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Development of a brain computer interface using inexpensive commercial EEG sensor with one-channel

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Abstract: Brain Computer Interface (BCI) is a system to connect brain of human and computer in order to realize a though of human. In recent years, many such interfaces have been researched and applied for practical applications. Up to now, BCI systems, which have already applied practically, use expensive and large devices to measure the electroencephalographs(EEG). They are for almost all of users to be used for medical treatments. As a result, the BCI systems can't get the popularization to use easily. So, subjects of this study are construction of a BCI system using inexpensive commercial EEG sensor with one-channel, and investigation of the ability to apply it for utilization in various way. In this paper, using the methods of analyses for EEG that have already existed or have improved, we show that the BCI system using inexpensive commercial EEG sensor with one-channel is also useful.

Keywords: robust, reinforcement learning, actor-critic, sliding mode control, inverted pendulum

I. INTRODUCTION

In recent years, Brain Machine Interfaces (BMIs) to operate devices using electrical signals generate during brain activity have been researched extensively. In particular, Brain Computer Interfaces (BCIs) to operate computer applications using the electroencephalograph (EEG) have many fruitful achievements.

These technologies are applied to support patients with paralysis, such a Amyotrophic Lateral Sclerosis (ALS) and spinal cord injury patients, etc. who are difficult to communicate others by means of gesture and speech [1]. By use of techniques of BCIs, improving of QOL (Quality of Life) is expected

However, these techniques are low awareness except some prevalent hospitals. Therefore, this study aims at creating a computer application using commercial EEG sensors at cheap and readily available. To realize that, we intend to improve conventional feature extraction methods, validation method. We use the single-channel EEG sensor called "MindSet" manufactured by NeuroSky Corp. [2].

In this research, BCI system using neural network classifiers with Fourier transform, averaging and feature extraction by nonlinear normalization [8] is used. First, to improve the above-mentioned conventional method, we propose to adopt 1) restricting the frequency bands within the scope seemed to be effective in identifying, 2) introducing the support vector machine classifiers. Second, performance verification of the proposed classifier is carried out using benchmark data. Finally, we also study the usefulness of the proposed BCI system with single channel EEG, that is, using the MindSet through the computer simulation of distinguishing color information on display.

II. Feature extraction and Identification technique

In this section, we explain the basic method [8] and the proposal technique based on [8].

2.1. The basic method

In this paper, we use the method using Self Organization Map (SOM) and Multi Layer Perceptron (MLP) [8]. This method uses the Fourier transform (Eq. (1)), the averaging and nonlinear normalization (Eq. (2)) in the feature extraction, and use SOM and MLP in the feature discrimination.

$$F(\omega) = \int_{t=0}^{T} f(t)\big(\cos(\omega t) - i\sin(\omega t)\big)dt \tag{1}$$

$$f(x) = \frac{\log(x-\min+1)}{\log(\max-\min+1)} \tag{2}$$

Examples of above mentioned each processing and the figu re of discriminator are shown in Figs. 1 and 2, respectively. In Fig.2, X means input vector, W means connecting weights between SOM and MLP

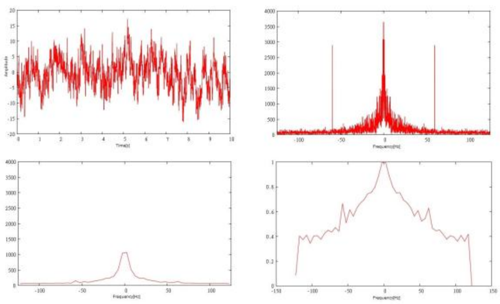

Fig. 1. Upper left: Electroencephalographic data. Upper right: Fourier Transform. Lower left: Equaliz ation. Lower right: Nonlinear normalization

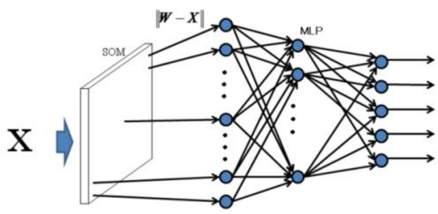

Fig. 2. Discrimination circuit by SOM and MLP

2.2 Improved method

Jie. Li, et al. [10] verified relation between frequency bands of EEG and the brain activity, that is, what frequency bands different stimulus and brain activities are related to. But, such things aren't considered in [8]. So, we intend to enhance the ability of feature extraction by changing the averaging used in [8] for restricting the frequency bands within the scope validated by [10].

Furthermore, in the feature discrimination, we intend to improve the ability of the feature discrimination by using Support Vector Machine (SVM) that is known to the model with the higher generalization performance for unlearned data rather MLP used in [8].

2.3 Multiple classification by SVM

SVM can't discriminate over 3 classes of data, because of the method of discrimination. Therefore, in this paper, in order to discriminate the multiclass of data using the SVM, we set multi SVMs.

For example, we have the data of 3 class labeled A, B and C . Then, a SVM can't correspond to discriminate of these data. So, we set any combination of the two among these three classes. Final judge is done by majority of each winner of the two. In the case of Fig. 3, we decide that input data X belongs to the class A. If the number of majority is the same, we judge it "No Decision".

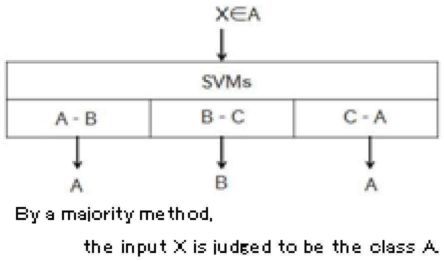

Fig. 3. Multi-class discrimination circuit by SVM

III. Simulation

In section 2, we showed the methods of EEG analysis. In section 3, we verify the performance of each methods through computer simulation using benchmark EEG data.

3.1 The Benchmark EEG data

The benchmark EEG data we used in the simulation is opened in web sites of Colorado University [3]. The data are taken at 250Hz on sampling ratio for 10 seconds on measurement time. And, these data have been measured using 6 EEG sensors and a EOG sensor to measure the electromyogram of eye movements as shown in Fig. 4. The number of the subjects to measure these signals is seven healthy young men. Furthermore, kinds of the mental tasks measured are shown to Table 1.

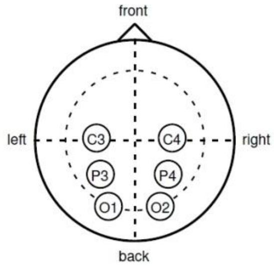

Fig. 4. Brain-waves measurement positions

Table. 1. Contents of mental tasks

Mental task	Contents
Baseline	It relaxes as much as possible.
Multiplication	It calculates multiplication mentally.
Letter-composing	It considers the contents of the letter.
Rotation	It imagines rotation of a three-dimensional object.
Counting	It imagines writing a number in order.

3.2 Term of simulation

The term of this simulation is shown in Table 2.

Table. 2. Simulation conditions

The simulation conditions of a feature extraction method	
The number of data samples after equalization	20
The restriction range of a frequency band	4～45[Hz]
The simulation conditions of SOM	
Initial connection weights	-0.1～0.1
Form of a map layer	Tetragonal-lattice type
The number of nodes of one side of a map layer	50
The number of times of study	30,000
Distance with the input vector of a map layer	Euclid distance
The simulation conditions of MLP	
Initial joint load	-0.1～0.1
The number of the units of a hidden layer	20
Activating function	Sigmoid function
Learning rate	10^{-2}
The number of times of learning	30,000
The simulation conditions of SVM	
The initial value of a Lagrange multiplier	0.0～1.0
Learning rate	10^{-3}

A kernel function and the parameters of each function	Polynomial kernel $K(x_1,x_2)=\left(ax_1^{\,T}x_2-b\right)^p$ $a=0.1, b=0.5, p=1$ Sigmoid kernel $K(x_1,x_2)=\tanh\left(ax_1^T x_2-b\right)$ $a=0.1, b=0.5$ Gauss kernel $K(x_1,x_2)=\exp\left(\frac{-\lVert x_1-x_2\rVert^2}{2\sigma^2}\right)$ $\sigma=2$
the number of SVM	10
The discernment determination method	Majority method

3.3 The process of simulation

In the simulation, we perform the following stems:

① Provide N sets of T kinds of Mental task data .
② Perform feature extraction on each of input sample N.
③ As training data, take n samples out of each mental tasks randomly, the rest of samples (N-T × n) are treated as test data.
④ Execute training for classifier by using the training data.
⑤ Determine the type of mental tasks of the test data using the learned classifier.
⑥ Repeat any times from ② to ⑤.

3.4 Simulation results

<u>The case of seven channels EEG data for all subjects</u>

The number of samples of EEG signals measured at each subject is 60 for each of 5 mental tasks, 12 samples is for test data in it, and the rest is for training data. Changing the test samples, repeat the above experiment five times.

Results of discrimination using each of the methods have been shown in Table 3.

In the results, the best result is the discrimination ratio of 75% of the improved method using Gaussian Kernel. This result is 4% better than the result of the conventional method with 71%. This improved result may be due to improvements of restricting the frequency bands in Feature Extraction and introduction of SVM. It can be seen that the Gaussian kernel is the most appropriate in the kernel trick used in this study.

Table 1 Discernment results by each method in the case of seven-channel electroencephalographic data for seven subjects

		B	M	L	R	C	Average
SOM + MLP	SOM 50	58	76	63	87	70	71
SVM	Alignment	50	62	58	70	60	60
	Polynomial	50	60	63	72	65	62
	Gauss	60	64	82	85	78	75
	Sigmoid	52	70	66	73	59	64

<u>In the case of one channel using EEG data for one subject</u>

Excluding EEG, Data are measured by 6-channel EOG electrodes and discernment of the data is carried out. The EEG data of the subject 1 is used. The data of subject 1 are measured 10 times per each of the five mental tasks, a total is 50 samples. Two samples for each 5 mental tasks, that is, 10 samples are taken as test data, and the remaining 40 samples are used as training data. Discernment testing is executed five times changing test samples.

In addition, the improved method uses the Gaussian kernel in SVM showing high recognition rate in Section 3.3 and 3.4.

Table 4 shows the discernment results of each method.

In this simulation, overall, the improved method with the Gaussian kernel shows better results. From this one channel used results, it is said that the improved method is effective even for a single-channel EEG data, like the case of multi-channel.

Table 2 Discernment result by each method in the case of one-channel electroencephalographic data for one subject

		B	M	L	R	C	Ave.	All the averages
SOM 50	C3	30	0	10	20	40	20	19
	C4	0	0	20	20	20	12	
	P3	20	10	20	0	70	22	
	P4	20	20	0	10	50	20	
	O3	0	0	0	0	90	18	
	O4	20	0	0	0	80	20	
SVM & Gauss kernel	C3	20	30	30	10	20	22	24
	C4	10	0	40	20	20	18	
	P3	30	30	0	0	60	24	
	P4	50	20	10	20	50	30	
	O3	0	40	30	0	80	30	
	O4	0	0	20	10	60	18	

IV. Experiment

Next, using a Gaussian kernel SVM showed good results in the simulation, discernment testing for EEG data obtained f rom single-channel EEG sensors, MindSet, is executed.

4.1 Inexpensive commercial EEG sensor with one-ch annel

The MindSet has two electrodes which are attached to left ear and forehead. It measures a potential difference between before-mentioned two electrodes. The sampling rate for measurement is 512Hz.

In addition, the MindSet has no recording equipment of EEG data, it only has the ability to measure EEG data. Therefore MindSetRearchTool, a research tool MindSet (MRT), is used to compensates for their function. The MRT has various functions: the EEG recording, saving features, which is also equipped with connectors for use with software such as MATLAB, numerical analysis software.

Fig. 5. MindSet made by NeuroSky Ltd.

4.2 Measuring method

The subjects is one healthy male in his 20s. Brain waves of the subject with the MindSet on the head sitting in a chair are measured. Mental task is looking the blinking image, changing black, red and blue, every two seconds and the EEG data are measured when viewing.

The measurement time is 10 seconds and the measurement is made for three colors each, then set in the one-minute break before the next measurement.

As described above, measurement is done 10 times for each mental task. The total number of data is 30. The subsequent experiments are done using these 30 data set.

4.3 Experimental conditions of Feature Extraction

Restricting range of frequency bands for feature extraction method in an improved process is 4-125 [Hz]. These EEG and EEG data are the different benchmarks such as intellectual thought during the simulation. Therefore the restricting range of frequency bands are set arbitrarily.

4.4 Experimental conditions of Support Vector Machines

Table 5 shows the condition of the SVM in this experiment.

Table 3. Experimental condition of SVM

The initial value of a Lagrange multiplier	0.0～1.0
Learning rate	10^{-3}
A kernel function and the parameter of each function	Gauss kernel $\sigma = 2$
The number of SVM	3
The discernment determination method	Majority method

4.5 Experimental procedure

Discernment test of experiments was carried out as same as in the simulation.

4.6 Experimental results

Under the experimental conditions described above, the results of discernment test are shown in Table 6. In this experiment, the lowest diecerment rate of 60%, the highest recognition rate of 80%, 70% were discerned on average. This is not said that very high recognition rate. However, it is said that the one channel EEG sensors "MindSet" EEG data can be discerned, this may show that 1 channel commercial EEG sensor are applicable to the engineering fields .

Table 4. Experimental result

	Black	Red	Blue	Average
Gauss kernel	60	70	80	70

5. Conclusions

By incorporating the existing proposal as the basis of the BCI system, BCI system with high generalization performance as shown in this simulation and experiment was able to be constructed. It is also found that mental tasks can be identified in single-channel EEG sensors.

However, results of this research are only shown to be useful for identifying a simple mental task. We don't have practical applications yet. Therefore, the goal of future studies are

① Seeking viable mental tasks can be identified by MindSet,

② Development of real-time BCI system that can be Identified.

The construction of viable applications using the MindSet is remained.

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