Improvement of Discrimination Performance Using Temporal Smoothing for Brain–Machine Interface Based Rehabilitation System

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***Abstract*— The aim of our study is to develop a brain–machine interface rehabilitation system for patients with leg paralyzed. Using this system, the patient's paralyzed legs are forcibly moved according to his intention of motion. This may activate a damaged neural circuit and improve the rehabilitation effect. In this study, we proposed a motion discrimination method for actual pedal exercise using electroencephalography (EEG) measured at several positions of the parietal region, and the discrimination performance was verified with healthy subjects. Although this method was uses the spatial EEG information, this often causes false detection owing to the sudden noise included in the measured EEG signals. In order to improve the discrimination performance, smoothing of the motion discriminator output was considered using temporal information. Thus, we developed a spatiotemporal filter-based discrimination method and its parameter determination method. Experimental results indicated that the discrimination performance of this method is over 10 percentage points higher than that of the general linear discriminant analysis method.**

I. Introduction

Recently, some brain–machine interface (BMI) based rehabilitation systems have been proposed for patients that are severely paralyzed owing to a neurological disease such as a stroke or spinal cord injury [1], [2], [3], [4], [5]. These systems force a patient to move his paralyzed part with the intention of motion detected from brain activity. This may activate neural circuits and restore damaged motor function [6].

In such a system, electroencephalography (EEG) is generally used to detect the patient's intention to attempt to move his paralyzed part from his brain activity. Most studies have used event-related desynchronization (ERD) as a feature for detecting the patient's intention [7], [8] . ERD is a phenomenon in witch the EEG power of a certain frequency band decreases more when a subject decrease when a subject executes some task than when he was resting. Therefore, the patient's intention may be estimated by using this decrease in power as a feature, and this was realized using a classification method such as a linear discriminant analysis (LDA) [9] or support vector machine (SVM) [10].

On the basis of this background, we have attempted to develop a BMI rehabilitation system for a patient with paralyzed legs. As a preliminary study, we have already studied a healthy subject's brain activity during ergometer pedal exercise using EEG and proposed a motion discrimination method that classes a subject's motion into two conditions: "pedaling" or "resting" [11], [12]. In this discrimination method, we used a band power spectrum of EEG signals in the range of 18–28 Hz measured at six or eight points around the parietal region as features. However, such features usually include a considerable amount of noise, causing discrimination error. In general, most BMI systems target users that received a feedback training program called the basket paradigm [13], [14], [15]. Although this training is known to increase the signal-to-noise ratio of the features, it requires several weeks and becomes a heavy burden for users. Therefore, a simple approach was considered to improve the discrimination accuracy without training for BMI users. In this approach, we simply smoothed the output of a spatial filter with a temporal filter that has same structure as an infinite-impulse response (IIR) filter. All of the parameters of this filter were optimized by a recursive least-squares method using learning data.

There are some methods for improving the discrimination performance using spatial and temporal filtering to discriminate right and left motor imagery [16], [17] or actual pedaling conditions [18]. However, these methods obtain the spatial and temporal filter parameters separately. On the other hand, our proposed method simultaneously determines all of the parameters to obtain high discrimination performance.

The experimental results indicated that the discrimination performance of this method is over 10 percentage points higher than that of the general LDA method.

II. Experimental setup

This section describes the EEG measurement setup. As shown in Fig. 1, a healthy 24-year-old subject sat on a chair with his eyes opened and exercised with a bicycle ergometer. The subject had never experienced any EEG feedback training. The pedal exercise was repeated with exercise periods and rest periods every 20 s. A cue for the ergometer exercise was provided to the subject by visual stimuli using a personal computer monitor.

The EEG electrodes (NE-121J, Nihon Kohden Corp., Japan) were placed at C_z, C_3, C_4, F_z, F_3 and F_4 of the international 10/20 system, and a reference electrode was placed on the forehead (F_{pz}), as shown in Fig. 2. These electrode positions cover the primary sensory and motor cortices and the supplementary motor area.

EEG signals were applied with a band-pass filter with from 0.5 to 300 Hz and amplified 10^5 times by with a

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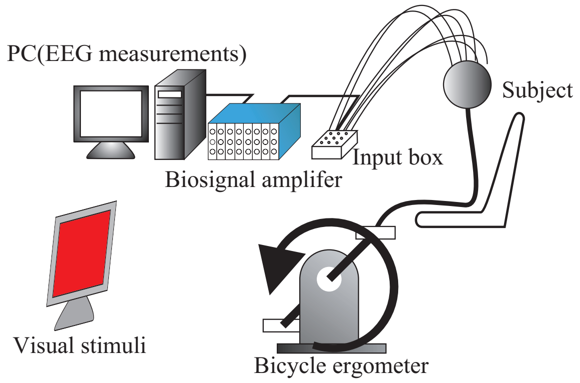


Fig. 1. Experimental setup.

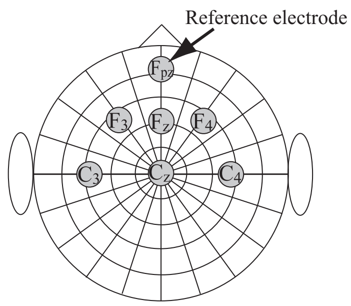


Fig. 2. Electrode positions for EEG recording.

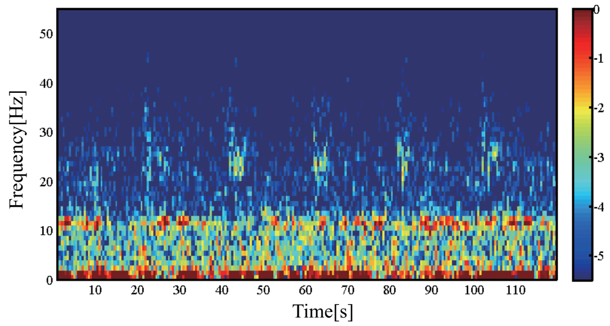


Fig. 3. Time–frequency analysis at the C_z position.

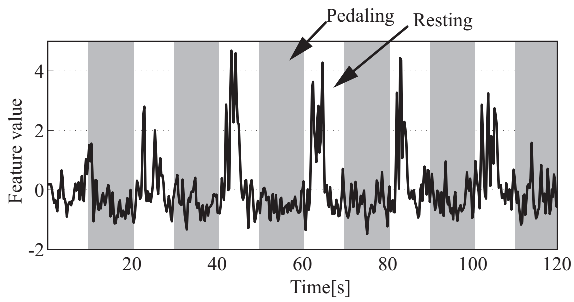


Fig. 4. 18–28 Hz band power changes at the C_z position.

biological amplifier(AB-611J, Nihon Kohden Corp., Japan). These signals were recorded at a 1 kHz sampling rate.

III. Feature Extraction and Conventional Motion Discriminating Method

A. Feature extraction

Here, we describe the feature extraction method from the measured electroencephalogram, which is used for motion discrimination. First, the common average reference (CAR) is applied to the measured signals [19], [20]. The CAR is commonly used in EEG, where it is necessary to identify small-signal sources in very noisy recordings. For EEG signals, E_i is measured by the difference between the i-th electrode and the F_{pz} electrode; its CAR E_k^{CAR} is given by

$$E_i^{\mathrm{CAR}} = E_i - \frac{1}{M}\sum_{k=1}^{M} E_k, \qquad (1)$$

where M is the number of EEG electrodes. (1) means that the CAR is obtained by subtracting the mean of all electrodes.

Next, a time–frequency analysis using a discrete Fourier transform (DFT) is applied to the obtained CAR from EEG. In this process, we use 1000-point-length CAR data to obtain a spectrum using a DFT and overlap 750 points of data to analyze the time variation of the spectrum. This provides us with a 4 Hz sampled spectrum with a 1 Hz frequency resolution.

Fig.3 shows an example of the time-frequency analysis results. As shown, it is found that the 18–28 Hz band power decreases for the subject executing a bicycle ergometer exercise. This power-decreasing phenomenon is known as event related desynchronization (ERD) [21].

As feature values for status discrimination, we use the centered (detrended) and scaled signals of each electrode, which are the square root of the 18–28 Hz power changes. Fig. 4 shows the feature value of this experiment measured at C_z.

B. Pedaling motion discrimination by linear discriminant analysis

LDA is a traditional supervised dimensionality reduction method [22] that is used for the discrimination problem of multidimensional data. In the field of BMI studies, LDA is generally used for detecting the motor imagery of subjects from features of the ERD [23].

LDA is a method that obtains a linear transformation matrix $W^{\mathrm{LDA}} = [w_1^{\mathrm{LDA}}, \cdots, w_M^{\mathrm{LDA}}]' \in \mathbb{R}^{M\times M}$ which is called the LDA transformation matrix and used for event discrimination by features. In this study, the feature values are set to $z_t = [z_{t1}, \cdots, z_{tM}]' \in \mathbb{R}^M$. The element z_{ti} is the feature as mentioned in previous section that is calculated from the electroencephalogram measured by i-th electrode at time t. Using the LDA transformation matrix and features, the LDA output is given by

$$x_t = w_1^{\mathrm{LDA}} z_t = [a_1, \cdots, a_M]\begin{bmatrix} z_{t1} \\ \vdots \\ z_{tM}\end{bmatrix} = \sum_{j=1}^{M} a_j z_{tj}, \qquad (2)$$

where $w_1^{\mathrm{LDA}} = [a_1, \cdots, a_M]$.

The discriminant result is obtained as the sign of x_t. The LDA transformation matrix W^{LDA} is defined as

$$W^{\mathrm{LDA}} = \underset{W}{\operatorname{argmax}} \left[\operatorname{tr} \left(\frac{W' S^b W}{W' S^w W} \right) \right], \quad (3)$$

where S^{w} is the within-class scatter matrix, and S^{b} is the between-class scatter matrix. These matrices are obtained from

$$\begin{aligned} S^{\mathrm{w}} &= \sum_{l=0}^{1} \sum_{i:y_i=l} (z_i - \mu_l)(z_i - \mu_l)', \quad (4) \\ S^{\mathrm{b}} &= \sum_{l=0}^{1} n_l (\mu_l - \mu)(\mu_l - \mu)', \quad (5) \end{aligned}$$

where $\mu_l = \frac{1}{n_l} \sum_{i:y_i=l} z_i$ and $\mu = \frac{1}{2} \sum_{l=0}^{1} \mu_l$.

In (4)–(5), $y_i = \{0, 1\}$ is the class label of each feature value ($class$ 0: resting, $class$ 1: pedaling), and n_l is the number of the $class$ l dataset. Then, (3) is solved as a generalized eigenvalue problem as follows:

$$S^{\mathrm{b}} w_k^{\mathrm{LDA}} = \lambda_k S^{\mathrm{w}} w_k^{\mathrm{LDA}}, \quad (6)$$

where the eigenvector w_k^{LDA} corresponds with the eigenvalue λ_k that is sorted in ascending order: $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_M$. Thus, most discriminative eigenvector w_1^{LDA} is obtained from the eigenvector that corresponds with the maximum eigenvalue λ_1. Thus, most discriminative eigenvector w_1^{LDA} is obtained from the eigenvector that corresponds with the maximum eigenvalue λ_1.

IV. Proposed spatiotemporal filtering and parameter determination

A. Proposed discrimination method using spatiotemporal filtering

Here, we propose a new discrimination method using the spatial and temporal information of features. To improve the discrimination performance, the output is smoothed with the addition of a temporal filter, which acts as an IIR filter, to the spatial filter, which has same structure as the LDA discriminator.

Our proposed discriminator is defined as follows:

$$x_t = \sum_{i=1}^{M} a_i z_{ti} + \sum_{j=1}^{N} b_j x_{t-j}, \quad (7)$$

where z_{ti} is a feature obtained at time t by EEG measured at i-th electrode, and a_i and b_j are filter parameters. x_t is the discriminator output at time t. On the right-hand side of (7), the first term operates as a spatial filter, similar to the structure of the LDA discriminator in (2), and the second term is an autoregressive (AR) term that functions as an IIR filter. The motion discrimination results are obtained as the sign of x_t, i.e., a subject is in the "pedaling condition" if the sign is positive and "resting condition" if it is negative.

B. Filter parameters determination by a recursive least square method

In this study, we determine a_i and b_j using a recursive least-squares method [24]. From (7), x_t is rewritten as

$$x_t = H_t \theta \quad (8)$$

where, H and θ are given by:

$$\begin{aligned} H_t &= [z_{t1}, \cdots, z_{tM}, x_{t-1}, \cdots, x_{t-N}], \\ \theta &= [a_1, \cdots, a_M, b_1, \cdots, b_N]'. \end{aligned}$$

To obtain the estimator $\hat{\theta}$ of the filter parameters θ, we employed a recursive least-squares scheme with learning data that consist of z_{ti} and the actual movement conditions at time t. This scheme is given by following equations:

$$\begin{aligned} H_t &= [z_{t1}, \cdots, z_{tM}, \hat{x}_{t-1}, \cdots, \hat{x}_{t-N}], \quad (9) \\ \hat{\theta}_t &= \hat{\theta}_{t-1} + \frac{P_{t-1} H_t'}{1 + H_t P_{t-1} H_t'} + (x_t - H_t \hat{\theta}_{t-1}), \quad (10) \\ \hat{x}_t &= H_t \hat{\theta}_t, \quad (11) \\ P_t &= \frac{1}{\rho} \left[\frac{P_{t-1} H_t' H_t P_{t-1}}{\rho + H_t P_{t-1} H_t'} \right]. \quad (12) \end{aligned}$$

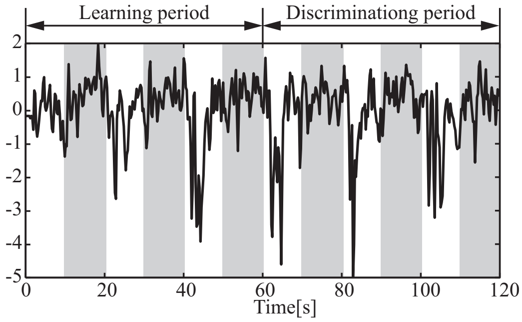
In above equations, x_t was set to -1 when the actual movement condition was resting and was set to 1 when the condition was pedaling. On the other hand, $\hat{x}_t$ is the discriminator output calculated from these equations. In this study, the initial values of this scheme are selected as $H_1 = [0, \cdots, 0, z_{11}, \cdots, z_{1M}]$, $\hat{\theta}_0 = [0, \cdots, 0]$, and $P_0 = I$. Moreover, it is assumed that the filter parameters are time invariant, and forgetting coefficient ρ was set to 1.

V. Results

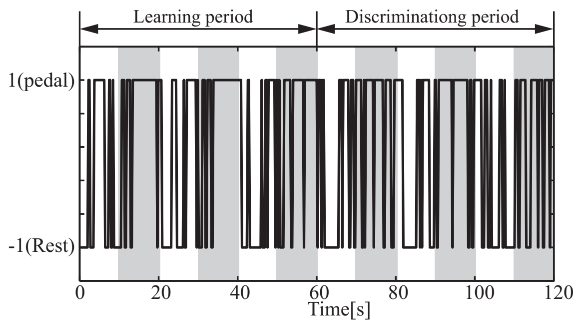
To confirm the effectiveness of our proposed discrimination approach, we carried out pedaling motion discrimination experiments for a healthy subject using LDA and the proposed method. In this experiments, the EEG data in Fig. 4 were used for discrimination. The subject's electroencephalogram during the bicycle ergometer pedal exercise was recorded for 120 s, and the first 60 s were used as learning data. The number of electrodes M was set to six in (2) and (7).

Fig. 5 (a) shows the LDA discrimination output calculated by (2). The LDA parameters w_1^{LDA} of (2) were obtained from the learning data. This output means that the subject is in the "pedaling condition" if the output has a positive value and "resting condition" if the output has a negative value. The LDA discrimination results are shown in Fig. 5 (b). Because a considerable amount of noise was included in the output of the LDA discrimination results, there were many false discriminations. When the LDA method was used for discrimination, the accuracy of the pedaling conditions for the last 60 s of data was 68.3%.

On the other hand, Fig. 6 (a) shows the proposed filter output. The parameters of our proposed method, $\hat{\theta}$, was obtained by the proposed recursive least squares scheme (9)–(12) using first 60 s of data. In this study, the order of the AR term N was set to 1.

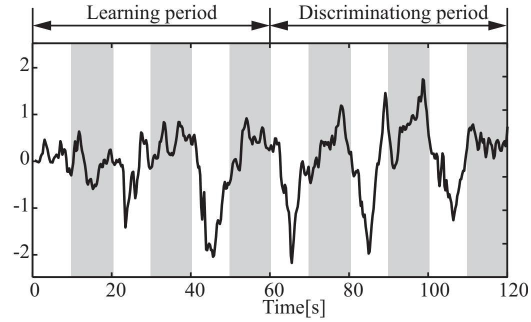


(a) LDA output.

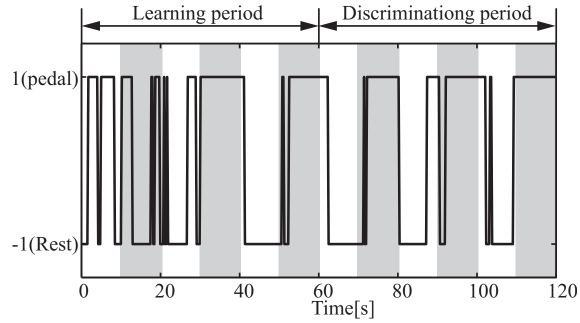


(b) Discrimination results obtained by the sign of the LDA output.

Fig. 5. Discrimination output and results of the LDA method



(a) Proposed method output.



(b) Discrimination results obtained by the sign of the proposed method output.

Fig. 6. Discrimination output and results of the proposed method.

Compared with the LDA discrimination output in Fig. 5 (a), it is found that high-frequency noise of the proposed filter output was reduced. The discrimination results calculated from the sign of the proposed filter output shown in Fig. 6 (b). The number of false discriminations in the results was less than the LDA results.

Consequently, the discrimination accuracy of the proposed method with the last 60 s of data was 80.8%. Thus, we confirmed that the discrimination accuracy of our proposed method was improved by over 12.5 percentage points than that of LDA.

VI. Conclusions

In this paper, we described a new discrimination method to improve the discrimination results of the pedaling movement condition from EEG. This method use spatial and temporal information for discrimination. Furthermore, we developed a new discriminator structure and its parameter determination method using a recursive least-squares method. The experimental results indicated that the discrimination performance of our proposed method was improved compare to the general LDA method.

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