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 by attention to low frequent auditory stimuli of an odd-ball task. There are 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 \( \eta(n) \),

\[
x_i(n) = \bar{x}(n - \tau_i) + \eta(n),
\]

where \( \tau_i \) is the delay time for the \( i \)th signal.

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

\[
p(x_i|\sigma, \bar{x}, \tau_i) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-[x_i - \bar{x}_{\tau_i}]^2}{2\sigma^2}\right),
\]

where \( \sigma^2 \) is the variance of \( \eta_i \), \( \bar{x}_i = [x_i(0), \ldots, x_i(T - 1)]^T \), and \( \bar{x}_{\tau_i} = [\bar{x}(\tau_i), \ldots, \bar{x}(T - 1 - \tau_i)]^T \), we also denote \( \bar{x} = \bar{x}_0 \). The joint probability density function for the set of samples, \( X = \{x_1, \ldots, x_N\} \) is

\[
p(X|\sigma, \bar{x}, \tau_1, \ldots, \tau_N) = \prod_{i=1}^{N} p(x_i|\sigma, \bar{x}, \tau_i).
\]

We then introduce a prior distribution for the delay \( \tau_i \). Since \( \bar{x}(n) \) is also variable to be estimated, without loss of generality, we assume that the average of \( \tau_i \) is zero. Suppose \( \sigma^2 \) is the variance of the delay time \( \tau_i \). Then the prior distribution is
given by
\[ p(\tau_i|\alpha) = \frac{1}{\sqrt{2\pi\alpha}} \exp\left(-\frac{\tau_i^2}{2\alpha^2}\right). \] (4)

Consequently, we have the posterior probability of \( \tau_i \) from Bayes’ theorem,
\[ p(\tau_1, \ldots, \tau_N|\mathbf{X}, \sigma, \mathbf{x}, \alpha) = \frac{p(\mathbf{X}|\sigma, \mathbf{x}, \alpha) \prod_{i=1}^N p(\tau_i|\alpha)}{p(\mathbf{X})} \] (5)
Since \( p(\mathbf{X}) \) is a constant for \( \tau_i \), the maximum a posteriori (MAP) estimators \( \tau_i^* \) and \( \mathbf{x}^* \) are obtained by maximizing
\[ \max_{\tau, \mathbf{x}} \log p(\mathbf{X}|\sigma, \mathbf{x}, \alpha) \prod_{i=1}^N p(\tau_i|\alpha). \] (6)
The problem (6) is reduced to
\[ \min_{\mathbf{x}, \tau} \sum_{i=1}^N \left( \left\| x_i - \mathbf{x}_{\tau_i} \right\|^2 + \mu \tau_i^2 \right), \] (7)
where \( \mu = \frac{\sigma^2}{\alpha} \). We can find \( \mu \) depending on the shape of P300 wave or the cross variation. If \( \alpha \) is close to zero and \( \mu \) is large, estimated \( \tau_i \) 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 \( \mathbf{x} \) and \( \tau_i \), we use the alternating optimization method which has two steps. The first step is optimizing \( \mathbf{x} \) with fixing \( \tau_i \) \( (i = 1, \ldots, N) \). The second step is optimizing \( \tau_i \) \( (i = 1, \ldots, N) \) with fixing \( \mathbf{x} \). 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
\[ \min_{\mathbf{x}} J_1 = \sum_{i=1}^N \left( \left\| x_i - \mathbf{x}_{\tau_i} \right\|^2 \right). \] (8)
In Eq. (8), we summate differences between \( x_i \) and shifted \( \mathbf{x} \) by \( \tau_i \). This is equivalent to summate differences between \( \mathbf{x} \) and shifted \( x_i \) by \( -\tau_i \). Therefore, Eq. (8) is equivalent to
\[ \min_{\mathbf{x}} J'_1 = \sum_{i=1}^N \left( \left\| (x_i)_{-\tau_i} - \mathbf{x} \right\|^2 \right), \] (9)
where \( (x_i)_{-\tau_i} \) is \( x_i \) shifted with \( -\tau_i \). Eq. (9) is minimized by the mean of \( (x_i)_{-\tau_i} \),
\[ \mathbf{x} = \frac{1}{N} \sum_{i=1}^N (x_i)_{-\tau_i}. \] (10)
The optimization problem for the second step is
\[ \min_{\tau_i} J_2 = \sum_{i=1}^N \left( \left\| x_i - \mathbf{x}_{\tau_i} \right\|^2 + \mu \tau_i^2 \right). \] (11)
This problem can be solved for each \( i \),
\[ \min_{\tau_i} \left\| x_i - \mathbf{x}_{\tau_i} \right\|^2 + \mu \tau_i^2. \] (12)

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

After we obtain the optimal delay \( \tau_i^* \) and averaged signal \( \mathbf{x}^* \), the principal component analysis (PCA) is performed to extract the components of P300. PCA extracts P300 features not only in the time-shifted average \( \mathbf{x}^* = \frac{1}{M} \sum_{i=1}^M x_i \), but also in the second-order moments in the training data. Let \( u_1, \ldots, u_M \) be major principal components of the training data \( (x_i)_{-\tau_i}, i = 1, \ldots, N \) and \( U = [u_1, \ldots, u_M] \in \mathbb{R}^{T \times r} \).

For unlabeled test signal, we first obtain the delay. Let
\[ s_i(\tau) = [s_i(0 - \tau) \ldots s_i(T - 1 - \tau)]^T \in \mathbb{R}^T, \] (13)
where \( i = 1, \ldots, M \) is the number of channels and \( \tau \) is delay. We estimate the optimal delay time \( \tau \in \mathbb{R} \) by minimizing Eq. (12) with \( \mathbf{x}^* \), that is
\[ \tau_i^* = \min_{\tau_i} \left\| s_i - \mathbf{x}_{\tau_i} \right\|^2 + \mu \tau_i^2. \] (14)
Then the feature vector is given by
\[ z = [s_1^T(\tau_1^*)U \, s_2^T(\tau_2^*)U \ldots \, s_M^T(\tau_M^*)U]^T. \] (15)
We classify the feature vector \( z \) 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).
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 \( \alpha \) wave. The sampling frequency was 512Hz. We used MATLAB as measuring software and an A/D converter (Contec AI 1664 LAX-USB).

## 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 \( \mu \). 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 \( \mu \). Figs. 10 and 11 show waveforms after target and non-target stimuli. In Fig. 11, the
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. 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 method is practical enough if we make a decision from several trials.

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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.