Eye-Blink Artifact Reduction Using 2-Step Nonnegative Matrix Factorization for Single-Channel Electroencephalographic Signals

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Abstract Artifact reduction from electroencephalographic (EEG) signals is an important process in the numerical analysis of brain activities. In general, independent component analysis (ICA) is employed for artifact reduction from multichannel EEG devices. On the other hand, single-channel EEG devices have recently become attractive because of their usability for measurement and their portability. However, it is ill-defined problem to design a numerical approach for eye-blink artifact reduction from single-channel EEG signals. In this paper, we therefore propose a new artifact reduction method based on 2-step nonnegative matrix factorization (NMF) for single-channel EEG signals. In an experiment, we conducted 2-step NMF to reject eye-blink artifacts using single-channel EEG signals recorded at Fp1. We also applied ICA to multichannel EEG signals and compared the results with those obtained by the proposed method. The experimental results show a relatively high signal-to-noise ratio (SNR) between the signals reconstructed using the proposed method and those obtained by ICA. Moreover, we confirm the coefficient of correlation of over 99% for estimating the recorded EEG signals by the proposed method.

Keywords: electroencephalographic signal, independent component analysis, nonnegative matrix factorization

1. Introduction

Biological signal processing has been widely studied in various situations such as rehabilitation [1], [2], behavioral analysis [3], and neuromarketing [4]. In particular, electroencephalographic (EEG) signal processing has recently attracted attention since EEG signals contain a mixture of endogenous brain activities.

EEG signal measurement devices are simply categorized into the following two types. One is a cap-type device with multichannel electrodes. This device can extensively capture brain activities. Therefore, this device is employed when we investigate whole brain activities. The other is a headband-type device with a single-channel electrode. Although this device captures local brain activities, it can be easily worn and imposes less stress or restriction to the wearer than a cap-type device. In this paper, we refer to the above two devices as a multichannel EEG device and a single-channel EEG device, respectively.

Physiological/biological artifacts, such as eye blinks, cardiac beats, oculeography, and muscle activities, are often mixed in EEG signals. Such artifacts are superimposed on the EEG signals and make EEG signal processing difficult because the EEG energy is generally lower than the artifact energy [5]. Therefore, removing the artifacts from EEG signals is an important process when we strictly analyze brain activities. The artifacts caused by eye blinks have particularly profound effects on EEG signals as the eyes are very close to the brain. Furthermore, humans are physiologically unable to maintain a gaze without eye blinks. In other words, eye-blink artifacts have a strong presence in EEG signals obtained when a person wears an EEG device with his/her eyes open.

Independent component analysis (ICA) is the most popular scheme for removing eye-blink artifacts [6], [7]. It has already been confirmed that ICA can effectively reject eye-blink artifacts. However, ICA has a drawback that it can only deal with overdetermined mixtures; this method entails using at least as many electrodes as the number of artifact sources plus one in order to obtain meaningful information. Therefore, ICA is unsuitable for analyzing EEG signals recorded by a single-channel EEG device.

There has been little research on developing a numerical approach for rejecting eye-blink artifacts from single-channel EEG signals. This problem did not arise until 5 years ago since most EEG signal processing schemes were based on a multichannel EEG device [8]. However, a single-channel EEG device is convenient owing to its usability for measurement and portability in real environments. Furthermore, single-channel EEG signal processing is now expected to be incorporated into mobile systems such as smartphones and tablet computers. Accordingly, eye-blink artifact reduction from single-channel EEG signals is now a major challenge in
EEG signal processing.
Damon et al. proposed an eye-blink artifact reduction method based on nonnegative matrix factorization (NMF) for a single-channel EEG device [9]. They reported that NMF can effectively decompose recorded EEG signals into brain activity components and eye-blink artifacts. However, their paper did not mention numerical evaluations from the viewpoint of reconstructing independent components estimated by ICA. In addition, the reconstructed EEG signals and the estimated eye-blink artifacts were i.e., in ref. 9 unable to be automatically determined by NMF.

Therefore, in this paper we propose a new eye-blink artifact reduction method based on 2-step NMF for a single-channel EEG device. In an experiment, multichannel EEG signals are recorded from four subjects who blink every 5 s in time with a metronome. The proposed method performs 2-step NMF to reject eye-blink artifacts from single-channel EEG signals recorded from Fp1. Moreover, we apply ICA to multichannel EEG signals in order to estimate the independent components and eye-blink artifacts from the recorded EEG signals. The experimental results of the proposed method are compared with the results of ICA to evaluate its validity for eye-blink artifact reduction. Furthermore, the reconstructed signals obtained by the proposed method are compared with the signals recorded from Fp1.

2. Experiments

2.1 Biological signal measurements

In this paper, we use a cap-type device named g.tec, which has multichannel electrodes, for the purpose of comparing the proposed method with ICA. We recorded EEG and vertical electrooculographic (EOG) signals with a 256 Hz sampling rate.

The EEG signals are recorded from the 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 signals are recorded as potential differences obtained between above and below the right eye using two electrodes. The reference and ground electrodes are placed at A1 and Fpz, respectively.

These recorded EEG and vertical EOG signals are used for eye-blink artifact reduction by ICA. On the other hand, the recorded Fp1 signals are used for eye-blink artifact reduction by the proposed method. The reason why we chose Fp1 for the proposed method is that the headband-type EEG device can only record at this position [8]. Therefore, if the validity of the proposed method is confirmed, our method will be applicable to single-channel EEG devices.

2.2 Experimental conditions

Three male subjects and one female subject aged 21-27 years old participated in the experiments. They were asked to sit on a chair and blink every 5 s in time with a metronome. This task was conducted 30 times. The subjects received an explanation of the experiment and gave their informed consent prior to their participation.

3. Methods

3.1 ICA

ICA is the most popular method for removing eye-blink artifacts from multichannel EEG signals and vertical EOG signals [6], [7]. This method is based on spatial filtering and does not require a clean reference channel. In ICA, multichannel EEG signals are temporally decomposed into independent components. The independent component with the highest correlation with the EOG signal among all the independent components is removed as an eye-blink artifact. In this paper, we used EEG signals acquired from Fp1 after applying ICA as reconstructed signals.

3.2 NMF

NMF is a multivariable analysis method as it can additively factorize a nonnegative matrix (e.g., power spectrum) into two nonnegative matrices [10]-[12]. NMF has been used in many situations, for example, automatic transcription [13], sound emphasis or separation [14], and band spreading [15]. It has also been used in EEG feature extraction for classification [16]. However, NMF was not used as an artifact reduction method until recently.

An \( M \)-dimensional nonnegative data vector \( y_n \) is expressed as the columns of an \( M \times N \) matrix \( Y \), where \( N \) is the number of data vectors in the dataset. \( y_n \) is called an observation vector. The matrix \( Y \) is approximately factorized into an \( M \times K \) nonnegative matrix \( H \) and a \( K \times N \) nonnegative matrix \( W \), where \( K \) is the number of bases, which is optimized for linear approximation of the observation vectors. \( y_n \) can be given by

\[
y_n = \sum_{k=1}^{K} h_k w_{k,n} \quad (n = 1, \ldots, N) \tag{1}
\]

where \( h_k \) and \( w_{k,n} \) denote the entries of \( H \) and \( W \), respectively. In other words, the corresponding Fp1 signal vector \( y_n \) is approximated by a linear combination of the basis vectors \( h_k \) weighted by the components of \( w_{k,n} \). Therefore, Eq. (1) can be rewritten as the following equation:

\[
Y \cong HW \tag{2}
\]

To obtain an approximate factorization, we can design iterative algorithms that quantify the quality of approximation. The iterative algorithms can provide a measure of the accuracy of approximation between two nonnegative matrices. This measure is not called a “distance” if it is asymmetric. Such a measure is referred to as the “divergence” [11]. There are various kinds of distances and divergences used in NMF, for example, the Euclidean (EU) distance, the Kullback-
Leibler (KL) divergence, and the Itakura-Saito (IS) divergence. In NMF, these measures can be written as

\[
D(Y, HW) = \sum_{m,n} D_i(y_{m,n} | h_{m,k} w_{k,n})
\]

where \((\cdot)\) is the kind of algorithm, i.e., the EU, KL, or IS divergence. In this paper, we employ the IS divergence as the measure of approximation accuracy since it is designed for the factorization of power spectra [17]. The iterative algorithm of the IS divergence repeats the following multiplicative update rules:

\[
h_{m,k} \leftarrow h_{m,k} \left( \frac{\sum_n y_{m,n} w_{k,n} / x_{m,n}^2}{\sum_n w_{k,n} / x_{m,n}} \right)^{1/2}
\]

\[
w_{k,n} \leftarrow w_{k,n} \left( \frac{\sum_m y_{m,n} h_{m,k} / x_{m,n}^2}{\sum_m h_{m,k} / x_{m,n}} \right)^{1/2}
\]

where

\[
x_{m,n} = \sum_k h_{m,k} w_{k,n}
\]

If the basis matrix \(H\) finds a structure that is latent in the data, the dimension of \(H\) will be smaller than the dimensions of \(Y\). Then it is concluded that good factorization is achieved. Therefore, the number of bases \(K\) should be less than the half of \(M\) when we use NMF to obtain meaningful bases. However, the appropriate number of bases is unknown in the case of EEG analysis. In this paper, we also investigate the appropriate number of bases.

3.3 Datasets

We acquired 14-channel EEG and vertical EOG signals in experiments. The total length of an EEG recording for one subject is 155 s (30 trials of 5 s recording and a margin of 5 s).

Firstly, we applied ICA to the 14-channel EEG and vertical EOG signals. As a result, we could decompose the recorded Fp1 signals into reconstructed Fp1 signals and removed Fp1 signals. A reconstructed Fp1 signal is a signal reconstructed from a recorded Fp1 signal without the independent component with the highest correlation with the vertical EOG signal. The removed Fp1 signal is the independent component removed from the recorded Fp1 signal as the eye-blink artifact.

Secondly, we extracted local signals from the recorded Fp1 signals, the reconstructed Fp1 signals, the removed Fp1 signals, and the vertical EOG signals. Each signal has a peak amplitude at 2.25 s (the 576th sampling point). This peak is caused by the eye-blink artifact. This is because the energy of an EEG signal is generally lower than the energy of an eye-blink artifact [5]. These four types of signal are shown in Fig. 1. After this process, we acquired 120 signals (30 signals multiplied by 4 types) of length 5 s (1280 sampling points) for each subject.

Thirdly, we applied a short-time Fourier transform (STFT) to the recorded Fp1 signals with a 256-sampling-point Hamming window and 128-sampling-point shifting. The acquired frequency components were squared to calculate power spectra. After this process, we obtained 330 power spectra (30 signals multiplied by 11 windows). The data included aliasing, therefore, they were modified to 129-dimensional power spectrum data. The 129-dimensional data were needed for the reconstruction of the original signal because the first and 129th components in the data are unique components.

As shown in Fig. 2, the 5th to 8th original power spectra overlap with the eye-blink artifact in the low-frequency region.
3.4 Proposed method

In this paper, we propose 2-step NMF for eye-blink artifact reduction using single-channel EEG signals. The proposed method is outlined in Fig. 3.

The power spectrum matrix of the reconstructed Fp1 signals $Y_1$ is factorized into two nonnegative matrices in the first step. We denote these matrices as $H_{1st}$ and $W_{1st}$. The matrix $H_{1st}$ attempts to express the matrix $Y_1$ using its bases ($K_1$).

Next, the power spectrum matrix of the original Fp1 signals $Y_2$ is also factorized into two nonnegative matrices in the second step. We denote these matrices as $H_{2nd}$ and $W_{2nd}$. The elements of matrix $H_{1st}$ have no relation to the elements of matrix $H_{2nd}$ because the initial values are set randomly and updated by multiplicative update rules.

In this paper, the matrix $H_{1st}$ was used as a fixed value in the second step. From this constraint, we attempt to use the matrix $H_{2nd}$ to express the matrix $Y_2$ using the remaining bases ($K_2$). Therefore, the eye-blink artifacts mixed with the original Fp1 power spectra are stored in the remaining bases. In both steps, we performed NMF with $K_1$ and $K_2$ bases. $K_1$ and $K_2$ both ranged from 2 to 64, because the sampling rate is set as 256 Hz. We call the above NMF scheme 2-step NMF.

Furthermore, we used the following equation to reconstruct the power spectrum data vector.

Reconstructed power spectra =

$$Y_2 = \sum_{k=2}^{K_1} \sum_{n=1}^{N} H_{1st} W_{2nd,k,n}$$

Estimated eye-blink artifact power spectra =

$$Y_2 - \text{Reconstructed power spectra}$$

By using Eqs. (7) and (8), we acquire the reconstructed power spectra and the estimated eye-blink artifact power spectra. They are transformed into time series signals by using an inverse Fourier transformation. The eye-blink artifacts estimated by 2-step NMF are compared with the signals removed by ICA to determine the appropriate values of $K_1$ and $K_2$ for eye-blink artifact reduction.

The signals reconstructed by ICA are complemented by the signals acquired from other electrodes. However, matrices $H_{2nd}$ and $W_{2nd}$ are based on only the matrix $Y_2$, therefore, the power spectra reconstructed by 2-step NMF will be similar to the matrix $Y_2$. In other words, the phase of the signal reconstructed by ICA and the phase of the signal reconstructed by 2-step NMF are completely different. Therefore, we only compare the removed (estimated eye-blink artifact) signal.

We use the signal-to-noise ratio (SNR) as a comparative measure:

$$\text{SNR} = 10 \log_{10} \frac{S}{N}$$

where $S$ is the variance of the signal removed by ICA and $N$ is the variance of the eye-blink artifact signal estimated by 2-step NMF. We calculated 3969 SNRs (63 bases multiplied by 63 bases) for each signal. Therefore, we calculated 476,280 SNRs (3969 patterns multiplied by 30 signals and 4 subjects) to investigate the appropriate number of bases for eye-blink artifact reduction.

4. Results and Discussion

4.1 Comparison of SNRs

The results of the average SNRs are shown in Fig. 4. According to this figure, the SNR is high when $K_1$ is small.

In NMF, a good approximation can be achieved only when the basis vectors find a structure that is latent in the EEG data. The matrix $H_{1st}$ has to correctly obtain the information in the EEG data in the first step. It is already known that a
A good approximation is easily obtained if the number of bases is less than half of the effective frequency range of the target data [18], [19]. The effective frequency range of EEG data is usually less than 30 Hz. Therefore, we assumed that the SNR will be high when $K_1$ is between 2 and 15 in the first step.

The experimental results show the validity of our assumptions for the first step. The SNR is markedly decreased if $K_1$ exceeds 15 (see Fig. 4). The effective frequency range of the EOG data is even lower than that of the EEG data. We also assumed that the SNR will be high when $K_2$ is less than 15. The results of average SNRs were assumed to form a symmetrical pattern with a diagonal line traversing Fig. 4 from the lower left corner to the upper right corner. However, this assumption was incorrect because the SNR is high when $K_2$ is large.

4.2 Comparison of spectra

In order to investigate the effects of the number of bases, we compare the results in various cases. The obtained power spectra are shown in Fig. 5. The top figure shows the recorded Fp1 power spectrum, the power spectrum recorded by ICA, and four cases of eye-blink artifact power spectra estimated by 2-step NMF. From Fig. 5, we noticed that the proposed method can obtain a good approximation except in the case of $K_1=20$ and $K_2=5$. This indicates that a small value of $K_1$ and a large value of $K_2$ lead to good reconstructions. In particular, the results for $K_1=5$ and $K_2=10$ are similar to the spectrum removed by ICA.

The bottom figure in Fig. 5 shows the recorded Fp1 power spectrum, the power spectrum reconstructed by ICA, and four types of signals reconstructed by 2-step NMF. The result illustrated in sky blue overlaps with the recorded Fp1 signal. In order to estimate the basis matrix $H$ and activation matrix $W$, we used a good approximation. Hence, $K_1$ has to be set between 2 and 15.

On the other hand, the matrix $Y_2$ is factorized into many bases when the matrix $H_{1st}$ is referred to in the second step. As a good approximation is achieved in the first step, the bases of the second step can express the waveform generated by an eye blink.

In 2-step NMF, the recorded waveform is factorized according to the property of NMF. If a good approximation is achieved in the first step, $K_2$ will be a small number for the factorization. Therefore, $K_1$ must be determined prudently. However, the factorization may fail if $K_2$ is too small. Therefore, we recommend setting the values of $K_1$ and $K_2$ as 5 to 10 and 40 to 50, respectively, to obtain good approximations, as evidenced by the experimental results.

4.3 Comparison of signals

The signals corresponding to the power spectra in Fig. 5 are shown in Fig. 6. The top figure in Fig. 6 shows the recorded Fp1 signal, the signal removed by ICA, and four types of eye-blink artifact signals estimated by 2-step NMF. The result illustrated in sky blue overlaps with the recorded Fp1 signal. We thus clearly demonstrated that 2-step NMF can remove eye-blink artifacts when $K_1$ is small and $K_2$ is large.

The bottom figure in Fig. 6 shows the recorded Fp1 signal, the signal reconstructed by ICA, and four types of signals reconstructed by 2-step NMF. The result drawn in green overlaps with the recorded Fp1 signal. In order to estimate the basis matrix $H$ and activation matrix $W$, we used...
the IS divergence. The IS divergence is a special case of the Bregman divergence, which is always nonnegative and zero if and only if there is equality between the estimated matrix $\mathbf{H} \mathbf{W}$ and the recorded matrix $\mathbf{Y}$ [20]. Furthermore, the IS divergence repeats the efficient multiplicative update rule to minimize the reconstruction error. However, the signals from 2-step NMF are similar to the recorded Fp1 signals because the signals were approximated from only single-channel EEG signals.

4.4 Reconstruction of recorded signals

We focus on the reconstruction of recorded signals by the proposed method. The recorded Fp1 power spectra and signals are shown in Fig. 7. In addition, the sum of the reconstructed and removed power spectra and signals are shown in Fig. 7. In both figures, the results are given for $K_1=5$ and $K_2=50$.

In the top figure in Fig. 7, the sum of the reconstructed and removed power spectra overlaps with the recorded Fp1 power spectrum. We consider that the error among the two signals was caused by the approximate value of the square root (see the bottom figure in Fig. 7). However, the sum of the reconstructed and removed signals (the sky blue line) resembles the recorded Fp1 signal (the black line) closely. The average SNR was 29.13 dB and the average coefficient of correlation was over 99%, higher than value obtained for ICA. From these results, we confirm the validity of the proposed method.

The electric potential of an eye blink does not discharge a specific amount of electricity each time because the energy depends on the movements of the eyelid [21]. Equalizing the adjustment of the force or the time variation pertaining to the eyelid movement is nearly impossible. In other words, each signal generated by an eye blink is slightly different. However, 2-step NMF factorized a nonnegative matrix into two nonnegative matrices with high accuracy and removed the eye-blink artifacts regardless of the eyelid movements. Therefore, 2-step NMF was confirmed to be an effective eye-blink artifact reduction method for single-channel EEG signals.

5. Conclusions

In this paper, we proposed 2-step NMF for eye-blink artifact reduction when using a single-channel EEG device. We acquired 14-channel EEG signals and vertical EOG signals from four subjects who blinked every 5 s in time with a metronome. Furthermore, we performed 2-step NMF to reject eye-blink artifacts using single-channel EEG (Fp1) signals as well as ICA using multichannel EEG signals and vertical EOG signals for comparison.

In an experiment, we investigated the SNRs of the resulting signals obtained by ICA and 2-step NMF to determine the performance of the reconstruction. We showed that a relatively high SNR can be obtained when we appropriately determine the numbers of bases $K_1$ and $K_2$ in 2-step NMF. The average coefficient of correlation of recorded signals for the proposed method was over 99%. Therefore, we confirmed the effectiveness of 2-step NMF for eye-blink artifact reduction using single-channel EEG signals.
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