Single Trial Discrimination between Right and Left Hand Movement-Related EEG Activity*

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Abstract. We propose an EEG-based discrimination method for the right/left hand movement in a single trial. The EEG was recorded during the voluntary movement and imagination of the hand movement. We made a feature vector for every second that represents the characteristics to reflect the process of the right/left movement. It was composed of the ERD, ERS patterns of the mu and beta rhythm and the coefficients of the autoregressive model best fitting for the data of the given period. Linear discrimination of their distributions in the vector space classified the right/left hand movement-related EEG activity efficiently.

1 Introduction

The ongoing EEG (electroencephalogram) signals are including useful information to reflect the neuronal processing for the specific mental and/or physical functions. There is a plenty of evidence indicating the frequency-specific changes of EEG may correlate to the sensory, motor and cognitive processing [1, 2, 3]. With high temporal resolution and a low cost, EEG is widely used in assessing brain processes. This EEG signals could be applied for the communication between the brain and an electronic system like a computer – a Brain-Computer Interface (BCI) [4].

The EEG changes reflecting the human intention related the limb movements or the imagination of the movements have been researched extensively and applied to BCI [5, 6]. During the preparation or imagination of the movements, the EEG signals show frequency-specific changes time-locked to the event. These event-related changes consist of decrease or increase of the power in given frequency bands, which might be due to decrease or increase in synchronous activities of the underlying neuronal populations. These are called event-related desynchronization (ERD) and event-related synchronization (ERS) respectively [7].

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In this study, the EEG signals were recorded during the performance and imagination of the hand movement and analyzed to generate feature vectors for every second EEG data. A feature vector was composed of the ERD, ERS patterns of the mu and beta rhythm and the coefficients of the autoregressive model best fitting for the data of the given period. Linear discrimination of their distribution in the vector space divided the right and left hand movement efficiently.

2 Method

2.1 EEG Data Acquisition

Thirty-five subjects aged 19 to 25 years participated in the study. All subjects were right-handed and free of neurological disorders. The EEG was recorded from the whole scalp with 32 Ag/AgCl electrodes placed according to the international 10-20 system (Neuroscan amplifier, sampling rate 1000Hz, bandwidth filtering 1.5~100Hz). Three kinds of experimental paradigms were used; *self-paced hand movement* in which subjects push a button with the index finger on their own pace in 12-18 s intervals, *tone-triggered hand movement* in which subjects perform the movements after the presentation of tone (1kHz, duration 100ms), and *tone-trigger imagination of hand movement* in which subjects were instructed to imagine performing the movement after the tone stimulation. The EEG was recorded continuously to be selected 12s epoch in each trial, time-locked with the movement-onset or tone stimulation.

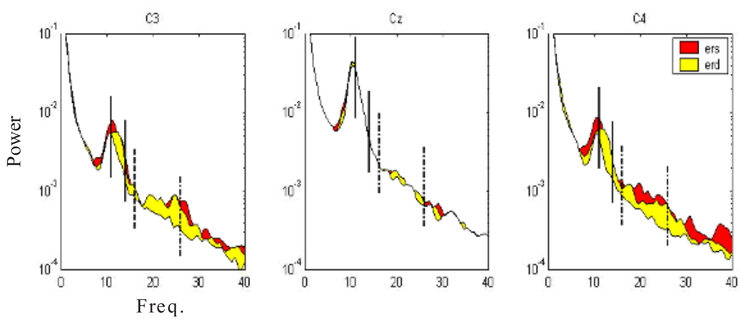

Fig. 1. Examples of 1sec power spectra from EEG data of C3, Cz, and C4 recorded during pre-movement reference period (center line), movement period (lower line), and post-movement period (upper line) while tone-triggered left hand movement. The frequency ranges displaying significant power decrease or increase are marked with a pair of vertical solid lines of 11~14Hz (μ) and a pair of dash-dot lines of 16~22Hz (β)

2.2 Power Spectrum and ERD/ERS Computation

To select the most reactive frequency components to reveal the ERD/ERS patterns related to the hand movement, the power spectra for three periods were compared. For the data from C3, Cz, and C4 electrodes, the power spectra of 1-s pre-movement period as a reference, 1-s movement period around the movement onset, and 1-s post-movement period after movement offset were calculated. Examples from a subject are presented in Fig. 1. In these examples, similar to the formal studies [8, 9], they showed different in the frequency band between 11-14Hz (mu) and 16-22 Hz (beta).

The ERD/ERS time curves were calculated for the selected frequency bands. This procedure involved band pass filtering, squaring of amplitude to obtain power values, averaging of power over all trials, normalizing, and computing of percentages with respect to the reference interval.

$$ERD/ERS(\%) = (P_{segment} - P_{reference}) / P_{reference} \times 100$$

2.3 Coefficients of Autoregressive Model

We adopted the coefficients of the autoregressive model as useful indices to discriminate right/left hand movement. In each trial, the EEG signals for 12-s epoch were divided into 1-s window segments with 500ms overlap. The coefficients of the autoregressive model best fitting for the data of each segment were calculated using the following model, in which delay time d=5, and mode order k=6.

$$x_n = a_1 x_{n-d} + a_2 x_{n-2d} + \cdots + a_k x_{n-kd}$$

Fig. 2 illustrates the time curve of the one coefficient (a1) piled up across all trials. They showed the different patterns for the right/left directions (the left hand movement in this figure) and time locked to the movement onset and offset. Therefore, these coefficients were included in our feature vector.

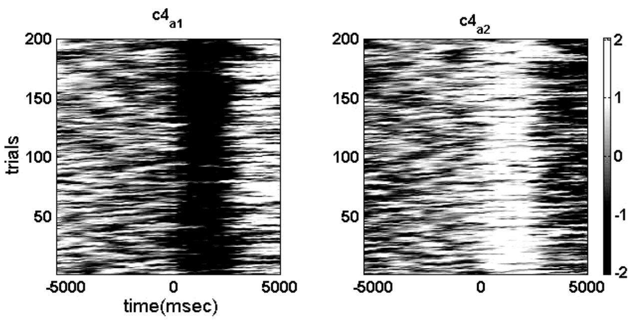

Fig. 2. The change of a coefficient of the autoregressive model in each trial while tone-triggered left hand movement. The x axis indicates the time (msec) from the movement onset, and y axis indicates the trial number

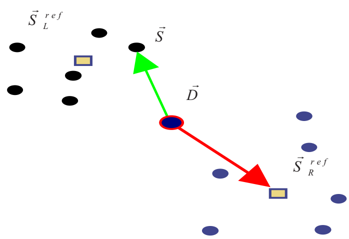

Fig. 3. Schematic diagram of the distribution of feature vectors in a vector space. If dark and thin circles represent the feature vectors of right and left movement, two rectangles ($\vec{s}_L^{ref}$, $\vec{s}_R^{ref}$) indicate the middle points of each group. The center point $\vec{D}(t)$ is an average of two rectangles. The value of d(t) is inner product of ($\vec{s}(t)$ - $\vec{D}(t)$) and ($\vec{s}_L^{ref}(t)$ - $\vec{D}(t)$), which is qualifying the position of the vector compared to the middle point of one group, $\vec{s}_L^{ref}(t)$ in this equation. If d(t) is positive value, therefore, it means the vector is included in the group. If negative, the vector is included in the other group

2.4 Feature Vector and Liner Discrimination

The feature vectors were composed with the characteristics proven to be useful for the right/left discrimination in our analysis. We made feature vectors for every 1-s window segments using the EEG signals from C3 and C4 sites. A feature vector includes 6 coefficients of autoregressive model for C3, 6 coefficients for C4, and the ratios of the power change in mu and beta bands for C3 and C4 (that is, ERD/ERS ratio in the period). To compare across trials, the values were standardized in each trial to the reference period of the formal 6 s before the tone onset.

$$\vec{S}(t) = (\overline{a}_1^{C3}, \overline{a}_2^{C3}, \ldots, \overline{a}_6^{C3}, \overline{a}_1^{C4}, \overline{a}_2^{C4}, \ldots, \overline{a}_6^{C4}, \overline{P}_{hi-\alpha}^{C3}, \overline{P}_{\beta}^{C3}, \overline{P}_{hi-\alpha}^{C4}, \overline{P}_{\beta}^{C4})$$

$$\overline{x} = \frac{x - \langle x \rangle_{ref}}{\sigma(x)_{ref}}$$

Feature vectors of every window segments were projected to the vector space (16 dimensions in this case) for their distributions to be discriminated linearly. Fig 3 explained the definition of d(t), quantified the position of each vector in the vector space.

$$\vec{S}_{L/R}^{ref}(t) = \frac{1}{N_{L/R}} \sum \vec{S}_{L/R}(t)$$

$$\vec{D}(t) = (\vec{S}_L^{ef}(t) + \vec{S}_R^{ref}(t))/2$$

$$d(t) = (\vec{S}(t) - \vec{D}(t)) \cdot (\vec{S}_R^{ref}(t) - \vec{D}(t))$$

$$if\ d > 0 \rightarrow Right$$

$$if\ d < 0 \rightarrow Lelf$$

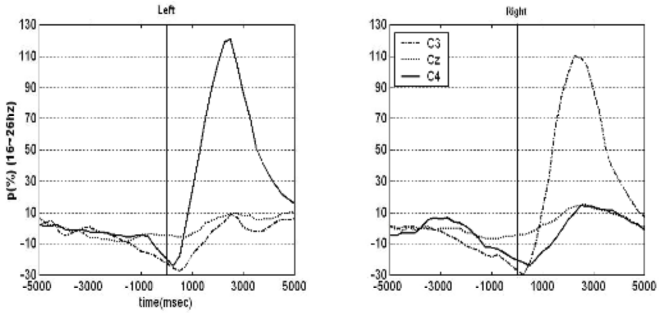

Fig. 4. Grand average time courses of β rhythm in C3 (dash-dot line) Cz (thin line), and C4 (solid line) while tone-triggered movement of left (left box) and right (right box) hand. The x axis indicates the time (msec) from the onset of the tone (the vertical bar). The y axis indicates the percentage of the relative power change, to show ERD and ERS specifically dominant in the contralateral somatomotor area

3 Results

Fig. 4 displays the grand average ERD/ERS time courses of the beta band activity from C3, Cz, and C4 data. For each side movement, it is seen that the post-movement power increases (ERS) are larger in the contralateral hemisphere than the ipsilateral hemisphere. In case of the mu band, a prominent ERD was found in the contralateral hemisphere, followed by ERS.

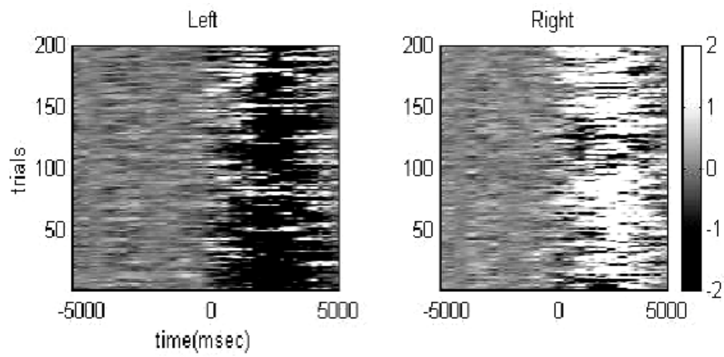

Fig. 5. The time course of d(t) value of the feature vector while tone-triggered movement of left (left box) and right (right box) hand. The x axis indicates the time (msec) from the movement onset, and y axis indicates the trial number

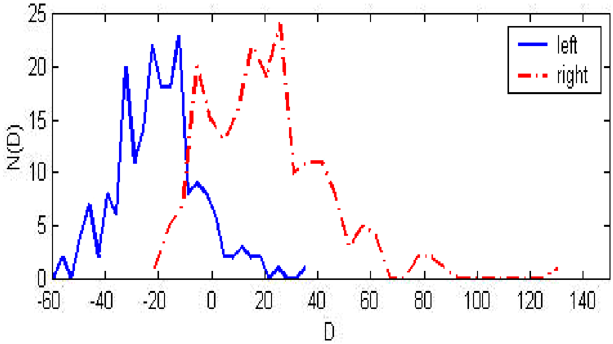

Fig. 6. Histogram of d(t) value of the feature vector while tone-triggered movement of left (solid line) and right (dot line) hand. The x axis indicates the value of d(t) and the y axis indicates the number of the feature vectors that have the value. In this subject, the recognition rates of left and right are 91% and 87%

Fig. 5 illustrates the time curve of the d(t) value piled up across all trials. They are changed consistently after movement onset by the right/left movement across the trials. We made a histogram accumulated by the value of d(t) for every right/left trials in each subject. As shown in Fig. 6, the distributions for the right and left movement could be discriminated well. Table 1 presents the recognition ratios for right/left movement using the linear discrimination of the feature vectors for 6 subjects.

Table 1. The recognition rate while tone-triggered hand movement

subject	Left(%)	Right(%)	Total(%)
HMA	82.0	68.0	75.0
JJH	81.0	76.5	78.7
CSY	75.5	66.5	71.0
KSM	91.0	80.0	85.5
JWR	71.5	79.3	75.5
PMJ	72.0	80.0	76.0
Total	78.8	75.1	77.1

4 Discussion

For the application to the BCI system, it is necessary that the EEG features related to the human intent were analyzed with the EEG signals in a single trial. The present study determined the features that could reveal the intention and performance of the right/left hand movement and proposed the discrimination method using the features in a single trial.

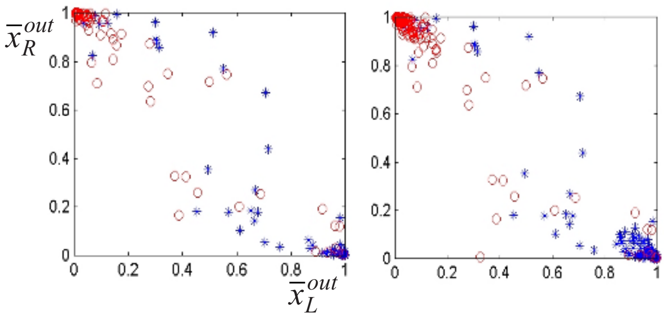

Fig. 7. The performance of the artificial neural network using the units of the feature vector as input nodes while tone-triggered hand movement. We set two output nodes for right and left, indicated in the y and x axis. Two kinds of test data set were applied to generate recognition rate 87% and 93%

As units of our feature vector, we used the single-trail ERD/ERS patterns that were well known as grand averaged ones. And the coefficients of the autoregressive model were used as other units, which showed consistent time-course changes across the trials and differences in the right/left movement.

We further tried to use an artificial neural network for the discrimination of the right/left movement. The units of our feature vectors after the movement onset in each trial were used as the value of the input nodes (multi-layered perception model, input node 80, one-layer hidden node 10, output node 2, and learning rule: feed-forward backpropagation). The preliminary result showed a similar recognition rate with the linear discrimination method (Fig. 7).

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