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Classification of haptic tasks based on electroencephalogram frequency analysis

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Abstract

In recent years, it is difficult to inherit high level sensory skill, because the number of experts is not so much or the experts are too busy to teach their skill to the beginners. Therefore, many learners do the experiential learning through visual and haptic digital teaching materials. In such a system, however, it is difficult to evaluate whether the learner could recognize the sensation and obtain the sensory skill. In the paper, we investigate whether the biological signal such as EEG can be used for the evaluation of the haptic task skill level.

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Keywords: brain machine interface(BMI); sensory skill; electroencephalogram (EEG); haptic device; neural network; principal component analysis

1. Introduction

A brain-machine interface (BMI) [1] is a technology that allows communication between a human or animal brain and an external technology. A BMI is an interface to obtain information such as blood flow and EEG in humans or animals, and to control the hardware and software using such information. Various different brain-machine interface technologies have been developed, through different methods and for diverse purposes, including in virtual reality technology. In recent years, the use of information and communication technology has become a hot topic in the medical or education field, e.g. virtual reality system with haptic device. Due to such system, learner can do experiential learning through visual and haptic digital teaching materials[2]. In such a system, however, it is difficult to evaluate whether the learner could recognize the sensation and obtain the sensory skill. In addition, it is difficult to

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classify the acquired skill level between beginner and expert. Therefore, it is necessary to quantify the perceptual information based on the biological signal of the users, e.g. blood pressure, heart rate, and electroencephalogram (EEG) [3,4]. In the paper, the EEG information is applied to obtain the biological signal.

In order to know what skills are recognized when the haptic device is operated, we develop a classification technique of cognitive status by measured EEG in this study. To do so, we investigate the better location to measure EEG, and a feature extraction method of EEG data.

In the paper, 2 kinds of haptic tasks (Catch and Touch) are classified based on the measured EEG. In the Catch task, the user operates the haptic device to catch the virtual object on the screen. In the Touch task, the user operates the haptic device to touch the object on the screen. Among these operations, we measured the EEG of the user at the 6 locations (F3, F4, C3, C4, P3 and P4 shown in Fig. 1). The following processes are executed to classify the haptic tasks. At first, the band-pass filter (8-30Hz) is applied to remove noise from EEG data. Then, in order to obtain the frequency components of the EEG, Fourier transform is performed and each frequency component is normalized to reduce offset influence. In the next step, principal component analysis is applied to gather important frequency component and get input data for neural networks. Finally, our method identifies the task from frequency component of EEG by neural networks.

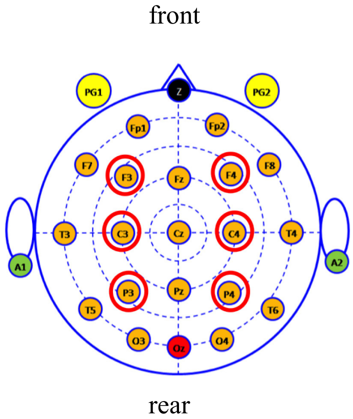

Fig. 1. Brain structure

2. Brain machine interface

2.1. Brain structure

The human brain consists of three main parts: cerebrum, cerebellum, and brainstem. The cerebrum can be classified into four cerebral lobes: frontal lobe, temporal lobe, parietal lobe, and occipital lobe, according to its characteristics of the groove and shapes. These cerebral lobes have different functions. In this study, we focus on the area called the sensory cortex, which consists of the primary somatosensory area in the front of the motor cortex and the parietal lobe on the rear of the frontal lobe. Sensory skill is a skill which can utilize sensory information such as touch, while observing the state of the object and the environment during a work. Therefore, it can be estimated that motor cortex has a strong relationship with sensory cortex.

2.2. EEG (Electroencephalogram)

In the cerebral cortex, there are tens of billions of neurons, and each of them is activated with brain activity. Impulse signal is used for exchanging information between the neurons. As a result, a weak electrical signal is generated on the cerebral cortex. EEG is the electrical signal which is measured at electrodes on a brain.

Various patterns of EEG can be measured with the activity of the brain. Frequency, amplitude, waveform, and phase can be used to represent the characteristics of the EEG. Among them, a most significant clinical characteristic is frequency. EEGs are classified in the Table 1 based on its EEG frequency. α wave is a brain wave that is often observed in parietal and occipital region, and is attenuated during eye closed and mental activity. Θ and δ wave can be seen in the sleep state or childhood and those waves are rarely seen in adult person in the awake state. Due to very similar frequency characteristics with EMG caused by physical movement, these frequency bands are often removed through the band-pass filter in BMI. β-wave is EEG which can be observed at central, frontal, or side of the head. The β-wave measured at the motor cortex is suppressed temporarily when the limb is moved. In this study, we focus on α and β wave, and remove the other waves by a band-pass filter.

Measured electrode arrangement is an internationally standardized by 10-20 electrode placement method. Each electrode is divided in four parts such as the frontal part (F), central part (C), parietal part (P), and occipital part (O). The EEG in cortex and motor cortex are measured at the six locations of P4, C3, C4, F3, F4 and P3 in the 10-20 electrode placement method.

Table 1. EEG frequency.

Wave	δ	Θ	α	β	γ
Hz	1-3	4-7	8-13	13-30	30-
State	Deep Sleep	Shallow Sleep	Relax	Normal	Excite

2.3. Brain machine interface

A brain-machine interface (BMI) is a technology that allows communication between a human or animal brain and an external technology. A BMI is an interface to obtain information such as blood flow and EEG in humans or animals, and to control the hardware and software using such information.

In order to construct the BMI system, it is necessary to obtain information from the brain of a human or animal. As a method of obtaining information as a brain activity, there are two methods of invasive measurement and non-invasive measurement. In the invasive measurement type, measuring probes are inserted into the human brain directly. It can measure the brain activity with high accuracy, but the problem of ethicality and safety exists. On the other hand, the non-invasive measurement type measures the cerebral activity to use scalp contacting head attachments. It is easy to measure the brain activities, but it is affected by noise of the volume conductor (skull and scalp) and the accuracy of data is lower than the invasive measurement type. Electroencephalogram (EEG) equipment is a kind of the non-invasive measurement type, and small size measurement equipment. It has a high spatial resolution and is used most widely or frequently in a field of research.

3. Experiment: Classification of haptic tasks

3.1. Experimental environment

Figure 2 shows our experimental environment. In the experiment, the subject manipulates the haptic device while looking at the screen of the PC. Haptic device generates a force and the force is transmitted to the subject through the haptic device. At the same time, EEG is measured from electrodes attached to the scalp of the subject. We use the BioSemi Active Two system to record EEG activity. The Active Two system has 64-channel probes and selects sampling rates which 2, 4, 8 or 16 kHz per channel. We use the Sensable Technologies PHANTOM Omni as haptic device. We use the PHANTOM which does not generate any forces.

In our experiment, we measured the EEG at the 6 positions (C3, C4, P3, P4 F3, F4)(as shown in Fig. 1). P3 and P4 are located in a sensory area, C3 and C4 are located in central groove, F3 and F4 are in motor cortex.

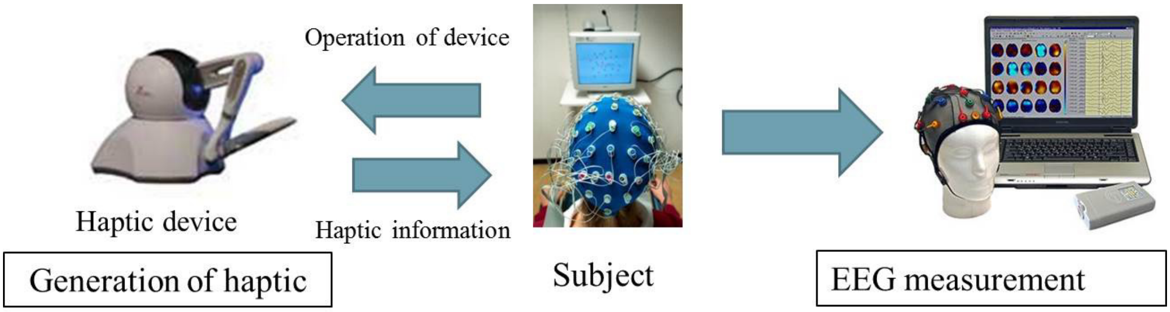

Fig. 2. Experimental environment

In the paper, we investigate the two types of tasks. In the first task, the subject pushes the button on the haptic device to grab a virtual object on the screen. Then haptic is feedback to the subject. This operation is called "Catch task". In the second task, the subject moves the controller of the haptic device to touch a virtual object on the screen. Then the subject feels that the subject touches an object. This operation is called "Touch task". These two tasks can be considered as a basic operation in the use of the haptic device. In both tasks, the number of experiments is 50 trials per subject. The sequence of one task is 5 seconds rest before task, 10 seconds task and 10 seconds rest after task.

3.2. Classification of haptic task based on electroencephalogram frequency analysis

3.2.1. Procedure of classification

In the paper, 2 kinds of haptic tasks (Catch and Touch) are classified based on the measured EEG. In the Catch task, the user operates the haptic device to catch the virtual object on the screen. In the Touch task, the user operates the haptic device to touch the object on the screen. Among these operations, we measured the EEG of the user at the 6 locations (F3, F4, C3, C4, P3 and P4 shown in Fig. 1). The following processes are executed to classify the haptic tasks. At first, the band-pass filter (8-30Hz) is applied to remove noise from EEG data. Then, in order to obtain the frequency components of the EEG, Fourier transform is performed and each frequency component is normalized to reduce offset influence. In the next step, principal component analysis is applied to gather important frequency component and get input data for neural networks. Finally, our method identifies the task from frequency component of EEG by neural networks.

1. EEG measurement
2. Band-pass filter
3. Fourier transform
4. Normalization
5. Principal component analysis
6. Identification by Neural Networks

We have selected α-wave and β-wave range data by the band pass filer (8-30 Hz) to eliminate noise (Table 1). To acquire the frequency distribution specification of the wave data, we have used FFT (Fast Fourier Transform).

We have normalized data of the frequency distribution power spectrum in order to eliminate the gain change effects.

$$f(x) = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Xmax: maximum of the power spectrum
Xmin: minimum of the power spectrum

A frequency which has a maximum characteristic value is the first principle. Main component scores are determined from characteristic vectors and frequency distribution power spectrum by the principal component analysis.

$$y_k = w_{k1}x_1 + w_{k2}x_2 + \cdots + w_{kn}x_n \tag{2}$$

y_k : k-th main component score
w_k : k-th characteristic vector
x : frequency distribution power spectrum

3.2.2. Identification by neural networks

We have used the three layers neural networks (Fig.3) to discriminate signals which electrodes are detected when the subject feels haptic. This neural network selects electrodes based on main component scores.

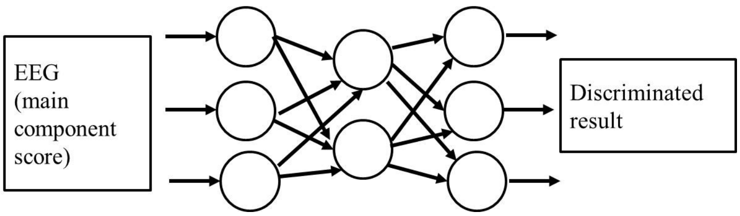

Fig. 3. Neural Networks.

4. Experimental results

4.1. Impact of the electrodes

In this experiment, to examine the relationship between the parts of the brain and haptic task, we compare the identification ratio in different measurement points of the EEG. We have four subjects in this experiment. As training data, we use the data which can identify task correctly. We have selected frequencies which has the main component scores corresponding to the cumulative contribution ratio that exceeds a prescribed value 60%, 70%, 80%, 90%. The output of this experiment are eight kinds of task: “Catch task of the subject A”, “Touch task of the subject A”, “Catch task of the subject B”, “Touch task of the subject B”, “Catch task of the subject C” , “Touch task of subject C”, “Catch the task of subject D", “Touch task of subject D”. In this experiment, we investigate identification accuracy of 19 combinations of measurement points: “C3”, “C4”, “F3”, “F4”, “P3”, “P4”, “C3 & C4”, “F3 & F4”, “P3 & P4”, “C3 & F3”, “C4 & F4”, “C3 & P3” , “C4 & P4”, “F3 & P3”, “F4 & P4”, “C3 & C4 & P3 & P4”, “C3 & C4 & F3 & F4”, “F3 & F4 & P3 & P4” and “C3 & C4 & F3 & F4 & P3 & P4”. The neural networks were trained by items of these main component scores of odd number measured data. The number of training data is

200. Even number measured data is used as test data. The number of test data is 200. Figures 4, 5, 6 and 7 show the identification result of task by the neural network with different cumulative contribution ratio. The horizontal axis represents the measurement points, and the vertical axis represents the average identification rate. These figures show the results in the case where the classifier can discriminate both task and subject correctly, and the case where the task can be classified only.

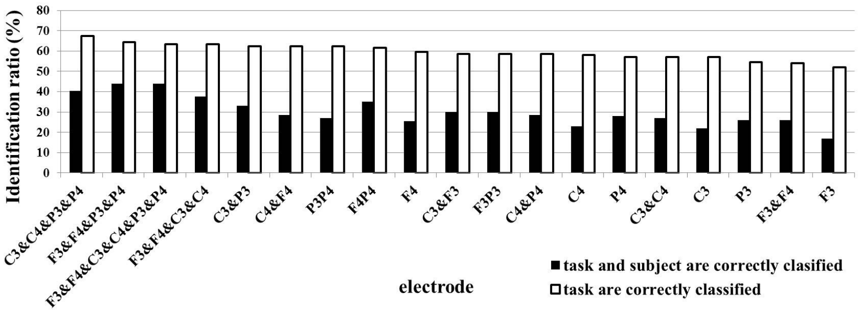

Fig. 4. Identification result (cumulative contribution rate is 60%)

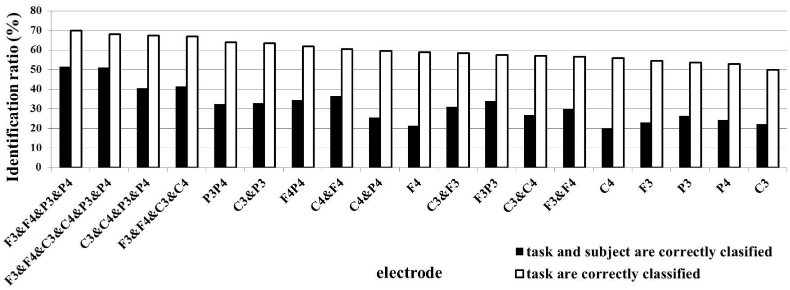

Fig. 5. Identification result (cumulative contribution rate is 70%)

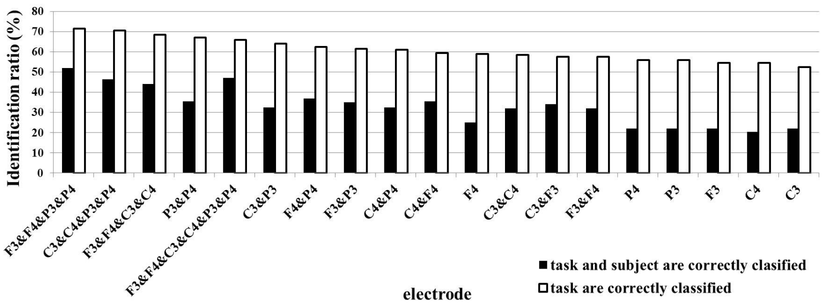

Fig. 6. Identification result (cumulative contribution rate is 80%)

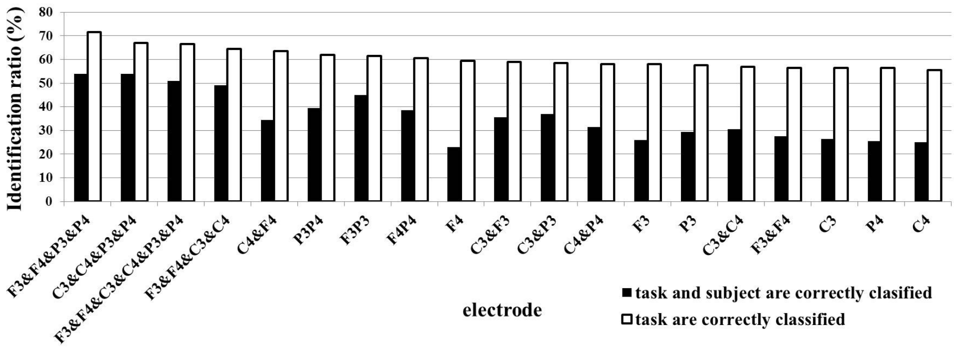

Fig. 7. Identification result (cumulative contribution rate is 90%)

From these results, in the case where the cumulative contribution ratio is 60%, “C3 & C4 & P3 & P4" shows higher recognition rate. In case of 70%, 80% and 90%, "F3 & F4 & P3 & P4" shows the highest identification rate.

4.2. Impact of haptic information

In this experiment, we investigate the performance of task identification due to the presence of haptic information. We have three subjects in this experiment. Then, we investigate whether the identifier can discriminate “Catch task with haptic information”, “Catch task without haptic information”, “Touch task with haptic information”, and “Touch task without haptic information”. The total number of combination is 12(4 combinations * 3 subjects). Measured electrodes are “F3 & F4 & P3 & P4” because these electrodes show higher performance in the previous section. We use 90% Table 2 shows classification results of each task and subject when 90% is used as the threshold value of cumulative contribution ratio. Figure 8 shows the identification ratio in the different cumulative contribution ratio.

Table 2. Identification result (cumulative contribution rate is 90%)

Subject A				Subject B				Subject C			
Catch		Touch		Catch		Touch		Catch		Touch	
With Haptic	Without haptic	With Haptic	Without haptic	With Haptic	Without haptic	With Haptic	Without haptic	With Haptic	Without haptic	With Haptic	Without haptic
40%	52%	60%	40%	44%	36%	44%	36%	36%	48%	40%	52%

From Fig. 8, identification ratio can be improved as the cumulative contribution ratio increase. This is because identifier can use more principal component scores due to higher contribution ratio. However, when the principal component score increases, the amount of calculation cost of the neural network also increases. Therefore it is necessary to set the threshold value appropriately.

From these results, the presence of the haptic information also affects the brain waves. Therefore, it is effective to classify the task based on the measured EEG.

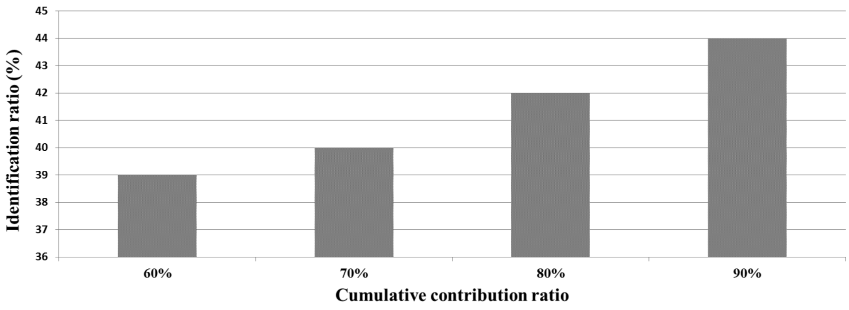

Fig. 8. Haptic information impact.

5. Conclusion

In order to know what skills are recognized when the haptic device is operated, we develop a classification technique of cognitive status by measured EEG in this study. To do so, we investigate the better location to measure EEG, and a feature extraction method of EEG data. In the paper, 2 kinds of haptic tasks (Catch and Touch) are classified based on the measured EEG. Among these operations, we measured the EEG of the user at the 6 locations. To classify the haptic tasks, the data have been analyzed by normalization and FFT PCA and discriminated by the neural networks. From our experimental results, we found that the EEG signals related with the haptic tasks can be detected in motor cortex and sensory cortex in a brain. In addition, the sensory signal is better suited for the detection of the haptic tasks than the motion signal. Therefore, from the fact that the haptic tasks can be distinguished by EEG, it can be expected that EEG signal can be used for the evaluation of the haptic task skill level.

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