Feature Extraction of P300 Signal Using Bayesian Delay Time Estimation

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***Abstract*—Brain-computer interfaces (BCIs) based on event-related potentials (ERP) are communicating tools with severely disabled people. P300 which is observed after 300 mili seconds from stimuli is widely used for the operation principle of BCIs. However the response time to the stimuli depends on a subject, trial, and also a channel. Many existing approaches ignore this variation and extract only low frequency component. We propose a method to estimate the response time of P300 using Bayesian estimation. The proposed method exhibited higher performance in our auditory BCI.**

I. Introduction

BCI aims to control a computer using brain signals without any movements [1]. Electroencephalography (EEG), Magnetoencephalography (MEG), and Functional Magnetic Response Imaging (fMRI) are mainly used for non-invasive measuring of brain activity [1]. EEG is widely used to acquire brain activity for BCI due to its noninvasive nature, low cost and ease of use [2, 3, 4]. One of the most popular features utilized in BCI is P300 [5, 6]. P300 is a brain response caused over the parietal lobe when a subject reacts to an auditory or a visual stimulus [7]. Fig. 1 shows an example of P300. In order to avoid noise interference, existing BCIs average time-locked signals from several trials [8].

These BCIs assume that P300 appears in the same response time. However, this assumption is sometimes unreasonable, and distorts the averaged signal. For example, changes in the degree of mental fatigue, habituation, or level of attention of the subject can affect the response time of P300 [8]. Especially, for auditory stimuli, the response time varies widely since the stimulus has duration and the timing of cognition depends on the stimulus. Thus, simple averaged signals may not have clear P300 waveform and have a possibility that its classification accuracy decreases.

In this paper, we therefore propose a method to estimate the delay in P300 based on Bayesian estimation, and apply the proposed method to an auditory P300 BCI. Moreover, we compare the proposed method with the simple averaging. The proposed method provided clear P300 waveforms and increased 6.3% classification accuracy compared to the conventional method on average.

II. Algorithm using Bayesian estimation

Let $x_i(n)$, $(n = 0, \ldots, T-1, i = 1, \ldots, N)$ be a discrete observed signal that has P300 response, where T is the number of sampling points, and N is the number of signals. Usually N equals to the product of the number of channels and the number of trials. We here introduce a model that $x_i(n)$ consists of true P300 response $\bar{x}(n)$ and noise $\eta_i(n)$,

$$x_i(n) = \bar{x}(n - \tau_i) + \eta_i(n), \tag{1}$$

where τ_i is the delay time for the ith signal.

Suppose that η_i follows the Gaussian distribution. Then the probability density function for $x_i(n)$ is given by

$$p(\boldsymbol{x}_i|\sigma, \bar{\boldsymbol{x}}, \tau_i) = \frac{1}{(\sqrt{2\pi}\sigma)^T} \exp\left(-\frac{\|\boldsymbol{x}_i - \bar{\boldsymbol{x}}_{\tau_i}\|^2}{2\sigma^2}\right), \tag{2}$$

where σ^2 is the variance of η_i, $\boldsymbol{x}_i = [x_i(0), \ldots, x_i(T-1)]^\top$, and $\bar{\boldsymbol{x}}_{\tau_i} = [\bar{x}(-\tau_i), \ldots, \bar{x}(T-1-\tau_i)]^\top$, we also denote $\bar{\boldsymbol{x}} = \bar{\boldsymbol{x}}_0$. The joint probability density function for the set of samples, $\boldsymbol{X} = \{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_N\}$ is

$$p(\boldsymbol{X}|\sigma, \bar{\boldsymbol{x}}, \tau_1, \ldots, \tau_N) = \prod_{i=1}^{N} p(\boldsymbol{x}_i|\sigma, \bar{\boldsymbol{x}}, \tau_i). \tag{3}$$

We then introduce a prior distribution for the delay τ_i. Since $\bar{x}(n)$ is also variable to be estimated, without loss of generality, we assume that the average of τ_i is zero. Suppose α^2 is the variance of the delay time τ_i. Then the prior distribution is

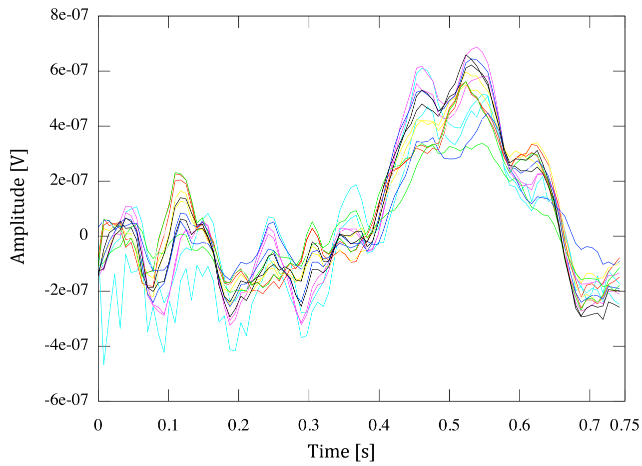

Fig. 1. Example of P300. Each signal is averaged over 200 times. The subject pays attention to low frequent auditory stimuli of an odd-ball task. There are 16 channels. P300 is observed around 0.5 seconds.

given by

$$p(\tau_i|\alpha) = \frac{1}{\sqrt{2\pi}\alpha}\exp\left(-\frac{\tau_i^2}{2\alpha^2}\right). \tag{4}$$

Consequently, we have the posterior probability of τ_i from Bayes' theorem,

$$p(\tau_1,\ldots,\tau_N|\boldsymbol{X},\sigma,\alpha,\bar{\boldsymbol{x}}) = \frac{p(\boldsymbol{X}|\sigma,\bar{\boldsymbol{x}}_{\tau_i})\prod_{i=1}^{N}p(\tau_i|\alpha)}{p(\boldsymbol{X})} \tag{5}$$

Since $p(\boldsymbol{X})$ is a constant for τ_i, the maximum a posteriori (MAP) estimators τ_i^* and $\overline{\boldsymbol{x}}^*$ are obtained by maximizing $p(\boldsymbol{X}|\sigma,\overline{\boldsymbol{x}}_{\tau_i})\prod_{i=1}^{N}p(\tau_i|\alpha)$,

$$\max_{\tau,\overline{\boldsymbol{x}}} \ \log p(\boldsymbol{X}|\sigma,\overline{\boldsymbol{x}}_{\tau_i})\prod_{i=1}^{N}p(\tau_i|\alpha). \tag{6}$$

The problem (6) is reduced to

$$\min_{\tau,\overline{\boldsymbol{x}}} \ \sum_{i=1}^{N}(\|\boldsymbol{x}_i-\overline{\boldsymbol{x}}_{\tau_i}\|^2+\mu\tau_i^2), \tag{7}$$

where $\mu = \frac{\sigma^2}{\alpha^2}$. We can find μ depending on the shape of P300 wave or the cross variation. If α is close to zero and μ is large, estimated τ_i is close to zero. Thus, when $\alpha \to 0$ and $\mu \to \infty$, the estimation is equivalent to the conventional simple averaging. In order to obtain optimal $\overline{\boldsymbol{x}}$ and τ_i, we use the alternating optimization method which has two steps. The first step is optimizing $\overline{\boldsymbol{x}}$ with fixing τ_i $(i=1,\ldots,N)$. The second step is optimizing τ_i $(i=1,\ldots,N)$ with fixing $\overline{\boldsymbol{x}}$. We can obtain a local minima by repeating two steps alternately because these steps monotonically decrease the objective function (7). The optimization problem for the first step is

$$\min_{\overline{\boldsymbol{x}}} \ J_1 = \sum_{i=1}^{N}\|\boldsymbol{x}_i-\overline{\boldsymbol{x}}_{\tau_i}\|^2. \tag{8}$$

In Eq. (8), we summate differences between $\boldsymbol{x}_i$ and shifted $\overline{\boldsymbol{x}}$ by τ_i. This is equivalent to summate differences between $\overline{\boldsymbol{x}}$ and shifted $\boldsymbol{x}_i$ by $-\tau_i$. Therefore, Eq. (8) is equivalent to

$$\min_{\overline{\boldsymbol{x}}} \ J_1' = \sum_{i=1}^{N}\|(\boldsymbol{x}_i)_{-\tau_i}-\overline{\boldsymbol{x}}\|^2, \tag{9}$$

where $(\boldsymbol{x}_i)_{-\tau_i}$ is $\boldsymbol{x}_i$ shifted with $-\tau_i$. Eq. (9) is minimized by the mean of $(\boldsymbol{x}_i)_{-\tau_i}$,

$$\overline{\boldsymbol{x}} = \frac{1}{N}\sum_{i=1}^{N}(\boldsymbol{x}_i)_{-\tau_i}. \tag{10}$$

The optimization problem for the second step is

$$\min_{\tau_i} \ J_2 = \sum_{i=1}^{N}(\|\boldsymbol{x}_i-\overline{\boldsymbol{x}}_{\tau_i}\|^2+\mu\tau_i^2). \tag{11}$$

This problem can be solved for each i,

$$\min_{\tau_i} \ \|\boldsymbol{x}_i-\overline{\boldsymbol{x}}_{\tau_i}\|^2+\mu\tau_i^2. \tag{12}$$

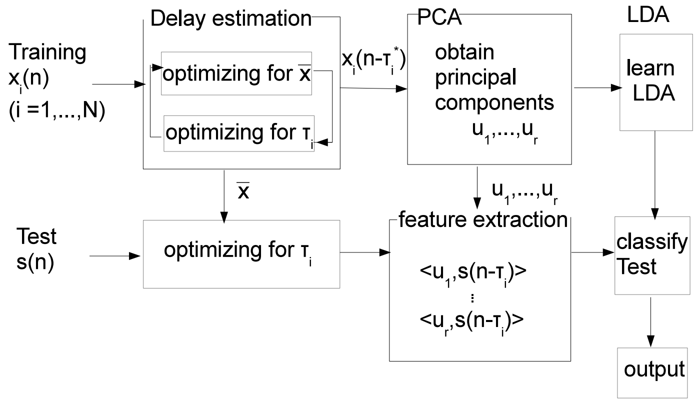

Fig. 2. Flow chart of the proposed method.

Since τ_i is discretized, we can find the optimal delay changing the value of τ_i. We set initial $\tau_i = 0$ for all i.

After we obtain the optimal delay τ_i^* and averaged signal $\overline{\boldsymbol{x}}^*$, the principal component analysis (PCA) is performed to extract the components of P300. PCA extracts P300 features not only in the time-shifted average $\overline{\boldsymbol{x}}^* = \frac{1}{N}\sum_{i=1}^{N}(\boldsymbol{x}_i)_{-\tau_i^*}$, but also in the second-order moments in the training data. Let $\boldsymbol{u}_1,\ldots,\boldsymbol{u}_r$ be major principal components of the training data $(\boldsymbol{x}_i)_{-\tau_i^*},(i=1,\ldots,N)$ and $\boldsymbol{U} = [\boldsymbol{u}_1,\ldots,\boldsymbol{u}_r] \in \mathbb{R}^{T\times r}$.

For unlabeled test signal, we first obtain the delay. Let

$$\boldsymbol{s}_i(\tau) = [s_i(0-\tau)\ldots s_i(T-1-\tau)]^\top \in \mathbb{R}^T, \tag{13}$$

where $i=1,\ldots,M$ is the number of channels and τ is delay. We estimate the optimal delay time つまり by minimizing Eq. (12) with $\overline{\boldsymbol{x}}$, that is

$$\tau_i^* = \min_{\tau_i} \ \|\boldsymbol{s}_i-\overline{\boldsymbol{x}}_{\tau_i}\|^2+\mu\tau_i^2. \tag{14}$$

Then the feature vector is given by

$$\boldsymbol{z} = [\boldsymbol{s}_1^\top(\tau_1^*)\boldsymbol{U} \ \ \boldsymbol{s}_2^\top(\tau_2^*)\boldsymbol{U}\ldots \ \ \boldsymbol{s}_M^\top(\tau_M^*)\boldsymbol{U}]^\top. \tag{15}$$

We classify the feature vector $\boldsymbol{z}$ into P300 class or non-P300 class using the linear discriminant analysis (LDA).

We summarize our method in Fig. 2.

III. Experimental procedure

We conducted an experiment to 5 subjects who are from 19 to 32 years old male. We measured the brain signal with an active 16ch EEG (g.GAMMAcap2, g.LADYbird (active), g.GAMMAbox manufactured by Guger technologies). The electrodes were located on FCz, FC2, FC1, Cz, CP1, CP2, Pz, POz, P3, P4, TP8, TP7, C3, C4, C5 and C6, the ground was AFz, and the reference was A2 (Fig. 3). Most of electrodes were placed on parietal areas to observe ERP, and the remaining electrodes were placed near the parietal area and temporal lobe areas. EEG signals were amplified by a biological signal amplifier (BA 1008, Digitex).

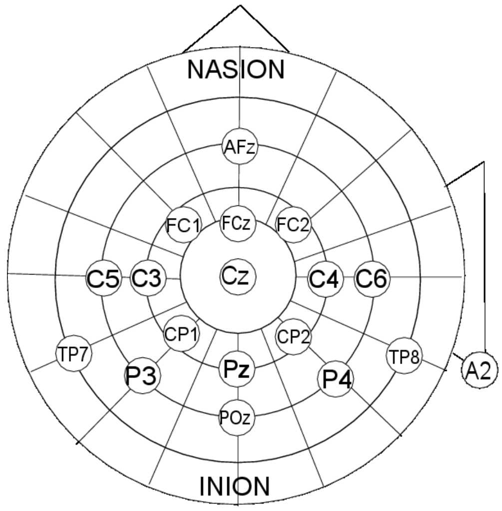

Fig. 3. Location of the electrodes. The positions are conformed to the extended 10-20 system. The ground is AFz and the reference is A2.

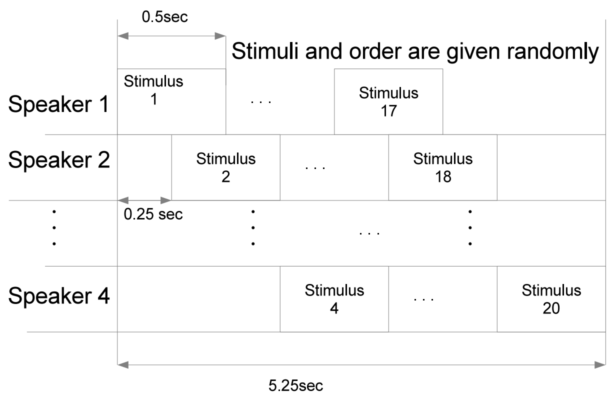

Fig. 4. Presentation scheme of the stimuli. There are four stimulus. Each stimulus is presented five times in one trial

We used four speech stimuli, “jou,” “ge,” “sa,” and “yu.” These respectively mean “up,” “down,” “left,” and “right” in Japanese. These stimuli are 0.5 seconds length, and presented randomly 20 times in one trial (each stimulus is presented five times in one trial). Each speech stimulus is given by one of four loud-speakers and these speakers were set from forth to back and from side to side. The order and the position of the stimuli are at random. However each speaker does not present stimuli in a row, and the same stimulus does not present in a row. 50 trials were recorded. We depict the presentation scheme of the stimuli in Fig. 4. Volume of the stimuli is adjusted to listener-friendly level by the subject.

The subject was asked to close his eyes during the experiment, and the target stimulus was given by a monitor for each trial. He paid attention to the target stimuli, and counted the number of the target stimuli. We applied 0.5Hz analog high-pass filter and 100Hz analog low-pass filter by the amplifier. We used 8-12Hz band stop filter to remove α wave. The sampling frequency was 512Hz. We used MATLAB as measuring software and an A/D converter (Contec AI 1664 LAX-USB).

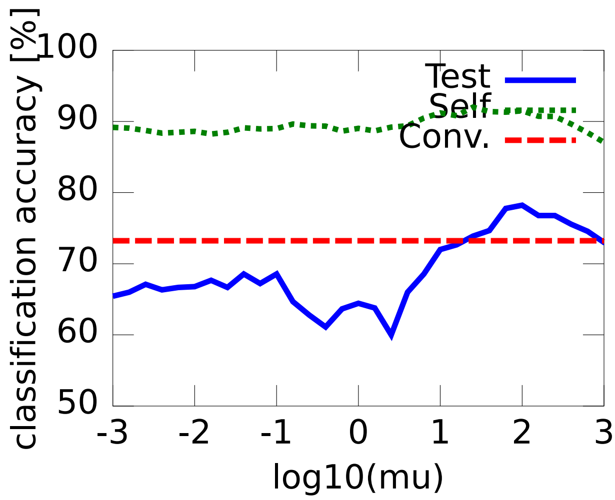

Fig. 5. Classification accuracies of Subject 1.

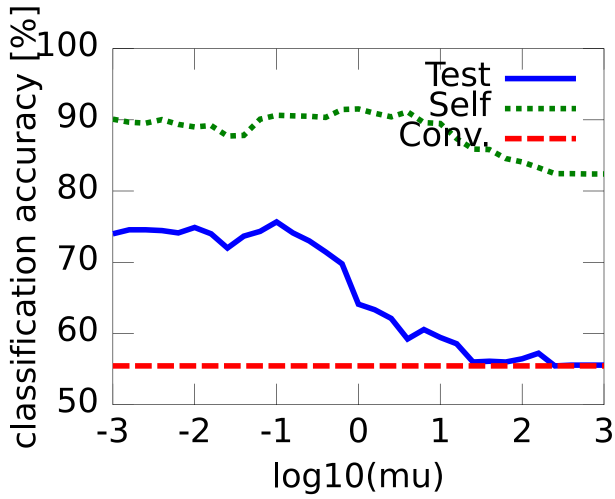

Fig. 6. Classification accuracies of Subject 2.

IV. Results

We performed five-fold cross validation, i.e., we randomly divided the whole trial set into five subsets, and one of them was used for the validation, and the other subsets were used for the training. We repeated the procedure 5 times, and obtained the averaged classification accuracy. We obtained the result with a rank r that makes the classification accuracy the highest.

Figs. 5 to 9 show the classification accuracies with respect to μ. $Conv.$ is the case of time-locked signal of conventional method. In these figures, the classification accuracies of the proposed method are higher than those of the conventional method when we chose an optimal μ. Figs. 10 and 11 show waveforms after target and non-target stimuli. In Fig. 11, the

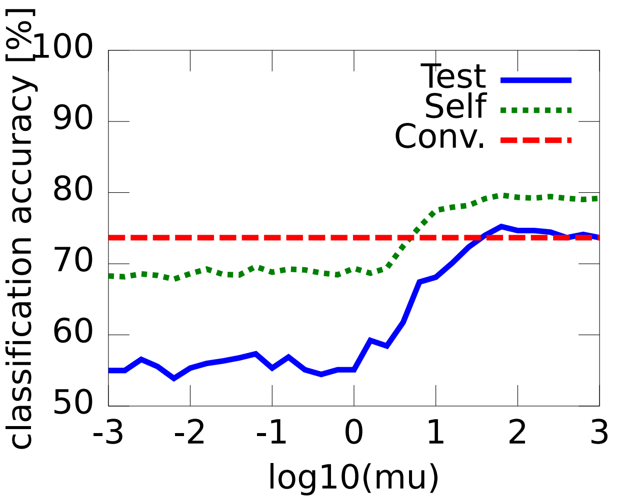

Fig. 7. Classification accuracies of Subject 3.

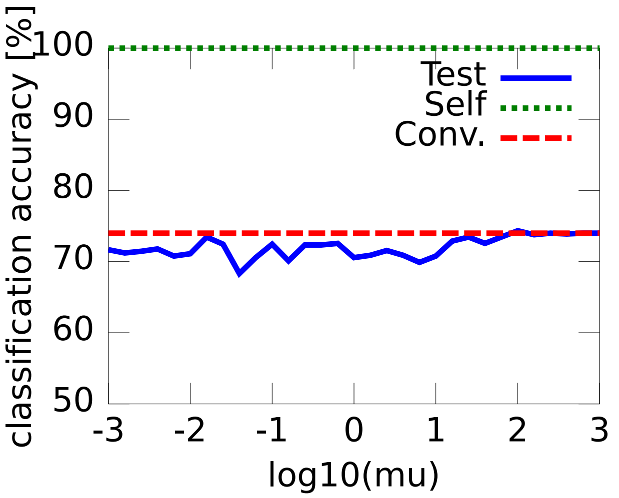

Fig. 8. Classification accuracies of Subject 4.

stronger peak is observed around 0.5s in P300 waveform of right graph, compare to that of left graph. By contrast, both of P300 waveforms seen in Fig. 10 are almost the same. Table I shows the highest classification accuracy and the improvement for each subject. Compared to the conventional method, the classification accuracy of subject 5 increased 4.6%. On the other hand, the improvement of subject 4 was the lowest among all subjects. That is because both of P300 signals seen in Fig. 10 are almost the same. Therefore we infer that it makes the improvement lower.

Consequently, we conclude that P300 waveform is related to the classification accuracy and the proposed method provided higher classification accuracy.

V. Conclusion

We have proposed a new method to estimate delay time of P300. The proposed method exhibited higher classification accuracy compared to the conventional method. Since this classification accuracy is from single trial, this proposed

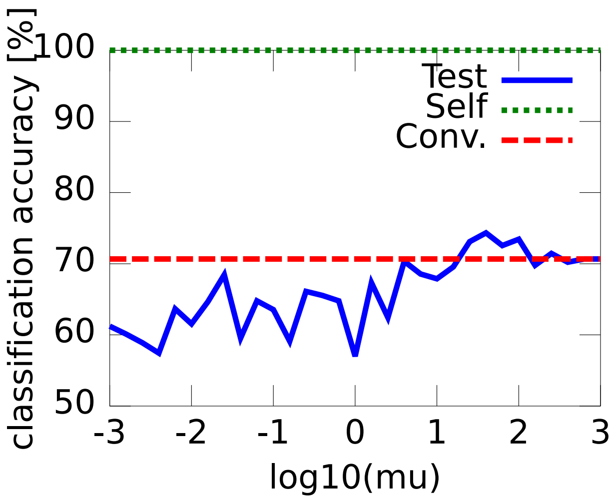

Fig. 9. Classification accuracies of Subject 5.

TABLE I
THE CLASSIFICATION RESULT OF CONVENTIONAL METHOD AND THE PROPOSED METHOD

	proposed [%]	conventional [%]	improvement [%]
Subject 1	78.2	73.2	5.0
Subject 2	75.7	55.4	20.3
Subject 3	75.2	73.7	1.5
Subject 4	74.3	74.0	0.3
Subject 5	75.3	70.7	4.6
Average	75.7	69.4	6.3

method is practical enough if we make a decision from several trials.

VI. Acknowledgement

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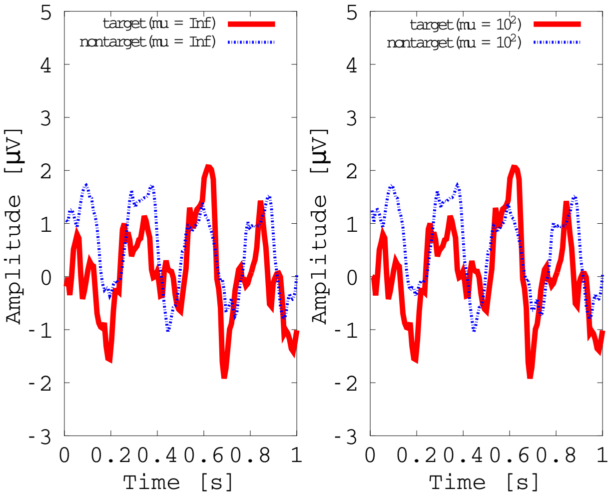

Fig. 10. Waveform of Subject 4. Left graph and right graph show the waveforms of conventional methods and proposed method respectively. Channel FC1 was cut out because it didn't work well.

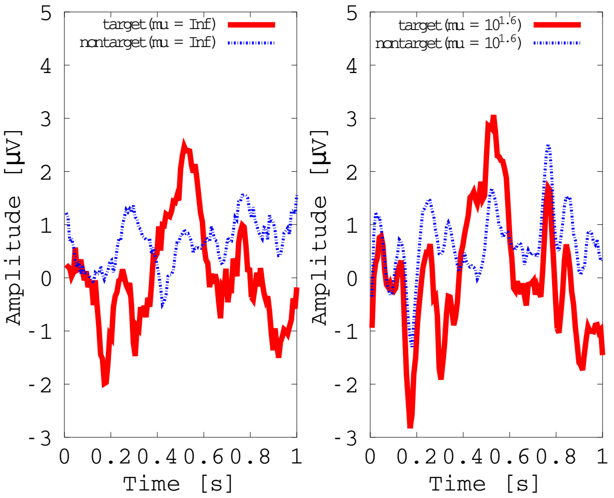

Fig. 11. Waveform of Subject 5. Left graph and right graph show the waveforms of conventional methods and proposed method respectively.

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