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Classification of Single Trial EEG during Imagined Hand Movement by Rhythmic Component Extraction

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***Abstract*— An electroencephalograph (EEG)-based brain computer interface (BCI) requires rapid and reliable extraction of features in EEG signal. Recently, the rhythmic component extraction (RCE) method has been proposed to extract features of multi-channel EEG. RCE can extract a signal component with a certain frequency from multi-sensor signals. In this paper, we applied RCE to extract a feature corresponding to hand movement imagery tasks from signals measured by EEG. This feature from a single trial EEG signal is classified between imaginary left/right hand movement EEG using machine learning. On two subjects, our experiment shows that the combination of RCE and fisher discriminant analysis outperforms common spatial patterns (CSP) in classification accuracy. It is also reported that other major classifiers together with RCE give better performance than CSP. Additionally, we consider the relationship between data length and classification accuracy. It is shown that the accuracy tends to decrease as the data length becomes small.**

I. INTRODUCTION

It is crucial to extract the brain activity of humans from measured brain signals in a brain computer interface (BCI). Non-invasive measurement devices such as electroencephalogram (EEG), magnetoencephalogram (MEG), and functional magnetic response imaging (fMRI) are widely used to observe brain activity. Because of its simplicity and low cost, EEG is a practical measurement device for use in engineering applications. In general, signals measured by EEG have good time resolution, however poor spatial resolution. Moreover, the amplifier gain is very large, and thus the obtained signal is highly affected by measurement noise.

BCI is a challenging application of signal processing and neuroscience. Motor imagery-based BCI is a promising realization [1]. Depending on the type of motor imagery, the difference of rhythmically oscillating components in EEG signal can be observed [2]. Therefore, this frequency component such as alpha, mu, beta rhythm, and event related potential are widely used as feature values in this type of BCI system. To extract these features, methods based on frequency analysis such as linear filtering and Fourier analysis are widely applied [1]. For classification of tasks, the so-called common spatial patterns (CSP), which is a method based on learning, is also well-known [3], [4].

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In general, CSP needs frequency filtering as preprocessing to increase classification accuracy [3]. Frequency filtering is a classical and simple single channel processing method to extract a specific frequency component. However, when measuring data in a noisy environment, it is difficult to differentiate a component generated by brain activity from a noise-related component. Moreover, the signal extracted by frequency filtering has only the specific frequency component, since other frequency components in the observed signal are discarded. This may decrease the accuracy in motor imagery-based BCI.

The rhythmic component extraction (RCE) method does not discard frequency components of the observed signal [5]. Like other methods for multi-channel signal processing, RCE extracts the target signal by using a linear combination of the observed signals. This method uses physically well established information, that is, frequency. However, unlike frequency filtering, this method does not filter out frequency components but "enhances" frequency components of interest by using a simple linear combination of channel signals. This way, RCE successfully extracts signals that have energy mostly in the frequency of interest. We expect RCE to increase the classification accuracy in motor imagery-based BCI.

We tried to classify the single trial EEG signal during imagined hand movement. RCE was able to extract a feature value from the observed signal. In this application, the extracted feature values are classified between left and right hands movement. For classification, the template matching (TM) method, the k-nearest neighbor (k-NN) method, fisher discriminant analysis (FDA), and CSP were examined. To compare with other feature extraction methods, we used channel signals to which FIR band-pass filter was applied and the Fourier spectra as feature values. Moreover, we discuss the relationship between the data length of a signal and classification accuracy for real-time processing.

II. THE RHYTHMIC COMPONENT EXTRACTION (RCE) METHOD

Rhythmic component extraction (RCE) is a method for extracting a component that concentrates its energy within a certain frequency range by using a weighted sum of the channel signals. This section reviews the theory of RCE proposed in [5]. Let $x_i[k]$ $(k = 0, \dots, N-1)$ be an observed signal in the ith channel, where $i = 1, \dots, M$. We extract a signal by using a linear combination of channel signals as follows

$$\hat{x}[k] = \sum_{i=1}^{M} w_i x_i[k], \tag{1}$$

where w_i is a weight coefficient to be determined by a certain criterion. The RCE method determines the weight coefficients in such a way that the energy in specific frequency components of $\hat{x}[k]$ is as large as possible while the energy in the other frequency components of $\hat{x}[k]$ is as small as possible. This idea is formulated in the following way.

Let $\hat{X}(e^{-j\omega})$ be the discrete-time Fourier transform (DTFT) of $\hat{x}[k]$, that is, $\hat{X}(e^{-j\omega}) = \sum_{k=0}^{N-1} \hat{x}[k]e^{-j\omega k}$, and let $\Omega_1 \subset [0, \pi]$ and $\Omega_2 \subset [0, \pi]$ be the frequency ranges of interest and those to be suppressed, respectively. It is sufficient to use positive frequencies because the EEG signal is real-valued. Then, the RCE cost function to be maximized is given as follows [5]:

$$J[w_1, \ldots, w_M] = \frac{\int_{\Omega_1} |\hat{X}(e^{-j\omega})|^2 d\omega}{\int_{\Omega_2} |\hat{X}(e^{-j\omega})|^2 d\omega}. \tag{2}$$

The maximization of the above cost function is reduced to a generalized eigenvalue problem in the following way. Define $\boldsymbol{X} \in \mathbb{R}$ as $[\boldsymbol{X}]_{ik} = x_i[k]$ and matrices $\boldsymbol{W}_1$ and $\boldsymbol{W}_2$ as

$$[\boldsymbol{W}_1]_{l,m} = \Re \int_{\Omega_1} e^{-j\omega(l-m)} d\omega, \tag{3}$$

$$[\boldsymbol{W}_2]_{l,m} = \Re \int_{\Omega_2} e^{-j\omega(l-m)} d\omega, \tag{4}$$

respectively, where $l, m = 0, \cdots, N-1$ and $\Re\cdot$ takes the real-part of the complex value. Then $J[\boldsymbol{w}]$ in (2) can be described in the matrix-vector form as

$$J[\boldsymbol{w}] = \frac{\boldsymbol{w}^T \boldsymbol{X}\boldsymbol{W}_1\boldsymbol{X}^T\boldsymbol{w}}{\boldsymbol{w}^T \boldsymbol{X}\boldsymbol{W}_2\boldsymbol{X}^T\boldsymbol{w}}, \tag{5}$$

where $\boldsymbol{w} = [w_1, \ldots, w_M]^T$ ($\cdot^T$ describes the transpose). The maximizer of $J[\boldsymbol{w}]$ is given by the eigenvector corresponding to the maximum eigenvalue of the following generalized eigenvalue problem:

$$\boldsymbol{X}\boldsymbol{W}_1\boldsymbol{X}^T\boldsymbol{w} = \lambda \boldsymbol{X}\boldsymbol{W}_2\boldsymbol{X}^T\boldsymbol{w}. \tag{6}$$

The problem can be solved by using a matrix square root of $\boldsymbol{X}\boldsymbol{W}_2\boldsymbol{X}^T$. Since $\boldsymbol{X}\boldsymbol{W}_2\boldsymbol{X}^T$ is symmetric, a matrix square root, $\boldsymbol{S}$, exists such that $\boldsymbol{X}\boldsymbol{W}_2\boldsymbol{X}^T = \boldsymbol{S}\boldsymbol{S}^T$. Note that $\boldsymbol{S}$ is not uniquely determined. Then, the optimal solution, $\boldsymbol{w}^*$, is given by

$$\boldsymbol{w}^* = \boldsymbol{S}^{-T}\hat{\boldsymbol{w}}, \tag{7}$$

where $\hat{\boldsymbol{w}}$ is the eigenvector corresponding to the largest eigenvalue of $\boldsymbol{S}^{-1}\boldsymbol{X}\boldsymbol{W}_1\boldsymbol{X}^T\boldsymbol{S}^{-T}$, where $\cdot^{-T} = (\cdot^{-1})^T$.

III. EXPERIMENTAL METHOD

We applied RCE to extract a feature from the EEG signal during a hand grip movement imagery task. The extracted feature values defined in Section III-B were classified by machine learning as described in Section III-C. Moreover, we tried to classify frame-series signals by frame processing.

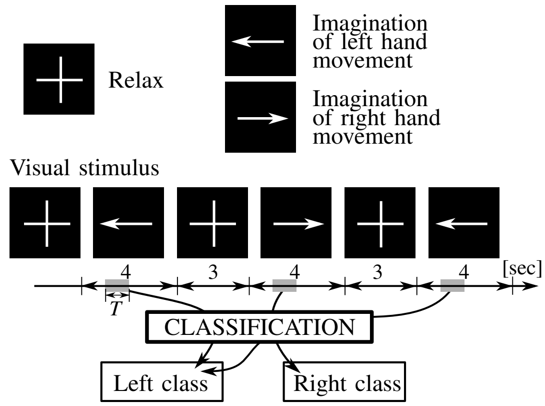

Fig. 1. The timing of the movement imagery task. The stimulus in form of an arrow gives the side of imagination and appears at repeat. An EEG signal of each trial for classification is observed 1s after the indication of the stimulus.

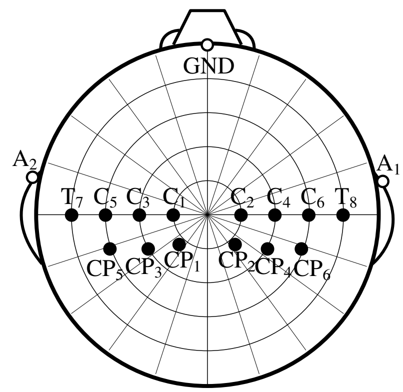

Fig. 2. The location of electrodes (International 10/10 system notation).

A. Data acquisition

Two healthy, male, right-handed subjects (age 22) took part in this experiment (subject S1 and S2). The subjects were seated in an armchair and watched a monitor. They were asked to keep their arms and hands relaxed. Depending on the direction of the arrow on the monitor, the subject was instructed to imagine a movement of their left or right hand as shown in Fig. 1. The subject's tasks were shown as follows.

1) The subject gazes at a fixation cross in the monitor.
2) After 3s, an arrow is presented on the monitor, and the subject imagines the one hand griping for 4s (the arrow was presented at repeat).
3) The fixation cross is presented, and the imagination is discontinued.
4) Return to 1).

EEG signals were recorded with 14 Ag/AgCl electrodes located around motor cortex areas as illustrated in Fig. 2 (reference: A_1+A_2, ground: forehead). The EEG signals were amplified and filtered in the frequency band of 0.08–100Hz by MEG-6116 (NIHON KOHDEN). Moreover, amplified signals were digitized at 500Hz by A/D converter, AIO-

163202F-PE (CONTEC). A set of EEG signals for classification consists of "left" class and "right" class for each of 100 trials. A one trial signal in this set was the observed signal after 1s from the visual stimulus. T (shown in Fig. 1) denotes the number of samples in this range (data length).

B. Feature values

For classification, we should extract feature values corresponding to each imaginary task of the subject. We tried to extract rhythmically oscillating components such as mu and beta rhythm by using the following methods.

1) Band-pass signal: The band-pass signal, $\boldsymbol{X}_{f_1-f_2}$ is the observed signals to which FIR band-pass filter in a $f_1 - f_2$Hz frequency band was applied, that is, $\boldsymbol{X}_{f_1-f_2} \in \mathbb{R}^{M\times N}$ as $[\boldsymbol{X}_{f_1-f_2}]_{ik} = x'_i[k]$ $(k = 0, \dots, N-1)$ where x'_i $(i = 1, \dots, M)$ is the band-pass signal of the ith channel and N is the data length. The order of the FIR filter was 100 in this experiment.

2) Fourier spectra of observed signals: The Fourier spectrum, $f_i[k]$ was obtained by discrete Fourier transform (DFT) of the ith channel signal. We define $\boldsymbol{F}$ as $[\boldsymbol{F}]_{ik} = f_i[k]$. Then $\boldsymbol{F}_{f_1-f_2} \in \mathbb{R}^{M\times N_f}$ is obtained from $\boldsymbol{F}$ of the frequency range of $f_1 - f_2$Hz. N_f is the length of the spectrum and depends on the sampling frequency and the data length.

3) Correlation coefficient by RCE: c_i is correlation coefficient between the ith channel signal and the signal extracted using RCE. Then correlation coefficient, $\boldsymbol{c}$ between all channel signals, $\boldsymbol{X}$ and the extracted signal, $\hat{\boldsymbol{x}}$ can be described as $\boldsymbol{c} = \boldsymbol{X}\hat{\boldsymbol{x}}^T$, where $\boldsymbol{c} = [c_1, \dots, c_M]^T$.

C. Classification methods

1) TM: The TM method classifies input data by evaluating the distance between the input data and templates belonging to a given class. In this paper, we used the mean value of learning data as the templates. The Euclidean distance was used as the definition of the distance.

2) k-NN: The k-NN method classifies input data by evaluating the distance between the input data and all learning data. The class of the input data determined as the majority of the k learning data that are nearest from to input data. In this paper, we used the Euclidean distance, and k was 5.

3) FDA: FDA constructs a linear dimension reduction from the input vector, $\boldsymbol{x}$ to a new feature value, y. A weight vector for reduction of linear dimensions was obtained by maximizing the inter-cluster distance between each class and minimizing the intra-cluster distance within a given class in the new dimension space. In this paper, input data was classified by evaluation of the distance between the threshold and the projected input data. We used the mean value of learning data projected onto the new dimension space as the thresholds.

4) CSP: CSP finds the direction which the observed signal should be projected onto so that the differences between any two classes are maximized (i.e. the variance of one class is minimized while at the same time, the variance of the other class is maximized) [3]. The directions are given by a weight vector whose rows give the weight of the channels. Useful features can be extracted from the EEG signal and then used for classification. In this paper, we extracted two spatial filters, $\boldsymbol{w}_p$ $(p = 1, 2)$ from the learning data. $\boldsymbol{w}_p$ minimizes the variance of the extracted signal corresponding to each class. Thus we can obtained two extracted signals corresponding to $\boldsymbol{w}_p$ respectively from the input data. By comparing the variances between each of the extracted signals, the class of the input data can be determined.

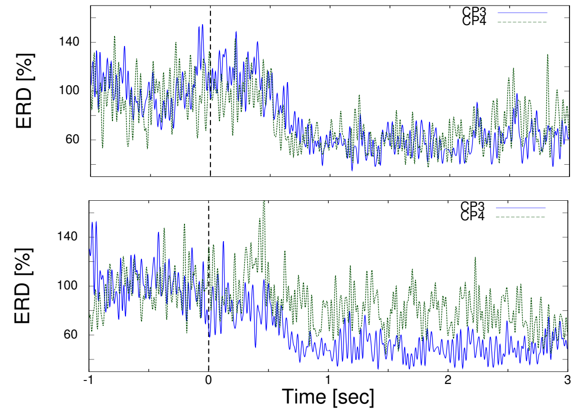

Fig. 3. ERD during imagined left (top) and right (bottom) hand movement in S1. The base of the power was the average of the power in "relax" task. The ERD were the average over 100 trials.

TABLE I

THE CLASSIFICATION ACCURACY FOR EACH METHOD. THE DATA LENGTH WAS 1S AND THE ACCURACY RATE IS GIVEN BY USING 5-FOLD CROSS VALIDATION. (SBJ; SUBJECT)

Sbj	Feature value		Accuracy [%] TM	5-NN	FDA	CSP
S1	Band-pass	$\boldsymbol{X}_{12-15}$	51.0	64.5	52.2	82.5
	Fourier spectra	$\boldsymbol{F}_{12-15}$	67.1	62.9	77.3	50.5
	RCE (12–15Hz)	$\boldsymbol{c}$	81.1	82.8	**83.1**	
S2	Band-pass	$\boldsymbol{X}_{12-15}$	50.5	50.9	51.9	70.1
	Fourier spectra	$\boldsymbol{F}_{12-15}$	63.2	58.6	68.1	51.1
	RCE (12–15Hz)	$\boldsymbol{c}$	71.8	67.1	**74.9**	

IV. RESULTS AND DISCUSSION

A. Brain activity during hand movement imagery

Figure 3 shows event-related desynchronization (ERD) in two electrodes (CP_3 and CP_4). The arrow was presented and the subject started the imagination of one hand movement at 0s. EEG signals were filtered to 8-26Hz before averaging. We can observe a decrease in power while the subject imagines the hand movement. In "right" task, the degree of this decrease in each electrode was different. This result suggests that the EEG signal during hand movement imagery can be classified by using the amplitude of the specific frequency range as the feature value.

B. Classification result

Table I shows the classification accuracy of two subjects for each set of feature values and each classification method. The data length of each trial was 1s and the accuracy rate was given by using 5-fold cross validation. We chose 12–15Hz as the frequency band of interest. This band was

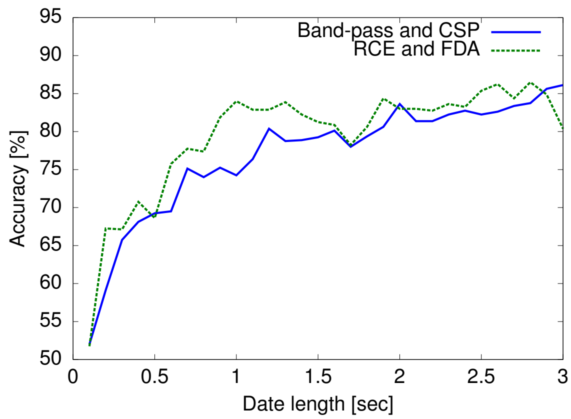

Fig. 4. The classification accuracy for changing data length in S1. The frequency range of interest is 12–15Hz. The accuracy rate is given by using 5-fold cross validation.

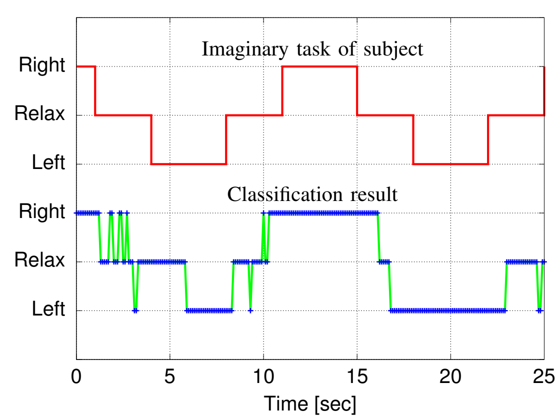

Fig. 5. The classification result by frame processing in S1. The frame length was 1s and the time delay between successive two frames is 0.2s. The feature value by RCE (12–15Hz) was classified to three classes (relax, left, and right) by FDA, and the number of learning data was 190, 95, and 95 trials for each class, respectively.

determined to provide the best performance for each classification method. For both subjects, the best classification accuracy was obtained using the combination of RCE and FDA. In addition, RCE was able to obtain good performance using the TM method and the k-NN method, which are comparatively simple methods. This result shows that RCE extracts important features corresponding to the imaginary tasks of hand movement.

C. Frame length

In the development of BCI, it is important to get a quick response to an imaginary input by the user. To this end, feature extraction and classification is needed in a short time range. Figure 4 shows the classification accuracy for the data length in S1. We can observe that the accuracy depends on the data length. The accuracy tends to increase as the data length becomes large in both methods.

We tried to apply RCE to a frame-series signal. The extracted feature was classified to relax, left, and right classes using FDA. To apply RCE to frame processing, we used adaptive RCE with regularization proposed in [6]. This method considers the correlation between the extracted signals of the previous and current frames to avoid the discontinuity in two successive frames. The time of the classification result corresponds to the last time contained in the current frame. Figure 5 shows an example of the classification result. We can observe slight incorrect classification and timing in this example. The timing of classification depends on the subject state of imagery. However, we can observe some delays in classification results, and it is shown that the speed of the response is influenced by the frame length. The result of frame processing suggests that an optimization extents of the frame length is needed to extract specific frequency components in EEG signals.

V. CONCLUSIONS AND FUTURE WORK

In this study, we used RCE to extract the features of a multi-channel EEG signal. The RCE method can extract a signal oscillating with a certain frequency from multi-sensor signals. We tried classification of the single trial EEG signals during imaginary left/right hand movement by using RCE and machine learning. In the case of our experiment, the difference of EEG signal between imaginary left and right hand movement were concentrated in the frequency band of 12–15Hz. In classification accuracy, the combination of RCE and FDA performed slightly better than other methods. Even though this experiment is only performed for two subjects, the result suggests that RCE is effective method for feature extraction in the classification of this type of EEG signal. Moreover, we showed the relationship between the data length of the EEG signal and the classification accuracy and discussed the importance of optimizing the data length in real-time processing. Though the classification accuracy tends to increase as the data length becomes large, the system may lack quick response.

For future work, we should confirm the influence of visual responses, because we used the visual stimulus for indication to the subject. In addition, more subjects may be needed to clarify the performance of RCE. Moreover, we will develop a real-time processing system using RCE for BCI.

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