Effective Approach to Character Input for Novice BCI Users

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***Abstract*— A brain-computer interface (BCI) character input experiment focusing on participants' BCI intelligibility was performed. In theory, a BCI can be operated by anyone if cognitive activity is possible. However, individual differences clearly occur in practice. Therefore, we supposed that this difference was related to BCI intelligibility. In a previous study, BCI experts and BCI novice users were compared. Therefore, in this study, we compared three types of subjects: experts, novice users, and novice users who received pre-guidance. The pre-guidance provided instructions about the tips, tricks, and traps of BCI operation. As a result, the classification rate was 80% or more, in all groups. However, high accuracy was only produced by the group that had BCI intelligibility. The accuracy results for novice users who did not receive pre-guidance was 13.6%, the results for experts was 62.4%, and the results for novice users who received pre-guidance was 71.1%. From these results, the effectiveness of pre-guidance for a novice user was demonstrated.**

Keywordst; BCI, P300 Speller, BCI intelligibility, Accuracy

I. INTRODUCTION

Individuals suffering from intractable nerve disease, including amyotrophic lateral sclerosis (ALS), often have difficulty communicating. Such individuals have benefited from the development of communication aids (CA), such as the dial and interactive equipment. Recently, the use of brain-computer interface (BCI) in CAs has been investigated. A BCI is a device that enables operation of equipment using electroencephalogram (EEG) as a switch. Therefore, if the central nervous system is normal, it is possible for an individual with limited motor function to operate some CA equipment.

We have designed a BCI system based on a needs survey of ALS patients and occupational therapists (OT) [1] [2]. The proposed BCI system is intended to be used by ALS patients. In the previous study, we conducted the EEG measurement according to the posture of the ALS patients' use of BCI [3]. This study includes experiments conducted on undergrads and OTs. Based on the results, we found that OTs had a lower accuracy than undergrads.

In this study, we have assumed that the lack of BCI intelligibility is the cause of the low accuracy. We have performed an experiment to compare expert and novice BCI users. We consider a new approach to improve accuracy for novice BCI users.

II. CHARACTER INPUT TYPE BCI

A. P300 Speller

In this study, we adopted the P300 Speller, which has been described by Donchin and Farwell [4], as a character input BCI. The P300 is a component of event-related potential (ERP), and the ERP is a potential variation that occurs transiently in relation to external or internal factors. P300 is an evoked potential with latency of approximately 300 ms that occurs in response to stimuli [5]. Hereafter, in this paper, BCI refers to the P300 Speller.

Figure 1 illustrates the BCI screen display used in this study. Characters are arranged in a 6 × 10 matrix. The rows and columns flash in a random order as visual stimuli. The EEG signals, synchronized with the flashes, are recorded for the responses to each row and column. After a set number of flashes, the average EEG waveform (ERP) corresponding to each stimulus is recorded. Among the ERP of each matrix, the P300 that is elicited by paying attention to the stimulus appears in a particular row and column. The user input character is estimated from intersection of a row and column where the P300 was most evoked.

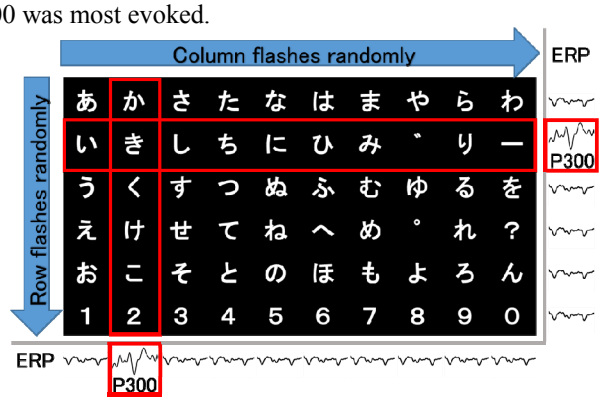

Fig1. P300 Speller Hiragana input method

B. *Classification of the ERP*

ERP classification is performed to determine where P300 occur most frequently in the matrix. However, P300 have individual differences, such as differences in amplitude and latency, relative to the degree of the attention. Therefore, it is necessary to adjust the classifiers for each individual by using supervised learning. In this study, linear discriminant analysis (LDA) is used for ERP classification.

LDA is a generative model that models conditional probability to achieve a linear classifier by assuming a multivariate normal distribution model. Such a linear classifier is expressed by Equation (1). Equation (1) performs two operations for $\boldsymbol{x}$ vector of D dimensions. The first operation obtains a hyperplane of $D-1$dimensional space, i.e., the decision boundary during training. The second operation obtains a scalar value by projecting into a one-dimensional vector during classification. In practice, training calculates the weight w and the bias w_0 of the decision boundary. Focusing on the sign of the scalar values, the determining region is two region. Therefore, this is a binary classifier [6]. Equation (2) represents the implementation of the classifier for the BCI. Here $class$ is a determining region classifier output, C_1 is an EEG containing a P300, and C_2 is an EEG without a P300.

$$y(x) = f(w^T x + w_0) \tag{1}$$

$$class(x) = \begin{cases} C_1 & w^T x + w_0 > 0 \\ C_2 & (otherwise) \end{cases} \tag{2}$$

However, this classifier does not always provide correct classification. To evaluate classifier accuracy, the classification rate [%] can be calculated using Equation (3). If classification rate is high, the character input accuracy is also good. In addition, the classification rate can also be regarded as an index of whether the user is able to focus on the stimulus properly.

$$Classification\ rate = \frac{collect\ classification}{all\ data}[\%] \tag{3}$$

III. EXPERIMENT

In a previous study, the results for accuracy were lower for OTs (16.7%) compared to undergraduates (52.9%) [3]. In this study, we have assumed that the low accuracy is caused by the level of BCI intelligibility and performed a comparison experiment with BCI experts and novice users. Evaluation of experiment results considered the classification rate [%] and character input accuracy [%]. Character input accuracy relates to the rate at which input strings are detected successfully.

A. *Participants*

Four people participated in the experiment (one undergraduate, three OTs). The undergraduate had studied the use of BCIs. Therefore, an undergrad was familiar with BCI, and the undergrad had experience as well. The OTs were from the Department of Rehabilitation at the Kitasato University East Hospital. Among the three OTs, one had experience with BCIs; however, two OTs had no experience. The OT with no experience received information about the operation of a BCI prior to participating in the experiment. This experiment was carried out on the basis of an ethical review of Kitasato University East Hospital (approval number: Treatment 12-749). The experiments were conducted in a room provided by the East Hospital's Department of Rehabilitation.

B. *Pre-guidance*

OT participants received pre-guidance on the BCI to reduce the difference between the experts and novice users. The guidance provided was as follows: (1) BCI character input by classifying the P300. It is necessary to train the classifier in order to classify P300. It is possible to train the classifier by performing character input. However, if poor training data is used, the accuracy of a classifier will be low. Please perform a task for classifier learning to concentrate on. (2) Character input method by flashing rows and columns of the matrix. Attention can be diverted when something other than the input character is flashing. When a non-input character is flashing, please try not divert attention from the input character in order to prevent false responses. (3) When the input character is flashed, please pay attention to the character in strong consciousness.

C. *Procedure, task and design*

The subjects performed the experimental tasks while in a supine position to simulate the use of a BCI by ALS patients (Fig.2). Gel injection type active electrodes (g.tec Inc. g.LADYbird) were used. The electrode configuration was based on the international 10-20 system to suit the supine position, as shown in Figure 3 (Fz, Cz, C3, C4, Pz, P3, Oz, and PO7). The reference electrode was at position A1, and the ground was at position Fpz. A unipolar derivation method was used. EEG signals were filtered with a band pass filter (0.5–30Hz). EEG signals were amplified using a biological amplifier (g.tec Inc. g.USBamp). Processing, recording, and analysis were performed using BCIsys, which was developed using MATLAB (MathWorks Inc.).

In this experiment, the copy spelling system was employed. Participants locked at the input characters on a monitor screen (Diamondcrysta WIDE RDT231WM) that was placed by the bed. The screen displayed a 6 × 10 matrix. The presentation screen was controlled by a notebook PC (GALLERIA QF655). The first step to train the classifier involved each row and column flashing 15 times. Then, the classifier was trained using LDA. Next based on the trained classifier, a character input task was performed. In this task, each row and column flashed 10 times. One task was set to the input of 6-7 characters, three tasks were performed.

Fig2. Supine position

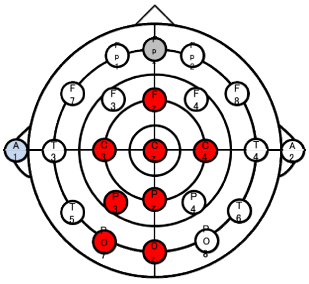

Fig3.Electrode placement

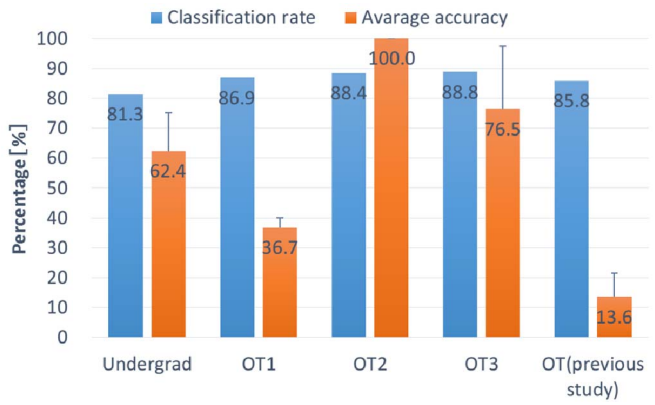

Fig4. Classification rate and average accuracy. BCI intelligibility of each subject: the undergraduate was an expert, OTs 1–3 were novice users who received pre-guidance and the OT from a previous study was also a novice user.

IV. RESULT

A comparison of the classification rate and character input accuracy for each participant is shown in Figure 4. Accuracy is determined by an average of three tasks. In addition, results for an OT from a previous study [3] are included to compare the differences for BCI intelligibility. The OT from the previous study was a novice BCI user, and does not received pre-guidance (the contents of the Ⅲ.Experiment B. Pre-guidance).

There was no significant difference among subjects for classification rate; the rate was 80% or greater for all participants. In contrast, there were differences among subjects for the BCI accuracy results. For BCI accuracy, the results were as follows: undergraduate, 62.4 ± 12.8%; OT1, 36.7 ± 3.3%; OT2, 100.0 ± 0.0%; OT3, 76.5 ± 20.8%; OT from the previous study, 13.6 ± 7.9%. It should be noted that the BCI accuracy rate for OT2 was 100% in all three tasks. The overall accuracy for the four participants was higher than that OT from the previous study.

V. DISCUSSION

Theoretically, assuming cognitive activity, it is possible for anyone to operate a BCI sufficiently. However, in practice, there is a difference in BCI accuracy for each user. Therefore, we assumed that this difference was due to BCI intelligibility. The experiment described in Section IV was performed to test this hypothesis. A comparison of expert and novice BCI users had been performed in a previous study [3]. Therefore, in this study, experts and novice users with and without pre-guidance participated in the experiment.

The classification rates for all participants were 80% or more. Therefore, it is evident that all participants were able to classify stimuli, i.e., cognitive activity required for BCI is proven to be better even for novice users. In addition, the OTs who received pre-guidance showed very high classification rates (average 88.0 ± 0.8% or greater). These OTs were instructed to concentrate on the classifier training task. This purpose of the guidance is to improve the training data, which in turn improves classifier accuracy (classification rate). In other words, it seems that the pre-guidance affected the classification rate.

If the classification rate is high, BCI accuracy should improve. However, BCI accuracy for an expert (62.4%) and novice users who received pre-guidance (71.1% average for three participants) was higher than that a novice user who did not receive pre-guidance (13.6%). The matrix flashing method was used for the BCI in this experiment. A tendency for attention to be drawn to non-input characters rather than the input character is problematic in this method. In the pre-guidance, OTs were instructed not to divert their attention from the input character, and they were also instructed to maintain strong focus when the input character flashed. As a result, they could input a character without diverting attention to the non-input character more reliably than novice users; the performance of OTs who received pre-guidance was comparable to that of expert BCI users.

There was a difference in understanding of the tips, tricks, and traps of the character input method for BCI between the novice users and experts. The difference in the understanding was reflected in the correct answer rate. For novice users, pre-guidance appeared to be effective because the classification rate and character input accuracy were improved if novice users received pre-guidance.

VI. CONCLUSION

When a BCI is used as a CA, the user is a patient. Moreover, many patients are novice BCI users. So far, in theory, it was considered that even a novice user could use the BCI if cognitive activity was possible. However, to increase accuracy of operations, it was found that a more in-depth understanding of the tips, tricks, and traps of BCI operation is helpful. Therefore, to achieve high accuracy, pre-guidance is important for novice BCI users.

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