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Classification by EEG frequency distribution in imagination of directions

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Abstract

This paper describes the method for classification of brain state by the measured electroencephalogram (EEG) frequency in directions (up, down, left, and right) imagination. Recently, Brain-Machine Interface (BMI) has been studied in a variety of ways due to the development of brain measurement technology. Therefore, we have used the BMI to identify the human selection of directions. Our method consists of data normalization, principal component analysis and neural network. The maximum value of the identification rate was 46% by using 3 electrodes (F4, F8 and T8) in the previous study. In this study, we improved the learning method of neural network for the improvement of identification rate of brain state. For that purpose, the measurement points of EEG and the number of subjects are increased. As a result, the maximum value of the identification rate was improved.

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Keywords: brain-machine interface; electroencephalogram; frequency; imaging directions; principal component analysis; neural network

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1. Introduction

In recent years, Brain-Machine Interface (BMI) has been improved with the rapid development of the cerebral function measurement technologies, and study of BMI has draws many people's attention[1]. BMI is used for a technology to control devices without their hands and feet, by measuring the brain activity of the user and inferring their active and will. There are two major BMI types which are brain-waves analysis (Electroencephalograph: EEG) and cerebral blood flow measurement by far-infrared rays (Near Infra-Red Spectroscopy: NIRS). In particular, the EEG is useful to control machines in real time because EEG has excellent time resolution. In addition, portable device of the EEG has been developed. In previous studies of EEG, the event-related potentials (ERPs) of brain activity has been used[2]. For example, P300 is one of the ERPs, the potential change that is measured at 300 milliseconds after brain activity has done. In P300's method, like lie detector, the expected number is identified by detecting repeatedly whether the P300 occurs or not. ERPs depends strongly on the measurement timing of the reaction and stimulation to the brain; therefore this method is necessary to consider the time when has brain activity been started. For this reason, we considered the identification of brain activity underlying condition has not been achieved in this technique.

In this paper, we have developed the identification method which recognizes the cognitive state directly from the brain activity. Our identification method uses EEG frequency distribution to identify which directions are imaged by the human. In our method, a band-pass filter has been used to select the brain wave data of frequency range from 8Hz to 30Hz. Frequency spectrum of the EEG has been generated by Fast Fourier Transform. The Principal Component Analysis (PCA) has been used to select the combination of the frequencies and measurement site. Furthermore, neural networks have been applied to classification of brain activities. This technique is not dependent on the measurement timing of the reaction and stimulation to the brain. Further, it is possible to associate one to one EEG brain activity state by classification of the frequency distribution of EEG.

2. Previous studies

To recognize human intention from the brain activity, there have been various studies on the identification of the directions[3,4], letters and numbers[5]. The most of these studies use P300 for analysis of the brain activity. P300 is the potential change of EEG that is measured at 300 milliseconds after the subject is stimulated. In these studies, it is believed that P300 reflect a brain activity against an important stimulus. For example, in the numerical identification using the P300, it is necessary to provide a plurality of numbers to recognize intended number from EEG data. If the system wants to detect the number in single figure from EEG data, it must present the numeric characters from "0" to "9". It may take a long time in some cases. Therefore, it was necessary to develop the identification method which recognizes the cognitive state directly from the brain activity.

Thereby, in our previous studies[6,7,8], we proposed the method for classification of brain state by the measured EEG frequency in imagination of directions (up, down, left, and right). Our method consists of data normalization, Fast Fourier Transform (FFT), Principal Component Analysis (PCA) and neural network. We have proposed the technique that is not dependent on the measurement timing of the reaction and stimulation to the brain. As a result, the maximum value of the identification rate of brain state was 46% by using 3 electrodes (F4, F8 and T8) in the previous study (Fig. 1). However, this rate is too low to control machines.

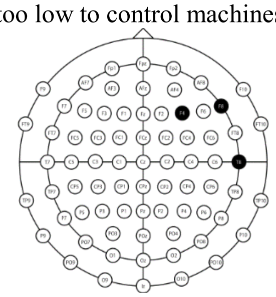

Fig. 1. Using electrodes in our previous study(F4, F8 and T8)

3. Experiment and analysis

We measured the EEG signal of the brain when the subjects were imaging the directions. We used BIOSEMI ACTIVE-TWO (the number of electrodes is 64, the sampling rate is high and adjustable, stand-alone) as measurement devices of EEG in our study.

3.1. Experiment

In this study, we had eight subjects who are healthy males in their twenties. They just imagined the four symbols of directions (“ ↑ ” as up, “ ↓ ” as down, “←” as left, and “→” as right) without seeing anything. Fig. 2 shows the four symbols of directions in our experimentation.

The subjects watched 4 arrow pictures before their experimentation. Each test set consists of 10 trials. Duration of one trial is 15 seconds which include 5 seconds task between 5 seconds rest (Fig. 3). We analyzed the EEG measured at 64 electrodes which are according to extended 10-20 system (Fig. 4).

Fig. 2. Four symbols of directions

Fig. 3. Experimental procedure

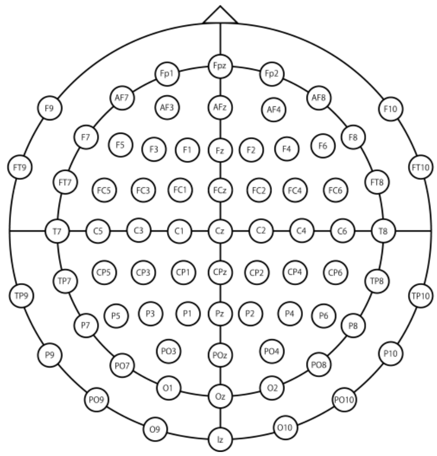

Fig. 4. Extended 10-20 system

3.2. Analysis

We analyzed the data according to the processes shown in Fig. 5. At first, we have selected alpha-wave and beta-wave range data by band-pass filter (8Hz ~ 30Hz) to remove noises from the raw data (Table 1). In the second step, the Fast Fourier Transform (FFT) transformed the raw data into frequency information. In the third step, the normalization process reduced the influence of offset voltage. In the fourth step, the principal component analysis (PCA) compressed data to obtain the important elements. Main component scores are determined from characteristic vectors and frequency distribution power spectrum by the principal component analysis (PCA). In the last step, the neural network learned the important elements of the training data and classified the test data.

Table 1. EEG frequency

Wave	δ -wave	θ -wave	α -wave	β -wave	γ -wave
Hz	1–3	4–7	8–13	13–30	30–
State	Deep Sleep	Shallow Sleep	Relax	Wakefulness	Excite

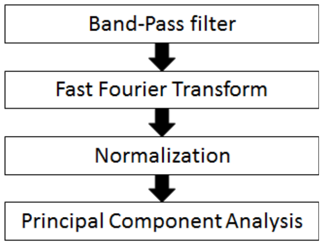

Fig. 5. Data processing

3.3. Neural Networks

We used the three-layer neural networks to classify EEG frequency distribution (Fig. 6). We have selected electrodes based on main component scores for input layer's node of neural networks. We have constructed two types of neural networks. One has been constructed by all data of subject A-H. The others have been constructed by each data of subject A-H. As a result, we made nine neural networks.

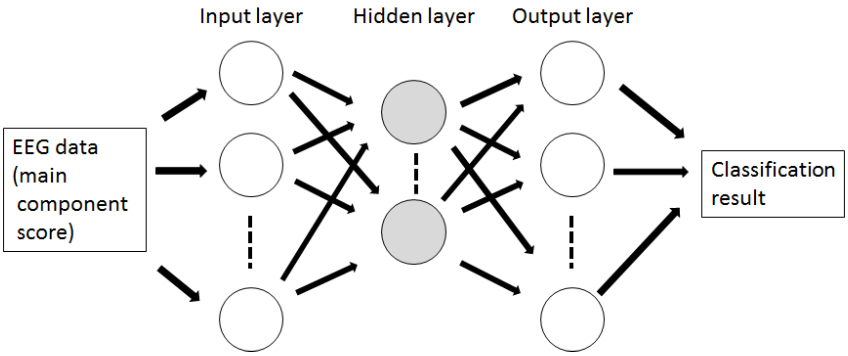

Fig. 6. Three-layer neural networks

In order to train the neural networks by 5-fold validation, we divided brain data into five classes (Class A-E). In Trial 1, the training data are made from the data of Class B-E, and the data of Class A is used for the classification validation. Each of neural networks has learned by these training data, and have classified the test data for five times. After learning and classifying, we calculated the average of the results (Fig. 7).

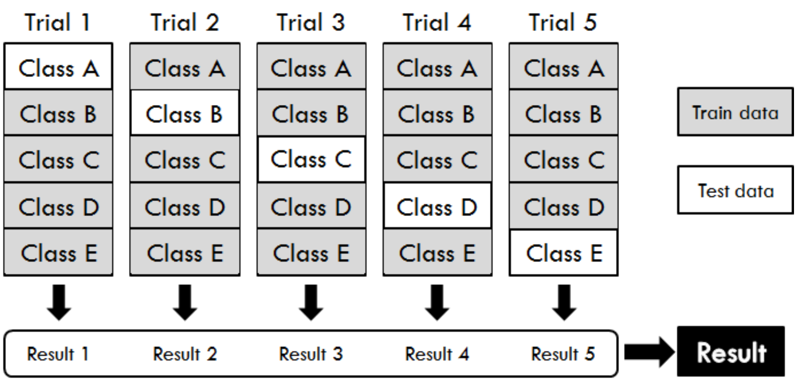

Fig. 7. 5-fold validation

4. Results

4.1. Classification in data of each subjects

Table 2-4 show the clustering results and the classification accuracy. Fig. 8-10 show the brain activation sites when three subjects imagined four symbols of directions without seeing anything.

As a result, in the occipital lobes and the temporal lobes, significant results have been obtained. Subjects have closed their eyes, therefore the experiment were carried out without seeing anything. Nevertheless, occipital lobes which deal with visual information were activated. We have considered why occipital lobes were activated, because subjects might have imagined symbols as visual information. In addition, the identification rates of "←" and "→" imaging case are high, however the classification rate of "↓" imaging case is low. The maximum value of the identification rate was 68.22% by using electrode of P9 (Subject D).

Table 2. Identification result (Subject B)

	Up	Down	Left	Right	AVG.
Fp1	21.26%	36.24%	50.00%	26.24%	33.44%
F3	61.26%	35.00%	43.76%	40.00%	45.01%
F5	17.48%	35.00%	90.00%	73.76%	54.06%
FT8	15.00%	46.24%	68.74%	90.00%	55.00%
CPz	63.76%	13.76%	46.24%	71.24%	48.75%
Pz	60.00%	43.76%	60.00%	86.24%	62.50%
P1	48.74%	38.76%	66.26%	98.76%	63.13%
P4	41.24%	31.28%	42.48%	91.24%	51.56%

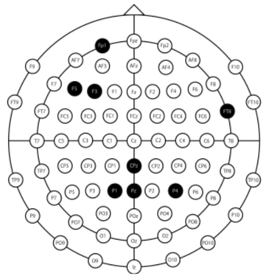

Fig. 8. The brain activation sites (Subject B)

Table 3. Identification result (Subject D)

	Up	Down	Left	Right	AVG.
AF3	32.52%	23.76%	97.52%	27.50%	45.33%
F1	7.52%	55.00%	78.76%	58.76%	50.01%
F7	20.00%	63.74%	48.76%	68.76%	50.32%
C3	21.24%	21.24%	97.50%	67.50%	51.87%
CPz	61.26%	12.50%	87.50%	51.24%	53.13%
CP1	61.26%	17.48%	92.50%	65.00%	59.06%
P2	47.50%	36.24%	96.26%	37.50%	54.38%
P5	71.24%	12.50%	97.50%	60.02%	60.32%
P9	62.50%	71.24%	55.00%	83.76%	68.22%
PO7	67.50%	31.24%	50.00%	77.50%	56.56%

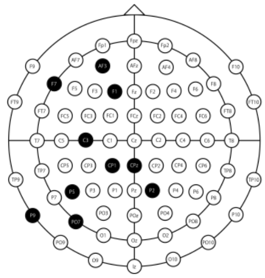

Fig. 9. The brain activation sites (Subject D)

Table 4. Identification result (Subject G)

	Up	Down	Left	Right	AVG.
F4	22.48%	61.24%	71.24%	53.74%	52.18%
F8	28.76%	51.24%	63.76%	45.00%	47.19%
T8	10.00%	18.74%	81.24%	38.78%	37.19%
Poz	63.76%	36.28%	98.76%	50.00%	62.20%

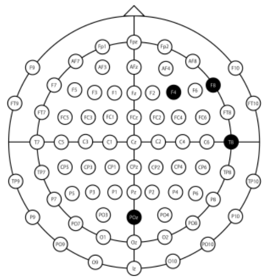

Fig. 10. The brain activation sites (Subject G)

4.2. Classification in data of all subjects

Table 5 shows the clustering results and the classification accuracy. Fig. 11 shows the brain activation sites when eight subjects imagined four symbols of directions without seeing anything.

As a result, in the occipital lobes, significant results have been obtained. However, the maximum value of the identification rate was 36.37% by using electrode of F7, and the average identification rate was about 30%. This is much lower than result of 4.1. As a result of 4.1, significant electrodes are different for each subjects. Therefore, data of insignificant electrodes might have disturbed the classification.

Table 5. Identification result (All subjects)

	Up	Down	Left	Right	AVG.
F7	20.00%	21.56%	52.82%	51.08%	36.37%
FT8	12.52%	10.80%	51.40%	47.50%	30.56%
C4	11.70%	23.56%	47.22%	61.86%	36.09%
P6	18.28%	17.50%	38.46%	66.58%	35.21%
P9	6.40%	18.26%	28.26%	74.98%	31.98%
PO7	19.36%	20.94%	19.38%	54.20%	28.47%
PO8	17.18%	20.00%	32.20%	41.90%	27.82%
O2	26.72%	25.34%	20.80%	33.42%	26.57%

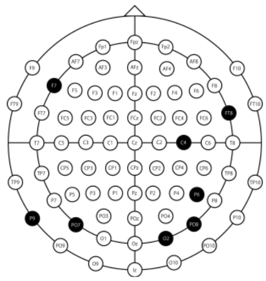

Fig. 11. The brain activation sites (All subjects)

5. Comparison with the previous studies

Table 6 shows the differences between the previous studies.

Table 6. Comparison to the previous studies

	Previous studies	This study
The number subjects	5	8
The number of measured electrodes	6	64
The number of neural networks	1	9
How to train the neural networks	odd parts of brain data	5-fold validation
The maximum value of the identification rate	46%	68.22%

In our previous studies[6,7], we analyzed the EEG measured at 6 electrodes which are according to extended 10-20 system. In this study, to identify which brain sites are activated in imagination of directions, we analyzed the EEG measured at 64 electrodes which are according to extended 10-20 system. As a result, the occipital lobes were activated, so subjects might have imagined symbols as visual information.

In our previous studies, we have constructed one type of neural network which has been constructed by all data of subjects. However in this study, we have constructed two types of neural networks. One has been constructed by all data of subjects. The others have been constructed by each data of subjects. As a result, we made nine neural networks.

In order to train the neural networks, in our previous studies, the training data were made from odd parts of brain data. The test data were made from even parts of brain data. The maximum value of the identification rate of brain state was 46% by using 3 electrodes (F4, F8 and T8). By contrast in this study, we divided brain data into five classes. Each of neural networks have learned by 5-fold validation, and have classified the remaining data as test data. As a result, the maximum value of the identification rate has been improved to 68.22% by using electrode of P9.

6. Summary

In this paper, we have developed the identification method which recognizes the cognitive state directly from the brain activity. Our identification method uses EEG frequency distribution to identify which directions are imaged by the human. Our method consists of a band-pass filter, FFT, PCA and neural networks. We have constructed two types of neural networks. One has been constructed by all data of subject A-H. The others have been constructed by each data of subject A-H. Furthermore, the neural networks have been trained by 5-fold validation. We measured the EEG signal of the brain when the subjects were imaging the directions (" ↑ ", " ↓ ", "←", and "→"). The Subjects just imagined the four symbols of directions without seeing anything.

As a result, the maximum value of the identification rate has been improved. Result of 4.1 (classification in data of each subjects), in the occipital lobes and the temporal lobes, significant results have been obtained. The maximum value of the identification rate was 68.22% by using electrode of P9 (Subject D). Result of 4.2 (classification in data of all subjects), in the occipital lobes, significant results have been obtained. The maximum value of the identification rate was 36.37% by using electrode of F7. In addition, significant electrodes are different for each subjects. For this reason, in the neural network which has been constructed by all data of subjects, data of insignificant points might have disturbed the classification.

In the future, we will try to improve the identification rate. In order to achieve this purpose, we will improve the learning efficiency of neural networks. Furthermore, we will study on the application method to BMI by using a portable measurement device to control machines in real time.

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References

1. R.Hasegawa. Development and Future of Brain-Machine Interface. *The Journal of the Institute of Electronics*, Vol.91, No.12, pp.1066-1075; 2008.
2. T.Tamura. Possibility of Approach from Information Processing Psychology to Implicitly Embedded Environmental Structures : An Event-Related Potentials Study on Predictability of Target Events Occurrence. *Memoirs of The Kitami Institute of Technology*, No.34, pp.247-257; 2002.
3. T. Yamanoi, H. Toyoshima, T. Yamazaki, M. Sugeno. Micro-robot Control by Use of EEG on Imaging Arrows. *24th Fuzzy System Symposium*, WD2-1, pp.200-203; 2008.
4. T. Yamanoi, A. Moritaka, H. Takayanagi, T. Yamazaki, M. Sugeno and H. Nonaka. Micro-robot Control by Use of EEG on Imaging Arrows II. *25th Fuzzy System Symposium*, 1B2-01, pp.1-4; 2009.
5. N.Masataka, T.Ohnishi, E.Imabayashi, M.Hirakata, H.Matsuda. Neural correlates for learning to read Roman numerals. *Brain and Language*, pp.276-282; 2007.
6. Y.Seto, S.Ako, T.Kashu, T.Sakagami, H.Miura, N.Matsuda, H.Taki, H.Obana. Analysis of brain state in the decision-making by using EEG. *The Papers of Technical Meeting on "Innovative Industrial System*". IEE Japan, IIS-13-036, pp.25-28; 2013.
7. Y.Seto, S.Ako, H.Miura, N.Matsuda, H.Taki. Analysis of brain state in imaging directions by using EEG. *The 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*; 2013.
8. S.Ako, Y.Seto, H.Miura, N.Matsuda, H.Taki. Analysis of brain state in imaging of numeric characters by using EEG. *AROB 19th*; 2014.