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Using a multichannel Wiener filter to remove eye-blink artifacts from EEG data

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ABSTRACT

This paper presents a novel method for removing ocular artifacts from EEG recordings. The proposed approach is based on time-domain linear filtering. Instead of directly estimating the artifact-free signal, we propose to obtain the eye-blink signal first, using a multichannel Wiener filter (MWF) and a small subset of the frontal electrodes, so that extra EOG sensors are unnecessary. Then, the estimate of the eye-blink signal is subtracted from the noisy EEG signal in accordance with principles of regression analysis. We have performed numerical simulations so as to compare our approach to the independent component analysis (ICA) that is commonly used in EEG enhancement. Our experiments show that the MWF-based approach can perform better than the ICA in terms of eye-blink cancellation and signal distortions. Besides that, the proposed approach is conceptually simpler and better suited to real-time applications.

1. Introduction

Electroencephalography (EEG) is a common method for diagnosing neurological disorders. However, it is difficult to analyse brain activity signals, since they are multichannel, non-stationary, and they are often contaminated by non-neural contents like eye movements, blinks, muscle activity, heartbeats and power line noise [1]. The electrical interferences associated with eyeball movements and blinks, also known as ocular artifacts, present serious problems for EEG data interpretation. In fact, several mechanisms are responsible for generating these interferences, see [2] for a detailed description. Generally, potentials generated by an eye-blink, are 10 times larger in amplitude than the neural activity at frontal electrodes and can last up to 400 ms [3]. Unfortunately, these behaviours are usually involuntary, thus controlling test subjects is unrealistic and nearly impossible, especially in cases of certain neurological disorders, e.g. hyperactivity, schizophrenia. In addition, some studies show that brain activity is affected by attempts to avoid blinking or to keep eyes closed [2,4]. On the other hand, some diagnostic need visual feedback, i.e. observation of moving objects.

Usually EEG data are preprocessed before interpretation and further analysis. The simplest approach is to manually select and reject deteriorated fragments, based on their time-frequency characteristics. This process can be time consuming and requires a trained technician that is able to identify such fragments. Moreover, this subjective task often leads to a significant data loss. Therefore, in recent years we observe a growing interest in automated detection and removal of ocular artifacts in EEG signals [5–7].

One approach to reducing artifacts related to eye-blinking is regression analysis [2,8], which uses electrooculographic (EOG) reference signals collected near the eyeballs. These signals are simply multiplied by propagation factors and subtracted from data registered by EEG electrodes. The method is easy to implement, but in general it is based on assumptions that are not necessarily true. Namely, EOG signals also contain brain activity from frontal lobes, thus subtraction tends to distort EEG signals. Furthermore, some systems cannot be equipped with EOG electrodes.

Other methods are based on spatial decompositions of EEG signals. These techniques usually do not require additional EOG sensors and perform blind source separation (BSS). An example is the principal component analysis (PCA) which was used to decorrelate EEG signal sources [9]. The PCA transforms multivariate data (correlated EEG signals) into a set of uncorrelated components. The artifact-free EEG signal can be reconstructed by rejecting components that correspond to eye-blinks. Unfortunately, the PCA relies on second order statistics only (i.e. covariance matrices), and thus the algorithm fails when amplitudes of the separated sources are comparable (within the same spectral band).

The independent component analysis (ICA) has been found to be highly effective in separating neural activity from ocular artifacts in EEG signals [10,11]. Unlike the PCA, the ICA relies on higher order statistics (e.g. kurtosis) and decomposes multivariate data

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into components that are statistically independent. Thus the ICA is capable of extracting some artifacts even when they are lower in amplitude than the background brain activity. Similarly as in the case of the PCA, after detecting artifacts in some components, EEG signals are reconstructed using only artifact-free components. While estimating independent components (ICs), the number of sources is often assumed to be equal to the number of electrodes. In fact, the former number is unknown, and the ICA does not guarantee the correct results, if there are more sources than electrodes.

Recently, a tensor decomposition has become surprisingly attractive for processing EEG data [12,13]. In these approaches, spatial, temporal and frequency informations contained in EEG recordings are processed simultaneously. The tensor decomposition finds application in multi-way blind source separation, dimensionality reduction, feature vector extraction and classification. It was also used for an automatic eye-blink removal [14].

Unfortunately, BSS-related approaches to eye-blink correction are usually unable to perfectly distinguish artifactual data and often a large amount of useful information is also removed. Moreover, they have a relatively high computational complexity and can present serious difficulties when implemented in real-time applications. Another issue is that any method, which relies on BSS, requires proper identification of blinking components, which in general is not an easy task [5,6]. A common solution to this problem is to use dipole model [15] for localization of a particular electrical activity within brain. In this approach each independent component is projected to the scalp, and fitted with a single dipole model. If a dipole is located within eye area, the corresponding component is automatically identified as the eye-blink artifact. The method proposed in [16] uses wavelet decomposition and adaptive thresholding technique for identification and correction of ocular artifacts. It was shown in [17] that artificial neural network (ANN) can be also used for this purpose, which gives better results than the adaptive thresholding technique. These approaches can be combined with ICA [18] in order to remove ocular artifacts from the contaminated ICs.

The primary goal of this work is to create a conceptually simpler alternative to BSS-related methods, which offers similar results and can be easily implemented in real-time systems. We propose to use a multichannel Wiener filter (MWF) [19] to estimate not a neural activity signals but eye-blink component at frontal lobes only. Such a choice is motivated by the observation that eye-blink signal is usually much less stationary than typical neural activity. Also the ratio of the average eye-blink signal power to the average power of the physiological brain activity (measured in signal-to-noise ratio terms) is relatively high, especially at frontal electrodes. The MWF-based estimate of the eye-blink component can be further used in place of the EOG signals. Namely, by using a propagation model similar to that of the regression analysis, we can estimate eye-blink signals measured at all electrodes. An artifact-free EEG signal at each electrode is obtained by subtracting the corresponding estimated eye-blink signal from data registered by this electrode. A similar approach has been proposed in [20], where the Wiener filter has been used as a post-processor to denoise the contaminated ICs. In opposition to [20], our technique uses a multichannel counterpart of the Wiener filter and does not require the ICA. The proposed method relies on second-order statistics mainly, but exploits spatial information encoded in cross-correlation matrices.

The rest of the paper is organized as follows. Section 2 describes the signal model and explains multichannel Wiener filtering. Section 3 presents the proposed method for eye-blink removal, while Section 4 gives some details that will help the reader understand how the method was implemented. Section 5 describes experimental settings and presents the achieved results. Finally, conclusions are given in Section 6.

2. Multichannel Wiener filter

2.1. Data model and notation

Let us consider a set of N EEG electrodes. Usually data are divided into L-sample frames in each channel. By assuming a linear mixing model and by using vector-matrix notation, the kth frame of the observation signal at the nth sensor/channel can be written as follows:

$$\mathbf{y}_n(k) = \mathbf{x}_n(k) + \mathbf{v}_n(k), \quad n = 1, 2, \ldots, N, \tag{1}$$

where $\mathbf{x}_n(k)$ and $\mathbf{v}_n(k)$ are respectively the original eye-blink component and the clean brainwave EEG vector, both of the size L. For the sake of completeness, we also define the cross-correlation matrix of arbitrary column vectors $\mathbf{a}(k)$ and $\mathbf{b}(k)$ as

$$\mathbf{R_{ab}} = E[\mathbf{a}(k)\mathbf{b}^T(k)], \tag{2}$$

where $E\{.\}$ is the expectation operator, and $(.)^T$ denotes the vector/matrix transpose.

Unless otherwise stated, an equation holds for any arbitrarily chosen point of time. Therefore, for the sake of brevity, the frame index k is often omitted in the rest of this paper.

2.2. Linear filtering

In the linear filtering framework [19] the clean signal is estimated directly, but herein we propose to estimate a noise component first, and then to subtract it from observation vectors. This procedure is theoretically equivalent to the conventional approach, but due to the nature of the EEG signals, it has certain practical advantages, which will be explained later.

The eye-blink component at the nth sensor can be estimated by applying a linear transformation to the observation vector:

$$\hat{\mathbf{x}}_n(k) = \mathbf{H}_n\mathbf{y}(k) = \mathbf{H}_n[\mathbf{x}(k) + \mathbf{v}(k)], \tag{3}$$

where

$$\begin{aligned}
\mathbf{y}(k) &= [\mathbf{y}_1^T(k)\ \mathbf{y}_2^T(k)\ \ldots\ \mathbf{y}_N^T(k)]^T,\\
\mathbf{x}(k) &= [\mathbf{x}_1^T(k)\ \mathbf{x}_2^T(k)\ \ldots\ \mathbf{x}_N^T(k)]^T,\\
\mathbf{v}(k) &= [\mathbf{v}_1^T(k)\ \mathbf{v}_2^T(k)\ \ldots\ \mathbf{v}_N^T(k)]^T,
\end{aligned} \tag{4}$$

and $\mathbf{H}_n$ is the optimal filtering matrix of size $L \times LN$. The estimation error is defined by

$$\begin{aligned}
\mathbf{e}_n(k) &= \hat{\mathbf{x}}_n(k) - \mathbf{x}_n(k)\\
&= (\mathbf{H}_n - \mathbf{U}_n)\mathbf{x}(k) + \mathbf{H}_n\mathbf{v}(k),
\end{aligned} \tag{5}$$

where

$$\mathbf{U}_n = [\mathbf{0}_{L\times(n-1)L}\ \mathbf{I}_L\ \ \mathbf{0}_{L\times(N-n)L}]. \tag{6}$$

The optimal filtering matrix is obtained by minimizing the mean-square error (MSE):

$$\begin{aligned}
J(\mathbf{H}_n) &= \mathrm{tr}[\mathbf{e}_n(k)\mathbf{e}_n^T(k)]\\
&= \mathrm{tr}[\mathbf{R}_{\mathbf{x}_n\mathbf{x}_n}] + \mathrm{tr}[\mathbf{H}_n\mathbf{R_{yy}}\mathbf{H}_n^T] - 2\mathrm{tr}[\mathbf{R}_{\mathbf{x}_n\mathbf{y}}\mathbf{H}_n^T].
\end{aligned} \tag{7}$$

By differentiating the above expression with respect to $\mathbf{H}_n$ and by setting the result to zero, we obtain [19]:

$$\mathbf{H}_n = \mathbf{R}_{\mathbf{x}_n\mathbf{y}}\mathbf{R}_{\mathbf{yy}}^{-1}. \tag{8}$$

As signal $\mathbf{x}_n(k)$ is not observable, the matrix $\mathbf{R}_{\mathbf{x}_n\mathbf{y}}$ must be estimated indirectly.