Feature Extraction for EEG Activity during 4 Limbs Motor Imagery in Time Domain

Kenji Hontani*, Ryosuke Shibata*, Makoto Maeda** and Katsuhiro Inoue*
*Kyushu Institute of Technology, 680-4, Kawazu, Iizuka-shi, Fukuoka 820-8502, Japan
**Kyushu Sangyo University, 3-1 Matsukadai 2-chome, Higashi-ku, Fukuoka 813-8503, Japan

E-mail: q677023k@mail.kyutech.jp

Abstract

Recently, many researchers have been studying the Brain Computer Interface (BCI). As one of its input signals, the EEG activity when users do motor imagery is analyzed in frequency domain to be detected ERD or ERS. Currently, however, these analysis methods require users’ long-term training to detect them and get higher EEG recognition accuracy[1]. In this paper, to avoid these problems, we consider the analysis method for the EEG activity in time domain when subjects do 4 limbs motor imagery. Further, by the feature extraction relating to Movement-Related Cortical Potential(MRCP), we assess the relationship between features and recognition accuracy.

1 Introduction

As the interface that can control devices in real time without touching them, Brain Computer Interface (BCI) has been used by measuring and analyzing EEG activity during users’ action, imagery or response to external stimuli. For instance, users are able to use this interface as a communication tool even if they have a physical handicap such as ALS. In general, external stimuli accompany users’ fatigue and motor imagery requires a long-term training to use BCI effectively. In this paper, in order to avoid these problems, we consider the analysis for the EEG activity about the time domain when people begin motor imagery a few seconds before, which relates to Movement-Related Cortical Potential(MRCP) such as Bereitschaftspotential(BP), Negative Slope(NS) and Contingent Negative Variation(CNV) [2][3][4]. Further, we evaluates the recognition accuracy of the analysis result as BCI systems.

2 EEG measurement experiment

So as to gather EEG data during 4 limbs motor imagery, we conducted EEG measurement experiment with 3 subjects. The brief information is shown in following Table 2.1.

Table 2.1: Information about subjects

| Subject ID | Age | Sex | Experience as subject |
|------------|-----|-----|-----------------------|
| A          | 21  | Male | None                  |
| B          | 22  | Male | None                  |
| C          | 23  | Male | None                  |

During this experiment, subjects sit on a sofa placed about 1m away from a display with a electrode cap worn in the shielded room (Fig.2.1). First, the subject hears a beep sound in first 2 sec according to the time chart such as Fig.2.2. After the beep, the instruction showing “Right Hand”, “Left Hand”, “Right Leg” or “Left Leg” appears on the display for 1.25 sec. Then, the subject imagines moving the appropriate limb that is shown by the previous instruction for 5 sec. In order to standardize the imagination of all subjects, we have them imagine the motion to lift something during the motor imagery of hands and bend their ankle during the one of legs. We regarded this process as 1 trial. In this experiment, we did 240 trials in a day and repeated them for 2 days per subject and used the EEG amplifier which has 512 Hz sampling rate.

Fig. 2.1: Situation during the experiment
In this experiment, we adopted 29 EEG electrodes according to Fig. 2.3. In addition to them, we measured EMG and EOG in the same time to confirm the existence of subjects’ motion or blink.

3 Analysis method

3.1 Feature Value

As an example of EEG data, we show addition average waveforms about 3 electrodes (C3, C4 and Cz). In Fig. 3.1, we regard the time when subjects start motor imagery as “0 sec”. We adopt the EEG activity data when subjects start motor imagery 0.4 to 2 sec before as the data that we analyze and extract feature value in this paper. In this time domain: [-2.0 sec -0.4 sec], we take the average of EEG amplitude per 0.2 sec and get 9 amplitude data in each electrode like Fig. 3.2 and adopt these calculation results as feature values.
In order to apply these future values in statistical pattern recognition, we compose 27 dimensions feature vector: $\mathbf{x}$ like following example:

$$
\mathbf{x} = [1\text{st value (1st electrode, 1st average value)}], [2\text{nd value (1st electrode, 2nd average value)}], \ldots, [26\text{th value (3rd electrode, 8th average value)}], [27\text{th value (3rd electrode, 9th average value)}].
$$

### 3.2 Evaluation function for feature values

We use following evaluation function: $J$ to find out which part in the feature vector is more effective during 4 classes (4 limbs’ EEG activity data) pattern recognition.

$$
J = \frac{|\mathbf{S}_B|}{|\mathbf{S}_W|}
$$

- $\mathbf{S}_W$: Within-class covariance matrix
- $\mathbf{S}_B$: Between-class covariance matrix

The placement of $\mathbf{S}_W$ and $\mathbf{S}_B$ in the space which is generated by feature vector is shown in Fig. 3.3.

The higher the value of $J$ is, the easier to separate classes. Transformation matrix $\mathbf{A}$ value of maximized $J$ can be determined eigenvectors of $\mathbf{S}_W^{-1}\mathbf{S}_B$. Finally, with cut dimension of the feature vector using the transformation matrix $\mathbf{A}$.

$$
\mathbf{y} = \mathbf{A}^{-1}\mathbf{x}
$$

With applying this calculation formula to feature values like Fig. 3.2, $J$ shows following time course in each subject and electrode (Fig. 3.4).

By reference to the above result such as Fig. 3.3, we did dimension reduction about original 27 dimensions feature vector and recomposed lower dimension vector to get higher accuracy in 4 limbs pattern recognition.
4 Result

4.1 Pattern recognition method

We use the feature vector obtained in previous chapter to Bayes discrimination method shown in below formulas: (1) to (3).

\[
k^* = \operatorname{ArgMin} \left\{ -\frac{1}{2}(\mathbf{x} - M_k)^T \Sigma_k^{-1} (\mathbf{x} - M_k) + \frac{1}{2} \ln |\Sigma_k| - \ln \Pr(C_k) \right\}
\]

\[
M_k = \frac{1}{N} \sum_{i=1}^{N} x^{(i)}
\]

\[
\Sigma_k = \frac{1}{N-1} \sum_{i=1}^{N} (x^{(i)} - M_k)(x^{(i)} - M_k)^T
\]

where \( \mathbf{x} = \begin{bmatrix} x^1 \\ \vdots \\ x^N \end{bmatrix} \)

Further, in order to calculate recognition accuracy and increase its credibility, we use 10 times 10-fold Cross-validation. Table 4.1 and Fig.4.1 show the results about the accuracy of 4 limbs pattern recognition. They show the differences of accuracy by subjects, date or the order of feature vector which is used to pattern recognition.

Table 4.1: Accuracy of 4 limbs pattern recognition [%]

| Subject ID | A_Day1 | A_Day2 | B_Day1 | B_Day2 | C_Day1 | C_Day2 |
|------------|--------|--------|--------|--------|--------|--------|
| 27 dimensions (Original) | 54.95  | 60.08  | 29.71  | 35.30  | 43.46  | 57.50  |
| 1st effective dimension | 47.75  | 45.08  | 29.50  | 38.70  | 43.63  | 55.79  |
| 3 effective dimensions | 70.65  | 64.79  | 29.50  | 45.55  | 60.54  | 77.13  |
| 6 effective dimensions | 72.55  | 68.79  | 30.54  | 57.50  | 65.46  | 79.08  |
| 9 effective dimensions | 72.85  | 70.33  | 28.21  | 51.75  | 62.17  | 74.71  |

![Fig. 4.1: Accuracy of 4 limbs pattern recognition based on Table 4.1](image)

Table 4.2: Accuracy of 2 limbs pattern recognition [%]

| Subject ID | A_Day1 | A_Day2 | B_Day1 | B_Day2 | C_Day1 | C_Day2 |
|------------|--------|--------|--------|--------|--------|--------|
| Hands (Left Hand – Right Hand) | 95.00  | 81.08  | 57.83  | 71.20  | 81.58  | 91.67  |
| Legs (Left Leg – Right Leg) | 93.80  | 94.75  | 52.58  | 80.20  | 89.33  | 94.92  |
| Left (Left Hand – Left Leg) | 72.10  | 85.50  | 58.67  | 66.40  | 67.75  | 79.58  |
| Right (Right Hand – Right Leg) | 80.20  | 69.75  | 51.67  | 66.80  | 67.92  | 84.83  |
| LH_RL (Left Hand – Right Leg) | 90.30  | 79.25  | 48.58  | 77.20  | 85.25  | 95.33  |
| RH_LL (Right Hand – Left Leg) | 95.70  | 94.67  | 52.50  | 82.90  | 82.42  | 93.08  |
According to this graph, it confirmed that the accuracies by lower dimensions’ feature vector are higher than the ones of original 27 dimension. Thus, to apply the information about evaluation function $J$ seems to be effective in pattern recognition. Furthermore, each subject’s accuracies are getting higher with the passing of dates. This point suggests that subjects do not need long-term trainings to increase accuracy if these methods are applied.

Table 4.2 and Fig.4.2 show the results of two kind of limbs pattern recognition. It shows that accuracies about contralateral limbs (Right hand-Left hand, Right leg-Left leg, Right hand-Left leg and Left hand-Right leg) were better than ipsilateral limbs (Right hand-Right leg and Left hand-Left leg). The accuracies were about 90% except Subject B. This fact suggests that our method is available to BCI systems in which two types of instruction are used although more studies will be needed to increase the number of instructions.

4.2 Relationship between accuracy and the value of evaluation function: $J$

In addition to Subject A, Subject C had over 70 % accuracy in 4 limbs pattern recognition. However, Subject B was not able to get the accuracy as high as the former 2 subjects. We considered this factor with the result of evaluation function: $J$. The rest of calculation result about $J$’s time course is shown below like Fig. 3.4 (Fig. 4.3 to 4.7).

According to the differences in 3 subjects about $J$, there are several common points or different points. As common point, both of subject A and C have the highest value of $J$ in almost the same time zone. As different point, subject B has relatively lower $J$’s value than the former 2 subjects and the time zone of $J$’s peak is also different. On 2nd day, however, the $J$’s peak is getting closer to the same time zone. It is assumed that the effective EEG activity information for pattern recognition is into common time domain among all subjects.
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5 Conclusion

In this paper, we considered the analysis for the EEG activity during 4 limbs motor imagery in the time domain when it relates to MRCP and the accuracy about 4 classes pattern recognition for BCI systems. We got about 60 % accuracy at the pattern recognition with 27 dimensions feature vector. Further, we confirmed the ones with cut dimension (3, 6 and 9) based on the calculation result of evaluation function: $J$ made the accuracy more than 10 % higher. By reference to the course of $J$, we got effective information for recognition about each subject, electrode or time domain.

As our future works, it is required that we extract new features of EEG activity which is more effective in higher recognition accuracy by several factors such as subjects, days, electrodes, limbs or time domain so as to construct more useful BCI systems.

References

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