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A Time-Domain Eye Blink Artifacts Rejection Technique for Single-Channel EEG Signals

Suguru Kanoga and Yasue Mitsukura

Keio University
3-14-1 Hiyoshi, Kohoku, Yokohama, Kanagawa 223-8522, Japan
Email: kanouga@mitsu.sd.keio.ac.jp, mitsukura@sd.keio.ac.jp

Abstract—In this paper, we propose a time domain eye blink artifacts rejection technique for single-channel electroencephalographic (EEG) signals. Independent component analysis (ICA) is most well-known method for removing eye blink artifacts of multi-channel EEG signals. However, there is no time domain eye blink artifacts rejection technique for the single-channel EEG signals. Therefore, we propose positive semidifinite tensor factrization (PSDTF) as new eye blink artifacts rejection technique of single-channel EEG signals and investigate the validity of PSDTF by direct comparison with ICA using signal-to-noise ratio (SNR). The results represented SNR whose average value is 8.99dB between ICA and PSDTF in regard to estimated artifact signals. For this results, we confirmed the validity of PSDTF for eye blink artifacts rejection of single-channel EEG signals in time domain.

1. Introduction

Electroencephalographic (EEG) signal processing has recently been attracted in various fields of research. Neuromarketing and rehabilitation are included for the examples of research field [1] [2]. EEG signal is attributed to a mixture of endogenous brain activities such as evoked potential. Therefore, we can know the endogenous brain activities by EEG signal processing.

In most measurements of EEG signal, a multi-channel EEG device is used for measurement. The device can measure extensive brain activities with a lot of electrodes. However, it takes long to wear itself on the head of subject and gives him or her an oppressive feeling. A single-channel EEG device can measure only one point of cortical surface. For this constraint, it is worn easily and gives less oppressive feeling than multi-channel EEG device. This device has come to be used in the last 5 years [3].

An electrical activity of the levator muscle which controls upper eyelid and is responsible for eye blinks, mixes in EEG signals as artifact when we measure EEG signals with either EEG device [4]. Eye blink artifacts make EEG signal analysis difficult because an EEG potential is generally lower than the potential of eye blink artifact [5]. Furthermore, eye blink artifacts absolutely mix in EEG signals while a subject wears an EEG device with his or her eyes open. Hence, removing eye blink artifacts from EEG signals is very important problem for getting brain activities accurately.

Independent component analysis (ICA) is the most well-known method for removing eye blink artifacts [6]. The method can separate the problem of source identification from that of source location. However, the drawback of this method is that it entails preparing two or more electrodes for getting meaningful informations. For this reason, ICA is not able to be used to single-channel EEG signal analyses.

In audio signal analysis, the source separation of single-channel audio signals is considered a situation similar to the above-referenced situation. Positive semidefinite tensor factorization (PSDTF) can factorize a set of positive semidefinite (PSD) matrices into the fewer PSD basis matrices for time domain separation of single-channel audio signals [7] [8]. We assumed that if eye blink artifacts basis matrices were acquired, we can get only EEG components from measured single-channel EEG signals by removing the artifacts bases in time domain.

Therefore, in this paper, we investigate the validity of PSDTF for eye blink artifacts rejection of single-channel EEG signals. 14 EEG and 1 vertical electrooculographic (EOG) signals are recorded from a subject who blinks every 3 s according to metronomic sounds, because we need the results of ICA as target and learning data. PSDTF with two step learning method is performed to reject eye blink artifacts using measured single-channel EEG (Fp1) signals and reconstructed EEG signals by ICA. The results of our proposed method are compared with the results of ICA to investigate the validity of PSDTF for eye blink artifacts rejection in time domain.

2. Source Separation

This section aims to explain the source separation methods in the context of this paper.

2.1. Independent Component Analysis

Independent component analysis (ICA) is effective source separation method where the courses of the sources are independent, and the number of sources is the same as the number of electrodes. Removing eye blink artifacts using multi-channel EEG signals and vertical EOG signals with ICA is well-known [6]. The multi-channel EEG signals are decomposed into temporary independent components as many electrodes. The independent component which is the highest correlation with the vertical EOG signal in all the independent components, will be removed from measured EEG signals as eye blink artifacts.

2.2. Positive Semidefinite Tensor Factorization

A positive semidifinite tensor factorization is a time domain source separation method [7] [8]. Given a three-mode tensor $\boldsymbol{X} = [\boldsymbol{X}_1, ..., \boldsymbol{X}_N] \in \mathbb{R}^{M\times M\times N}$, where M and N are the width of samples and the number of samples in the dataset. Each slice $\boldsymbol{X}_n \in \mathbb{R}^{M\times M}$ is a real symmetric positive semidefinite (PSD) matrix.

PSDTF can approximate each PSD matrix $\boldsymbol{X}_n$ by a convex combination of PSD matrices $\{\boldsymbol{V}_k\}_{k=1}^{K}$ (K basis matrices).

$$\boldsymbol{X}_n \approx \sum_{k=1}^{K} h_{k,n}\boldsymbol{V}_k = \boldsymbol{Y}_n, \tag{1}$$

where $h_{k,n} \geq 0$ is a weight at the n-th slice. It can be rewritten by following equation,

$$\boldsymbol{X} \approx \sum_{k=1}^{K} \boldsymbol{h}_k \otimes \boldsymbol{V}_k = \boldsymbol{Y}, \tag{2}$$

where $\otimes$ indicates the Kronecker product.

For finding a good approximate factorization, we use a log-determinant (LD) divergence [9] which is based on a Bregman matrix divergence [10].

$$C_{LD}(\boldsymbol{X}_n|\boldsymbol{Y}_n) = -\log|\boldsymbol{X}_n\boldsymbol{Y}_n^{-1}| + \mathrm{tr}(\boldsymbol{X}_n\boldsymbol{Y}_n^{-1}) - M. \tag{3}$$

This divergence is always non-negative and is zero if and only if $\boldsymbol{X}_n = \boldsymbol{Y}_n$. The LD divergence repeats the following multiplicative update rule to minimize the cost function $C_{LD}(\boldsymbol{X}|\boldsymbol{Y}) = \Sigma_n C_{LD}(\boldsymbol{X}_n|\boldsymbol{Y}_n)$ and to estimate $\boldsymbol{H} = [\boldsymbol{h}_1, ..., \boldsymbol{h}_K] \in \mathbb{R}^{N\times K}$ and $\boldsymbol{V} = [\boldsymbol{V}_1, ..., \boldsymbol{V}_K] \in \mathbb{R}^{M\times M\times N}$.

$$h_{kn} \leftarrow h_{kn}\sqrt{\frac{\mathrm{tr}(\boldsymbol{Y}_n^{-1}\boldsymbol{V}_k\boldsymbol{Y}_n^{-1}\boldsymbol{X}_n)}{\mathrm{tr}(\boldsymbol{Y}_n^{-1}\boldsymbol{V}_k)}}. \tag{4}$$

Furthermore, we acquire the following equation by letting the partial derivative as for $\boldsymbol{V}_k$ equal to be zero.

$$\boldsymbol{V}_k\boldsymbol{P}_k\boldsymbol{V}_k = \boldsymbol{V}_k^{old}\boldsymbol{Q}_k\boldsymbol{V}_k^{old}, \tag{5}$$

where PSD matrices $\boldsymbol{P}_k$ and $\boldsymbol{Q}_k$ are given by

$$\boldsymbol{P}_k = \sum_{n=1}^{N} h_{kn}\boldsymbol{Y}_n^{-1}, \quad \boldsymbol{Q}_k = \sum_{n=1}^{N} h_{kn}\boldsymbol{Y}_n^{-1}\boldsymbol{X}_n\boldsymbol{Y}_n^{-1}. \tag{6}$$

By using the Cholesky decomposition $\boldsymbol{Q}_k = \boldsymbol{L}_k\boldsymbol{L}_k^T$, where $\boldsymbol{L}_k$ is a lower triangular matrix, we can acquire the multiplicative update rule with regard to $\boldsymbol{V}_k$.

$$\boldsymbol{V}_k \leftarrow \boldsymbol{V}_k\boldsymbol{L}_k(\boldsymbol{L}_k^T\boldsymbol{V}_k\boldsymbol{P}_k\boldsymbol{V}_k\boldsymbol{L}_k)^{-1/2}\boldsymbol{L}_k^T\boldsymbol{V}_k, \tag{7}$$

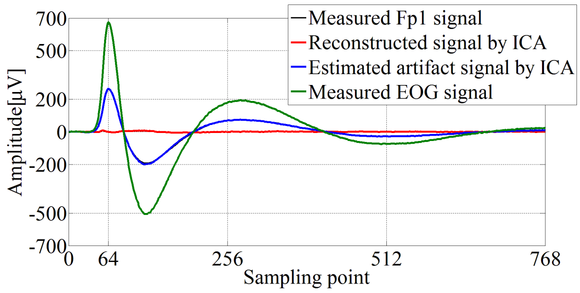

Figure 1: The average signals of measured Fp1, reconstructed Fp1 by ICA, estimated artifact by ICA, and measured vertical EOG

where the positive semidefiniteness of $\boldsymbol{V}_k$ is satisfied.

This will enable to model the mixture signal consisting of multiple basis signals which follows a Gaussian process with a convex combination of the corresponding kernels.

3. Preparing Datasets

3.1. Biological Signal Measurements

In this paper, we used a multi-channel EEG device, g.tec for measurements. The device recorded 14 EEG and 1 vertical EOG signals with a sampling rate of 256 Hz.

The EEG signals were recorded from Fp1, Fp2, F3, Fz, F4, T3, C3, C4, T4, P3, Pz, P4, O1, and O2 positions, referring to the international 10-20 system. The vertical EOG signal was recorded as potential difference from upper and lower right eye by using two disposable electrodes. The reference and ground electrodes were set up on A1 and Fpz, respectively.

3.2. Experimental Conditions

A male aged 23 years old participated in the experiments. The subject was asked to sit on a chair and blink every 3 s according to metronomic sound. The task was performed 30 times. The subject received an explanation of informed consent and permitted it prior to his participation.

3.3. Datasets

Through the experiments, we acquired 14 EEG and 1 vertical EOG signals. Total length of a signal is 95 seconds (30 trials of 3 s and margin of 5 s).

Firstly, we performed ICA with all signals. By using this method, we acquired reconstructed EEG signals which has no eye blink artifacts and estimated eye blink artifact signals. The signals appertaining to Fp1 were chosen for applying PSDTF because most of single-channel EEG devices can record only this point. The average signals of measured Fp1, reconstructed Fp1 by ICA, estimated artifact by ICA, and measured vertical EOG are shown in Fig.1. The estimated artifact signal by ICA (the blue line)

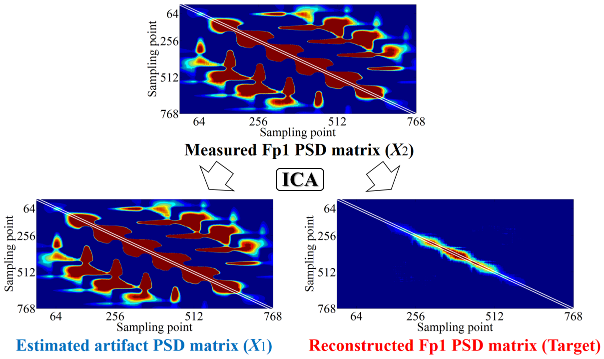

Figure 2: PSD matrices from measured Fp1 (top), reconstructed Fp1 (bottom right), and estimated artifact (bottom left)

has an overlap with the measured Fp1 signal (the black line). From this figure, you know the effectiveness of ICA.

Moreover, you know the signal caused by eye blink has a periodicity like sine wave. We focus on the periodicity of estimated artifact signal by ICA.

Secondly, we prepared PSD matrices for applying PSDTF. The matrices are calculated as $\boldsymbol{X}_n = \boldsymbol{x}_n\boldsymbol{x}_n^T$ from measured Fp1, reconstructed Fp1, and estimated artifact signals. The local signals $\{\boldsymbol{x}_n\}_{n=1}^N$ were extracted by using Gaussian window with a width of 768 samples ($M = 768$) and a shifting interval of 96 samples (375ms). For this conditions, 240 samples were acquired ($N = 240$) on a PSD matrix. The 3 types of PSD matrices are shown in Fig.2.

Their diagonal components are equivalent to square value of the signals in Fig.1 ($\boldsymbol{X}_n = \boldsymbol{x}_n\boldsymbol{x}_n^T$).

4. Two Step Learning

Our purpose is to decompose a given PSD matrix into the sum of K PSD matrices. If only specific components of $\boldsymbol{V}_k$ have the influence of eye blink artifacts, we can reject the eye blink artifacts by using other components.

Therefore, we performed PSDTF with two step learning method. Specifically, we used the measured Fp1 and the estimated artifact PSD matrices. The reconstructed Fp1 PSD matrix was not used in learning, however, this matrix is managed as target (See Fig.2).

On the first step, the estimated artifact PSD matrix ($\boldsymbol{X}_1$) was used to decompose into $\boldsymbol{H}$ and $\boldsymbol{V}$. We defined these matrices as $\boldsymbol{H}_{1\text{st}}$ and $\boldsymbol{V}_{1\text{st}}$. The matrix $\boldsymbol{V}_{1\text{st}}$ expresses $\boldsymbol{X}_1$ using its PSD matrices (K_1).

On the secoFnd step, the measured PSD matrix ($\boldsymbol{X}_2$) was used to decompose into $\boldsymbol{H}$ and $\boldsymbol{V}$. We defined these matrices as $\boldsymbol{H}_{2\text{nd}}$ and $\boldsymbol{V}_{2\text{nd}}$. Usually, the components of $\boldsymbol{V}_{2\text{nd}}$ have no relation to the components of $\boldsymbol{V}_{1\text{st}}$ because the initial values are set as randomly and updated by the multiplicative update rules.

In this paper, the PSD matrix $\boldsymbol{V}_{1\text{st}}$ was used as initial value in the second step. Furthermore, the values were not

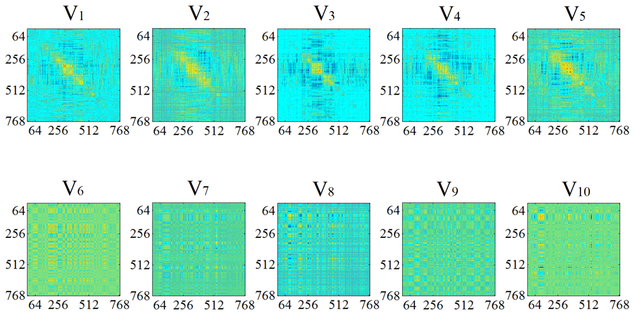

Figure 3: Estimated artifact PSDs by PSDTF (top line), Reconstructed PSDs by PSDTF (bottom line)

updated by the multiplicative update rules. For this constraint, the matrix $\boldsymbol{V}_{2\text{nd}}$ expresses the PSD matrix which includes EEG components using its PSD matrices (K_2).

Each PSD matrix $\boldsymbol{V}$ and their activations $\boldsymbol{H}$ were estimated with $K_1 = 5$, $K_2 = 5$. The number of iterations was 200 in each step.

After these processing, the following equations were applied for getting reconstructed signal and estimated artifact signal by PSDTF.

$$Reconstructed\ signal\ by\ PSDTF =$$
$$\boldsymbol{X_2} * w * \mathrm{diag}\left(\sum_{n=1}^{N}\sum_{k=K_1+1}^{K_1+K_2}\frac{h_{2\text{nd}\,k,n}\boldsymbol{V}_{2nd\,k}}{\boldsymbol{Y}_{2\text{nd}\,n}}\right), \quad (8)$$

$$Estimated\ artifact\ signal\ by\ PSDTF =$$
$$\boldsymbol{X_2} * w * \mathrm{diag}\left(\sum_{n=1}^{N}\sum_{k=1}^{K_1}\frac{h_{2\text{nd}\,k,n}\boldsymbol{V}_{1st\,k}}{\boldsymbol{Y}_{2\text{nd}\,n}}\right), \quad (9)$$

where w indicates the Gaussian window. $\boldsymbol{Y}_{2\text{nd}\,n}$ is given by

$$\boldsymbol{Y}_{2\text{nd}\,n} = \sum_{k=1}^{K_1+K_2} h_{2\text{nd}\,k,n}\boldsymbol{V}_{2nd\,k}\ . \quad (10)$$

The comparison method is signal-to-noise ratio (SNR).

$$SNR = 10\log_{10}\frac{S}{N}\ , \quad (11)$$

where S is the variance of estimated artifact signal by ICA and N is the variance of estimated artifact signal by the proposed method. Therefore, we can say that good approximation could be achieved if the value of SNR is high.

5. Results and Discussions

5.1. Separation of PSD matrices

The result of source separation in each step is shown in Fig.3. We noticed that the elements of matrix $\boldsymbol{V}_{1\text{st}}$ ($\boldsymbol{V}_1 \sim \boldsymbol{V}_5$) were high value in the center of elements which skirt or are the diagonal elements. On the other hand, all elements

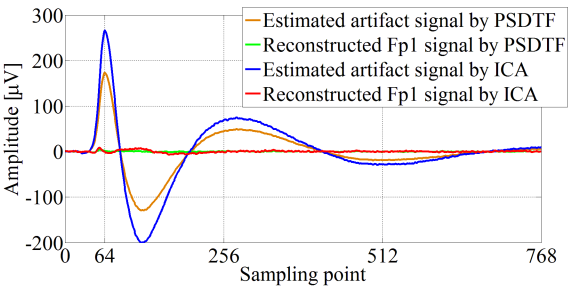

Figure 4: The reslts of PSDTF and ICA

were low value in the matrix $\boldsymbol{V}_{2\text{nd}}$ ($\boldsymbol{V}_6 \sim \boldsymbol{V}_{10}$). From this figure, good approximation was achieved by using PSDTF with two step learning.

We used the results of ICA on the first step. Therefore, it is necessary to investigate whether the estimated artifact basis matrix $\boldsymbol{V}_{1\text{st}}$ can be substitute for others in our future works. The basis matrix might come to be eye blink artifacts rejection filter if the basis matrix have generality.

5.2. Eye Blink Artifacts Rejection

The results of PSDTF and ICA is shown in Fig.4. The results of ICA (the blue and red lines) are identical with the lines which are in the Fig.1.

The average of SNR was 8.99dB between ICA and PSDTF in regard to the estimated artifact signals. The accuracy of PSDTF depends on the number of iteration. In this paper, we defined the value as 200, however, higher accuracy will be obtained as the number increases.

Waveforms generated by eye blink doesn't necessarily shape the same because it was based on the movements of eyelid. Therefore, adequate basis matrix $\boldsymbol{V}_{1\text{st}}$ and activation matrix $\boldsymbol{H}_{2\text{nd}}$ will be needed for eye blink artifacts rejection of single-channel EEG signals in time domain.

6. Conclusions

In this paper, we investigated the validity of PSDTF for eye blink artifacts rejection of single-channel EEG signals. 14 EEG and 1 vertical EOG signals were recorded from a subject who blinks every 3 s according to metronomic sounds. PSDTF was performed to reject eye blink artifacts using single-channel EEG (Fp1) signals and reconstructed EEG signal by ICA. The results represented SNR whose average value is 8.99dB between ICA and PSDTF in regard to the estimated artifact signals. For this results, we confirmed the validity of PSDTF for eye blink artifacts rejection of single-channel EEG signals in time domain.

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