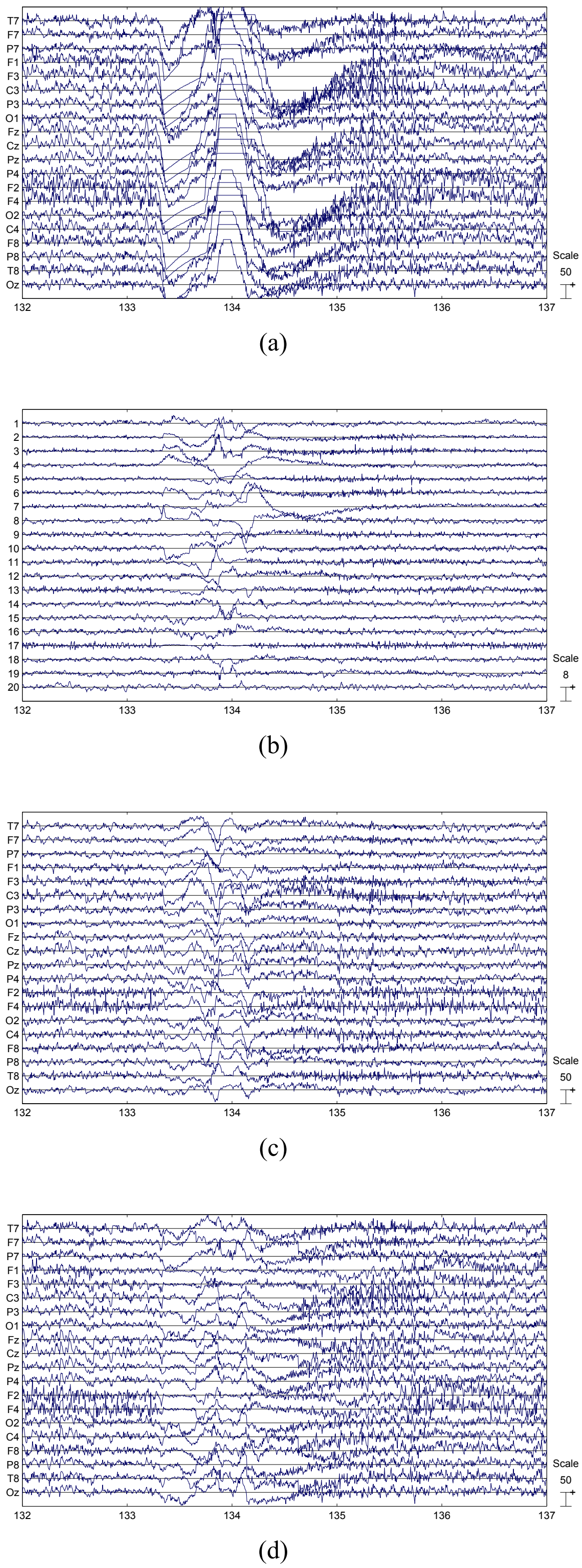

Fig. 3. (a) 5 seconds of EEG signals contaminated with a clipping artifact (b) The separated components using fastICA (c) corrected EEG signals using fast ICA (d) corrected EEG signals using the AB algorithm

be observed there is no change in the recovered data at instants where the artifact does not occur.

V. DISCUSSION AND CONCLUSIONS

In this paper we propose a simple and fast algorithm that can automatically remove artifacts (such as ocular movement and eye blinks) with high amplitude. Artifacts with lower amplitude cannot be removed with this algorithm; however, that may not be of great consequence because low–amplitude artifacts have a less confounding effect on the desired brain signals than do large–amplitude artifacts. In addition to its simplicity, the proposed algorithm is successful with certain types of signals that other ICA based algorithms fail to deal with. Since the proposed algorithm corrects EEG data directly, it does not require any assumptions about the number of sources or whether or not they are statistically independent. Finally, the proposed algorithm is fast enough to be applied in real time with a reasonably powerful computer.

VI. ACKNOWLEDGEMENTS

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