

ISASE 2019

Performance Improvement of Motor-Imagery BCI Using Multi-Mental Tasks

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Abstract: We studied a motor-imagery brain-computer interface (MI-BCI). An MI-BCI is an interface that allows a computer to be operated by changes in brain activity that occurs when the operator imagines moving a body part. For example, with MI-BCI it is possible to assign left-hand motor-imagery to power an ON/OFF command. One of the problems with MI-BCI is its low performance, especially since MI-BCI has few commands. We aimed to improve the performance of MI-BCI by adding to the number of commands. Currently, MI-BCI has four commands based on “left hand,” “right hand,” “legs,” and “tongue” motor imagery. Therefore, we attempted to add to the number of MI-BCI commands by classifying eight kinds of brain motor-imagery activity: “no imagery,” “left hand,” “right hand,” “legs,” “both hands,” “left hand + legs,” “right hand + legs,” and “both hands + legs.” Motor imagery that involves multiple body parts, for example, “both hands,” is referred to as a multi-mental task. Multi-mental tasks involve a combination of simultaneous motor imagery, for example including the left and right hands and the legs. This makes it possible to increase the number of commands to 2^N (where N is the number of body parts). Eighteen healthy males in their twenties participated in this study. The use of multi-mental tasks enabled us to improve MI-BCI performance in two out of three subjects. Multi-mental tasks can be used to add choice to MI tasks. Performance improvements using an MI-BCI were made possible by choosing MI tasks associated with high accuracy.

Keywords: MI-BCI, ERD/ERS, Multi-mental task

1. INTRODUCTION

A motor-imagery brain-computer interface (MI-BCI) is an interface that can send commands to devices designed to move the body using an electroencephalogram (EEG) generated by imagining the movements. Unlike others BCIs, MI-BCI can send commands to computers under voluntary timing.

In this research, we aimed to improve the performance of MI-BCI. The information transfer rate (ITR) is a performance index used for BCIs. ITR is the amount of information traffic per unit time. It is calculated using Eq.1, where M is the number of commands, P is the

accuracy, and T is the time (in seconds) required for one command selection. For this research, we improved the performance of an MI-BCI by adding to the number of commands used.

Several studies have been conducted which aimed to add to the number of MI-BCI commands. Townsend et al. increased the number of commands by adding the tongue to the MI task classification [1]. However, there was no discussion on whether additional body parts could be added. Geng et al. classified four EEG states: “no imagery,” “left hand,” “right hand,” and “both hands,” by combining MI for both left and right hands [2]. The simultaneous MI of different body parts is called a multi-mental task. The number of commands becomes 2^N (where N is the number of MI body parts) due to the multi-mental task. However, there are still just four commands, so this research cannot be said to have added to the number of MI-BCI instructions.

For the current research, we aimed to improve the ITR of MI-BCIs by using eight mental tasks: “no imagery,” single mental tasks (“left hand,” “right hand,” and “legs”) and multi-mental tasks (“both hands,” “left hand + legs,” “right hand + legs,” and “both hands + legs”).

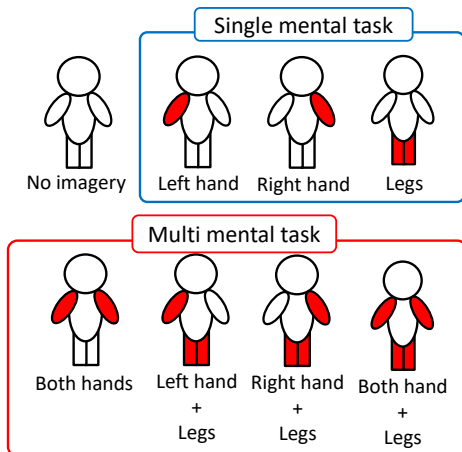


Figure 1: Motor imagery mental tasks

$$ITR = \left(\log_2 M + P \log_2 P + (1 - P) \log_2 \left(\frac{1 - P}{M - 1} \right) \right) \times \frac{60}{T} \text{ [bits/min]} \quad \text{Eq.1}$$

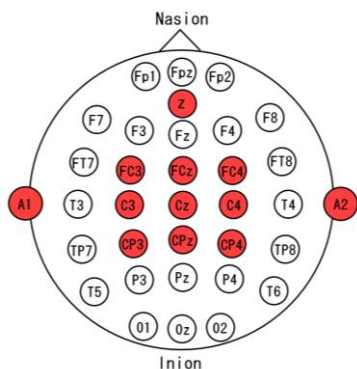


Figure 2: Electrode arrangement

2. MEASUREMENT

2.1 Measurement outline

The study subjects were 18 healthy males in their twenties. Figure 2 shows the electrode arrangement used. The international 10–20 method was used, with reference electrodes A1 and A2, and nine electrodes centered on the top of the head (FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, and CP4) used as probe electrodes. The z electrode was used to check impedance.

The flow of measurements is shown in Figure 3. Subjects remained in a resting state for 15 seconds after measurements were begun. Subjects then performed a motor-imagery task for 3 seconds followed by a resting state for 6 seconds, and this was then repeated 30 times. Subjects undertook MI tasks based on images presented to them. The contents of the task were in the order of “no imagery,” “left hand,” “right hand,” “both legs,” “both hands,” “left hand + legs,” “right hand + legs,” and “both hands + legs.” We gave instructions to imagine grasping for the hand MI task and to imagine walking for the leg MI task.

2.2 EEG analysis/Feature extracts

When MI is performed, the frequency power decreases

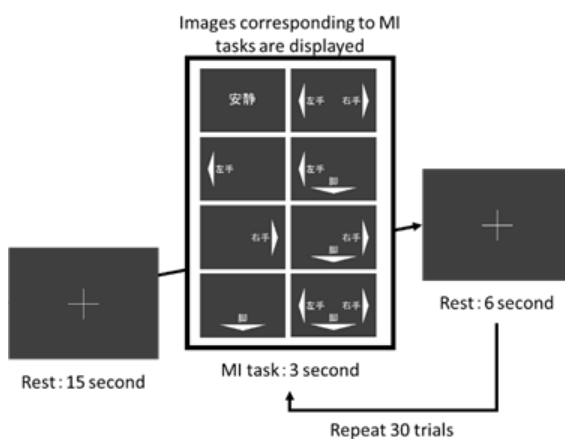


Figure 3: Measurement flow

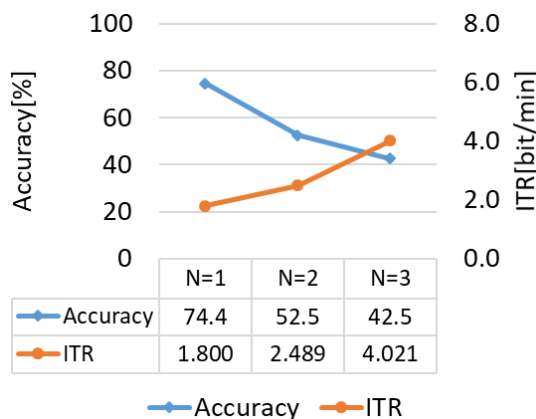


Figure 4: ITR and accuracy by adding the number of body parts (Sub.1)

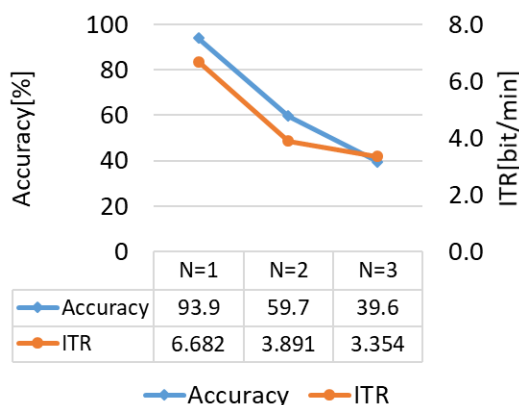


Figure 5: ITR and accuracy by adding the number of body parts (Sub.2)

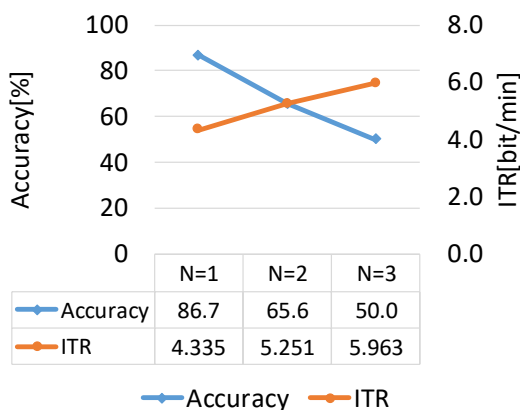


Figure 6: ITR and accuracy by adding the number of body parts (Sub.3)

in the motor cortex by 8 to 13 Hz. This phenomenon is called event-related desynchronization (ERD) [3]. We focused on ERD and classified EEGs relating to it. EEG classification was performed on three subjects who exhibited an ERD response. The MI task-time frequency power was extracted as a feature value using a short-time Fourier transform (time window: 3 sec, movement width: 0.3 sec). We classified MI tasks using feature values. In the classification, one versus rest classification by linear support vector machine was used, and three-fold cross verification was applied.

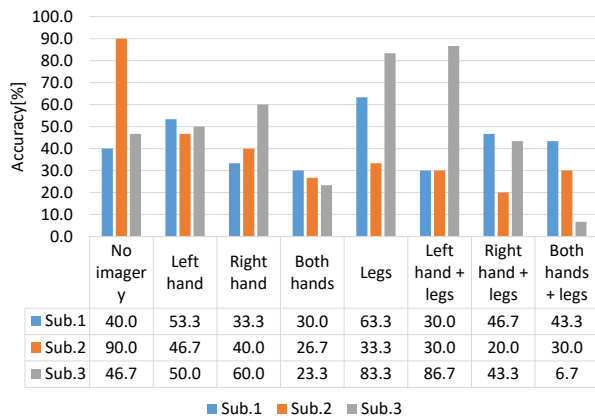


Figure 7: Accuracy of each MI task

3. CLASSIFICATION RESULTS

3.1 Improvement of ITR by adding body parts

Figures 4-6 show changes in accuracy and ITRs by adding to the number of MI body parts. Sub.1 and 3 showed an increased ITR when body parts were added to the MI task. However, for Sub.2 the ITR decreased when body parts were added to the MI task.

3.2 Eight-class classification

Figure 7 shows classification results using eight-class classification. Accuracy of more than 85% was obtained for “no imagery” and for “left hand + legs” by Sub.2 and 3, respectively. However, there was a misclassification by Sub.1 for “right hand + legs,” by Sub.2 for “left hand + right hand” and “right hand + legs,” and by Sub.3 for “left hand + right hand” and “left hand + right hand + legs.” This confirmed that for each subject there were different high-accuracy and low-accuracy MI tasks.

3.3 Selection of MI tasks

Each subject showed low accuracy for some MI tasks. Therefore, we tried to improve the ITR by excluding low-accuracy MI tasks. One-by-one we removed the lowest accuracy MI tasks, other than “no imagery.” Figures 8–10 show changes in accuracy and ITR following the removal of low-accuracy MI tasks. In the lower part of the figure, the MI tasks used for the classification are shown. The maximum ITR was shown for 4 classes in Sub.1, 3 classes in Sub.2 and 5 classes in Sub.3.

4. DISCUSSION

It was confirmed that adding MI body parts improved the ITR for two out of three subjects; this suggests that the use of multi-mental tasks can improve the performance of MI-

BCI.

It was found that high accuracy MI tasks differed among subjects. Therefore, we tried to improve ITR by choosing MI tasks that were associated with high accuracy. Furthermore, we confirmed that multi-mental tasks included the maximum ITR for all subjects. This suggested that ITR improvements for MI-BCI can be achieved by using multi-mental tasks.

Ultimately, only one more command was added to the number used in previous studies. However, the choice of MI tasks for use with the MI-BCI was increased by the inclusion of the multi-mental tasks. These multi-mental tasks contributed to improving the performance of MI-BCI because MI tasks could be specifically tailored to BCI users.

5. CONCLUSION

In this research, we aimed to improve MI-BCI performance by increasing the number of commands used. To increase the number of commands, we proposed the use of multi-mental tasks. As a result, we found that MI tasks with high accuracy were different for each subject, and we succeeded in improving the ITRs by using these MI tasks. In addition, it was confirmed that the multi-mental tasks included all subjects’ maximum ITR, highlighting the usefulness of these tasks.

One of the advantages of multi-mental tasks is the ability to add MI task choices for MI-BCIs. In the future, we aim to improve the performance of MI-BCIs by including multi-mental tasks with the tongue added as an MI task.

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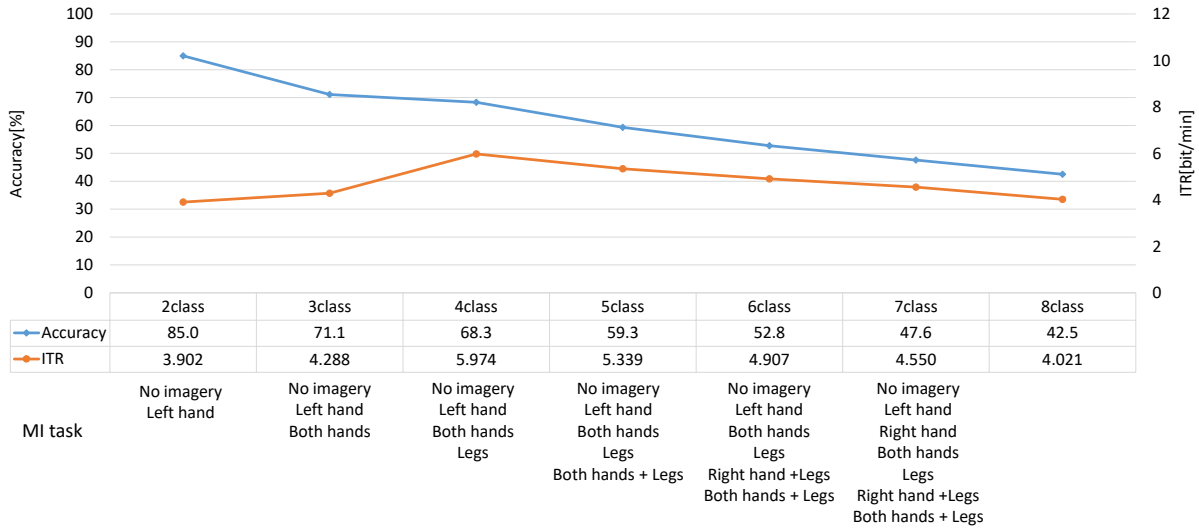


Figure 8: ITR and accuracy by selection of MI task (Sub.1)

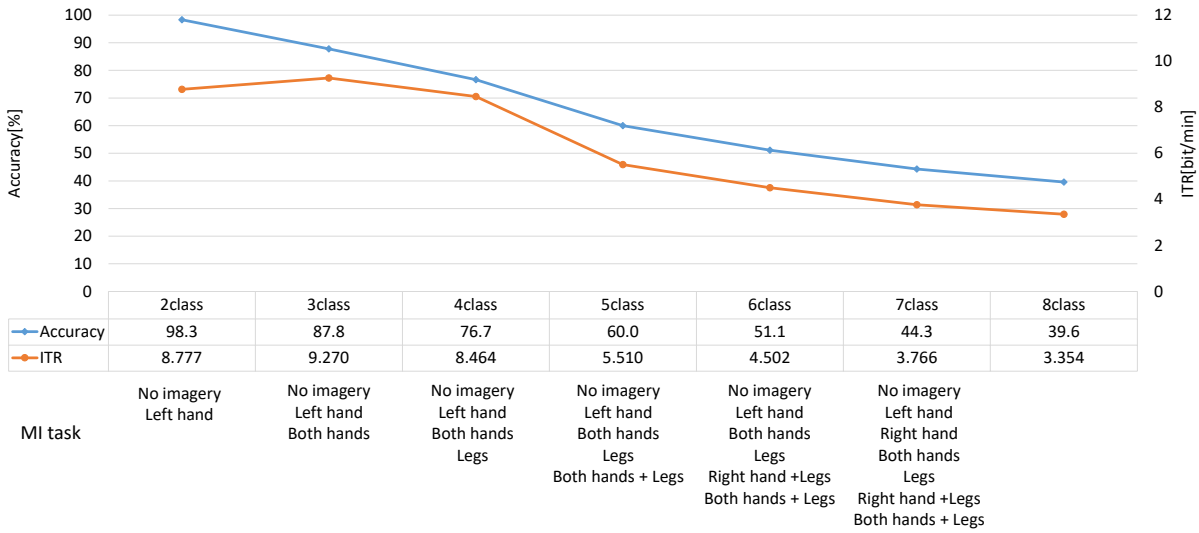


Figure 9: ITR and accuracy by selection of MI task (Sub.2)

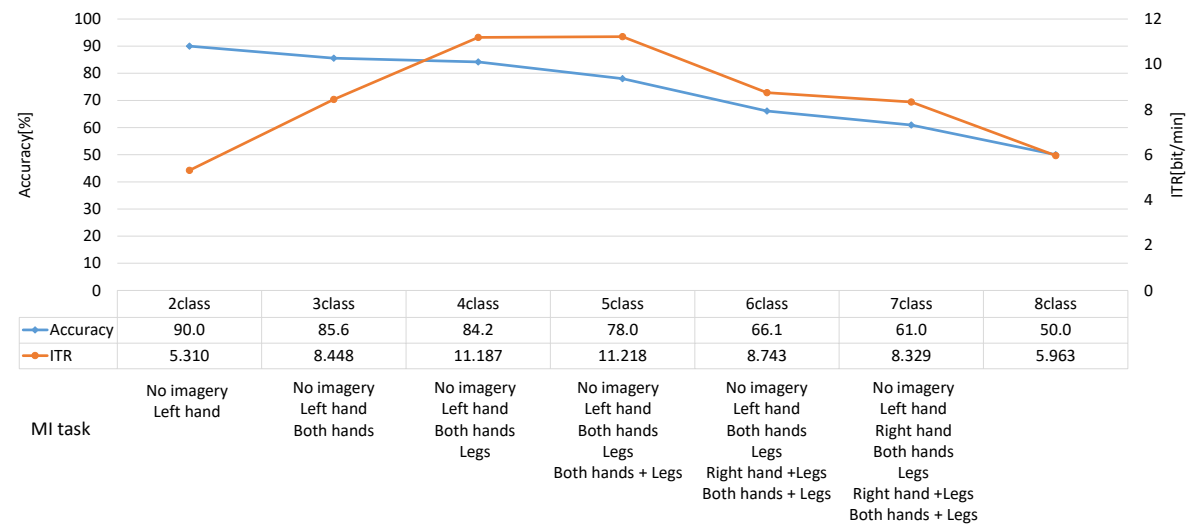


Figure 10: ITR and accuracy by selection of MI task (Sub.3)