Incremental Learning to Reduce the Burden of Machine Learning for P300 Speller

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***Abstract*—The P300 speller is one of the BCI applications, which allows users to select letters just by thoughts. However, due to the difference of P300 in each person and with the passage of time, users are required to do machine learning every time before use (pre-training). This pre-training is a burden to users. This paper proposes an incremental learning using unknown data to reduce the training time. Consequently, this paper shows that the proposed method gives not only the reduction of the training time but also directly use of P300 speller without pre-training by using the data of last time.**

I. Introduction

Brain-Computer Interfaces (BCIs) allow users to communicate and control external devices without using muscles[1]. Because of this usability, BCIs are appealing to severely paralyzed patients like those with amyotrophic lateral sclerosis (ALS)[2]. Moreover, they are also appealing to healthy people as amusement applications. As for the measurement of brain activity, the electroencephalogram (EEG) has been used well for BCIs because it is noninvasive and inexpensive. P300 speller, which is first introduced by Farwell et al. in 1988, is an EEG-based word input system[3], and it extracts P300 as the target feature for the classification task. The P300 speller typically has 36 characters containing alphabets and numbers on 6×6 matrix (Fig. 1). Each row and column is flashed one by one with random order, which is called stimulus presentation, for the fixed number of times. It discriminates the user's desired character using P300 evoked by the highlight of a row or a column that includes the attended character by the user.

The patterns of Event Related Potential (ERP) including P300 differ from subject to subject and time to time. Therefore, just before actual use, the classifier has to be training with training data, which is called "pre-training." Because of this, users are required to input a set of prepared characters to record training data. With a well trained classifier, P300 speller can recognize the user's P300 pattern to complete the word input task properly. However, due to the low signal-to-signal ratio of P300, it is hard to train a classifier using small number of training data. Thus, large number of training data is needed to discriminate P300 data from non-P300 data with high accuracy. In a lot of previous researches[4][5], 20 or more characters are used for the training data which takes around 20 minutes and gives a lot of burden to users. Considering its practical use, the method which can reduce the pre-training time as well as maintain good discrimination accuracy is needed. Thus, this paper aims to reduce the pre-training time maintaining a high level of accuracy.

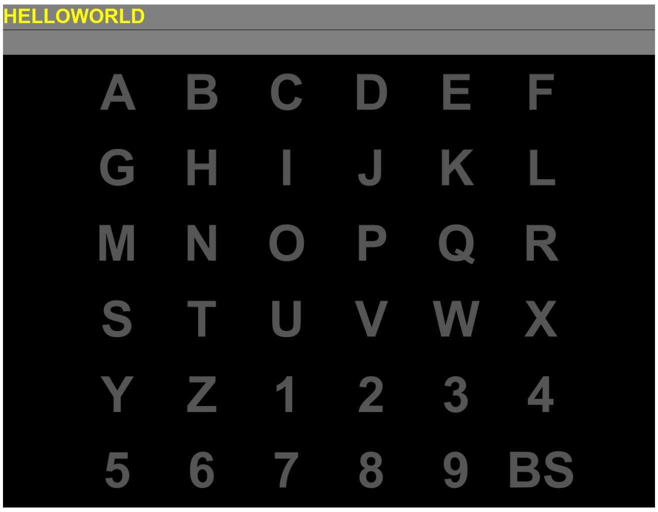

Fig. 1. Interface of P300 speller

In the conventional P300 speller, a classifier is trained based on the pre-training data. However, when the test data have high reliability, they could be used as well as the training data to improve the performance of the classifier incrementally. When this incremental training is available, it is expected to reduce the pre-training data and the time for it. Moreover, it is also expected that the classifier can be fit for another use with the passage of time. The problem to use the test data as the training data is that the connect label of the discriminated data is unknown. If the incorrectly classified data is added to the training data, the fitness of the classifier will become worse and the accuracy will be decreased. Fortunately, "Backspace" is prepared for P300 speller to delete the incorrectly detected characters[6]. Thus, using the Backspace, the correctness of the detected characters can be calculated - If the characters is not deleted by the Backspace, the data of that character can be treated as a correct input and it will be added to the incremental training data set. Otherwise, if the character is

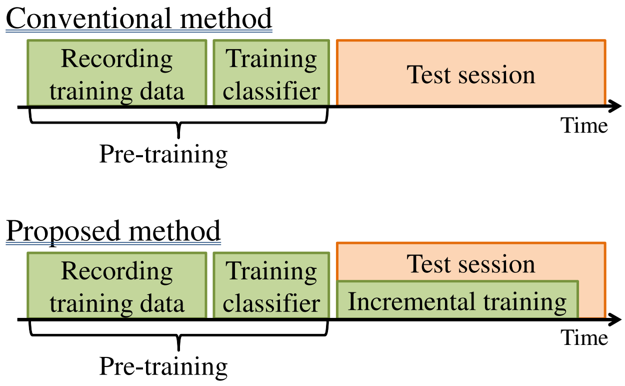

Fig. 2. Conventional method and proposed method

deleted, it will be treated as an incorrect input and will not be added to the training data. In this paper, using this unique characteristics of P300 speller, an incremental training method based on unknown data is proposed.

II. Proposed Method

As shown in Fig. 2, the conventional P300 speller trains the classifier based on the pre-training data. In contrast, the proposed method trains the classifier based on not only the pre-training data but also the test data incrementally. However, if the incorrectly classified data is added to the training data, the fitness of the classifier will become worse and the accuracy will be decreased. Therefore, in this method, the "Backspace" is treated as reliable the absolute input, because the probability that an incorrect input becomes the Backspace is very low, 1/30 for incorrect discrimination in Fig. 1, even if the accuracy of the system is low. For example, the proposed method adds the test data of a discriminated character into the training data set, then if the character is deleted by the Backspace, it is also deleted from the training data.

III. Experiment

A. Experimental Setting

In this experiment, the P300 speller implemented in BCI2000[7], a general-purpose system for brain-computer interface research, was employed. EEGs were recorded from five electrodes: Fz, Cz, Pz, O1 and O2[8] referenced to the linked-ears, with the sampling rate of 100 Hz using Polymate AP216 (DIGITEX LAB. CO., LTD, Tokyo, Japan). The stimulus onset asynchrony (SOA) was 200 ms: each stimulus was presented for 100 ms with an inter-stimulus interval (ISI) of 100 ms. 120 stimuli were presented per a character. A high-pass filter with a cut-off frequency of 1 Hz was applied to EEGs. Then the data was extracted with a time window from 0 ms to 650 ms after each stimulus and down-sampled to 20Hz. Linear Discriminant Analysis (LDA) was employed as the classifier.

Four healthy subjects (sub1 - sub4, all male) volunteered to participate in this experiment. First, the subjects were required to input two characters, "O" and "W," for the pre-training data. After the classifier was trained using the pre-training data set, each subject performed four test sessions. Either the conventional method or the proposed method was alternately assigned to the test sessions in the order that brought a balance among subjects. In the test sessions, subjects were required to input 10 characters, "HELLOWORLD." If an incorrect character was inputted, the subject should try to delete it by inputting "Backspace." Moreover, due to the avoidance of prolonged experiment, when the number of characters except deleted ones by "Backspace" became 10, the test session was finished even if the inputted characters did not fit the target ones. This experiment is called "Exp.I."

Another experiment was done, which is called "Exp.II," to confirm if the proposed method could apply to the difference of P300 with the passage of time. One week after Exp.I for every subject, Exp.II was done. In Exp.II, the pre-training data recorded in Exp.I was used as that in Exp.II. In the test sessions, the task and the target characters were same as those of Exp.I.

B. Experimental Setting

This paper utilizes "Utility[6]" as the performance evaluation defined in Eq. (1).

$$U = \frac{(2P-1)\log_2(N-1)}{d} \qquad (1)$$

where N is the number of classes (in this experiment, N = 36), P is the accuracy, and d is the discrimination time. Note that if $P < 0.5$, $U = 0$. Utility corresponds to the information transfer rate when the spelling is done perfectly using "Backspace" that can delete incorrect characters. Thus, it is thought to be a practical performance measure for the P300 speller.

IV. Result and Discussions

Fig. 3 shows the comparison of the accuracy between the conventional method and the proposed method. Moreover, Fig. 4 shows Utility of these experiments.

As shown in Fig. 3, in Exp.I, there was not a big difference in performance between the conventional method and the proposed method especially in sub 2 and sub 4. In the conventional method, the accuracy of Exp.II much decreased comparing with that of Exp.I. In contrast, in the proposed method, there was not a big difference in performance between Exp.I and Exp.II. Utility shows similar result to the accuracy. A Two-way (Exp.I vs. Exp.II and the conventional method vs. the proposed method) repeated-measures ANOVA[9] was conducted with the respect to Utility, and the result showed there was no statistically significant difference between Exp.I and Exp.II (p(Exp.I vs Exp.II) = 0.248) while there was statistically significant difference between two methods (p(conventional method vs. proposed method) = 0.0114 $<$ 0.05). Moreover, the average Utility of all subjects ("AVG." in Fig. 4) shows the better result of the proposed method than the conventional method.

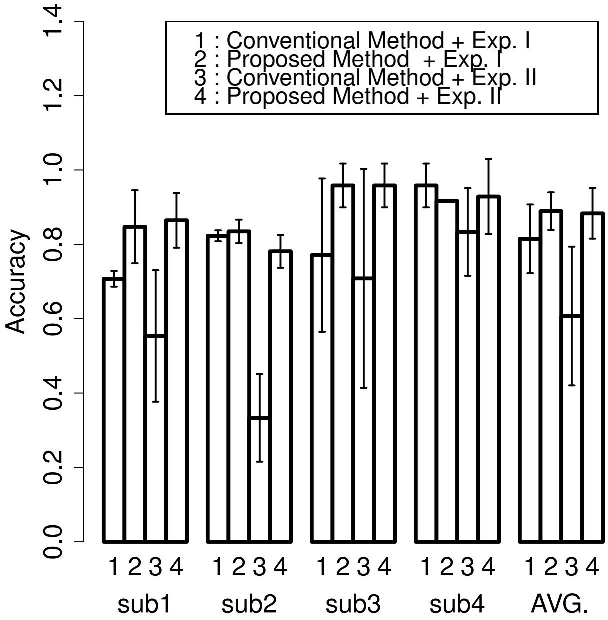

Fig. 3. Classification accuracy

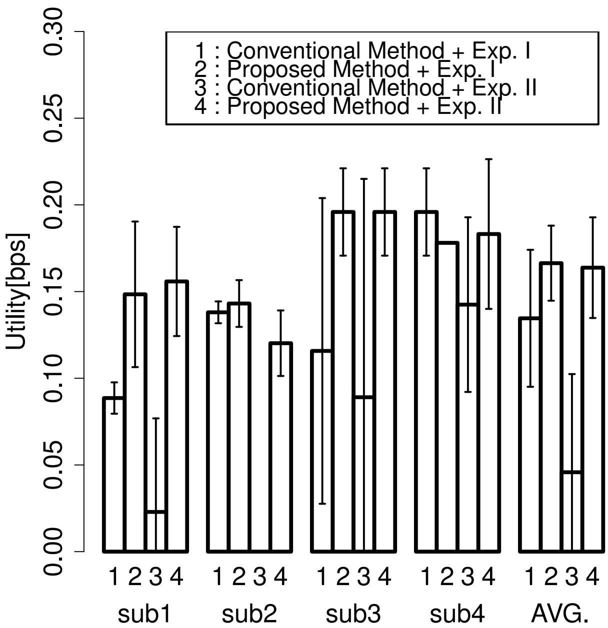

Fig. 4. Utility

Fig. 5 shows the change of the averaging accuracy per a letter when the number of stimuli increase in each subject. In all subjects, the proposed method reached the same accuracy faster than the conventional method. It shows that the proposed method is more practical than the conventional method.

V. Conclusion

In this paper, an incremental learning method for P300 speller was proposed. In general, to spell with high accuracy, P300 speller needs a large number of training data for pre-training. This paper showed that the proposed method performed high accuracy with a small number of training data. Moreover, due to the difference of P300 with the passage of time, users are required to recode pre-training data just before every actual use in the conventional method. This paper also showed that the proposed method gave the spelling with high accuracy again with the pre-training data recorded one week before.

In this paper, the classification accuracy of "Backspace" was assumed to be 1.0 while "Backspace" could be also detected incorrectly. Thus, the incremental learning method considering the accuracy of "Backspace" should be studied in the future work.

Acknowledgment

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References

[1] J. Wolpaw *et al.*, "Brain-computer interfaces for communication and control," *Clinical neurophysiology*, vol. 113, no. 6, pp. 767–791, 2002.

[2] D. Kaub-Wittemer *et al.*, "Quality of life and psychosocial issues in ventilated patients with amyotrophic lateral sclerosis and their caregivers," *Journal of pain and symptom management*, vol. 26, no. 4, pp. 890–896, 2003.

[3] L. Farwell *et al.*, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalography and clinical Neurophysiology*, vol. 70, no. 6, pp. 510–523, 1988.

[4] Y. Kaneda *et al.*, "Performance evaluation of reliability-based selective repeat automatic repeat request applied to p300 speller by online experiment," *Technical Report of IEICE*, vol. 110, no. 461, pp. 35–40, 2011.

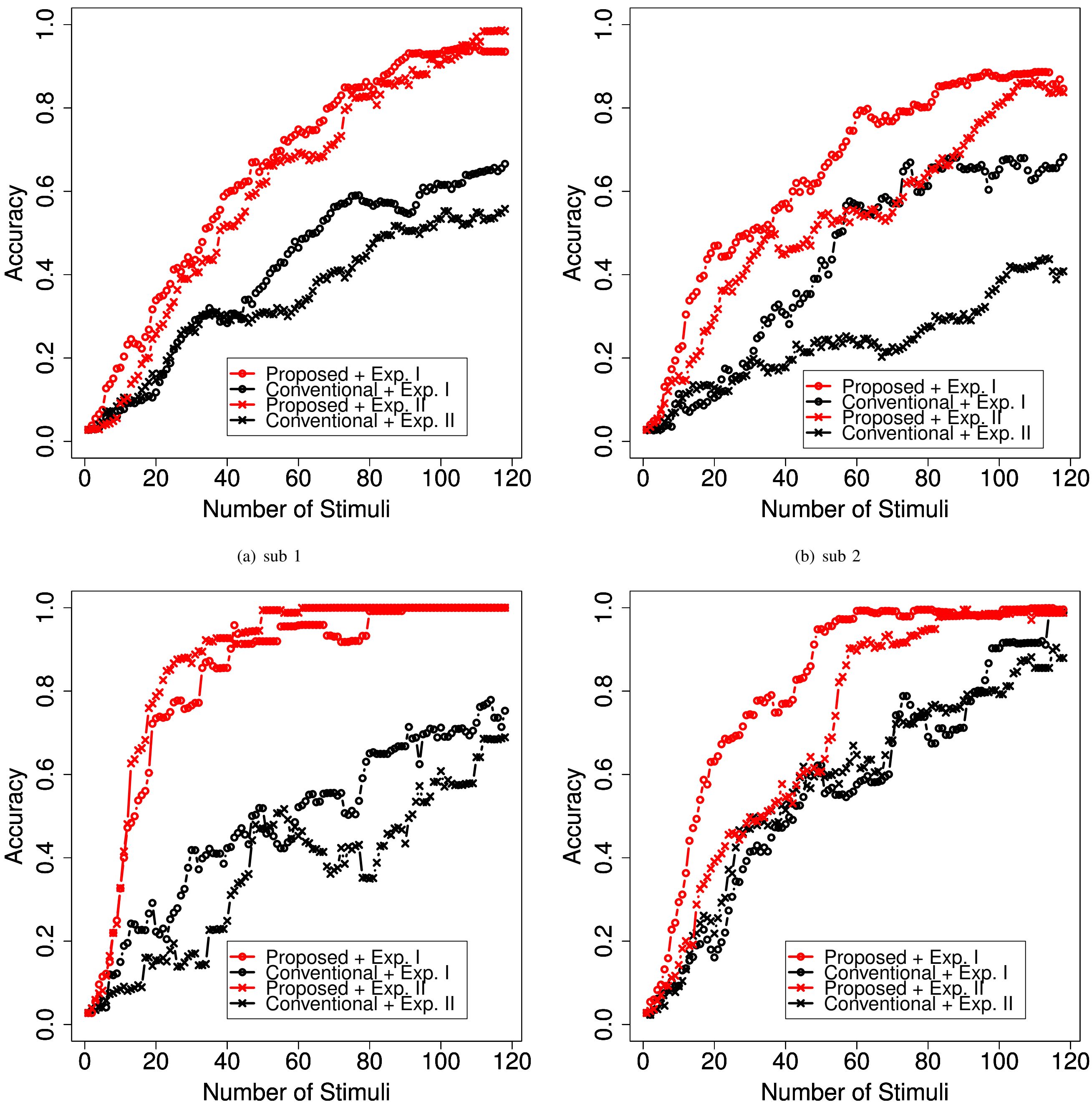
[5] A. Rakotomamonjy *et al.*, "Bci competition iii:dataset ii- ensemble of svms for bci p300 speller," *IEEE Transactions on Biomedical Engineering*, vol. 55, no. 3, pp. 1147–1154, 2008.

[6] B. Dal Seno *et al.*, "The utility metric: a novel method to assess the overall performance of discrete brain–computer interfaces," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,*, vol. 18, no. 1, pp. 20–28, 2010.

[7] G. Schalk *et al.*, "A general-purpose brain-computer interface (bci) system," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 6, pp. 1034–1043, 2004.

[8] H.H.Jasper, "The ten-twenty electrode system of the international federation," *Electroencephalography and clinical neurophysiology*, vol. 10, no. 2, pp. 371–375, 1958.

[9] D. G. Kleinbaum *et al.*, *Applied regression analysis and other multivariable methods*. Duxbury, 1997.



(a) sub 1

(b) sub 2

(c) sub 3

(d) sub 4

Fig. 5. Relationship between accuracy and number of stimuli