EEG Feature Classification Based on Grip Strength for BCI Applications

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Abstract

Braincomputer interface (BCI) technology is making advances in the field of humancomputer interaction (HCI). To improve the BCI technology, we study the changes in the electroencephalogram (EEG) signals for six levels of grip strength: 10%, 20%, 40%, 50%, 70%, and 80% of the maximum voluntary contraction (MVC). The measured EEG data are categorized into three classes: Weak, Medium, and Strong. Features are then extracted using power spectrum analysis and multiclass-common spatial pattern (multiclass-CSP). Feature datasets are classified using a support vector machine (SVM). The accuracy rate is higher for the Strong class than the other classes.

Keywords: Brain-computer interface, Electroencephalogram, Multi-common spatial pattern

1. Introduction

Human-computer interaction (HCI) is important thing for the communication with humans and devices. In the field of HCI, research related to braincomputer interfaces (BCIs), where devices are controlled using the electroencephalogram (EEG) signals of the brain, is being conducted for various applications. In this field, when a human is induced in a particular state, the extraction and application of his/her EEG features are necessary. Epileptic patients are characterized by recurring seizures, which results in abnormal EEG signals. A doctor can confirm a spike in the EEG, which is unlike a normal EEG, using BCI technology during a seizure or during a seizure-free period, and can therefore make an accurate diagnosis of the disease [1].

Similarly, application equipment such as wheelchairs can be controlled using the extracted EEG while considering the property of laterality in the brain when a human thinks or moves his/her body. Detection and feature extraction of the EEG signals are necessary for the application to a device based on the induced human state [2].

A previous study by the authors reported a correlation between the grip strength and the EEG signal of the general brain region, and analysis and classification of grip strength for artificial hand [3-5]. In this study, the participants gripped a strength measurement device at intervals of 10% of their maximum voluntary power. The previous study showed that the stronger the grip, the greater the power value in the three regions of the brain (frontal, central, and parietal). Following the previous research, this study investigates the relationship between the EEG signal and the strength for delicate motion control of an artificial arm of quadriplegic patients. In this experiment, the EEG of the participants was measured while they exerted their grip strength. The grip strength was divided into three classes: Weak, Medium, and Strong. In

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this study, the linear change in the β and γ waves was determined and then feature extraction and classification algorithms were applied.

2. Background

2.1 Related Works

The brain consists of four regions: the frontal lobe, parietal lobe, temporal lobe, and occipital lobe. EEG signals related to motor control are obtained from the motor cortex, which is located between the frontal lobe and the parietal lobe. Event-related desynchronization (ERD) / event-related synchronization (ERS) occurs when humans perform voluntary motor behavior. ERD decreases the amplitude of the EEG signal in α waves before voluntary motor behavior, and ERS increases the amplitude of the EEG signal in β waves after voluntary motor behavior [6].

2.2 Power Spectrum Analysis

Power spectrum analysis translates time series data into frequency dimension, and therefore, this algorithm is useful for bio-signal analysis. This study analyzed β and γ waves to identify the voluntary behavior related to ERS.

2.3 Multiclass-Common Spatial Pattern

The CSP algorithm is used for feature extraction. Although CSP initially used only two classes, there is research on using multiple classes. This study applied a multiclass-CSP algorithm reported by Tang et al. [7]. CSP is a method that maximizes the variance of the selected class and the variance of the other non-selected classes is minimized so that the features of the EEG signal can be obtained. This process can be presented [7, 8] as follows:

$$w = \arg \max_{w \in \mathbb{R}^N} \left\{ \frac{w^T R_{x|c} w}{w^T R_{x|c'} w} \right\} \quad (1)$$

where $R_{x|c}$, $R_{x|c'}$ are the covariance matrices of the variable $\mathbf{X}$, and N is the channel input signal for given values of c and c' , respectively. To apply the three classes in this study, the covariance matrices of each signal are defined as follows:

$$c = c_I \text{ and } c' = c_{D1} + c_{D2} \quad (2)$$

where c_I is the covariance matrix of the increasing signal for one of the three classes and c_{D1} , c_{D2} are the covariance matrices of the decreasing signal for two of the three classes. Using

the eigenvectors of the generalized eigenvalue, Eq. (1) can be transformed as follows:

$$R_{x|c} w = \lambda R_{x|c'} w \quad (3)$$

The eigenvectors in Eq. (3) correspond to a spatial matrix $\mathbf{W}$, and thus, the signals can transform the modified signal $\mathbf{Z} = \mathbf{W}\mathbf{x}$.

This study used $\mathbf{x}$ as the acquired EEG signal from the 21-channel EEG system and identified the differences among the three classes. Through the spatial matrix $\mathbf{W}$ of the CSP it can be seen that the signal for one of the two classes increased and the signal of the third class decreased.

2.4 Support Vector Machine

For classification, this study used the support vector machine (SVM) algorithm. The SVM algorithm, which is one of the supervised learning algorithms, sorts data into two or more classes using a support vector [9].

The input feature data are determined after the training. The training data comprise a maximum-margin hyperplane, which divides the space following the positions of the classes. When the training set belongs to a certain class, the decision function is defined as follows:

$$f(x) = \sum_{i=1}^N w_i \varphi(x) + b \quad (4)$$

In Eq. (4), φ denotes the predefined functions of x , w is the input vector, and b is the bias. The equation can be used to determine the optimal hyperplane in the binary classification problem as follows:

$$MaxQ(\alpha) = \sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j K(x_i x_j) \quad (5)$$

subject to

$$MaxQ(\alpha) = \sum_{i=1}^N \alpha_i y_i = 0 \alpha_i \geq 0 i = 1, \dots, N \quad (6)$$

In Eq. (5), α_i is the Lagrange coefficient. In order to determine the object function $Q(\alpha)$ that satisfies the maximum value, the decision function can be defined as follows:

$$f(x) = \sum_{i=1}^N \hat{\alpha}_i y_i K(x_i x_j) + \hat{b} \quad (7)$$

Figure 1. Experiment devices: (a) a digital dynamometer, (b) electroencephalogram equipment.

In Eq. (7), $\hat{\alpha}_i$ and $\hat{b}$ denote the weighted vectors. This equation classifies the input data. If $f(x) > 0$, the data is classified in +1 class; if $f(x) < 0$, the data is classified in -1 class.

3. Experiment

Five healthy right-handed subjects aged 25–28 years (four males and one female), without any neurological diseases, participated in the study. The grip strengths of their left and right hands were measured.

3.1 Digital Dynamometer

This study measured the grip strength by using a digital dynamometer (Model KS-301; Lavisen Inc., Seoul, Korea) and displayed the results through a digital LCD (21 mm). The dynamometer is shown in Figure 1(a), which has a maximum gauge of 90 kg/198 lbs, a unit of measure of 0.1 kg/0.2 lbs, and an allowable error of 0.5 kg/1 lbs.

4. EEG Measurement Device

To measure the EEG signals of five subjects, this study used a 64-channel EEG system (SynAmps 2; NeuroScan Inc., Charlotte, NC, USA) shown in Figure 1(b). This device can record eye movements using two electrodes placed above and below the left eye. The reference electrodes were placed below both ears and the ground electrode was placed between Fpz and FZ on the forehead. The impedance of each electrode was less than 20 k Ω and the sampling frequency was 250 Hz.

After EEG data acquisition, this study analyzed the data using the Curry7 software, which is an acquisition and analysis program for the EEG data. Noise due to eye blinking was removed from the measured EEG data and the remaining data were then analyzed with 21-electrode channels. Figure 2 shows the electrodes located in the motor region of the brain (FCZ,

Figure 2. Position of the measurement electrodes.

Figure 3. Experimental procedure.

FC1, FC2, FC3, FC4, FC5, FC6, FCZ, C1, C2, C3, C4, C5, C6, CPZ, CP1, CP2, CP3, CP4, CP5, and CP6).

4.1 Experimental Method

During the experiment, five subjects watched the digital dynamometer LCD displaying their grip strength in the shield room and wore the earphone. Figure 3 shows the experimental procedure. The task was to grip the strength measurement device with their left and right hands. The subjects exerted grip strength at six power levels: 10%, 20%, 40%, 50%, 70%, and 80% of the maximum voluntary contraction (MVC). The subjects maintained voluntary contractions for 5 s. When they heard a beeping sound (1,500 Hz for a duration of 200 ms) from the left speaker of earphone, the subjects contracted all their fingers on the dynamometer until they heard a beeping sound (500 Hz and a duration of 200 ms) from the right speaker. The rest time was 10 s between the events.

The total experimental time was 85 s and data for 2 s were extracted while maintaining the grip strength for comparison with each event. The extracted data sections were those corresponding to 2 s before the stimulus (BS) and 2 s after the stimulus (AS). The subjects performed the task with both hands

Figure 4. Electroencephalogram (EEG) data process. CSP, common spatial pattern; SVM, support vector machine.

10 times, and the measured grip strength had an error rate of 5%.

4.2 Feature Extraction Dataset

This study applied two algorithms, power spectrum analysis and multiclass-CSP, for feature extraction. Figure 4 shows the acquisition process of the feature dataset.

1. Raw EEG data is filtered through the band-pass filter in β and γ bandwidths.
2. The filtered EEG data for β and γ bandwidths are extracted through power spectrum analysis and multiclass-CSP.
3. SVM classifies the feature datasets into three classes.

In this paper, we acquired EEG data for five subjects at six levels—10%, 20%, 40%, 50%, 70%, and 80% of the MVC—which consisted of three classes: Weak (MVC 10%–20%), Medium (40%–50%), and Strong (70%–80%). Table 1 shows the structure of the feature dataset. From the β and γ bandwidths of each class, EEG signals were extracted from the feature data through power spectrum analysis and CSP. One-feature data, which is the mean value of the 21-channel power (AS-BS), were extracted by using power spectrum analysis; two-feature data, which are the maximum and minimum eigenvalues of data obtained from CSP, were extracted at AS by using CSP. The feature dataset consisted of six dimensions. In this study, the SVM algorithm classified the feature dataset into three classes. Five-fold cross-validation was employed as follows:

1. The training set comprised 75% of the input data and the testing set comprised the remaining data (25%).
2. The training set comprised 50% of the input data and the testing set comprised the remaining data (50%).

Table 1. Structure of the feature dataset

	Algorithm	Feature data	Dimension
β	Power spectrum	Mean value	1
	CSP	Maximum and minimum value	2
γ	Power spectrum	Mean value	1
	CSP	Maximum and minimum value	2

CSP, common spatial pattern.

Figure 5. Average of power spectrum analysis for each subject (*L*, *M*, *Y*, *K*, *H*) in three classes (Weak, Medium, Strong). Top, β (13–30 Hz); bottom, γ (30–50 Hz).

These two training and test sets were classified using SVM, and the accuracy rate was calculated.

5. Experimental Results

5.1 Power Spectrum Analysis Results

Figure 5 shows the power spectrum graph. Except for subject *M*, the higher the grip strength, the greater the increase in the EEG power values in β waves. Further, in γ waves, the power value was the greatest when subjects used strong grip strength. However, except for subject *H*, the γ power value is smaller for Medium than for Weak, unlike the β wave bandwidth.

5.2 Classification Accuracy Results

Table 2 shows the results of the accuracy rate of the five-fold cross-validation from the two-test set. Most accuracy rates were highest for the Strong class compared to the other classes. The highest accuracy rate, with an average of 71.3%, was exhibited

Table 2. Accuracy rate (%) of each subject

	Weak	Medium	Strong
L	53.3	42	76
M	30	29.3	53.3
Y	58	40	56.7
K	6	36.7	67.3
H	66.7	61.3	86

by **H**. With the exception of **K**, the accuracy rate was the lowest for the Medium class as compared to other classes.

6. Conclusions

This study investigated the change in EEG signals for β and γ bandwidths and analyzed the feature datasets with six dimensions using power spectrum analysis and CSP. The feature datasets consisted of three classes and the SVM algorithm was used to classify the datasets. The accuracy rate for most subjects was higher for the Strong class as compared with other classes. Moreover, because of the lower change in the EEG signal for the Weak and Medium classes, the class accuracy rate for these classes was low. In future study, we will try to modify the classification to obtain better accuracy rate for the Weak and Medium classes. If the change in the EEG signal and strength can be precisely classified, or if the EEG-channel associated with the strength can be determined, this study could be applied to many BCI fields.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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