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A Near-Infrared Spectroscopy Study on the Classification of Multiple Cognitive Tasks

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Abstract*—This study examined a method for discriminating multiple cognitive tasks with single-trial classification with the goal of developing a brain-computer interface with which more information is reflected with near-infrared spectroscopy (NIRS). NIRS has a slightly higher spatial resolution compared to that of electroencephalography (EEG), and it may be able to better delineate the functional separation within the brain compared to EEG. Moreover, NIRS may increase the information reflected by the brain-computer interface and reduce the communication-of-information time. Therefore, we proposed a method for selecting features that was based on Weber's law in the frequency domain, and this study aimed to improve the classification accuracy. We conducted experiments with 3 kinds of cognitive tasks (specifically, mental arithmetic task, Stroop task, and graphic task) that were performed at random and measured the brain activity of the participants with NIRS during the experiment. From this experimental data, the features were sorted out with the proposed method. Then, we examined the 2-class classification accuracy with a support vector machine with features that were extracted by the proposed method. We then examined the 3-class classification accuracy, and the results suggested the potential for discriminating multiple cognitive tasks with a brain-computer interface.

***Index Terms*—BCI (Brain Computer Interface), NIRS (Near-infrared Spectroscopy), Speller, Cognitive Tasks**

I. INTRODUCTION

Recent developments in noninvasive neuroimaging technologies have allowed for research on brain-computer interfaces (BCI) [1]. A BCI is a system that is used to operate a machine, such as a computer, directly and without physical manipulation, by using information on brain activity as the input. Therefore, BCIs are expected to act as a system that supports a physically handicapped person's decision making or communication. Some people that could greatly benefit from BCI devices are those with crippling disorders, such as amyotrophic lateral sclerosis [2] or severe paralysis. Many previous studies of BCI have used electroencephalography (EEG) to measure brain activity such as the P300 of event-related brain potentials (ERP) [3–5]. However, EEGs have a low spatial resolution, and, thus, source estimation with EEG is difficult. Moreover, there is the problem that data will be contaminated by noise. As a method for reducing noise, limiting the surrounding electric appliances or using a shield room have been suggested. However, when the daily use of BCI in a home is desired, these methods are thought to be difficult. Moreover, because it is necessary to equip a scalp with an electrode with paste in order to perform EEG measurements, the adjustment of position is difficult. With a progressive nervous disease resulting from amyotrophic lateral sclerosis or apoplexy, a patient may exhibit complete paralysis, even though the patient has completely intact sensory and cognitive function. The state of the patient who is in complete paralysis is called total locked-in syndrome (TLIS), and there is no successful example of a patient with TLIS utilizing EEG-based BCI at present [6]. For these reasons, it is thought that a BCI approach that replaces EEG is required. Near-infrared spectroscopy (NIRS) is a noninvasive cerebral function measurement instrument that is similar to EEG.

It is an optical instrument. NIRS is small and as low-cost as EEG, and it does not place many restrictions on the user. Moreover, paste is not necessary when wearing the NIRS on the head. NIRS systems have low electronic noise. Therefore, it is thought that NIRS is suitable for daily use. In addition, it has been reported that the reaction of brain activity that is related to an event is measurable with NIRS, as with EEG [7]. Compared to EEG, the spatial resolution of NIRS is high, although the time resolution of NIRS is lower. Therefore, NIRS may be able to detect particular features of a reaction, such as functional separation within finer regions of the brain. For these reasons, research on brain function elucidation with NIRS has advanced in recent years [8–13]. Moreover, in a previous study, the possibility of BCI with NIRS in a patient with TLIS has been shown [14]. Therefore, the application of NIRS to BCI is expected [15–18]. It is known that the brain activity that corresponds to blood-flow changes that are measurable by NIRS requires time for a reaction. In fact, it has been shown that the peak of the reaction of brain activity that corresponds to blood-flow changes that are measured by NIRS is observed about 5 to 8 s after stimulus presentation [7, 15]. However, it is possible to control activation intentionally instead of only examining a reaction that takes time. For example, tasks that are generally called cognitive tasks, such as a mental-arithmetic (-calculation) task [19, 20], a Stroop task [21, 22], a verbal fluency task [23,24], and a working memory task [25], have been reported as a means to which the activation of a prefrontal region of the brain is intentionally elicited. Furthermore, the features of a smaller regional reaction in a prefrontal region [26] may be determined by using NIRS as the measurement instrument. If 2 or more cognitive tasks can be discriminated by using NIRS as the measurement instrument, it may be possible to develop an interface for BCI with which much discriminable information can be reflected at a given time by using the results of the classification of questions like "*What task is the participant performing now?*" as a switch. For example, in many

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previous studies that used EEG as the measurement instrument, the choice that was highlighted on the display was discriminated between the object that the participant wanted to choose (Target) and the object that the participant did not want to choose (Nontarget) according to whether P300 was observed. By repeating the discrimination of these binaries (ON/OFF, Yes/No, etc.), the system chooses 1 choice from 2 or more choices. Moreover, in a previous study of BCI that used NIRS as the measurement instrument (NIRS-based BCI), which is examined in [16], the system was able to make the choice by matching brain activity changes to the Target/Nontarget. This brain activity change was caused by whether a participant was imagining grasping a ball lightly in a hand or not. Here, if 2 or more cognitive tasks can be discriminated by a single trial, the information on 2 or more choices can be added in order to highlight 1 object on the display. This results in not only an increase in reflected information, but also to the shortening of the communication-of-information time, which is the time taken to choose 1 from 2 or more choices by the system. A previous study [27] that used functional magnetic resonance imaging (fMRI), which is described as a cerebral function measurement instrument that is based on the same metabolism as NIRS, has succeeded in increasing the number of choices that can be discriminated by increasing the number of tasks to 3. However, fMRI is expensive and large, and causes much restriction for the user. Thus, it is difficult to use in everyday life situations.

Therefore, the necessity for technology transfer to a system that is movable and portable like NIRS has been described [27]. fMRI has very high spatial resolution, and the high level of this resolution has led to discrimination accuracy. For technology transfer, therefore, at first, it is necessary to examine the potential of whether 2 or more tasks can similarly be discriminated with NIRS. Therefore, in this study, a method for discriminating 2 or more cognitive tasks in a single-trial was examined with the goal of the development of an interface with which more information is reflected for BCI with NIRS. The measurement sites were in the prefrontal cortex region. The prefrontal region is considered to be an important area for the cerebral activity underlying cognition, information selection, and decision making. Moreover, it is thought that the prefrontal region is suitable as an input for a BCI that is to be used daily because it is an area that is not affected by hair. In this study, we experimented with 3 kinds of cognitive tasks: a mental arithmetic (calculation) task, a Stroop task, and a graphic task among the activation tasks of the prefrontal region. Then, we tried to discriminate each task with the data that was obtained in the experiment. In addition, for the selection method of the features for classification, we proposed a method to extract data that applied Weber's law in the frequency domain of fast Fourier transform (FFT)-transformed NIRS time series data. A support vector machine (SVM) was used for learning and classification, and the classification accuracy by the feature-selection method for learning and classification was examined with a 2-class classification. Discrimination accuracy was added to the 2-class classification to make the 3-class classification, and the accuracy was examined. Thus, the potential of the proposed method was verified.

II. NIRS-BASED BCI

In this study, we examined the method in order to improve the interface, especially for NIRS-based BCI. This section describes the outline of the system of NIRS-based BCI and the outline of our goal interface.

A. Outline of the system

The outline of the system of BCI that is found in most previous studies is described below (refer to figure 1).

i. First, a system displays an interface screen on a display. The display usually shows the choices, the information of intentional control that a participant should perform (mental arithmetic, image that grasps a right hand, etc.), and the timing of intentional control. The participant sees these pieces of information on the display and performs decision making according to the setup task.
ii. The system measures the participant's brain activity with the use of a measurement instrument (NIRS) and transmits the data that is measured to a computer.
iii. On the computer, preprocessing and learning and classification are performed on the received data, and the participant's decision making that is based on a classification result is reflected on the display.

In the development of a BCI, in many cases, the performance of the BCI is verified online (measurement, preprocessing, learning and classification, and feedback in real time) or offline (verifying the classification accuracy by cross-validation to the data that was measured in the experiment).

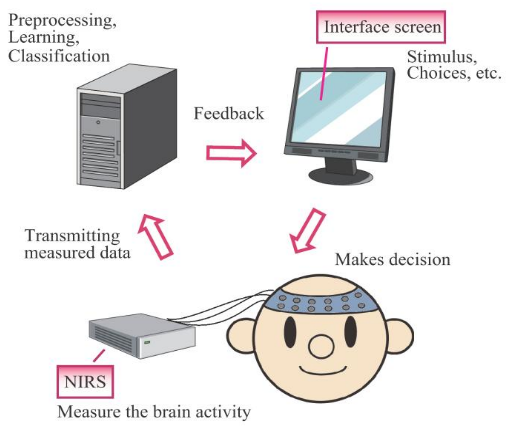

Fig 1. Outline of the Brain-Computer Interface (BCI) system with near-infrared spectroscopy (NIRS).

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B. Interface

The image of the case of using the interface to choose 1 from 2 or more choices by combining binary selection (for example, ON/OFF), which was examined in a previous study, is shown as the *Simple binary switch* in figure 2. For example, please consider the case of a participant who would like to generate the command for communicating a message that "*I want to drink water*". First, the participant chooses the choice of "*I want something to drink*" from the choices that are shown on the display. The participant chooses the state of performing intentional control (called the ON state) when the choice of "*I want something to drink*" is highlighted. After the command of "*I want something to drink*" is chosen, the choice for choosing the kind of drink that the participant wants to drink is displayed. The participant chooses the choice of "water" from these choices, and, when the command "*water*" is highlighted, the participant chooses the ON state again. The command of "*I want to drink water*" is generated by the selection operation of these 2-level choices. When the amount of information that can be reflected by a single choice is a 2-class choice, the choice and level increase in order to be able to choose a more complicated command. Therefore, the number of times for a selection in an operation increases, and the time for the selection also increases. If the information that can be reflected by a single choice can be assigned to 2 or more cognitive tasks and can be discriminated, the command of "*I want to drink water*" may be able to be generated by only a 1-level choice. The image for the *Multi task* switch of figure 2 illustrates this. For example, in the case in which the participant tries to choose the choice "*I want to drink*" from the choices that are shown on the display, the state of intentional control is assigned as follows: the case in which the participant wants to drink water is *Task 1*, the case in which the participant wants to drink juice is *Task 2*, and the case in which the participant does not want to drink does not involve choice (this case is called the OFF state). By performing *Task 1*, the participant can generate the command "*I want to drink water*" with only a single choice. Although the system must display the information for which the task is assigned to which choice (command), if the amount of information that is reflected by a single choice increases by more than 2 classes, the input of a complicated command becomes easy and can also reduce the required time. Moreover, if the system tries to generate a complicated command through multilevel choices, the correction is difficult even when the selection goes wrong at only 1 certain level. The frequency of correction by failure may be able to be reduced by making the level shallow.

III. EXPERIMENT WITH COGNITIVE TASKS

It is necessary to consider extending the ON state to a plural state in order to reflect 2 or more types of information that are represented by a single choice, as described in Section 2.2. Therefore, in this study, we first decided that we would focus on the extension of the ON state and examine the discrimination potential of 2 or more cognitive tasks. In order to examine the discrimination potential of 2 or more cognitive

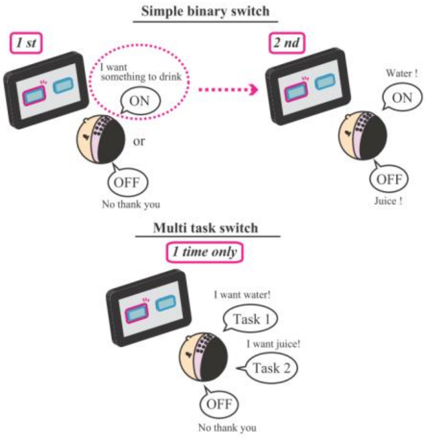

Fig 2. Images of selection with the BCI

Tasks, experiments were performed while measuring the brain activity of the participant with NIRS during task performance. Three kinds of cognitive tasks were shown on a display in random order. In this experiment, learning and classification were not performed online, and only the measurement of the brain activity was performed at the time of the task trials. The validation of classification accuracy was analyzed offline after the end of the experiment with the data that was obtained in the experiment. First of all, in this study, in order to verify whether the participant was conducting each task carefully and in order to verify the difficulty that the participant experienced for each task, we conducted an experiment in which a click operation (input of the answer of a task with a mouse) was performed (refer to Section 3.2). Then, we examined an experiment without a click operation (movement factor) (refer to Section 3.3). The details of each classification accuracy verification are given in Section 4.

A. Brain activity measurement

The instrument that was used for the measurement of brain activity in our experiment was NIRS (OEG-16; Spectratech Inc., Yokohama, Japan). NIRS is an instrument that measures the changes in hemoglobin concentrations in the blood with the amount of near-infrared (IR) light change that occurs between entering and returning in vivo due to the hemoglobin absorption of the near-IR light. In the OEG-16, changes in the oxygenated hemoglobin (oxy-Hb) and deoxygenated hemoglobin (deoxy-Hb) concentrations are measurable by using the near-IR light of 2 kinds of wavelengths (770 nm and 840 nm). The measurement sites in the experiment were over the prefrontal region, as shown in figure 3, and the number in the figure indicates the channel numbers. Moreover, figure 4 shows the arrangement of the probes (optodes) of the OEG-16 and the relationship between the probes and the channels. By arranging 6 near-IR light emission probes (e1–e6) and 6 near-IR light detection probes (d1–d6) in the shape of a matrix by turns at intervals of 30 mm, measurement with a total of 16 channels is possible. The sampling interval of the OEG-16 is 0.65 s or 0.08 s (the sampling interval at 0.08 s was attained by upgrade of the instrument). In this study, the sampling interval was 0.65 s in experiment 1 (refer to Section 3.2), and the sampling interval was 0.08 s in experiment 2

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(refer to Section 3.3). In this study, only the data pertaining to the changes in oxy-Hb concentration were used to learn and discriminate by the system in the analysis after the experiment [18,28].

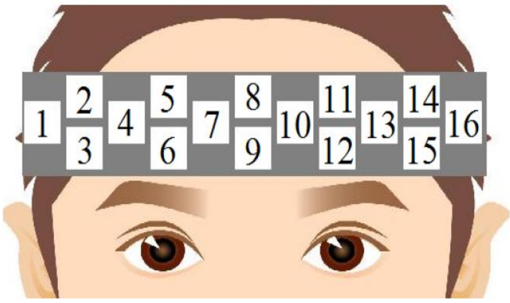

Fig 3. Measurement sites

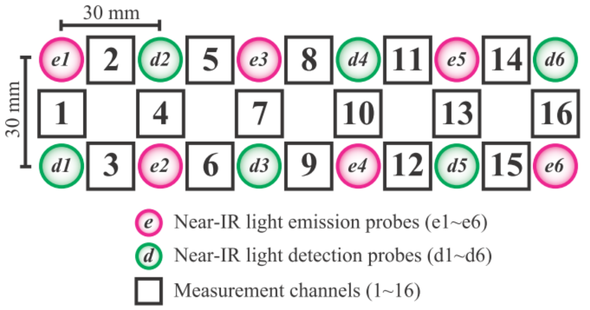

Fig 4. Probe configuration. IR, infrared

B. Experiment 1: The experiment with the click operation

The details of the experiment with the click operation (input of the answer of a task) are given below. The goal of this experiment was to verify that the participant was conducting the task carefully and the difficulty that the participant experienced for each task.

1. Participants.

Five students (4 males, 1 female, 21–22 years of age) at the University of Toyama participated in the experiment. They were informed about the experiment and that biological information would be obtained. Figure 5 shows the setting for our experiment. A participant wearing a NIRS on his/her head sat on a chair a short distance away from the front of a display, and the participant answered the questions for each task that were shown on the display. The details of the tasks are given in Section 3.2.2.

2. Task design of the experiment

The task flow in our experiment is shown in figure 6. First, in order to stabilize the participant's changes in oxy-Hb concentrations, a rest period was set (figure 6, Rest). During the rest period, a white X was displayed in the middle of the screen. Then, the participant performed any of 3 kinds of cognitive tasks (calculation task, Stroop task, or graphic task) for 10 s until the X was displayed again (figure 6, Task). For each task, the participant had to choose the answer to the displayed question as soon as possible from 4 choices that were shown in the lower part of a screen with a mouse. If an answer was given, the next question was displayed. The participant tried to answer as many questions as possible within 10 s. The type of task did not change during 1 task block (10 s). For example, in the case of the calculation task, only calculation questions were sequentially updated for 10 s. The Rest and Task periods formed a single trial (12 or 20 s). For each task, the participant performed 50 trials (a total of 150 trials in 1 experiment). The order of appearance of each task in the experiment was random. The details of each cognitive task are given below.

Fig 5. Experimental setup

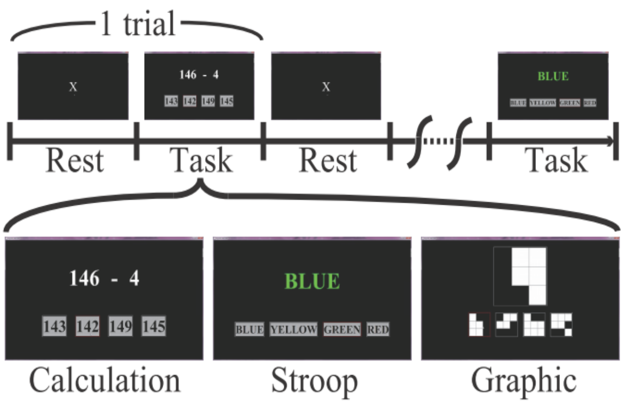

Fig 6. Scheme of the experimental task

Calculation task. A subtraction problem, which involved the subtraction of a 1-digit number from a 3-digit number, was shown in the middle of the screen. The participant solved the displayed problem and chose the right answer (figure 6, Calculation, the right answer is 142). Both the 3-digit number and the 1-digit number of the subtraction problem were chosen by a random number generator and shown at random. Moreover, the choices for the answer other than the correct answer were chosen by the random number generator based on the normal distribution among which mean value is the correct answer value.

Stroop task. An English word for a color (for example, BLUE) was shown in the middle of the screen. The participant was asked to give the color of the word that displayed the color word (figure 6, Stroop, the correct answer is GREEN). The English words showing the color that were shown on the screen were for 4 colors: RED, BLUE, GREEN, and YELLOW [22]. The choices were also the same. Moreover, the English word that was shown and its color were random.

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Graphic task. The participant chose the match of the graphic that was shown in the middle of the screen from the choices. The matching graphic could be rotated (figure 6, Graphic, the correct answer is the leftmost choice). Each graphic consisted of 3 × 3 blocks. Moreover, the graphic was generated at random.

Each participant performed the above-mentioned experiment 2 times. In the first experiment, both the Task and Rest periods were set to 10 s. However, in the second experiment, the Task period was set to 10 s, which was the same as in the first experiment. However, in every third trial, the Rest period was 10 s, and the other Rest periods were changed to a shorter setup (2 s). This was done in order to examine the possibility that the time for the whole task could be shortened by shortening the rest period in order to facilitate implementation in the BCI.

C. Experiment 2: The experiment without the click operation

In order to further examine the usefulness of cognitive tasks in the BCI, the same experiment was conducted with the same task design but without the movement factor (click operation). The details are given below.

1. Participants

Five students (4 males, 1 female, 22–24 years of age) at the University of Toyama participated in the experiment. They were informed about the experiment and that biological information would be obtained. Three of the participants were the same as those that participated in the experiment with the click operation.

2. Task design of the experiment

The task flow in this experiment was the same as that described in Section 3.2.2. However, the task flow in this experiment differed in that answering the questions (the click operation) was not needed. First, in order to stabilize the participant's changes in oxy-Hb concentration, a rest period was set. During the rest period, a white X was displayed in the middle of the screen. Then, the participant performed any of 3 kinds of cognitive tasks (calculation task, Stroop task, or graphic task) for 10 s until the X was displayed again. In the Task period, the problem that was shown was updated automatically at regular time intervals. Therefore, the participant was asked to consider the answer of a displayed question (the participant confirmed in the participant's head which choice was the correct answer) before the question was updated. The updating speed of the question in the Task period was set for each task based on the results (average of the reaction time of each answer) of the experiment with the click operation. Before actually measuring the data of the brain activity of a participant, the participant practiced for about 5 min so that they understood the flow of this experiment. This was done to check that the switchover time for each question was suitable (not too slow and not too fast so that they were impossible to answer). As in the experiment with the click operation (Section 3.2), the Rest and Task periods formed a single trial, and, for each task, the participant performed 50 trials (total of 150 trials). The order of appearance of each task in the experiment was random. For the time setup in the Rest period, the Rest period was 10 s every third trial, and, for the other Rest periods, the period was set to be shorter (2 s).

IV. RESULTS

The classification potential of each cognitive task was examined with the 5 participants' oxy-Hb data that were measured in the experiment. A SVM [29] was used for the learning and classification module in this study. A SVM is a pattern recognition 2-class method, which classifies a sample into 2 values. One can expect high discrimination capability from a SVM, even if there is little learning data available. We used the LIBSVM [30] for implementing a SVM and a Gaussian kernel for the kernel. A SVM can respond to multiclass data by combining a 2-class SVM in order to discriminate 2 or more kinds of cognitive tasks. Therefore, if the classification accuracy of the 2 classes improved, the discrimination accuracy of 2 or more classes should also be improved. For this reason, we first analyzed the feature extraction method based on the data that were measured in experiment 1 in order to improve the classification accuracy in the 2-class classification. Then, with the data of experiments 1 and 2, we tried to perform discrimination with the 3-class classification and examined the discrimination accuracy.

A. Behavioral results

In this section, verification of each participant's answer response time (Reaction time: RT) and wrong answers (Error rate: ER) during the experiment was performed. Figure 7 shows the results of each participant for the first experiment of experiment 1 (2-times experiment), and figure 8 shows the results of each participant in the second experiment. Moreover, in each figure, (a) shows each participant's average value and the standard deviation for the RT, and (b) shows the ER. For each participant's RT in the first and second experiments, significant differences in every combination of the 2 kinds of cognitive tasks of all 3 kinds of tasks were found with t-tests. As a result, except for the combination of the Stroop task and the Graphic task of participant D in the second experiment, significant differences were seen for all of the combinations of all of the cognitive tasks for all of the participants (2-sided t-test, 3-group multiple comparison correction by the Bonferroni method). The significant differences (p values) for the combination of the Stroop and Graphic tasks of participant E in the first and second experiments were less than 0.05/3, while the other significant differences were less than 0.001/3. The differences in RT were thought to be due to the characteristics of each task and the difficulty that the participants experienced on each task. These results suggested that each of the 3 kinds of cognitive tasks that were used in this study was a task with different characteristics for all of the participants. Furthermore, each participant's ER showed that variation was seen for every task and that the difficulty of the tasks differed. Each ER was low.

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Therefore, these findings suggested that each participant understood the contents of each task and that he/she was able to sufficiently perform the experiments. As mentioned above, it was considered that every combination of the 2 cognitive tasks for the 3 kinds of tasks may be able to be classified. Therefore, the features of the data were examined, as described in the following paragraph.

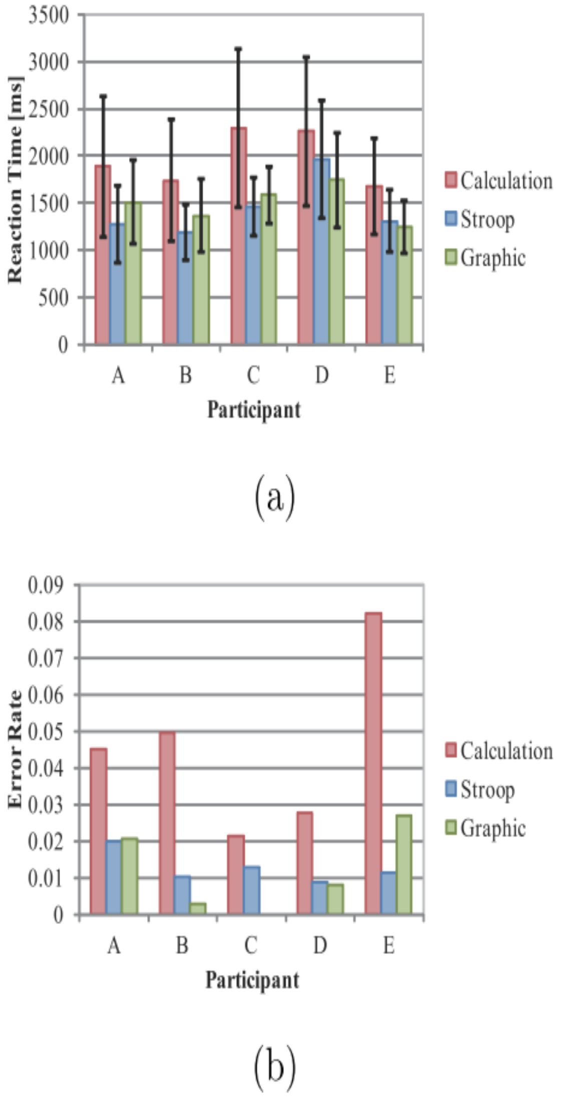

Fig 7. Behavioral results (first experiment).

B. Analysis of the feathres of the data of the oxy-Hb concentrations change

In order to examine classification potential, the features for learning and classification for the data of the oxy-Hb concentration changes that were obtained in experiment 1 were analyzed. First, the data in the time domain (the data obtained by NIRS in the experiment) were examined. Next, the data in the frequency domain to which FFT was applied in the time domain were examined. Furthermore, we proposed a method for treating the data relatively by applying Weber's law to the data in the frequency domain, and we then examined this method.

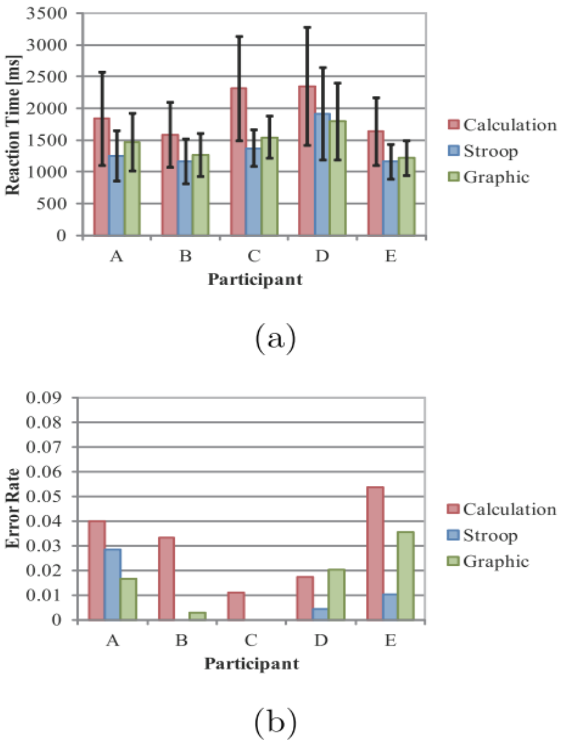

Fig 8. Behavioral results (second experiment).

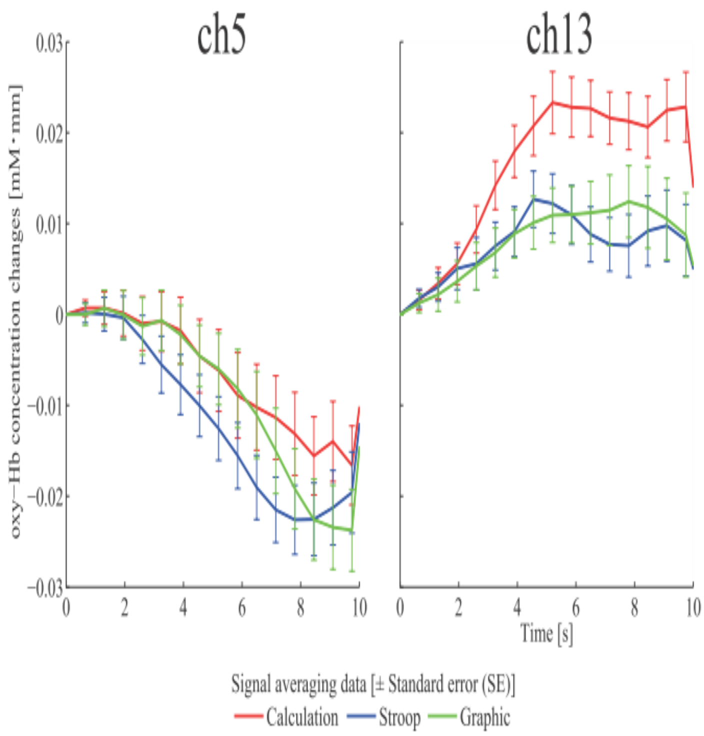

Fig 9. Examples of oxygenated-Hemoglobin (oxy-Hb) concentration changes in the time domain. Ch, channel.

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FEATURES USING A TIME DOMAIN

From the results of Section 4.1, the classification possibility of each task that used the oxy-Hb concentration changes was examined in the time domain. When the data of the oxy-Hb concentration changes in the time domain were analyzed, a Savitzky-Golay smoothing filter (S-G filter) [31] was applied to the measurement data as a preprocessing procedure in order to reduce artifacts, including living body noise. Compared to the moving average that uses various windows, the S-G filter highly conserved the position of the peak of the data and the amplitude of the data. Moreover, as for the S-G filter, processing is able to perform in the time domain directly. Figure 9 shows the oxy-Hb concentration changes (average value and standard error) in each task for channels 5 and 13 of participant A. The vertical axis indicates oxy-Hb concentration change, and the horizontal axis indicates task performance time. According to figure 9, the differences in oxy-Hb concentration changes in channel 13 were remarkable between the calculation task and the Stroop task and between the calculation task and the graphic task. No difference was found between the Stroop task and the graphic task. Moreover, remarkable differences were not observed in the oxy-Hb concentration changes between each task in channel 5, although a difference in some was found. Therefore, these findings suggested that the differences between the calculation task and the Stroop task and between the calculation task and the graphic task can be classified with high classification accuracy with the oxy-Hb concentration changes of channel 13 and that it was difficult to classify the difference between the Stroop task and the graphic task. Moreover, when the oxy-Hb concentration changes in channel 5 were used, these results suggested that a certain amount of classification accuracy was acquired but that highly precise classification was not possible. Therefore, examinations in another domain might be considered a method for raising the classification accuracy, and frequency domain is discussed in Section 4.2.2.

FEATURES USING A FREQUENCY DOMAIN

According to the results of Section 4.2.1, in the time domain, the data that are effective in classification may not be obtained, and highly precise classification may not be performed. Therefore, in this section, we examine another domain that is not a time domain. We verified the frequency domain and whether features that are classifiable appeared between each task. A frequency domain is a method that is commonly used in the analysis of brain waves. In this study, in order to increase the superficial time resolution, we set the number of data to 512 points with zero padding and applied FFT to this data. With the zero padding, we increased the data that may become the features without increasing the measurement channels. Figure 10 shows the average value and standard error of the data to which FFT was applied for each task in channel 5 of participant A, and remarkable features were not seen in the time domain. In figure 10, the data to which FFT was applied of the 512 points were too fine and were hard to see, and, thus, the results of applying FFT to 256 points is illustrated. In the verification of the discrimination accuracy in Sections 4.3 and 4.4, FFT to 512 points was used. In the left of figure 10, the horizontal axis indicates the amplitude, and the vertical axis indicates the frequency. Moreover, the right of figure 10 is a figure that expanded the range of 0.25–0.35 Hz of the figure on the left. According to the right figure of figure 10, a remarkable difference was not seen in the time domain in channel 5 of participant A, but a difference between the calculation task and the Stroop task and between the Stroop task and the graphic task was able to be classified with the frequency domain. That is, the features appeared with a frequency domain in some frequencies and with the channel where the feature was not regarded in a time domain. As mentioned above, by changing a domain, the feature appeared, and this suggested that classification accuracy improved more than with a time domain. However, in order to acquire high classification accuracy for all of the combinations of each task, it is thought that a contrivance is still required. Therefore, in Section 4.2.3, we examine further the domain to which Weber's law was applied to the FFT-transformed amplitudes (This type of domain is referred to as a Weber domain).

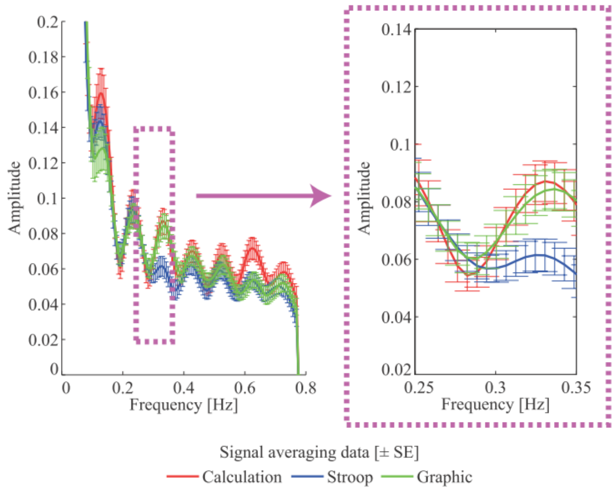

Fig 10. Example of oxy-Hb concentration changes in the frequency domain

FEATURES USING A WEBER DOMAIN

Although the possibility of classification accuracy improvement between 2 or more tasks was seen by using a frequency domain in Section 4.2.2, that possibility was not enough. Therefore, this section examines the Weber domain with Weber's law that was applied to the data of the frequency domain in order to further improve the classification accuracy. In this study, because the results in the time domain were worse than the results in the frequency domain, the method of applying Weber's law to the data in the time domain was not examined. Weber's law states that the increment in the strength of the stimulus that can be perceived as different always becomes a constant ratio to the strength of the stimulus [32]. This law has been applied to sensory

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organs, such as the skin. Because this study focused on the biological information of brain activity, we thought that classification accuracy would improve when Weber's law was applied. In fact, approaches to analyzing the neural responses in cognitive activity have been described by applying a number of laws, including Weber's law and Weber-Fechner's law (developed Weber's law) [33, 34].

Therefore, this study defined the value w_i by Weber's law in the frequency f_i as follows.

$$w_i = \frac{A_{f_{i+1}} - A_{f_i}}{A_{f_{i+1}}} \tag{1}$$

Here, A_{f_i} is the amplitude in the frequency f_i.

Figure 11 shows the average value and standard error of the data to which Weber's law was applied to the FFT-transformed data of channel 5 of participant A. In the figure on the left of figure 11, the horizontal axis indicates the value that was transformed by Weber's law (w_i) and the vertical axis indicates the frequency. Moreover, the right of figure 11 is the figure with the range of 0.25-0.35 Hz of the left figure expanded. When the differences in the features between each task in each participant's data were examined in the frequency domain, it seemed that there was no feature that could be classified with high accuracy. However, a frequency was found that had a different value between each task with the use of Weber's law in the frequency domain. Therefore, classifying with a high degree of accuracy all of the combinations of each task was thought possible by using the features in Weber domain, unlike when using only the time or frequency domains.

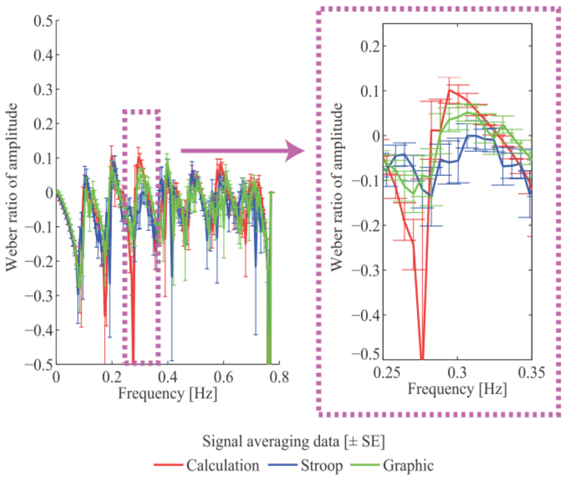

Fig 11. Example of oxy-Hb concentration changes in the Weber domain.

C. Validation of classification accuracy in 2-class classification (Experiment 1)

In Sections 4.2.1 to 4.2.3, we examined which domain, the time domain, the frequency domain, and/or the Weber domain, was the most suitable for feature extraction. The features in the frequency domain had more significant differences between each task than those in the time domain. However, the features in the Weber domain had more significant differences between each task than those in the frequency domain. Therefore, these findings suggested that using the features in the Weber domain allowed high classification accuracy. Then, in this section, classification accuracy was actually verified with SVM. The features that were used for learning and classification sorted the data in which significant differences (p value) were below the t-test threshold (*TT*) by performing a t-test for the data in each domain. In the t-test, a F-test is first performed on the combination of each data group in order to test whether the distribution is the same. Then, whether a system has to use the t-test assuming the same distribution or has to use the t-test assuming a different distribution is determined by the p value of the F-test. The results of having verified the classification accuracy of the combination of each task by 5-fold cross-validation is shown in figure 12. Additionally, the classification accuracy was verified by changing the value of *TT*. Figure 12 shows the average classification accuracy of 5 participants in each domain. The upper row of figure 12 shows the results of the first experiment, and the lower row show the results of the second experiment. The horizontal axis indicates the threshold *TT*, and the vertical axis indicates the classification accuracy. When the threshold of features (*TT*) was varied, the graph illustrated in blue shows the changes in the classification accuracy in the time domain. Red shows the changes in the frequency domain. Green shows the changes in the Weber domain, which is the proposed method. Figure 12 shows that the average classification accuracy was over 80% in the combination of every task in the Weber domain. This result demonstrated that the Weber domain had accuracy that was notably better than those for the time domain and the frequency domain. Moreover, the results of the time domain showed that the classification accuracy was almost constant regardless of the threshold *TT*. However, for the frequency domain, when a threshold *TT* was small, there was a tendency for sufficient classification accuracy. Furthermore, in the Weber domain, when a threshold *TT* was small, there was a notable tendency for sufficient classification accuracy. Therefore, in the Weber domain, the features that were effective in classification were extracted by using t-tests.

In this study, we demonstrated that classification accuracy improved greatly by using a Weber domain at the time of feature extraction. Weber's law is a method of treating data not absolutely, but relatively. Brain activity has many indefinite elements and individual differences, and, even in the same task, it is thought that the patterns of brain activity differ for every task trial. Therefore, when measuring brain activity, treating brain activity data relatively like the proposed method may be effective. Furthermore, we verified the maximum classification accuracy of the 3 kinds of task combinations in every domain for each participant and measured the maximum classification accuracy's average value and minimum value. The results that summarize these values are shown in table 1. According to table 1, the averages of the minimum values of the maximum classification accuracies in the 5 participants in each domain (time domain,

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frequency domain, and the Weber domain) were 59.6%, 59.4%, and 80.2%, respectively, in the first experiment. Moreover, in the 2nd experiment, they were 62.6%, 62.8%, and 85.8%, respectively. In the 2-class classification, when the number of trials per class is 40, the classification accuracy at 60.0% has indicated significance with a probability of 1%, and the classification accuracy at 65.0% has indicated significance with a probability of 5% [35]. Here, in this study, the number of trials per class was 50 trials. Therefore, these findings suggested that the results in the time and frequency domains had slightly better accuracy than that of random trials. For some participants, the classification accuracy had no difference compared to random trials. However, the results in the Weber domain were significantly better than those of random trials, and, for all participants, classification accuracy was significantly better than those of random trials.

Discriminating multiclass data with the SVM was conducted with 2 or more SVMs that classified the 2-class classification. Therefore, if the Weber domain that was proposed in this study is used, we suggest that the discrimination of multiclasses may be able to be performed with high accuracy.

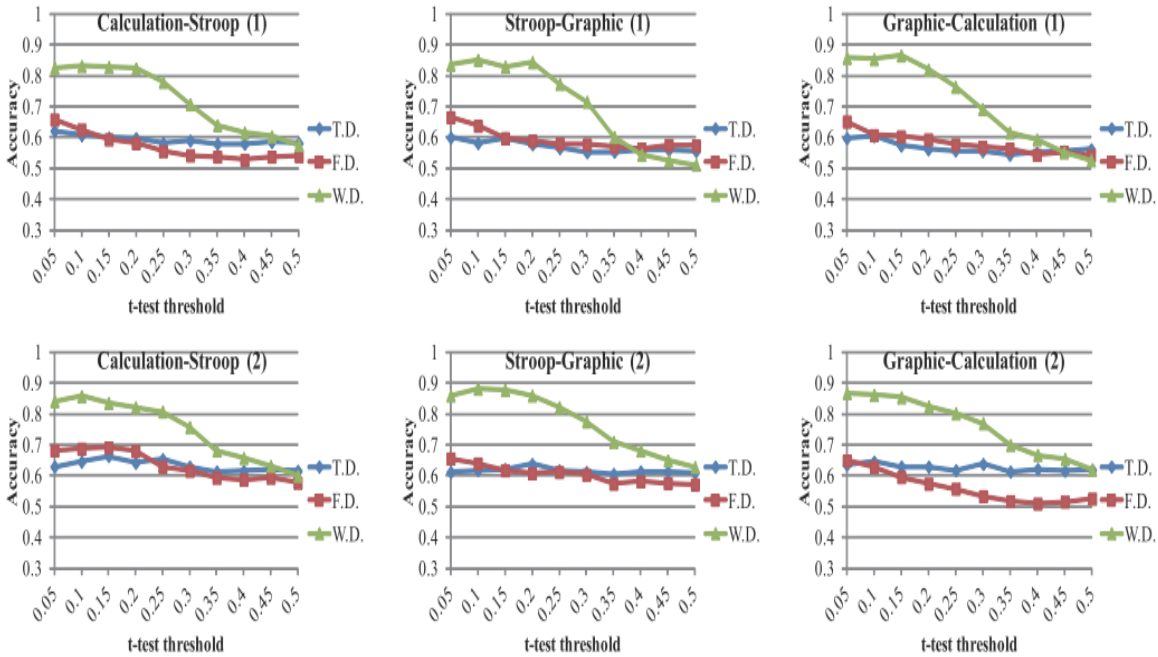

Fig 12. Average classification accuracy of all participants in each domain

Table 1. Results of the classification accuracy in detail

Participant	Domain	1st experiment CS	SG	GC	Minimum	2nd experiment CS	SG	GC	Minimum
A	Time	0.62	0.66	0.70	0.62	0.81	0.68	0.79	0.68
	Frequency	0.72	0.69	0.68	0.68	0.85	0.69	0.69	0.69
	Weber	0.81	0.86	0.85	0.81	0.86	0.94	0.94	0.86
B	Time	0.60	0.60	0.56	0.56	0.64	0.71	0.63	0.63
	Frequency	0.53	0.68	0.58	0.53	0.66	0.55	0.74	0.55
	Weber	0.88	0.94	0.88	0.88	0.88	0.90	0.90	0.88
C	Time	0.70	0.63	0.62	0.62	0.68	0.66	0.69	0.66
	Frequency	0.67	0.56	0.75	0.56	0.69	0.69	0.66	0.66
	Weber	0.77	0.83	0.81	0.77	0.81	0.84	0.89	0.81
D	Time	0.68	0.60	0.60	0.60	0.63	0.62	0.60	0.60
	Frequency	0.70	0.59	0.78	0.59	0.63	0.70	0.66	0.63
	Weber	0.88	0.87	0.90	0.87	0.87	0.90	0.85	0.85
E	Time	0.61	0.58	0.60	0.58	0.64	0.65	0.56	0.56
	Frequency	0.68	0.75	0.61	0.61	0.72	0.64	0.61	0.61
	Weber	0.91	0.89	0.68	0.68	0.90	0.91	0.89	0.89
Average	Time	0.642	0.614	0.616	0.596	0.680	0.664	0.654	0.626
	Frequency	0.660	0.654	0.680	0.594	0.710	0.654	0.672	0.628
	Weber	0.850	0.878	0.858	0.802	0.864	0.898	0.894	0.858

CS : Calculation-Stroop task
SG : Stroop-Graphic task
GC : Graphic-Calculation task

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D. Validation of classification accuracy in 3-class classification (Experiment 1: The experiment with the click operation)

In the classification accuracy verification by 2-class classification with SVM, it was shown that cognitive tasks could classify with high accuracy based on the Weber domain. Therefore, we tried 3-class discrimination by using 3 of the SVMs of 2-class discrimination of 1-on-2 (the number of all of the combinations of every 2 kinds of cognitive tasks was 3). In the discrimination, the class that had the maximum output value of SVM was discriminated as a classification result in each trial. Moreover, of the features that were used for learning and discrimination, the tendencies of the data for each SVM may differ because the task that each SVM is going to identify is different. Therefore, in each combination of each task, feature extraction was performed with a t-test. Furthermore, the combination of the kernel parameter that may become a combination that is suitable for each SVM was examined by changing the value of the kernel parameter. The kernel parameter that elicited the best result was adopted for each SVM by examination. The discrimination accuracy in the 3-class classification was verified in 5-fold cross-validation with the above methods. The discrimination results are shown in table 2. According to table 2, the average discrimination accuracy for all 10 types of data (experimental data times 2 for each of the 5 participants) was 70.5% (maximum, 78.0%; minimum, 63.3%). Here, according to [35], for all of the results, the discrimination accuracy exceeded the chance level in the random trial by 3-class classification (in case of 40 trials/class and 1% significance level, the chance level is 45.0% [35]; in this study, 50 trials/class). This result showed that the cognitive tasks can significantly discriminate in the 3-class classification. Therefore, a BCI that uses a Weber domain for the features and discriminates the 3 kinds of cognitive tasks may be able to be created.

Table 2. Results of the classification accuracy in the 3-class classification (experiment 1).

	Classification accuracy (%)		
Participant	1st experiment	2nd experiment	Average
A	64.0	70.0	67.0
B	70.0	74.7	72.3
C	74.7	74.7	74.7
D	63.3	78.0	70.7
E	70.0	65.3	67.7
Average	68.4	72.5	70.5

E. Validation of classification accuracy in 3-class classification (Experiment 2 : The experiment without the click operation)

We verified the discrimination accuracy in the 3-class classification with the data that were obtained in experiment 2 by 5-fold cross-validation. The discrimination methods were the same as that described in Section 4.4. However, the sampling interval of NIRS (OEG-16) was changed by an upgrade of the instrument in this experiment. The upgraded sampling interval was 0.08 s. The data that were collected for 10 s during task performance (about 128 samples per 1 channel) were increased to 1024 by zero padding in order to raise the apparent time resolution, and these data were used. Moreover, the frequency of around 1 Hz or more became possible to measure by the increase in the sampling frequency. The frequencies of around 1 Hz or more had the high possibility that artifacts from the pulse in the metabolic response and so on will mix. Because the influence of noise was considered, a cut-off frequency was set at 0.75 Hz in the discrimination accuracy verification, and only data of 0.75 Hz or less were used. The discrimination accuracy results are shown in table 3.

According to table 3, the average discrimination accuracy of all of the participants' (5 people) was 73.2% (Maximum, 84.0%; Minimum, 59.3%). Compared to the 70.5% of the average discrimination accuracy in the 3-class classification in experiment 1 with the click operation, a decrease in the discrimination accuracy due to the exclusion of the movement element was not seen. Therefore, in the case of the task design that did not involve the click operation, it is thought that discrimination can be significantly performed as well as in the experiment with click operation. However, because the discrimination accuracy of 1 participant (participant A) was below 60%, further examination is required in implementing the BCI.

Table 3. Results of the classification accuracy in the 3-class classification (experiment 2).

Participant	Classification accuracy (%)
A	59.3
B	84.0
C	70.0
D	76.0
E	76.7
Average	73.2

V. DISCUSSION

This study examined a method of classifying 2 or more cognitive tasks in a single trial with the goal of the development of an interface for which a greater amount of information is reflected by NIRS-based BCI. Therefore, in this study, we proposed a method with the Weber domain that applied Weber's law to the frequency domain data in which FFT had been applied to the time series data that were measured by NIRS for feature extraction for use in learning and classification. Then, first, in order to verify the validity of the proposed method of the combination of the 2 classes of the 3 kinds of cognitive tasks, the classification accuracy was examined with SVM. As a result, in the verification of the classification accuracy in the 2-class classification, the average classification accuracy of the 5 participants in the Weber domain was over 80% for the combination of all of the tasks. Moreover, we showed that the suitable features might be extractable with a comparatively easy method (for example, a t-test) with the Weber domain. For feature extraction, even when there was a significant difference in the independent data, the combination of these data showed that a significant difference may be lost (conversely, even when there is no significant difference in the independent data, a significant difference may arise by combining those data.) [36]. That is, although determining suitable features is a difficult problem, it is thought that suitable features may be able to be extracted with t-tests, which are a comparatively easy method, with the Weber domain that was proposed in this study. Furthermore, because the average classification accuracy exceeded 80%, discrimination in multiclasses with SVM may be performed with high accuracy. Then, the potential of 3-class discrimination was also examined. As a result, even in the task design that eliminated the movement (click) operation, the average discrimination accuracy became 73.2%. This result exceeded chance level [35] in all of the participants, which took the confidence interval into consideration by 1% of the significance level in the 3-class discrimination. Therefore, this study demonstrated the potential for the increase in the amount of communication and the transfer time reduction by a BCI that was based on 2 or more cognitive tasks with the Weber domain. Moreover, for all of the features, the classification accuracy in the experiment with the shortened rest period was not reduced compared to the experimental results with the standard rest period. These results suggested that shortening the rest period had a very small effect on discrimination accuracy. Furthermore, therefore, our study suggested that shortening of the rest period is possible. If the rest period can be shortened, it seems that shortening the rest period would contribute to the time reduction for the communication of information by the BCI. As mentioned above, a BCI that discriminates the 2 or more cognitive tasks with the Weber domain for extraction of the features may be able to be developed. It is thought that much information can be transmitted at the same time with such a BCI. In addition, the transfer time may also be able to be shortened. However, when implementing, further discrimination accuracy improvements are required. Moreover, examinations are also needed of the concrete indicators (for example, the presentation method of choices and task, and interface design) that are required for implementing the increase in the amount of information by the 2 or more cognitive tasks to the BCI. A consideration of the intelligibility for a participant is necessary. Furthermore, a consideration of the ease of the concentration for the performance of a task is also necessary.

VI. CONCLUSION

This study examined a method of classifying 2 or more cognitive tasks in a single trial with the goal of the development of an interface with which a greater amount of information is reflected in NIRS-based BCI. If 2 or more cognitive tasks can be discriminated by brain activity, 2 or more types of information can be added to a single-selection operation, and this will lead to an increase in the amount of communication of information and a shortening of transfer time in the BCI. Therefore, in this study, we proposed a method that used the Weber domain that applied Weber's law to the frequency domain data in which a FFT was applied to the time series data that were measured by NIRS for feature extraction for use in learning and classification. As a result of the verification, the average classification accuracy in the 2-class classification of 5 participants in the Weber domain was over 80% for the combination of all of the tasks. Moreover, we showed that the suitable features might be extractable with a comparatively easy method with the Weber domain. Furthermore, when the possibility of 3-class discrimination was also examined, even in the task design that eliminated the movement operation, the average discrimination accuracy became 73.2%. For this reason, we think that the potential for an increase in the amount of communication and a reduction in the transfer time by NIRS-based BCI that was based on 2 or more cognitive tasks with the Weber domain was demonstrated. In the future, we are going to perform these experiments with many participants in order to verify a general potential. Furthermore, the application to an actual BCI system (for example, spelling supporting system) is due to be considered.

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