EOG-RELATED NOISE REJECTION IN EEG SIGNAL WITH EYE MOVEMENT TASK BY TENSOR PRODUCT EXPANSION WITH ABSOLUTE ERROR

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ABSTRACT

Eye movement origin electrooculogram (EOG) artifacts yield significant problems for the saccade-related electroencephalogram (EEG) and its analysis. The denoising of EOG artifacts is important task to analyze the relationship between a saccade and a brain function. In this paper, a tensor product expansion with absolute error (TPE-AE) is applied to reduce the EOG artifacts from the EEG signal. The TPE-AE has some difficulty to separate the EOG from the saccade-related EEG data due to a background noise from a spontaneous EEG activity. We show that the TPE-AE, which calculates two outer products, is useful to reduce EOG components related to the eye movement.

1. INTRODUCTION

Attention is being placed on the saccade-related EEG data to investigate the brain function in saccadic eye movement. EEG related to the saccade have researched to achieve a Brain Computer Interface (BCI) based on eye tracking system that uses saccadic EEG[1, 2]. However, the artifact due to a blinking and eye movement interfere with correct analysis of EEG related to saccadic eye movement.

The typical EEG signal processed with the ensemble averaging indicates that the sharp changes of a potential due to the saccade-related EEG and the eye movement EOG are recorded before and after the saccade, respectively. This EOG yields the difficulty of a saccadic EEG analysis. Moreover, the ensemble averaging requires EEG data of many trials to find characteristics of saccade-related EEG, and is not suitable to extract a change of a latent time related to the saccade.

Another technique is to reduce EOGs due to a saccadic eye movement and an eye blinking. In order to characterize the saccadic EEG, the EEG data excluding the eye blinking noise should be used for accurately analysis. However, denoising technique rejects important components for EEG analysis since the recorded potential during the saccadic eye movement contains both the saccade related EEG and EOG. Note that the word EOG used here means the artifact due to a saccadic eye movement.

Funase shows that a fast independent component analysis with reference signal (FICAR) can analyze single trial EEG data to realize a practical use of BCI[3, 4, 5]. The FICAR method focuses on the extraction of the saccadic EEG explained by the ensemble averaging by using a reference signal. Therefore, a feature extraction of other components associated with a saccade is not considered.

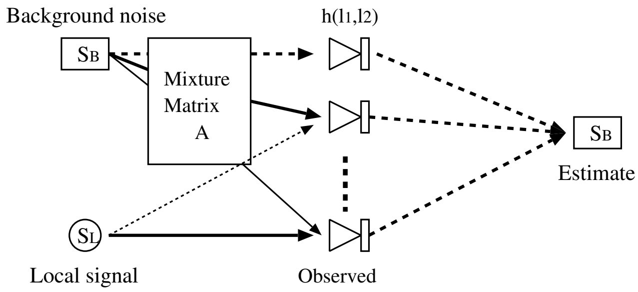


Figure 1: Model of noise reduction using outer product expansion

Saccade-related EOG artifacts yield significant problems for the EEG and its analysis. The EOG artifact denoising is important task to analyze the relationship between the saccade and the EEG. In order to find the saccadic EEG, a high-pass filter which rejects from 0 to 4 Hz is often employed to avoid the effect of the EOG. Generally speaking, however, this lower frequency band may include many EEG components corresponding to a recognition and consciousness.

In this paper, a tensor product expansion with absolute error (TPE-AE) is applied to reduce EOG artifacts in the EEG signal. The conventional TPE-AE has some difficulty to separate the EOG from the saccade-related EEG data due to a separability limitation. We apply the novel TPE-AE, which calculates two outer products, to the denoising problem. Results show that the TPE-AE employed in this paper is effective to reduce the EOG component in the EEG data.

2. TPE-AE

TPE-AE is the signal separation based on a tensor product expansion[6, 7, 8, 9]. Assume that the observed signal consists of two source signals, the one is observed in most signals (a background noise) while another is seen in just few signals (a local signal). In this case, the latter signal can be considered as the outlier. TPE-AE estimates a background noise from the observed signal as shown in Fig.1, while major blind source separation, i.e. independent component analysis, often estimates the *n* sources from *n* input signals.

An absolute error is employed in TPE-AE as a criterion to calculate the outer product [10, 11], since the absolute error have little influence of outliers. Let $h(l_1,l_2)$ be an input 2-D matrix consists of observed signals. The outer product and its bias component of $h(l_1,l_2)$ is given by the L1-norm

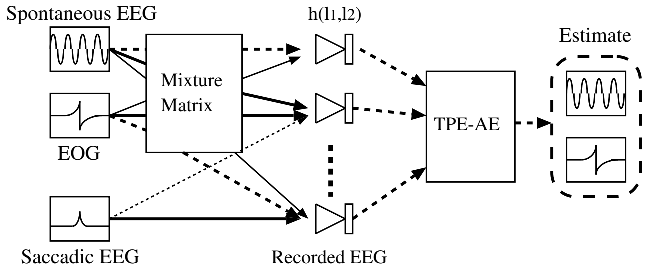


Figure 2: Model of noise reduction for saccadic EEG data

minimization as shown in (1).

$$J = \sum_{l_1=1}^{q_1} \sum_{l_2=1}^{q_2} |h(l_1, l_2) - (f_1(l_1) f_2(l_2) + f_3(l_2))| \qquad (1)$$

where J is an error function, $f_1(l_1) f_2(l_2)$ and $f_3(l_2)$ are an outer product which approximates AC and DC components, respectively. q_1 and q_2 is the length of the signal and the number of signals, $f_1(l_1)$ and $f_2(l_2)$ is l_1th and l_2th element of a vector, respectively. $f_1(l_1)$, $f_2(l_2)$ and $f_3(l_2)$, which yield minimum J, gives us the background noise included in the observed signal $h(l_1, l_2)$.

The simple and reasonable method based on Monte Carlo Simulation (MCS) was applied to calculate the optimal $f_1(l_1)$, $f_2(l_2)$, $f_3(l_2)$. MCS produces optimal solutions by extensive trials using random numbers. The feasibility and separability conditions of this method for the background noise estimation are confirmed [10].

TPE-AE can reduce the background noise generated by one source, however, the EEG data with an eye movement includes two undesired signals due to the EOG and a spontaneous EEG. We reduce the undesired signal in EEG data by estimating two terms of the outer product (Fig.2). TPE-AE applying to the EEG data does not require the estimation term for DC component since the EEG data is corrected and processed through a high-pass filter. Therefore, (1) is rewritten as (2).

$$J = \sum_{R=1}^{r} \sum_{l_1=1}^{q_1} \sum_{l_2=1}^{q_2} |h(l_1, l_2) - f_{1R}(l_1) f_{2R}(l_2)| \qquad (2)$$

where R and r indicates the index and number of an estimated term for TPE-AE. The EOG and a spontaneous EEG is estimated as $f_{11}(l_1) f_{21}(l_2)$ and $f_{12}(l_1) f_{22}(l_2)$.

3. EEG ANALYSIS

3.1 EEG data collection

The recording is performed in the shielded dark room in order to reduce an electromagnetic noise and a visual stimuli. The visual target (LED) is set on the board located 30cm away from the nasion of the subject. One LED is placed in front of the subject, two LEDs are located on 25 and -25 degree from the center LED (Fig.3). One LED of three LEDs is illuminated randomly to avoid the prediction of the subject which LED is blinking next. The EEG during the saccadic eye movement that a subject moves his eye toward the illuminated LED placed on a right or left side is recorded iteratively.

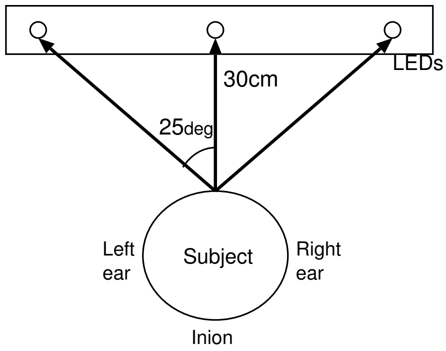


Figure 3: Placement of LEDs

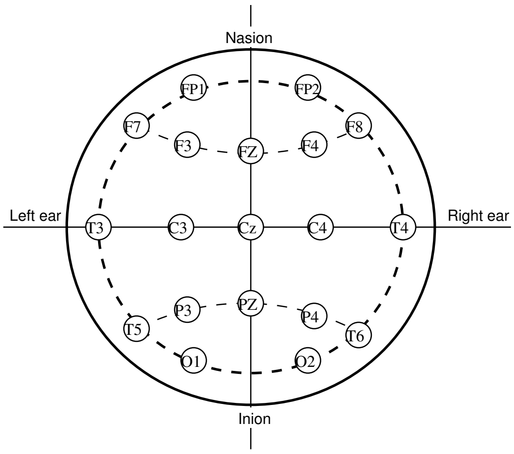


Figure 4: International 10-20 electrode system

EEG data is collected from 19 electrodes, which are placed at the location based on the international 10-20 system as shown in Fig.4. In order to detect an eye movement and an eye blinking, two pairs of sensors are attached to the right-left side (HEOG) and top-bottom side (VEOG) of the right eye. All potentials are digitally sampled at 1000Hz, and collected for the offline signal processing. A high-pass filter (cut-off 0.53Hz) and a low-pass filter (cut-off 120Hz) is applied to the collected EEG data, while the EOG data is recorded through a high-pass filter (cut-off 0.1Hz) and a low-pass filter (cut-off 15Hz).

The EEG data according to 50 right saccades and 50 left saccades from the center is collected by visual target task. The EEG data used here is 25 for each saccade since some of recorded data contain an artifact related to eye blinking and other body movement. 50 EEG signals related to 25 right and 25 left saccades are adopted to the denoising process.

3.2 Denoising procedure

The flow of denoising process using TPE-AE is shown in Fig.5. The input vector $h(l_1, l_2)$ consists of 19 EEG signals for two seconds whose starting time indicates 1 second before the eye movement. Outer products are estimated from EEG signals using TPE-AE. The denoising is performed by subtracting outer products from the input signal. These processes are applied to 50 EEG data for denoising undesired

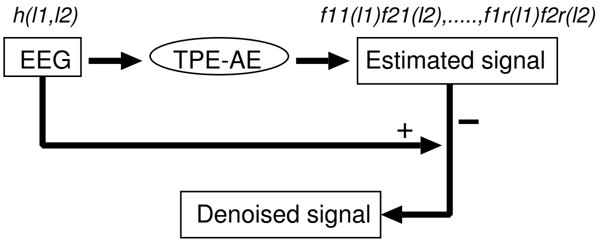


Figure 5: Flow of denoising by TPE-AE

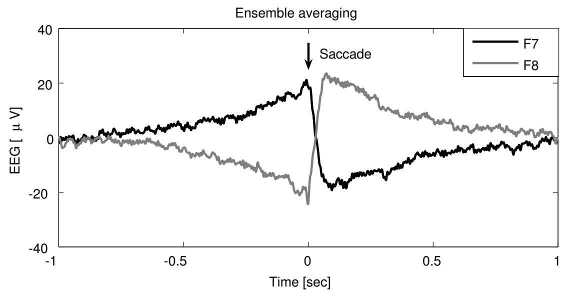
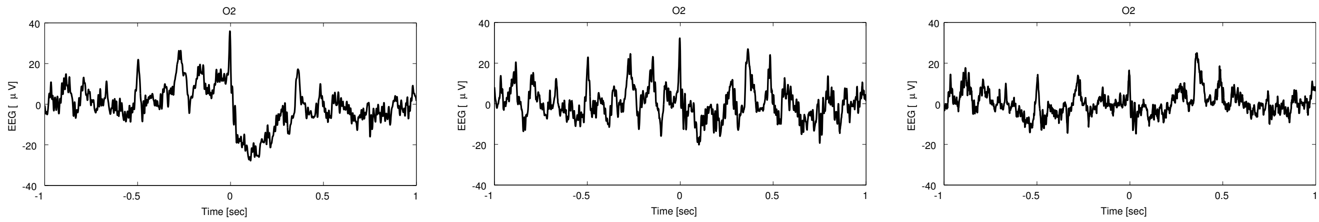
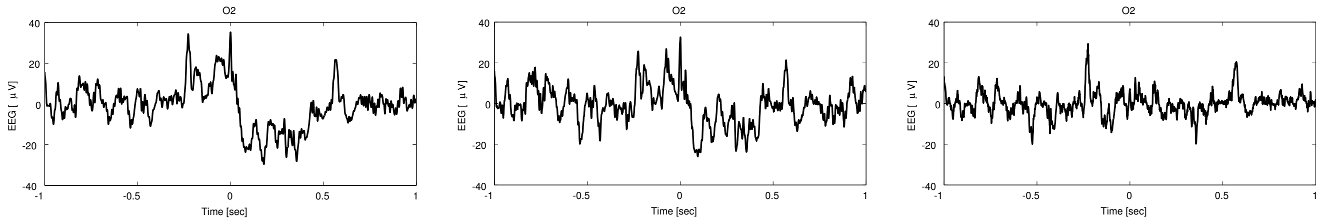


Figure 6: EEG of ensemble averaging in right saccade



(a):EEG (b):Denoised signal by TPE-AE $r = 1$ (c):Denoised signal by TPE-AE $r = 2$

Figure 7: EEG and its denoised signal using TPE-AE (1st right saccade)



(a):EEG (b):Denoised signal by TPE-AE $r = 1$ (c):Denoised signal by TPE-AE $r = 2$

Figure 8: EEG and its denoised signal using TPE-AE (6th right saccade)

signals due to the EOG and a spontaneous EEG. In this paper, TPE-AE which calculated one/two outer product is referred as TPE-AE $r = 1/r = 2$

4. EXPERIMENTAL RESULT

4.1 Typical EEG data in saccade

The typical EEG data with right-eye movement recorded on the left and right occipital lobe (F7 and F8 in international 10-20 system) is shown in Fig.6. This data is the ensemble average calculated from 25 EEG data. The horizontal axis is the time, whose 0 [sec] indicates the starting time of an eye movement to right. The vertical axis indicates the measured potential. The amplitude of EEG signal on F7 and F8 is sharply increased and decreased after the eye movement, respectively. This component is the dominant undesired signal related to the EOG due to the eye movement.

4.2 Example of denoising for single trial EEG

The denoising result of the undesired signal for the EEG signal with eye-movement is described here. Fig.7 and Fig.8 indicates the EEG on O2 and its denoised signal when the subject moves his eyes toward the right side. The denoised signals is the data processed using TPE-AE whose estimated outer product r is 1 and 2. The result shown in Fig.7 and Fig.8 is for first and 6th right saccade, respectively. The horizontal axes of these graphs indicate the time cause, where 0 [sec] represents the starting time of eye movement.

From Fig.7, a sharp decrease of the potential recorded from 0 to 0.1sec is reduced by using TPE-AE $r = 1$ and $r = 2$. This result is not common to all the results we tried. The sharp decrease in EEG is not always extracted by using TPE-AE $r = 1$. The sharp change corresponding to a 6th right saccade in Fig.8(a) is reduced by TPE-AE $r = 2$ (Fig.8(c)) while this change remains in the result of TPE-AE $r = 1$ (Fig.8(b)). In the case of almost all saccadic EEG data, a sharp decrease after the eye movement is reduced by using TPE-AE $r = 2$.

As previously noted, the EOG related undesired signal is not estimated completely by using TPE-AE $r = 1$. The TPE-AE which calculates one outer product can extract the dominant component in input signals. It is difficult to estimate the EOG related undesired signal by using TPE-AE because a spontaneous EEG observed at all over the subjects' head is extracted. Therefore, the undesired signal related to EOG is extracted successfully by estimating two outer products us-

Table 1: Difference of the averaged amplitude spectrum between EEG and denoised EEG [dB]

(a): 0-4Hz (EOG) for right saccade

	Fp1	F7	F3	T3	C3	T5	P3	O1	Fz	Cz	Pz	Fp2	F8	F4	T4	C4	T6	P4	O2	Ave.
TPE-AE(r=1)	1.6	2.0	2.5	0.4	7.1	4.3	6.0	4.6	10.5	13.4	7.3	1.5	5.4	1.6	0.7	0.6	1.3	0.9	2.2	3.9
TPE-AE(r=2)	2.6	**7.9**	4.5	3.2	**8.4**	**5.1**	**6.9**	**4.9**	**12.3**	**14.1**	**8.0**	3.0	**9.2**	4.6	1.9	**7.4**	**8.3**	**9.9**	**10.8**	**7.0**
Ensemble	**11.6**	0.6	**7.4**	**9.7**	2.6	1.5	1.1	0.6	0.5	1.0	2.2	**6.9**	-0.9	**8.6**	**9.3**	5.6	2.2	2.3	0.4	3.9

(b): 0-4Hz (EOG) for left saccade

	Fp1	F7	F3	T3	C3	T5	P3	O1	Fz	Cz	Pz	Fp2	F8	F4	T4	C4	T6	P4	O2	Ave.
TPE-AE(r=1)	1.8	1.8	2.2	0.4	7.8	5.9	8.1	5.0	10.9	**12.3**	7.4	2.0	5.9	1.0	1.0	-0.1	0.2	-0.3	0.7	3.9
TPE-AE(r=2)	4.9	**11.6**	5.9	3.6	**8.7**	**7.5**	**10.8**	**9.8**	**11.0**	**12.3**	**9.7**	**3.7**	**6.9**	**4.8**	2.8	**6.0**	**2.8**	2.6	**3.1**	**6.8**
Ensemble	**5.9**	0.4	**6.1**	**7.1**	3.8	0.8	0.9	0.3	2.3	1.9	0.5	-1.4	0.3	3.7	**10.3**	3.7	2.2	**4.8**	2.5	3.0

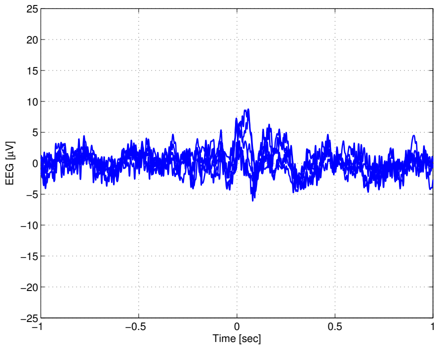


Figure 9: Ensemble averaging data for group A (Fp1, F3, T3, Fp2, F4, T4)

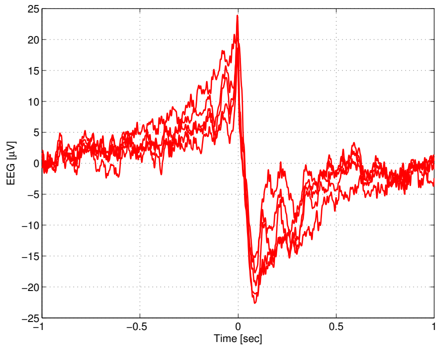


Figure 10: Ensemble averaging data for group B (C3, T5, P3, O1, Fz, Cz, Pz)

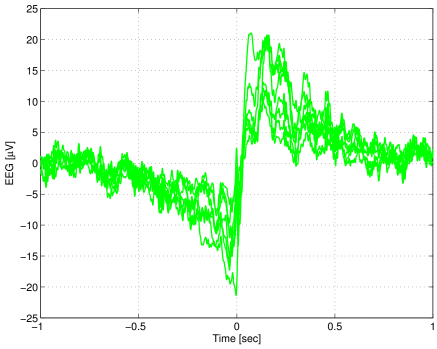


Figure 11: Ensemble averaging data for group C (F7, F8, C4, T6, P4, O2)

ing TPE-AE.

4.3 Evaluation in frequency domain

In order to evaluate the denoising performance of TPE-AE, a decrease of the EOG component from 0 to 4Hz is employed here. Table 1 represents the decrease of the EOG component between an averaged amplitude spectrum of raw EEG and its denoised EEG in decibel base. In order to extract the difference, 25 amplitude spectra of an input signal, i.e. raw EEG, denoised EEG processed with ensemble averaging, TPE-AE $r = 1$ and $r = 2$, are calculated by using the fast Fourier transform. TPE-AE $r = 1, 2$ in Table 1 indicates the difference between the averaged amplitude spectrum of raw EEG and its denoised EEG extracted by TPE-AE. Ensemble indicates the result after subtracting the averaged amplitude spectrum of recorded EEG from its ensemble averaging data. Table 1 (a) and (b) shows the difference corresponding to an eye movement toward right and left side, respectively.

From Table 1 (a), EOG component corresponding to the saccadic task to a right is decreased an average of 3.9, 7.0 and 3.9 decibel by using the TPE-AE $r = 1$, $r = 2$ and the ensemble averaging, respectively. Table 1 (b) indicates that the TPE-AE $r = 1$, $r = 2$ and ensemble averaging perform a decrease of the EOG component, which is related to the left saccade, with an average of 3.9, 7.0 and 3.9 decibel, respectively.

In Table 1 (a), TPE-AE $r = 2$ reduces the EOG component more than other denoising methods excluding Fp1, F3, T3, Fp2, F4 and T4. We call Fp1, F3, T3, Fp2, F4 and T4 a group A. The ensemble averaging data of group A corresponding to the right saccade shown in Fig.9 indicates that the sharp change of a potential after the saccade is smaller than a potential recorded on F7 and F8 (see Fig.6). Therefore, a decrease of EOG component in the group A is relatively small. The EOG in C3, T5, P3, O1, Fz, Cz and Pz processed with a TPE-AE $r = 1$ is decreased at the same level as $r = 2$. The potentials recorded on C3, T5, P3, O1, Fz, Cz and Pz are defined as a group B. The EEG data excluding the group A and group B is referred as group C whose EOG component is reduced by using TPE-AE $r = 2$. The ensemble averaging data for group B and C is shown in Fig.10 and Fig.11, respectively. The horizontal axes of these figures represents a time span where 0 [sec] indicates the starting time of the eye movement. The vertical axes show the measured potential. From Fig.10, EEG is decreased rapidly after the saccade, while EEG shown in Fig.11 represents the abrupt increase after the eye movement. These results indicates that the influence of EOG is recorded as three patterns of trends that are the increase, decrease and few change of a potential after an eye movement.

As we described above, EEG data during an eye movement includes an EOG and a spontaneous EEG. A spontaneous EEG represents the similar trend at almost all positions, while EOG indicates three patterns of EEG change. Therefore, the EEG applied to this research includes two dominant components whose mixing coefficient is significantly different. A spontaneous EEG and EOG component, which has a similar mixture coefficient measured on a spontaneous EEG (in this case, the EOG trend shown in group B), are extracted by TPE-AE $r = 1$ wrongly since it can estimate the background noise from one source. On the other hand, TPE-AE $r = 2$ decrease the EOG component in EEGs recorded on group B and C which include a little influence of the saccade.

These results show that the proposed TPE-AE $r = 2$ is effective to reduce EOG artifacts related to the eye movement.

5. CONCLUSION

This paper presents the method for reducing the EOG artifacts corresponding to the saccadic eye movement. We confirmed that a TPE-AE, which estimates two outer products, is effective to reduce EOG artifacts in a raw EEG. Remaining problems are to only remove the EOG component and to extract the saccade-related EEG from denoised signals.

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