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引用	北海学園大学工学部研究報告(44): 45-53
発行日	2017-01-13

# Brain Computer Interface by Use of EEGs on Recalling Robot Image

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## Abstract

Authors measured electroencephalograms (EEGs) as subjects recognized and recalled ten types of images of robot (PLEN.D, dmm.com) movement presented on a CRT monitor. During the experiment, electrodes were fixed on the scalps of the subjects. Four EEG channels allocated on the right frontal and temporal cortices (Fp2, F4, C4 and F8 according to the international 10–20 system) were used in the discrimination. The authors analyzed a single trial EEGs of the subjects precisely after the latency at 400ms, and determined effective sampling latencies for the discriminant analysis to ten types of images. Sampling data 1 was collected at latencies from 400ms to 900ms at 25ms intervals for each trial. Sampling data 2 was collected from 399ms to 899ms at the same interval and sampling data 3 was collected from 398ms to 898ms at the same interval. Thus, data was an 84 dimensional vector (21 time point  $\times$  4 channels). The number of external criteria was 10 (the number of different movement), and the number of explanatory variables was thus 84. The canonical discriminant analysis was applied to those tripled single trial EEGs. Results from the canonical discriminant analysis were obtained using the jackknife method. And discrimination ratio was 100% for each of three subjects. The discriminant results were transmitted to the robot PLEN.D by the blue tooth. We could control the robot with ten commands by single trial EEGs of the subjects who only recalled corresponding robot images.

**Keywords :** Electroencephalogram, Image Recognition, Image of Robot Movement, Single Trial EEGs, Robot Control, Brain Computer Interface, Canonical Discriminant Analysis

## 1. INTRODUCTION

In the human brain, the primary processing of a visual stimulus occurs in areas V1 and V2 in the occipital lobe. Initially, a stimulus presented to the right visual field is processed in the left hemisphere and a stimulus presented to the left visual field is processed in the right hemisphere. Next,

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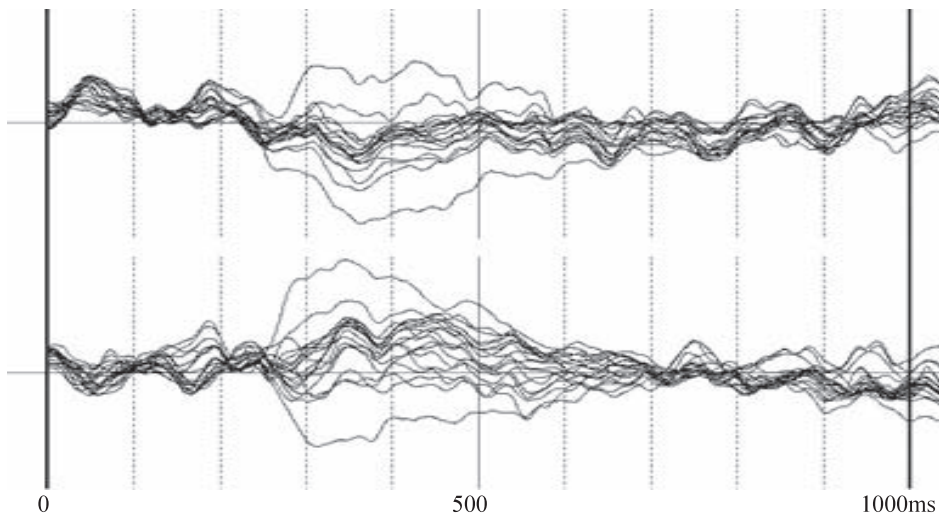
processing moves on to the temporal associative areas [1].

Higher order processing in the brain is associated with laterality. For example, language processing in Wernicke's area and Broca's area is located in the left hemisphere in 99% of right-handed people and 70% of left-handed people [2], [3]. Language is also processed in the angular gyrus (AnG), the fusiform gyrus (FuG), the inferior frontal gyrus (IFG), and the prefrontal cortex (PFC) [4].

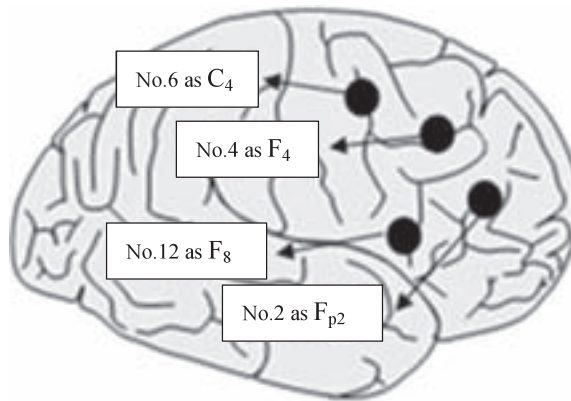
Using equivalent current dipole localization techniques [5] applied to summed and averaged electroencephalograms (EEGs), we previously reported that for input stimuli comprised of arrow symbol, equivalent current dipoles (ECDs) can be localized to the right middle temporal gyrus, and estimated in areas related to working memory for spatial perception, such as the right inferior or the right middle frontal gyrus. Further, using Chinese characters (Kanji) as stimuli, ECDs were also localized to the prefrontal cortex and the precentral gyrus [6], [7].

However, in the case of silent reading, spatiotemporal activities were observed in the same areas around the same latencies regardless of the stimulus (Kanji or arrow). ECDs were localized to the Broca's area which is said to be the language area that controls speech. And also after on the right frontal lobe, the spatiotemporal activities go to so-called working memory area. As in our previous studies, we found that latencies of main peak were almost the same, but that the polarities of potentials were opposite (**Fig. 1**) in the frontal lobe during higher order processing [6].

Research into executive function using the functional magnetic resonance imaging indicates that the middle frontal lobe is related to the central executive system, including working memory. Functions of the central executive system include to selecting information from the outer world, to holding it



**Fig. 1.** Comparison between ERPs for rightward (above) and for leftward (below)



**Fig. 2.** Electrodes placement on the right hemisphere

temporarily in memory, to ordering subsequent actions, to evaluating these orders and making decisions, and finally erasing temporarily stored information. Indeed, this art of the frontal cortex is the headquarters of higher order functions in the brain.

Previously, we compared signal latencies at each of three channels of EEG, and found that the channel 4 ( $F_4$ ), 6 ( $C_4$ ) and 12 ( $F_8$ ) were effective in discriminating EEGs during silent reading for four types of arrows and Kanji characters. Each discrimination ratio was more than 80% [8].

When the data were tested with the jack knife (cross validation) statistical technique, their discriminant ratios generally decreased. Thus, for the recent study, we have improved the technique by adding another EEG channel (channel 2 :  $F_{p2}$ ) (**Fig. 2**). With these changes, discriminant analysis with the jack knife method resulted in means of discriminant ratios were 100%.

## 2. MEASUREMENT OF EEGS ON RECOGNITION AND RECALL OF ROBOT MOVEMENT IMAGE

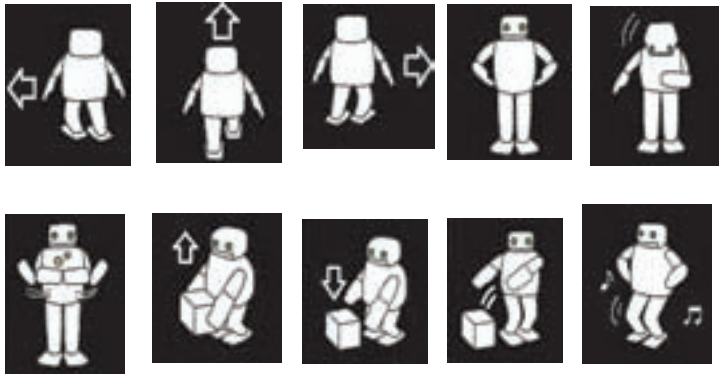
Subjects were three 22-year-old university students, who had normal visual acuity, and were right-handed. The subjects wore an electrode cap with 19 active electrodes and attended visual stimuli that were presented on a 21-inch CRT monitor placed 30cm in front of them.

Subjects kept their heads steady by placing their chins on a chin rest fixed to a table. Electrode positions were set according to the international 10–20 system and two other electrodes were fixed on the upper and lower eyelids for eye blink monitoring. Impedances were adjusted to less than 50k $\Omega$ . Reference electrodes were put on both earlobes and the ground electrode was attached to the base of the nose.

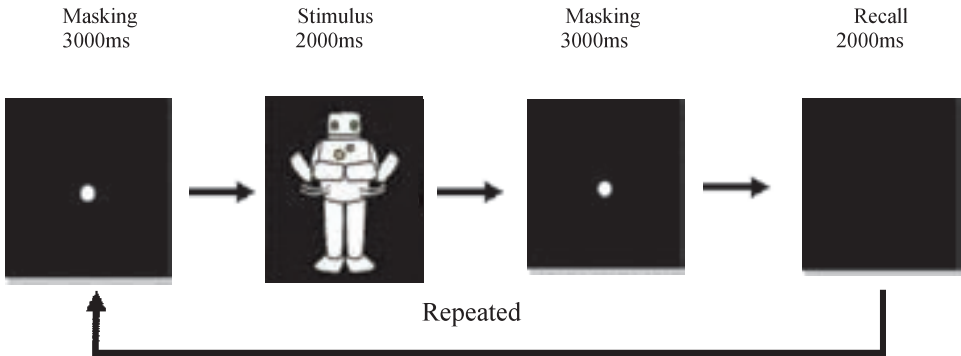
EEGs were recorded on a multi-purpose portable bio-amplifier recording device (Polymate,

TEAC). The frequency band was set between 1.0 Hz and 2000 Hz. Output was transmitted to a recording computer. Analog outputs were sampled at a rate of 1 kHz and stored on computer hard disk.

During the experiment, subjects were presented with 10 images of robot movement (**Fig. 3**). Each trial began with a 3000ms fixation period, followed by the robot movement image (encoding period) for 2000ms, another fixation (delay) period for 3000ms, and finally a 2000ms recall period. During the recall period, subjects imagined the robot movement image that had just been presented. Each movement pattern was presented randomly, and measurements were repeated several times for each movement. Thus, the total number of experiment was about 100. We recorded EEGs the encoding and recall periods (**Fig. 4**) and these EEGs are applied to discriminate the robot movement by use of the canonical discriminant analysis.



**Fig. 3.** Ten types of robot movement presented in the experiment

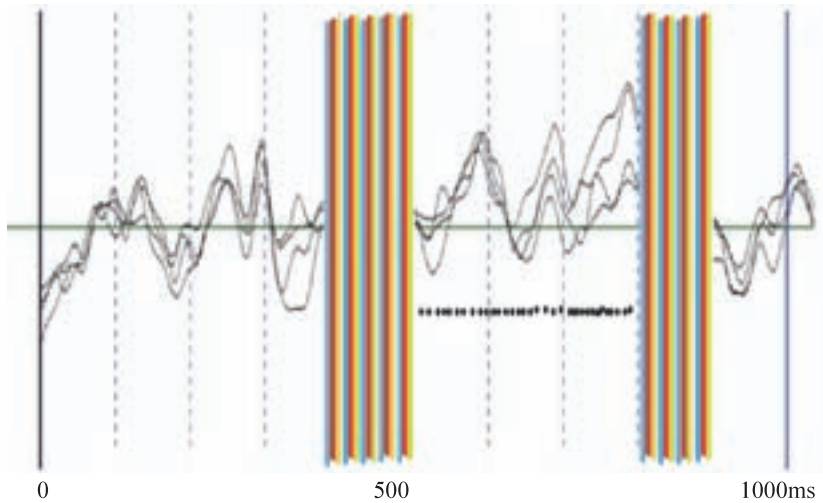


**Fig. 4.** Time chart of the experiment

### 3. SINGLE TRIAL EEGS DISCRIMINATION USING CANONICAL DISCRIMINANT ANALYSIS

Single-trial EEG data, recorded in the experiment with directional symbols were used in a type of multivariate analysis called canonical discriminant analysis. From the results of our past research [6], the silent reading pathway with directional symbols goes to the right frontal area at the latency after 400ms. Therefore, in the current experiment, we sampled EEGs from 400ms to 900ms at 25ms intervals. We call it the data1. We also sampled data from 399ms to 899ms and from 398ms to 898ms. Each set of samples was collected 25ms intervals, yielding 21 data points from each channel for each sampling period. By these three sets of data, the number of sampling EEG data are tripled, we call these the tripled data.

Of the 19 channels, we analyzed data from channels  $Fp_2$  (No. 2),  $F_4$  (No. 4),  $C_4$  (No. 6), and  $F_8$  (No. 12), according to the International 10–20 system (**Fig. 1**), because these points of channels lie above the right frontal area. Although EEGs are time series data, we regarded them as vector values in the 84 dimensional space (4 channels  $\times$  21 time points) (**Fig. 5**).



**Fig. 5.** Selected channels of EEGs and their sampling points : Colored bold lines denote sampling pointchart of the experiments Selected channels of EEGs and their sampling points.

It is better to minimize number of electrode for the practical use. So our previous work had investigated to what the minimal numbers of EEG channels and data samples are for the best results [7]. Especially, we wanted to determine the minimal sampling number necessary to obtain a perfect discrimi-

nant ratio (100%) at each channel for the same. In that set of experiments, we used EEGs from the same period, however, the sampling interval was 50ms. These results showed that four types of order might be able to control robot. We must note that these discriminant analyses must be performed individually for each single trial of data. Thus, the discriminant coefficients are determined for each single data set. To improve the accuracy of single-trial discriminant ratios, we have adopted the jack-knife (cross validation) method.

#### 4. CANONICAL DISCRIMINANT ANALYSIS FOR EEGS DATA

Canonical discriminant analysis [8] is a dimension –reduction technique related to the principal component analysis and the canonical correlation analysis. Given a classification objective variable and several explanatory variables, canonical discriminant analysis derives canonical variables (linear combinations of the explanatory variables) that summarize between–class variation in much the same way that principal components summarize total variation.

Given two or more groups of observations with measurements on several interval variables, canonical discriminant analysis derives a linear combination of the variables  $x_1, x_2, \dots$ , and  $x_p$  that has the highest possible multiple correlation with the groups. This maximal multiple correlation is called the first canonical correlation. The coefficients of the linear combination are the canonical coefficients or canonical weights. The variable defined by the linear combination is the first canonical variable or canonical component. The second canonical correlation is obtained by finding the linear combination uncorrelated with the first canonical variable that has the highest possible multiple correlation with the groups. The process of extracting canonical variables can be repeated until the number of canonical variables equals the number of original variables or the number of classes minus one, whichever is smaller.

The expression of the fundamental canonical discriminant analysis is as follows :

$$y = a_1x_1 + a_2x_2 + \dots + a_nx_n - b,$$

where  $y$  is the canonical discriminant function,  $x_i$  is the discriminating variable, and  $a_i$  is the coefficient which produce the desired characteristics of the function, and  $b$  is the residual.

The first canonical correlation is at least as large as the multiple correlations between the groups and any of the original variables. If the original variables have high within–group correlations, the first canonical correlation can be large even if all the multiple correlations are small. In other words, the first canonical variable can show substantial differences among the classes, even if none of the original variables does.

For each canonical correlation, canonical discriminant analysis tests the hypothesis that all smaller canonical correlations are zero in the population. An  $F$  approximation is used that gives better small-sample results than the usual  $\chi^2$  approximation. The variables should have an approximate multivariate normal distribution within each class, with a common covariance matrix in order for the probability levels to be valid.

The new variables with canonical variable scores in canonical discriminant analysis have either pooled within-class variances equal to one; standard pooled variance, or total-sample variances equal to one; standard total variance. By default, canonical variable scores have pooled within-class variances equal to one.

## 5. RESULTS OF DISCRIMINATION OF EEGS DATA

We gathered each single trial EEGs data to play as learning data. For each type of image recall, the number of experiments was around sixty. These data were resampled three times, in three types of sample timing ; sampling data 1 are taken from latency of 400ms to 900ms at 25ms interval (21 sampling points), sampling data 2 are taken from latency of 399ms to 899ms at 25ms interval and sampling data 3 are taken from latency of 398ms to 898ms at 25ms interval. Each data has one criterion variable i. e. ten types of image of robot movement, and 84 explanatory variates. Because explanatory variates consist of four channels by 21 sampling data, the learning data are 360 with 84 varieties. We had tried so called the jackknife statistics, so we took out one sample to discriminate, and we used the other samples left as learning data, and the method was repeated. For ten types of silent reading, the number of experiments is smaller than ten. The data were resampled three times, in three different sample time ranges : the data tripled. Each datum has one criterion variable (ten images) and 84 explanatory variates (the EEG data). Because explanatory variates consisted of 21 sampling points and four channels data, the learning data are around 30 with 84 varieties. And each criterion variable has ten type indices. We had tried so called the jack knife statistical method, we took out one sample to discriminate, and we used the other samples left as learning data, and the method was repeated one by one sample.

The subjects were three undergraduate students, and we repeated the experiments in a few days. We tried to discriminate ten type movement images by EEG samples using the canonical discriminant analysis. Each canonical discriminant coefficient was determined by each participant and by each series about 60 experiments. As results, the discriminant ratios were perfect 100% in all cases.

## 6. CONCLUDING REMARKS

We triple sampled EEG data from four channels (Fp<sub>2</sub>, F<sub>4</sub>, C<sub>4</sub>, and F<sub>8</sub>) at 25ms intervals between 400 ms and 900ms just after image presentation. These data were resampled three times, in three types of sample timing ; sampling data 1 are taken from latency of 400ms to 900ms at 25ms interval (21 sampling points), sampling data 2 are taken from latency of 399ms to 899ms at 25ms interval and sampling data 3 are taken from latency of 398ms to 898ms at 25ms interval [9],[10]. The presented and recalled images are 10 robot movements. Discriminant analysis using jack knife method for 10 objective variates yielded each discriminant rate for the three subjects was 100%. We could control the robot PLEN.D by the Bluetooth from PC which is stored EEGs.

## Acknowledgements

This research was partially supported by a grant from the Ministry of Education, Culture, Sports, Science and Technology for the national project of the High-tech Research Center of Hokkai-Gakuen University in March 2013. The experiment was approved by the ethical review board of Hokkaido University.

The authors express their gratitude to former under graduate students of Yamanoi Laboratory, especially Ms Miho Kitajima, for their assistance in the EEG experiments.

This article was presented at the 7th International Symposium (ISCIA2016) held on November 5th 2016 in Beijing China.

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