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P300 Spellerにおける未知データを用いた追加学習による学習時間の短縮に関する一検討

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あらまし 近年, Brain-Computer Interface (BCI) の研究が盛んであり, コミュニケーションのためのBCIであるP300 spellerが知られている. しかし, 事前に学習データを計測する必要があり, 被験者にとって負担になっている. 本稿では, 事前学習データの計測時間を短縮するため, 未知データを用いた追加学習法を提案し, P300 spellerへの適用の効果をオフライン実験とオンライン実験により検証する.

キーワード ブレイン・コンピュータ・インターフェイス, P300 speller, 追加学習, 学習時間

A study on reduction of pre-training time based on incremental training with unknown data for P300 speller

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Abstract Recently, Brain-Computer Interfaces (BCIs) have been researched actively. The P300 speller, one of the communication tools of BCI, is well known. The process of recording training data places a lot of burden to the user before actual use. To reduce time for recording training data, this paper proposes an incremental training method, and evaluates the effectiveness of the proposed method by offline and online experiments.

Key words Brain-Computer Interface, P300 speller, Incremental training, Training time

1. Introduction

Recently, Brain-Computer Interfaces (BCIs) have been researched actively. In a BCI system, the brain activity is recorded in real time and translated into simple commands, which are transfered to the electronic devices or computers. By the development of BCI research, many patients who have lost their voluntary control ability due to certain diseases such as Amyotrophic Lateral Sclerosis (ALS) could control external devices or communicate with others just by thinking [1]. The P300 speller, which is first introduced by Farwell and Donchin in 1988, is an EEG-based word input system [2], and it extracts P300 as the feature for the classification task. The P300 speller typically has 36 characters containing alphabets and numbers on a 6×6 matrix (Fig.1), and one of the rows or the columns is highlighted at random. It identifies 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, before actual use, the spelling system has to be trained with training data. With a well trained classifier, P300 speller can recognize the user's P300 pattern to complete the word input task properly. Due to the low signal-to-noise ratio, it is hard to train a classifier using a single independent EEG data. However, a classifier trained with a large number of training data is effective to discriminate P300 data from non-P300 data statistically. Therefore, users need to input a set of prepared characters to record training data and the system needs to train the classifier with these data in advance. In many previous researches [3] [4], 20 or more characters are used for training data which takes a long time (about 20 minutes) and brings a lot of burden to users. Considering its practical application, a method which can reduce the training time as well as maintain good classification accuracy is needed. Thus, this paper aims at reducing the pre-training time with a small loss of accuracy (increasing the efficiency of the training). A way to reduce the time-consuming training process is to use a small training data at the beginning, then, a large number of test data could be used for incremental training. However, the label of the test 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 [5]. Thus, using the Backspace, the correctness of the detected characters can be calculated - If the character 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 training data set. Otherwise, if the character is deleted, it will be treated as an incorrect input and will not be added to the training data. In this paper, considering this unique characteristics of P300 speller, an incremental training method based on unknown data is proposed.

A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R
S	T	U	V	W	X
Y	Z	1	2	3	4
5	6	7	8	9	BS

Figure 1 6×6 P300 matrix display

2. Proposed Method

The proposed method adds the test characters into the training data set, then if the characters are deleted by the Backspace, then they will be also deleted from the training data. In this method, the Backspace is treated as reliable input, because the probability that an incorrect input becomes Backspace is very low even if the accuracy of the system is low. In a P300 speller, given the accuracy of a certain system, the correctness of the inputted Backspace can be calculated theoretically. However, to make the problem simple, here it only considers an independent Backspace input - a consecutive Backspace serial is not considered. The input patterns are divided into two patterns : $A < BS > A$ means the deleted character is the same as the character that is inputted after Backspace. $A < BS > C$ means the deleted character and the character inputted afterward is different. For these different patterns, there are two different equations of the correctness.

First, while the accuracy of the system is p, the expectation of an input of Backspace is given by

$$(1-p)+(1-p)^2+(1-p)^3+...+(1-p)^k+... \qquad (1)$$

$$= \lim_{n\to\infty} \frac{(1-p)(1-(1-p)^n)}{1-(1-p)} = \frac{1-p}{p} \qquad (2)$$

Thus the probability of an input patten $A < BS > A$ with correct Backspace is

$$\frac{1-p}{p} \cdot p \cdot (1-p) = (1-p)^2 \qquad (3)$$

And the probability of an input pattern $A < BS > A$ with incorrect Backspace is

$$[1-\frac{1-p}{p}] \cdot (1-p) \cdot p = (1-p) \cdot (2p-1) \qquad (4)$$

Therefore when a pattern of $A < BS > A$ appears, the correctness of the Backspace is

$$\frac{(1-p)^2}{(1-p)^2+(1-p)\cdot(2p-1)} = \frac{1-p}{p} \qquad (5)$$

Similarly, the probability of an input pattern $A < BS > C$ with correct Backspace is

$$\frac{1-p}{p} \cdot p = 1-p \qquad (6)$$

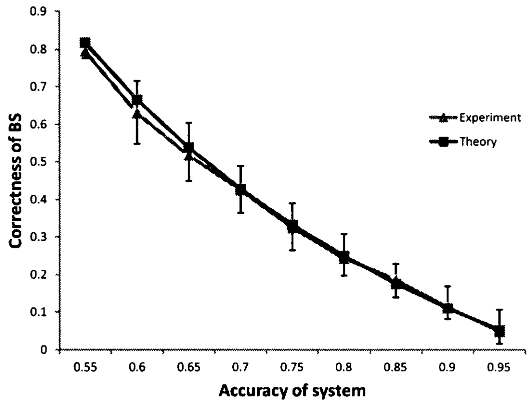
And the probability of the input pattern $A < BS > C$ with incorrect Backspace is

$$[1-\frac{1-p}{p}] \cdot (1-p)^2 = \frac{(2p-1)(1-p)^2}{p} \qquad (7)$$

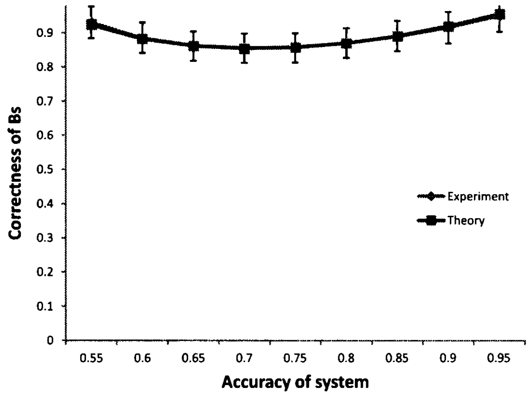
Thus when a pattern of $A < BS > C$ appears, the correctness of the Backspace is

$$\frac{(1-p)}{\frac{(2p-1)(1-p)^2}{p}+(1-p)} = \frac{p}{4p-p^2-1} \qquad (8)$$

When the accuracy is lower than 50%, the expectation of inputting backspace is infinite. More detailed knowledge has been explained in [5]. Therefore, setting different classification accuracy from 0.5 to 0.95 in each session, 10 sessions were carried out. For each session, 50,000 characters were inputted and the correctness of Backspaces was tested. Figure 2(a) shows the correctness of the input pattern $A < BS > A$ which means the deleted character and re-inputted character was same. The result shows when the accuracy is low, the



(a) A<BS>A



(b) A<BS>C

Figure 2 Correctness of Backspace

correctness of Backspaces is high. As shown in Fig 2(a)2(b), the theoretical equation above explains the simulation result well.

Finally, the number of the pattern $A < BS > C$ was 35 times more than the pattern $A < BS > A$, thus , this paper treats the detected Backspaces as correct classification.

3. Offline Experiment

3.1 Experimental Data

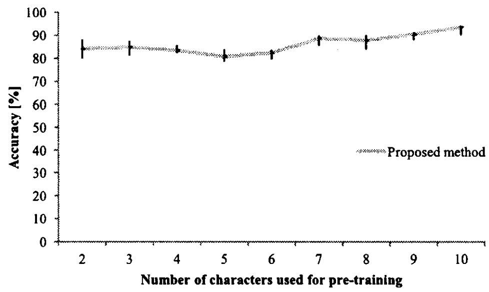
The experiments were based on BCI Competition III data set II [6]. It is an EEG data which was recorded through P300 speller task by two subjects (Sub A, Sub B). The data includes 85 characters for training data and 100 characters for test data. The data was recorded by 64 electrodes and band-pass filtered from 0.1-60Hz then digitized at 240Hz. Each row and column in the matrix was randomly intensified (1 sequence with 6 rows and 6 columns intensification) and totally repeated for 15 sequences.

3.2 Preprocessing and Classifier

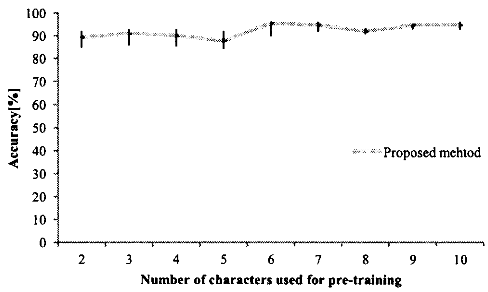
The EEG data was bandpass filtered from 0.1-60Hz first. Then the data was extracted with a time window 0ms to 650ms after each flashing and down sampled to 20Hz (14 data points). Linear Discriminant Analysis (LDA) was employed as classifier.

3.3 Result and Discussion

Conventional method and the proposed method were applied in the offline experiment. To find out the proper number of characters for pre-training, the relationships between the number of characters for pre-training and the accuracy were tested in experiment 1. The result is shown in Fig. 3. The number of characters used for pre-training was set from 2 characters to 10 characters. The result shows a small improvement according to the increment of pre-training characters with the proposed method, and it can be concluded that two characters were enough for pre-training to achieve the same accuracy with the conventional method in which more than 30 characters were needed for pre-training. The improvement of the accuracy is shown in Fig. 4. According to the result, the proposed method achieved better accuracy in both Sub A and Sub B.

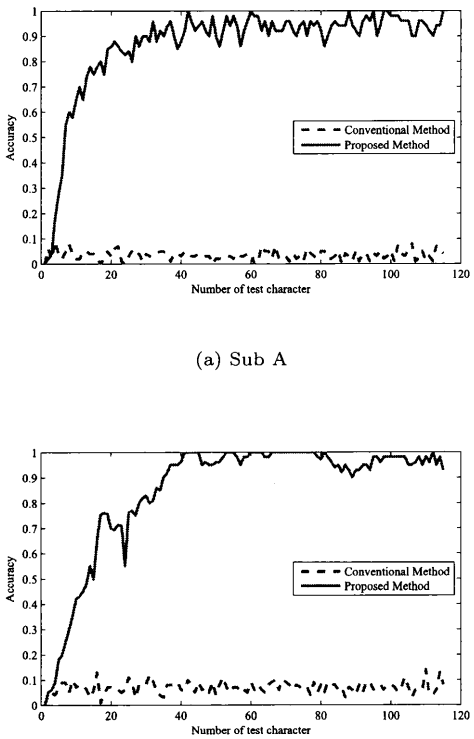


(a) Sub A



(b) Sub B

Figure 3 Accuracy with different number of characters for pre-training



(a) Sub A

(b) Sub B

Figure 4 Improvement of accuracy

4. Online Experiment

4.1 Experimental Data

Based on the result of offline experiment, the proposed method was implemented to the online system. Using the modified P300 speller system, 4 subjects (Sub 1, Sub 2, Sub 3, Sub 4) were participated in the experiment. For each subject, two sessions were carried out with the proposed method. Based on the conventional method with fixed number of training data, two sessions were carried out for each subject as well for comparison. Two characters were inputted as training data and 10 characters, "HELLOWORLD" were requested to input for two sessions. If an incorrect character was inputted, the subject should try to delete it by inputting Backspace.

4.2 Preprocessing and Classifier

The sampling rate was 128Hz and data was collected by 14 electrodes. The EEG data was bandpass filtered from 0.1-60Hz first. Then the data was extracted with a time window 0ms to 650ms after each flashing and down sampled to 20Hz (14 data points). Linear Discriminant Analysis (LDA) was employed as classifier.

4.3 Result and Discussion

The result of comparison of the conventional method (fixed number of training data) and the proposed method is shown in Fig. 5. This figure shows that the proposed method had got a significantly higher accuracy in all subjects. In the result of Sub 1, the accuracy improved the most among four subjects while Sub 2 and Sub 3 achieved rather high accuracy with the conventional method as well. However, there was still improvement in Sub 2 and Sub 3 with the proposed method.

Regarding to Sub 1 and Sub 4, although accuracies were both low by the conventional method, the improvement of accuracy was different. Sub 1 achieved high accuracy while only small improvement was found in Sub 4. By analyzing the recorded data of Sub 1 and Sub 4, it can be found that if 10 characters were used for conventional training, the Sub 4 could also achieve high accuracy. For a further inspection on different results on Sub 1 and Sub 4, the actual input results of two subjects are shown in Table 1 and Table 2. With the conventional method, although the accuracy was low, there were more incorrectly classified characters in which either row or column was correct in Sub 1 than in Sub 4. The accuracies of P300 classification of two subjects were 69.2% and 36.4%, respectively. Thus, when the system updated training data set, the test data of Sub 1 more likely contained correctly classified P300 data than that of Sub 4, even though they were incorrectly classified character data. Fig. 6 shows the detailed relationship between the number of characters in training data and the classification accuracy. The accuracy improvement of Sub 1 was faster than that of Sub 4. In Sub 1, the accuracy was achieved over 70% by training with 4 characters, which almost reached the maximum accuracy. However, only small improvement was found in Sub 4 with the increment of training data. Thus, it can be confirmed that Sub 4 needed more training data than other subjects, which caused very slow improvement of accuracy with the proposed method. It can be considered that if the test session was long enough, the performance of the proposed method in Sub 4 would improve significantly as well.

5. Conclusion

In this paper, to reduce the pre-training time, an incremental training method was proposed. BCI Competition III data set II was employed for offline experiment. By applying incremental training method based on unknown data, the relationships between the accuracy and the number of characters used for pre-training were illustrated. Higher accuracy was achieved comparing to the conventional method with fixed training data. Also, the feature of continues accuracy improvement was clarified. Furthermore, based on the online P300 speller system with incremental training, online experiments were carried out. Four subjects participated in the experiment and the result showed significant improvement in accuracy in all subjects. Based on small training data, the proposed incremental training method achieved higher accuracy. It means that the proposed method needs much shorter training time to achieve same accuracy with the conventional method. As for the future work, the method which considers the actual accuracy of the Backspace should be tested. Also, based on the reliability of the Backspace, the correctness of the inputted alphabet should be discussed

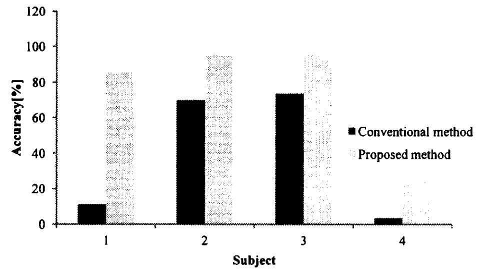


Figure 5 Online result comparison between proposed method and conventional method

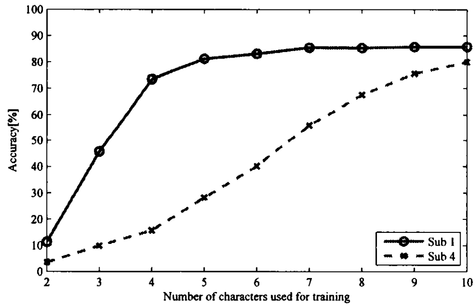


Figure 6 Comparison of Sub 1 and Sub 4 in condition of different number of training data

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[6] http://www.bbci.de/competition/iii/

Table 1 Input result of Sub 1

Proposed method														
Session 1	*N*	BS	H	E	L	L	*N*	BS	O	W	O	R	L	D
Session 2	*B*	BS	H	E	L	L	O	*3*	BS	W	O	R	L	D
Conventional														
Session 1	*G*	*7*	*6*	$\underline{\text{G}}$	$\underline{\text{M}}$	BS	BS	$\underline{\text{S}}$	$\underline{\text{V}}$	$\underline{\text{A}}$	*5*	$\underline{\text{T}}$	*R*	*F*
Session 2	*J*	*4*	*9*	*F*	*L*	*R*	$\underline{\text{K}}$	BS	$\underline{\text{Q}}$	*5*	*4*	*5*		

Table 2 Input result of Sub 4

Proposed method																				
Session 1	H	$\underline{\text{B}}$	BS	$\underline{\text{A}}$	*7*	$\underline{\text{K}}$	*8*	*4*	$\underline{\text{E}}$	*R*	BS	BS	*L*	BS	*9*	*X*	$\underline{\text{M}}$	*4*		
Session 2	$\underline{\text{M}}$	$\underline{\text{3}}$	*L*	BS	$\underline{\text{N}}$	BS	*7*	BS	$\underline{\text{C}}$	*X*	*R*	$\underline{\text{I}}$	*R*	BS	*X*	BS	$\underline{\text{W}}$	$\underline{\text{O}}$	*4*	$\underline{\text{S}}$
Conventional																				
Session 1	$\underline{\text{Y}}$	*9*	$\underline{\text{U}}$	*R*	*R*	$\underline{\text{W}}$	*8*	BS	$\underline{\text{G}}$	$\underline{\text{O}}$	$\underline{\text{E}}$	$\underline{\text{O}}$								
Session 2	*J*	$\underline{\text{W}}$	$\underline{\text{J}}$	*4*	$\underline{\text{B}}$	$\underline{\text{N}}$	$\underline{\text{B}}$	*7*	*F*	E										

(Note1) Normal : Correctly classified

(Note2) Italic : Either a row or column is correctly classified

(Note3) Underline : Incorrectly classified