An Evaluation of EEG Ocular Artifact Removal with a Multi-channel Wiener Filter Based on Probabilistic Generative Model

Hayato Maki[1], Tomoki Toda[2], Sakriani Sakti[2], Graham Neubig[2], and Satoshi Nakamura[2]

Abstract— Data contamination by ocular artifacts such as eye blinks and eye movements is a major barrier that must be overcome when attempting to analyze electroencephalogram (EEG) and event-related potential (ERP) data. To handle this problem, a number of artifact removal methods has been proposed. Specifically, we focus on a method using a multi-channel Wiener filters based on a probabilistic generative model. This method assumes that the observed signal is the sum of multiple signals elicited by psychological or physical events, and separates the observed signal into each event signal using estimated model parameters. Based on this scheme, we have proposed a model parameter estimation method using prior information of each event signal. In this paper, we examine the potential of this model to deal with highly contaminated signals by collecting EEG data intentionally contaminated by eye blinks and relatively clean ERP data, and using them as prior information of each event signal. We conducted an experimental evaluation using a classical attention task. The results showed the proposed method effectively enhances the target ERP component while reducing the contamination caused by eye blinks.

I. INTRODUCTION

Due to its high temporal resolution, electroencephalogram (EEG) has been one of the major techniques to investigate human brain dynamics [1]. However, it is very sensitive to external artifacts such as eye blinks, body movements, and so forth, which is a major common problem to all EEG studies.

In an experimental paradigm using event-related potential (ERP), the whole recording is cut into small intervals containing a single stimulus. Each of interval is called a trial. Trial signals are usually averaged synchronously to attenuate the effect of background EEGs while preserving the amplitude of ERPs.

However, this synchronous averaging is not effective for removing external artifacts, because artifacts have far larger potentials, several tens or hundreds times as large as neural sources. Consequently, external artifacts distort the averaged signal because the number of available trials is rarely enough to drown out the effect of artifacts. Therefore, in order to avoid such distortion, it is common usually discard trials in which the potential exceeds some predefined threshold either in specific electrodes or in all electrodes, then average remaining trials. Nevertheless, this procedure is problematic or even unacceptable when, as is often with the case with ERP studies, the number of available trials is small or artifacts happen frequently, as the number of remaining trials is too small to perform reliable analysis. In addition, this procedure makes it impossible to conduct an experimental paradigm in which the occurrence of artifacts is inevitable such as visual tracking experiments. Especially, ocular artifacts are the most troublesome among various artifacts since they are likely to happen frequently, especially during visual experiments. In fact, Small [2] reported that almost all trials were contaminated by ocular artifacts in his visual ERP experiment conducted on children with autistic disorders.

For the reasons above, methods to remove the effect of artifacts from recorded EEG data are necessary. A recent successful approach to the problem of noise reduction of EEG signals is independent component analysis (ICA), which decomposes a multi-channel signal in a set of sources with maximally independent components (ICs). However, it has limitation on the number of separable ICs, N ICs from N electrodes, which makes the decomposition imperfect as the number of EEG sources is much higher than the number of ICs [3], [4], [5]. In addition, ICA-based methods require subjective decision making [6] or arbitrary tuning of the thresholds [7] to distinguish artifacted ICs from non-artifacted ICs, which is known as the permutation problem.

Another approach [8], [9] using a multi-channel Wiener filter designed based on a probabilistic generative model has been proposed to address the limitation of ICA. This approach refers to the multi-channel signal related to the k-th event simply as the "k-th event signal" and separates an observed signal not into signals generated by individual sources but into event signals. This method has been successfully applied to unsupervised EEG event signal separation using multi-channel EEG signals [10]. Furthermore, in our previous paper [11], we extended this method by using prior information of the target event signal, allowing us to specifically enhance the target event signal. This approach was shown to improve enhancement performance and effectively remove background EEGs from single-trial ERPs. Moreover, in contrast to BSS techniques including ICA, this method has no problems of permutation, which is often troublesome in EEG/ERP research. However, the effectiveness of our approach was verified only for removing background EEGs and it is still not clear it can remove more severe noise such as ocular artifacts.

In this paper, we extend this work to ocular artifact removal from ERP data by considering prior information of event signals elicited by eye blinks. This procedure is essential because the frequency spectra of potentials given by ocular artifacts and ERP components are similar. For an experimental evaluation, we use ERPs intentionally contaminated by eye blinks and show the proposed method can effectively remove the effect of the ocular artifacts and enhance the target event signal of ERPs.

II. PROPOSED METHOD

A. Observation Model

Given I channels, the k-th event signal $\mathbf{c}_k(n,f) = \left[c_{k,1}(n,f),\cdots,c_{k,I}(n,f)\right]^\top$ at time n and frequency f in the time-frequency domain is expressed as

$$\mathbf{c}_k(n,f) = \sum_{l \in E_k} \mathbf{h}_l s_l(n,f), \tag{1}$$

$$\mathbf{h}_l = [h_{1l},\cdots,h_{Il}]^\top, \tag{2}$$

where $\{\cdot\}^\top$ is the transpose, $s_l(n,f)$ is the l-th source signal from various sources, such as synapse, muscle, and so on, given by a

complex value, E_k is a set of the sources activated in the k-th event, and h_{il} is the transfer function from the l-th source to the i-th channel assuming that $0 \leq h_{il} \leq 1$. The observed multi-channel EEG signal is $\mathbf{x}(n,f) = [x_1(n,f), \cdots, x_I(n,f)]^\top$ expressed as

$$\mathbf{x}(n,f) = \sum_{k=1}^{K} \mathbf{c}_k(n,f), \tag{3}$$

where K is the number of events.

B. Probabilistic Generative Model

We assume that the probability density function of the source signal $s_l(n,f)$ is modeled by the following zero-mean complex Gaussian distribution,

$$p(s_l(n,f)) = \mathcal{N}_c(s_l(n,f); 0, v_k(n,f)), \quad l \in E_k, \tag{4}$$

where the variance $v_k(n,f)$ varies in the time-frequency domain depending on the k-th event. Further assuming that the source signals are non-correlated to each other, the probability density function of the k-th event signal $\mathbf{c}_k(n,f)$ is modeled by a multivariate complex Gaussian distribution as follows:

$$p(\mathbf{c}_k(n,f)) = \mathcal{N}_c(\mathbf{c}_k(n,f); \mathbf{0}, \mathbf{R}_{c_k}(n,f)), \tag{5}$$
$$\mathbf{R}_{c_k}(n,f) = E\left[\mathbf{c}_k(n,f)\mathbf{c}_k(n,f)^H\right] \tag{6}$$
$$= v_k(n,f)\mathbf{R}_k, \tag{7}$$
$$\mathbf{R}_k = \sum_{l \in E_k} \mathbf{h}_l \mathbf{h}_l^\top, \tag{8}$$

where $\{\cdot\}^H$ is the complex conjugate transpose. The spatial covariance matrix $\mathbf{R}_{c_k}(n,f)$ is factorized into the time-frequency invariant spatial covariance matrix $\mathbf{R}_k$ and the time-frequency variant variance component $v_k(n,f)$.

We also assume that only one event signal is active in each time-frequency slot as follows:

$$\mathbf{x}(n,f) = \mathbf{c}_{z(n,f)}(n,f), \tag{9}$$

where $z(n,f)$ is the index of the active event signal. Consequently, the probability density function of the observation signals $\mathbf{x}$ in the time-frequency domain is modeled by a Gaussian mixture model as follows:

$$p(\mathbf{x}|\theta) = \prod_{n,f} p(\mathbf{x}(n,f)|\theta)$$
$$= \prod_{n,f} \sum_{k=1}^{K} \alpha_k \mathcal{N}_c(\mathbf{x}(n,f); \mathbf{0}, v_k(n,f)\mathbf{R}_k), \tag{10}$$

where α_k is a prior probability that the k-th event signal is active. The model parameter set θ consists of α_k, $v_k(n,f)$, and $\mathbf{R}_k$ of each mixture component.

C. Spatial Correlation Prior

The Wishart distribution is known as the conjugate prior distribution of the precision matrix of a multivariate Gaussian distribution with known mean vectors. The prior distributions of time-frequency invariant spatial covariance matrices are designed as follows:

$$p\left(\mathbf{R}_k^{-1}|\Psi_k^{-1}, q\right) = \frac{1}{Z}|\mathbf{R}_k^{-1}|^{\frac{q-I-1}{2}} \exp\left(-\frac{1}{2}\mathrm{Tr}\left[\Psi_k \mathbf{R}_k^{-1}\right]\right), \tag{11}$$

where Z is the normalizing constant, Ψ_k is a I-by-I symmetric positive definite matrix, and q_k is the degrees of freedom.

How to learn hyper parameters

Let us denote a pre-recorded signal that contains the k-th event at time t by $\hat{\mathbf{c}}_k(t)$. While we can't observe single event signal itself

because EEG signals always contain multiple event signals, we can design an experiment that elicits a specific ERP component, and we can record EEG signals intentionally contaminated by a specific artifact e.g., eye blinks. Thus we can record EEG signals in which a target event signal is supposed to be observed and also record EEG signals which contain a non-target signal to establish a contrast between them.

Based on these recorded signals, we calculate the hyper parameters iteratively as follows:

1: {Initialization}
   $v_k(n,f) \leftarrow 1$
2: **repeat**
3:   {Iterative update}

$$\Psi_k \leftarrow \left(\sum_{n,f} \frac{\bar{c}_k(n,f)\bar{c}_k^H(n,f)}{\bar{v}_k(n,f)}\right)/NF$$
$$\hat{v}_k(n,f) \leftarrow \left(\bar{c}_k(n,f)^H \Psi_k^{-1} \bar{c}_k(n,f)\right)/I$$

4: **until** convergence
5: $\Psi_k \leftarrow NF\Psi_k$

where $\hat{c}_k(n,f)$ is the pre-recorded signal that contains the k-th event at time-frequency slot (n,f), N is the total number of time frames, F is that of frequency bins, and $\bar{v}_k(n,f)$ is an estimation of the variance component $v_k(n,f)$. The other hyper parameter q_k is calculated as $q_k = NF$.

D. EEG Signal Enhancement with Spatial Correlation Priors

Given the observation signals $\mathbf{x}$, the model parameter set θ is estimated by maximizing the posterior probability density function of the time-frequency invariant spatial covariance matrices, $\mathbf{R} = \{\mathbf{R}_1, \cdots, \mathbf{R}_K\}$, as follows:

$$\hat{\theta} = \arg\max_{\theta} p(\mathbf{R}|\mathbf{x}, \theta_{\backslash\mathbf{R}}, \Psi_k, q) \tag{12}$$
$$= \arg\max_{\theta} \prod_{n,f} p(\mathbf{x}(n,f)|\theta) \prod_{k=1}^{K} p\left(\mathbf{R}_k^{-1}|\Psi_k, q\right), \tag{13}$$

where $\theta_{\backslash\mathbf{R}}$ is the model parameter set except for $\mathbf{R}$. This maximization process can also be effectively solved with EM algorithm. The following auxiliary function, which is the conditional expectation of the complete-data log likelihood evaluated for the posterior probability in the equation (13) and some parameter set θ is maximized with respect to θ,

$$\mathcal{Q} = \sum_{n,f,k} m_k(n,f)\left(\log(\alpha_k) - I\log(v_k(n,f))\right.$$
$$\left. + \log(|\mathbf{R}_k^{-1}|) - \frac{1}{v_k(n,f)}\mathbf{x}(n,f)^H \mathbf{R}_k^{-1}\mathbf{x}(n,f)\right)$$
$$+ \sum_{k=1}^{K}\left(\frac{q_k-I-1}{2}\log|\mathbf{R}_k^{-1}| - \frac{1}{2}\mathrm{Tr}\left[\Psi_k \mathbf{R}_k^{-1}\right]\right)$$
$$+ \text{Const.} \tag{14}$$

In the E-step, the posterior probability $m_k(n,f)$ is calculated at each time-frequency slot as follows:

$$m_k(n,f) = \frac{\alpha_k \mathcal{N}_c(\mathbf{x}(n,f); \mathbf{0}, v_k(n,f)\mathbf{R}_k)}{\sum_{k'=1}^{K} \alpha_{k'} \mathcal{N}_c(\mathbf{x}(n,f); \mathbf{0}, v_{k'}(n,f)\mathbf{R}_{k'})}. \tag{15}$$

In the M-step, model parameters $\hat{\alpha}_k$, $\hat{v}_k(n,f)$, $\mathbf{R}_k$ are updated as follows:

$$\hat{\alpha}_k = \frac{\sum_{n,f} m_k(n,f)}{\sum_{n,f,k'} m_{k'}(n,f)}, \tag{16}$$

$$\hat{v}_k(n,f) = \frac{1}{I}\mathbf{x}(n,f)^H \mathbf{R}_k^{-1}\mathbf{x}(n,f), \tag{17}$$

$$\hat{\mathbf{R}}_k = \frac{1}{\dfrac{q_k-I-1}{2}+\sum_{n,f} m_k(n,f)}\left(\frac{1}{2}\Psi_k\right.$$
$$\left.+\sum_{n,f}\frac{m_k(n,f)}{\hat{v}_k(n,f)}\mathbf{x}(n,f)\mathbf{x}(n,f)^H\right), \tag{18}$$

where $\hat{v}_k(n,f)$ and $\hat{\mathbf{R}}_k$ are iteratively updated as they depend on each other. Finally, the target event signal is extracted from the observed EEG signals using a multi-channel Wiener filter as follows:

$$\hat{\mathbf{c}}_k(n,f) = \hat{\mathbf{R}}_{c_k}(n,f)\hat{\mathbf{R}}_x^{-1}(n,f)\mathbf{x}(n,f), \tag{19}$$

$$\hat{\mathbf{R}}_{c_k}(n,f) = m_k(n,f)\hat{v}_k(n,f)\hat{\mathbf{R}}_k, \tag{20}$$

$$\hat{\mathbf{R}}_x(n,f) = \sum_{k=1}^{K}\hat{\mathbf{R}}_{c_k}(n,f), \tag{21}$$

where $\hat{\mathbf{c}}_k(n,f)$ is the k-th event signal separated from $\mathbf{x}(n,f)$.

In the proposed enhancement method, we don't have to select the target event signal from the separated event signals as in the conventional blind source separation methods, because the target signal corresponds to the mixture component with the target prior distribution. We may also deal with event signals not modeled with the prior distributions by just using additional mixture components without the prior distributions.

III. EXPERIMENTAL EVALUATION

While we showed in [11] that the previously described method is effective in separating ERPs from background EEGs, it is not clear whether these results generalize to ocular artifacts. This section reports the result of an experiment in which we apply the proposed method to an ERP data set contaminated by eye blinks to evaluate its performance.

All EEG signals were recorded from 25 scalp electrodes at locations based on a modified International 10-20 system, digitally sampled at 1000 Hz, and downsampled to 200 Hz. A subject, who was a right-handed 22 years old woman without any neurological disorders participated in all experiments.

A. Prior Information Acquisition

In order to collect prior information of event signals that corresponded to P3 and eye blinks respectively, we conducted the following EEG data recording.

First, we conducted an oddball paradigm experiment to obtain a template of P3. A random sequence of auditory stimuli including 2 kHz and 1 kHz sine waves was presented to the subject. 1 kHz sounds were presented 200 times as Non-target stimuli and 2 kHz sine wave were presented 50 times as Target stimuli. The subject was told to count the number of Target stimuli without any body movement. Single-trial ERPs of each condition were averaged and the result is shown in Fig. 1 (a). As expected, Target stimuli elicited larger P3 components. We used the averaged signal elicited by Target stimuli as a template of P3 wave and used it to calculate hyper parameters Ψ_1 and q_1. Similarly, Ψ_2 and q_2 were calculated using the averaged signal elicited by Non-target stimuli.
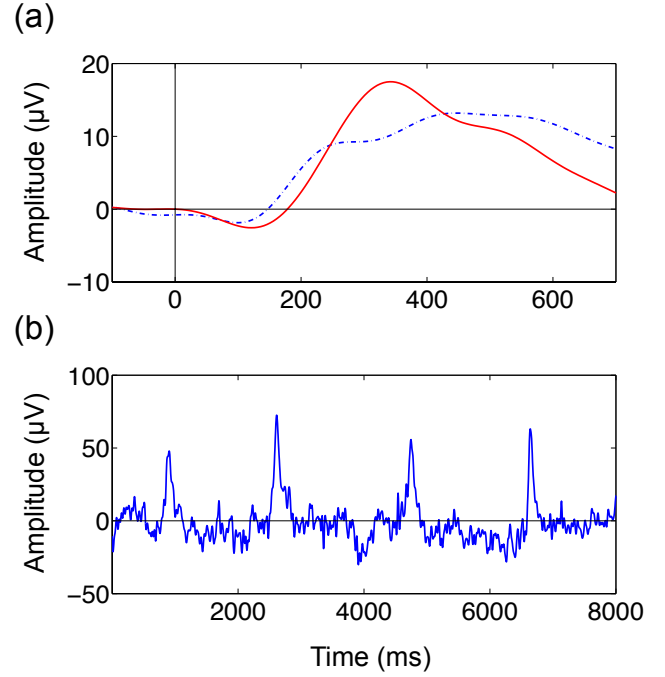

Fig. 1. (a) The result of the oddball experiment. The red line is for the averaged signal Target stimulus and the blue line is for Non-target stimulus. (b) An EEG signal recorded while the subject was making eye blinks every 1.5 second. Peaks that have large potential are effects of eye blinks. All plotted signals were recorded at channel Cz.

Next, we recorded an EEG signal for 2 minutes while the subject was making an eye blink every 1.5 seconds, which was used to calculate hyper parameters Ψ_3 and q_3 and shown in Fig. 1 (b). The amplitude peaks is considered to be generated by the eye blinks.

B. Test Data Acquisition

To collect the data for evaluation, we used a modified oddball paradigm where the subject was told to make an eye blink every time she heard the either type of stimulus and count the number of presence of Target stimuli only.

C. Result

We averaged the Target trial signal and Non-target signal of the test data respectively. As expected, both of the averaged signals have extremely large potentials (over 100 μV) and P3 component were buried under the effect of eye blinks, which makes the potential of the Non-target averaged signal larger than Target averaged signal (Fig. 2 (a)). We applied the proposed method to the test data set to remove the effect of the eye blinks setting the total number of the events $K = 3$, and averaged the signals for each condition. The result is shown in Fig. 2 (b). The proposed method removed the large potentials made by eye blinks in both conditions, and made the difference between them clear.

Furthermore, we show scalp maps of the test data before and after the proposed method was applied (Fig. 3). Many studies have reported that P3 wave activates about at the central area of the scalp [12]. Before the proposed method is applied, we can see test data is obviously contaminated by eye blinks as the area near the eyes is more highly activated instead of the central area. After its application, we can see the activation of the central area, and see that the potentials elicited by eye blinks have been removed.
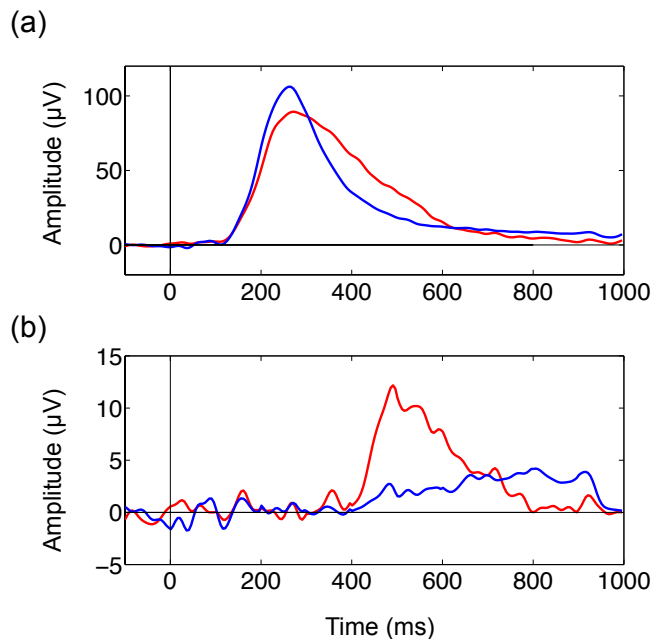
(a)

(b)

Fig. 2.   The test data given by the modified oddball paradigm. (a) The red solid line is for the averaged signal Target-stimuli and the blue dot line is for Non-target stimuli. (b) The test data processed by the proposed method.

IV. CONCLUSIONS

In this paper, we addressed the problem of ocular artifact removal from EEG data. We assumed a probabilistic generative model for each event signal and estimated model parameters using prior information obtained from pre-recorded signals, which enabled us to enhance only the target signal without the permutation problem. Experimental evaluation showed that the proposed method can effectively remove the effect of eye blinks in recorded ERP data.

ACKNOWLEDGMENT

REFERENCES

[1] Ernst Niedermeyer and FH Lopes da Silva. *Electroencephalography: basic principles, clinical applications, and related fields*. 2005.
[2] Joyce G Small. Sensory evoked responses of autistic children. *Infantile Autism*, 1971.
[3] Sylvain Baillet, John C Mosher, and Richard M Leahy. Electromagnetic brain mapping. *IEEE Signal Processing Magazine*, 2001.
[4] Arthur K Liu, Anders M Dale, and John W Belliveau. Monte Carlo simulation studies of EEG and MEG localization accuracy. *Human brain mapping*, 2002.
[5] David M Groppe, Scott Makeig, and Marta Kutas. Identifying reliable independent components via split-half comparisons. *NeuroImage*, 2009.
[6] Tzyy-Ping Jung, Scott Makeig, Marissa Westerfield, Jeanne Townsend, Eric Courchesne, and Terrence J Sejnowski. Removal of eye activity artifacts from visual event-related potentials in normal and clinical subjects. *Clinical Neurophysiology*, 2000.
[7] Carrie A Joyce, Irina F Gorodnitsky, and Marta Kutas. Automatic removal of eye movement and blink artifacts from EEG data using blind component separation. *Psychophysiology*, 2004.
[8] Ngoc QK Duong, Emmanuel Vincent, and Rémi Gribonval. Underdetermined reverberant audio source separation using a full-rank spatial covariance model. *IEEE Transactions on Audio, Speech, and Language Processing*, 2010.

[9] Ryutaro Sakanashi, Shigeki Miyabe, Takeshi Yamada, and Shoji Makino. Comparison of superimposition and sparse models in blind source separation by multichannel Wiener filter. *Proceedings of the Annual Summit and Conference of the Asia-Pacific Signal and Information Processing Association (APSIPA ASC)*, 2012.
[10] Yusuke Kurihana, Shigeki Miyabe, Tomasz M. Rutkowski, Yoshihiro Matsumoto, Takeshi Yamada, and Shoji Makino. (in Japanese) Signal Separation of EEG using Multivariate Probabilistic Model. *Technical Report of IEICE, MBE*, 2013.
[11] Hayato Maki, Tomoki Toda, Sakriani Sakti, Graham Neubig, and Satoshi Nakamura.   EEG Signal Enhancement using Multichannel Wiener Filter with a Spatial Correlation Prior. *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, 2015.
[12] David Friedman, Yael M Cycowicz, and Helen Gaeta. The novelty P3: an event-related brain potential (ERP) sign of the brain's evaluation of novelty. *Neuroscience & Biobehavioral Reviews*, 2001.
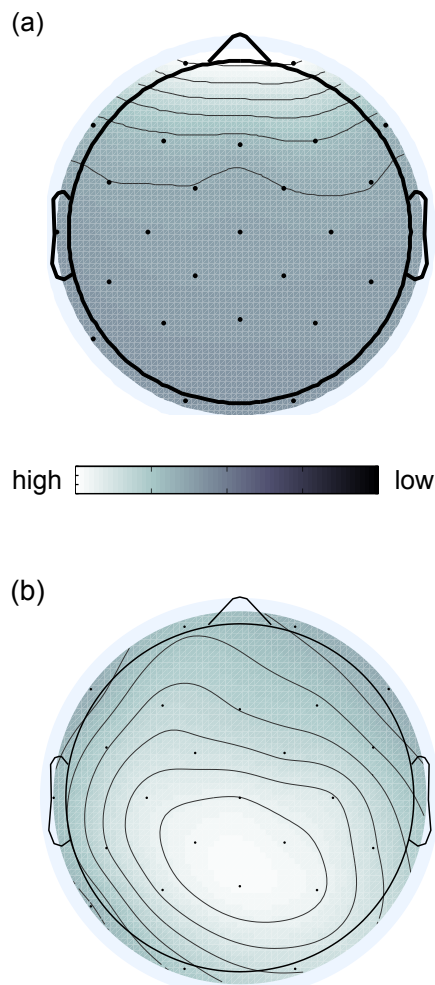
(a)

high low

(b)

Fig. 3.   The scalp maps given by (a) test data and (b) test data processed by the proposed method. Both of them were drawn at the peak latency of their own averaged signals elicited by Target-stimuli.