Predicting occurrence of errors during a Go/No-Go task from EEG signals using Support Vector Machine*

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***Abstract*—Human error often becomes a serious problem in dairy life. Recent studies have shown that failures of attention and motor errors can be captured before they actually occur in the alpha, theta, and beta-band powers of electroencephalograms (EEGs), suggesting the possibility that errors in motor responses can be predicted. The goal of this study was to use single-trial offline classification to examine how accurately EEG signals recorded before motor responses can predict subsequent errors. Ten subjects performed a Go/No-Go task, and the accuracy of error classification by a Support Vector Machine (SVM) was investigated 1000 ms before presenting the Go/No-Go cue. The resulting mean classification accuracy was 62%, and strong increases and decreases in activities associated with errors were observed in occipital and frontal alpha-band powers. This result suggests the possibility that future errors can be predicted using EEG.**

I. INTRODUCTION

Human errors cause a serious problem because simple action or behavior by a human operator may cause significant changes of machines or networks. Recently, to elucidate the neuronal mechanisms underlying error, researches have measured human brain activity using noninvasive neuroimaging techniques: electroencephalography (EEG) and magnetoencephalography (MEG) [1,2]. An EEG study showed that before errors occurred, frontal theta band was negatively correlated with the contralateral temporal beta band [2]. In addition, an MEG study showed that strong increases in alpha-band power occur in the occipital lobe before errors [1].

However, these studies examined data that was averaged across all trials, and whether brain activity (i.e., EEG or MEG signals) actually predicts errors at the single-trial level is still unclear. In this study, we therefore examined the possibility that EEG signals can predict errors on single trials. Accuracy of error prediction was determined by spectral analysis and single-trial classification using Support Vector Machine (SVM). The SVM-feature values were selected based on published work.

II. METHODS

A. Subjects

Ten normal right-handed men (ages 20–23: mean 22.3) participated in this study. The ethics committee of the Nagaoka University of Technology approved this study.

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B. Equipment

We measured EEG signals using a digital electroencephalograph (ActiveTwo, Biosemi, Amsterdam, the Netherlands) with 64 electrodes attached to the subjects' scalps. Data were digitized at 2048 [Hz]. The electrodes were placed in accordance with the international 10-20 system, and a reference electrode was attached to each earlobe. Artifacts were monitored with a pair of bipolar electrodes located below the eyes.

C. Experimental Procedures

We adopted the Go/No-Go task used by Mazaheri et al. [1]. Fig. 1 shows the experimental protocol. The visual stimuli (cue) were single digits between 1 and 9 that were presented in the lower left visual field. Cue digits were presented randomly.The fixation cross at the center of the screen was always present. Each stimulus was displayed for 200 ms and the inter-trial interval was 1500 ms. The stimuli were presented in 12 blocks of 151 trials. Participants were asked to respond to all digits except '5' by pressing a button with the right index finger. Thus, the digit '5' was the No-Go stimulus and the other digits were Go stimuli. Trials in which subjects responded to the Go stimuli were defined as Hits and those in which they did not respond to the No-Go stimulus were defined as Correct. Trials with erroneous responses to the digit 5 were termed Error trials.

D. Preprocessing

Because EEG signals include artifacts caused by blinking and eye movements, we eliminated trials in which the absolute value of the signal recorded at either of the electrodes under the eyes was greater than 70 μV, and eliminated the entire block if the number of eliminated trials within the block exceeded 30%. In addition, the signals were filtered with a band-pass digital Butterworth filter of the third order (2–30 Hz), and the last 1000 ms before stimulus onset was from each trial used for analysis.

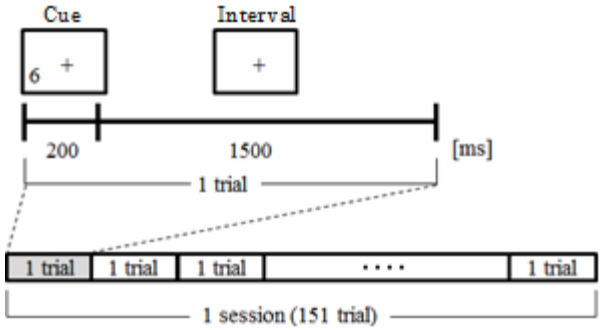

Fig. 1. Experimental protocol.

III. ESTIMATION OF ERROR CLASSIFICATION ACCURACY

A. Support Vector Machine

Support vector machine (SVM) was used for classification of Correct and Error trials.

The discrimination function of SVM $f(x)$ is

$$f(x) = \mathrm{sgn}[\sum_{i=1}^{l} y_i \alpha_i^* K(x, x_i) + \beta^*]. \quad (1)$$

where l is the number of samples, $x_i (i = 1, \ldots, l)$ is a learning sample (i.e. feature vector), $y_i (i = 1, \ldots, l)$ is a teaching signal, sgn means the sign stands for signature, and $a_i^* (i = 1, \ldots, l)$ is the optimum solution of the quadratic problem defined as

$$\max_{a} \quad \sum_{i=1}^{l} \alpha_i - (1/2) \sum_{i,j=1}^{l} \alpha_i \alpha_j y_i y_j K(x_i, x_j)$$

$$\text{subject to} \quad 0 \le \alpha_i \le C, \quad i=1,\ldots,l$$

$$\sum_{i=1}^{l} \alpha_i y_i = 0. \quad (2)$$

A linear Kernel function K is defined as

$$K(x_i, x_j) = x_1^T x_2 \ . \quad (3)$$

The penalty parameter C of (2) is a positive integral constant. Threshold b^* in (1) is given by

$$\beta^* = (1/|I|) \sum_{i \in I} \{y_i - \sum_{j=1}^{l} y_j \alpha_j^* K(x_i, x_j)\}, \quad (4)$$

where I contains $0 < \alpha_i^* < C$ in the support vectors.

B. Training of SVM parameters

Estimation of SVM parameters was performed by ten-fold cross-validation that was repeated three times. The classification accuracy was calculated as the number of trials classified correctly divided by the total number of trials.

A permutation test was conducted to check whether classification accuracy by SVM was significantly higher than chance level. The permutation test is a technique used when the number of samples for two groups is different, and was performed with the following steps: 1) Data of each group was randomly permuted. 2) The SVM analysis was performed on the random data. 3) Steps 1) and 2) were repeated 100 times to make a distribution for random sampling. 4) Then we checked the significance by comparing the classification accuracy of the cross-validation and the accuracy at the significance level ($p = 0.05$) of the permutation test.

C. Feature Selection

Six features potentially related to motor errors were selected for examination. 1) occipital alpha band (8–13 Hz; 7 elctrodes: POz, PO3, PO4, Oz, O1, O2 and Iz), 2) frontal theta band (3–5 Hz; 3 electrodes: Fpz, Fp1 and Fp2) and contralateral temporal beta band (18–24 Hz; 9 electrodes: C3, C5, CP3, CP5, T7, TP7, P3, P5 and P7), 3) occipital alpha band, frontal theta band and contralateral temporal beta band, 4) whole-brain alpha band, 5) whole-brain theta and beta bands, 6) whole-brain alpha, theta and beta bands. The feature vector used for SVM constituted the power spectrum data from the multiple electrodes. Spectral analysis was conducted on the signal data from each electrode. Data from each electrode was normalized (Z-score) and concatenated..

IV. RESULTS

A. Behavioral Data

The mean number of No-Go trials was 211.3 ± 2.6. The numbers of Error (mean ± SD: 110.5 ± 40.0) and Correct (mean ± SD: 100.8 ± 40.7) trials were comparable. The grand average of mean reaction times for Error trials (mean ± SD: 292 ± 40 ms) was significantly shorter than for Hits (mean ± SD: 329 ± 58 ms; $p < 0.001$, two-sided t-test). The mean error rate was 52.4 ± 19.1%.

B. Classification Results

Table 1 showed the mean and maximum classification accuracies for each feature and the number of the subjects in which classification accuracy was significantly higher than chance. Feature 4 (whole-brain alpha) showed the highest prediction accuracy (mean: 62%; maximum: 74%), which was significant in five of the ten subjects. Fig. 2 shows the classification accuracy of feature 4 for each subject.

Fig, 3 shows the classification accuracy of Error and Correct trials when whole-brain alpha band was used. Subject E shows higher classification accuracy for both Error and Correct trials. However, results for some subjects showed unbalanced accuracies for Error and Correct trials.

C. Activation maps

Based on these results, we determined the brain regions that showed increases or decreases spectral powers. Fig. 4 shows the average spectrum power difference of all the subjects between Error and Correct trials. We found strong activation in the frontal and somatosensory areas before errors occurred, and decreased power in the occipital area (Fig. 4A). Further, we found strong activation over the contralateral frontal area (Fig. 4B) and a weak decrease in power over the contralateral motor area (Fig. 4C).

TABLE I. CLASSIFICATION ACCURACY

Feature quantity	*Average [%]*	*Maximum [%]*	*The number of subjects showing significance*
Occipital α	52	60	3
Frontal θ, Temporal β	53	59	4
Occipital α, Frontal θ, Temporal β	53	61	3
Whole area α	62	74	5
Whole area θ,β	58	67	4
Whole area α,θ,β	57	67	7

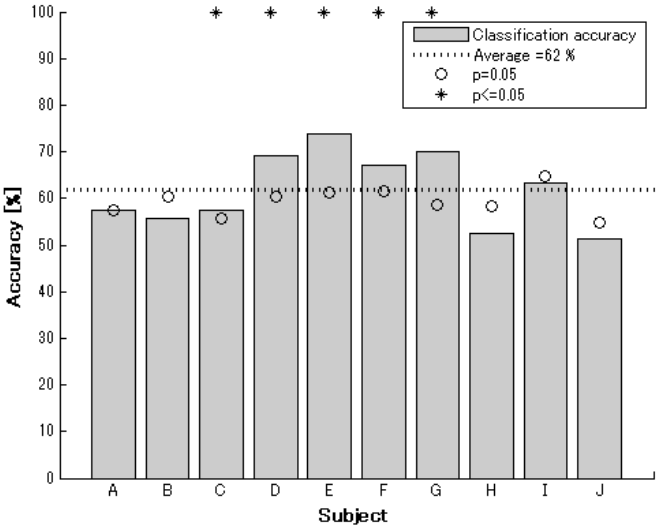

Fig. 2. The whole classification accuracy using alpha band of whole brain areas.

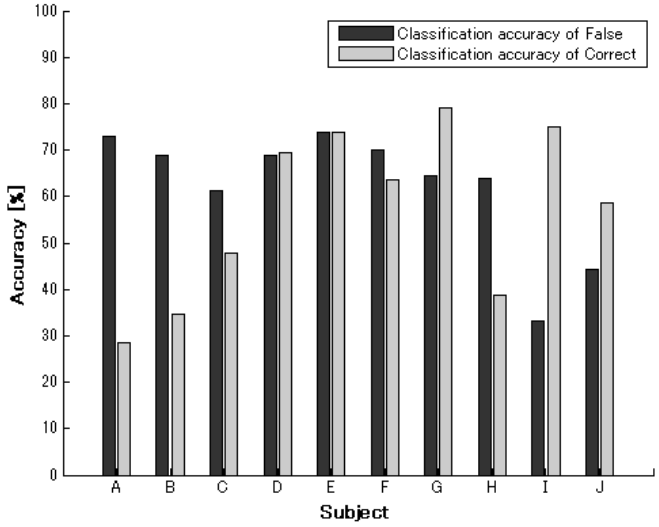

Fig. 3. Classification accuracy of Error and Correct using alpha band of whole brain areas.

V. DISCUSSION

Here, we considered the possibility of predicting the trial-by-trial performance on a Go/No-Go task with EEG signals.

In the visual system, occipital alpha lateralization has been shown to predict visual sensitivity [3] and to play a causal role in visual perception [4]. Here, reduction in occipital alpha-band activity was observed before Error trials that could be the mis-prediction of stimulus or a mistake in motor inhibition. A negative correlation between the frontal theta band and contralateral motor cortex beta-band power spectrum has been reported [2]. However, in this work, we did nopt observe a correlation between theta and beta bands. This could be owed to differences in the experimental tasks or environment between studies.

High classification accuracy was not found in the particular brain regions and specific frequency bands (features 1–3) that have been related to error prediction in other studies [1,2]. However, when specific frequency bands were examined at the whole-brain level (features 4–6), classification accuracy was improved. Feature 4 (whole-brain alpha) yielded the highest average classification accuracy and the maximum classification accuracy. This indicates that increasing or decreasing alpha-band power in regions other than the occipital lobe are related to error prediction. On the other hand, the classification acccuracies for Correct and Error trials were unbalanced for some subjects (Fig. 3). It is unclear why this imbalance was observed, but individual difference of task performance could account for this result.

Future studies should focus on which factors can better predict errors and how to better select the important features used for classification accuracy.

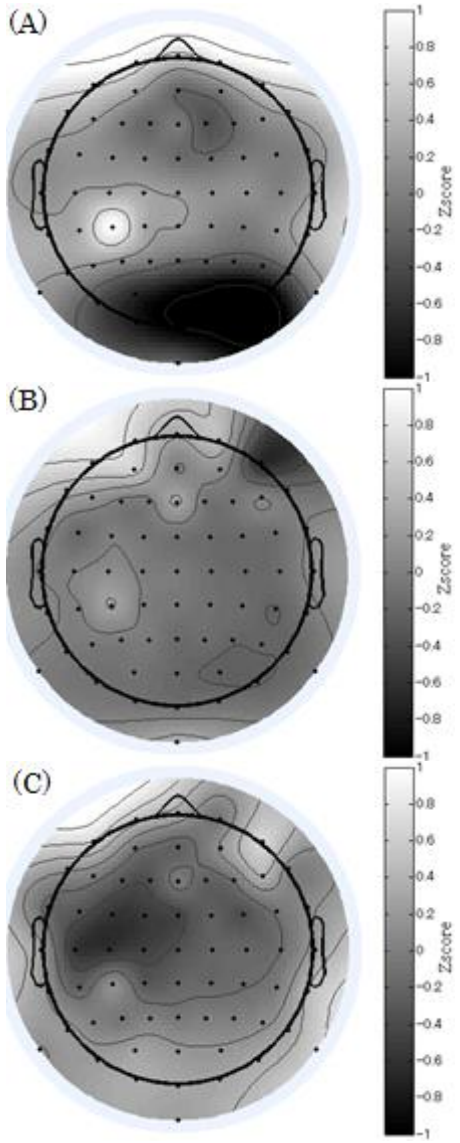

Fig. 4. Difference of each power between Error and Correct trials averaged over subjects. The normalized (Z-scored) powers are shown. (A) Alpha band (8-13Hz), (B) Theta band (3-5Hz), (C) Beta band (18-24Hz).

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