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N100-P300 Speller BCI with detection of user's input intention

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Abstract

P300 which is evoked by a subject's mental task, has been used for an operation principle of brain computer interfaces (BCIs) such as P300-speller. In this paper, we propose a novel EEG based spelling BCI, N100-P300 speller which uses N100 response in addition to P300. Thanks to using both N100 and P300, the proposed method achieves higher information transfer rate (ITR) than P300-speller. Furthermore, the proposed framework enables us to detect user's input intention with a high degree of accuracy. Our experiment by ten subjects showed that ITR of the proposed system was an average of 0.25bit/sec higher than P300-speller, and the detection accuracy of user's input intention was 90.5 %.

1 Introduction

Many types of brain computer interfaces (BCIs) have been developed in the last decade, employing various measuring devices and operation principles [6]. P300-speller which is one of the non-invasive BCIs, is used widely because of its simpleness, high information transfer rate (ITR), and reliability [1]. Several methods to improve the classification accuracy and ITR of P300-speller have been investigated [4, 3, 2].

In practical BCI, detection of user's input intention is a significant function. When we use some input interface, we do not always input information. We sometimes think, wait for a response, or do something else. Although P300-speller can detect user's input intention using P300 response, its detection is not accurate.

In this paper, we investigate new BCI spelling system using N100 as well as P300 in order to improve ITR and the detection accuracy of the user's input intention compared to P300-speller. In the proposed method, nine kinds of stimulus images including a 2×3 matrix containing four commands are used (Fig. 1 (a)). P300 is used to detect the target stimulus image containing the desired character. N100 is used to detect the target position that the user gazes on. By using both N100 and P300 features, ITR of the proposed method was 0.25bit/sec higher than that of P300-speller in our experiment by ten subjects. In addition, the detection accuracy of user's input intention was an averaged of 32.7% higher than that of P300-speller.

2 Proposed method

2.1 Detection of target character

26 alphabets (A, B, ⋯, Z) and 10 numerals (0,1, ⋯, 9) are used as spelling commands in the proposed system as well as P300-speller. The characters are arranged in nine stimulus images having four characters and two blanks in the 2×3 matrix (Fig. 1 (a)). The desired character is detected by the following three steps: (i) the target image containing the desired character is detected by using P300; (ii) the target position that the user gazes on is detected by using

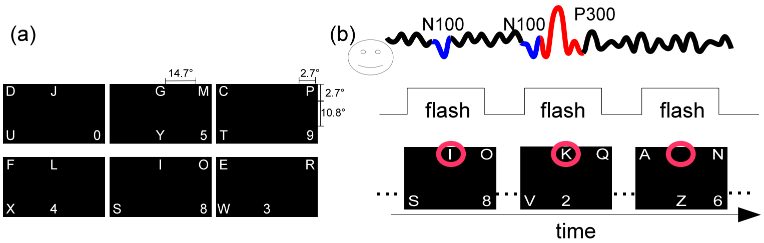

Figure 1: Stimulus images and how to type. (a) Stimulus images. (b) Stimulations and ERP responses for the target character 'K'. Circles means the user's gazing position. (c) How to detect the desired character.

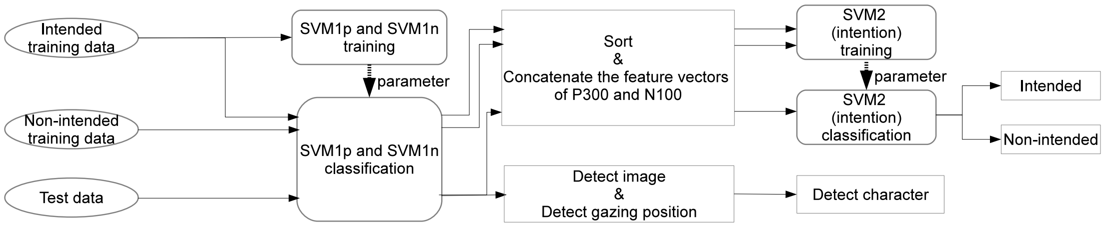

Figure 2: Outline of the proposed method.

N100; (iii) the desired character is detected by the combination of the target image and the target position.

P300 is elicited by mental tasks such as counting how many times the desired character is flashed as well as P300-speller. N100 is elicited by any visual stimuli. In order to detect the user's gazing position by using N100, two blank positions are arranged for each stimulus image. Since N100 is elicited by any visual stimulus without a mental task [5], we can detect the user's gazing position by comparing N100 responses for the blank and non-blank positions. Each position has six characters and three blanks for the nine images. The position of characters is informed to the users beforehand by displaying the positioning table to them near the screen. An example of the detection scheme of the desired character 'K' is shown in Fig. 1-(b),(c).

Two linear support vector machines (SVMs) are independently used to detect N100 and P300. We respectively denote them by SVM1n and SVM1p.

2.2 Detection of the user's input intention

We categorize the user's condition into two classes, *intended* and *non-intended*. N100 and P300 responses are obtained during the intended condition, whereas both of them are not elicited during the non-intended condition. This difference is adopted to detect the user's intention.

Feature vectors to detect the intention are made by concatenating the output values of SVM1n and SVM1p. Output values of SVM1n corresponds to the six positions in the stimulus images. Output values of SVM1p corresponds to the nine stimulus images. These output values are sorted in ascending order before the concatenation. A linear SVM (denoted by SVM2) is trained by the training data of SVM1n and SVM1p, and pre-recorded training data that the user does not intend to input. The procedure is depicted in Fig. 2.

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3 Experiment and Result

Ten healthy subjects (22-24 years old males) conducted experiments of P300-speller and the proposed system 60 times alternately. These experiments include 20 trials that the user does not input the command without gazing on the display every three times. 40 samples of intended condition and 20 samples of non-intended condition were recorded for each subject. P300-speller flashes 24 times (= 12 flashes × two loops), and the proposed system flashes 18 times (= nine flashes × two loops) in a trial. Each row and column is presented two times in P300-speller, whereas nine kinds of stimulus images are presented two times in the proposed method per one trial. The flash has 125 ms duration with 62.5 ms inter stimulus interval (ISI). The proposed system takes 3.375 s in a trial, whereas P300-speller takes 4.5 s. The subjects were asked to gaze on only one position that the target character is presented and silently count the number of times the target character flashes. If the maximum instantaneous amplitude of EEG is greater than 100 μV, we discarded the trial, and repeated the trial again.

EEG was recorded by using an active EEG (Guger technologies) with a sampling frequency of 512 Hz and a bio-signal amplifier (Digitec) with 0.5Hz analogue high-pass filter and 100 Hz analogue low-pass filter. 16 electrodes (FCz, FC2, FC1, Cz, CP1, CP2, Pz, POz, P3, P4, TP8, TP7, C3, C4, C5, and C6 of the extended international 10-20 system) were used [5]. AFz was used as the ground and A2 was used as the reference. The second-order Butterworth band pass filter (1-13 Hz) and the third-order Butterworth band stop filter (49-51 Hz) were used to extract feature and remove the hum noise, respectively. Signal was downsampled from 512 Hz to 64 Hz.

P300 and N100 components were extracted from 125 ms to 625 ms and from 100 ms to 250 ms after the stimulus, respectively. P300 signals were averaged for each stimulus image in both methods. N100 signals were averaged for each position. The soft margin parameter C for SVM, such that shows highest averaged accuracy over the five validations for each subject, was selected from {0.1, 1, 10, 100, 1000}. ITR [bit/s] is used as the performance index since the length of one trial is different [6]. ITR is calculated by $B = \frac{1}{T}\{\log_2 N + P\log_2 P + (1-P)\log_2(\frac{1-P}{N-1})\}$ [bit/s], where T [s] is the time of one trial, P is the classification accuracy, and N is the number of commands. The classification accuracy and ITR were evaluated by 5-fold cross-validation. Hence, the number of training data was 32, and that of test data was eight for SVM1n and SVM1p. For SVM2, the number of training data was 48, (32 samples was from intended trial and 16 samples was from non-intended trial.) The number of test data was 12, (eight samples was from intended trial and four samples was from non-intended trial.)

For P300-speller, since only P300 is used as feature, we obtained the classifier SVM1p and SVM2 to detect the target character and the user's input intention, respectively. SVM1p outputs 12 values corresponding to flashes of six rows and six columns. We sorted these values and obtained a 12-dimensional feature vector to detect the user's input intention.

Table 1 shows the averaged classification accuracies, standard deviations, and ITR. ITR of the proposed method is an average of 0.25bit/sec higher than that of P300-speller because i) the trial length of the proposed system is shorter than that of P300-speller; and ii) the classification accuracy of N100 is higher than that of P300 because N100 signal is averaged over six times, on the other hand, P300 signal is averaged over two times. Moreover, the detection accuracy of the user's input intention of the proposed method is an average of 32.7% higher than that of P300-speller because both N100 and P300 components are used to discriminate the user's intention. The improvement is statistically significant (t-test, $p<0.05$).

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Table 1: Averaged classification accuracy and ITR; "P300" is accuracy of detecting P300 response, and "N100" is accuracy of detecting N100 response. "Intention" is accuracy of detecting the user's input intention. "Character" is accuracy of detecting the desired character.

Method	Accuracy of feature		Without detection of the user's input intention		With detection of the user's input intention		
	P300 [%]	N100 [%]	Character [%]	ITR [bit/sec]	Intention [%]	Character [%]	ITR [bit/sec]
P300-speller	80.9 ± 7.4	–	67.8 ± 15.6	0.60 ± 0.22	57.8 ± 8.5	56.0 ± 21.9	0.46 ± 0.27
Proposed	74.0 ± 18.4	88.5 ± 10.4	70.3 ± 17.1	0.85 ± 0.34	90.5 ± 10.6	66.0 ± 18.6	0.78 ± 0.35

4 Conclusion

We have proposed a novel design for a spelling system using both N100 and P300 to reduce the number of flashes per trial, increase ITR, and detect the user's input intention. The advantages of proposed system are i) it takes shorter time to input one command since the number of flashes can be reduced to nine flashes; ii) the performance of detecting the input intention by using N100 and P300 is 32.7% higher compared to P300-speller in our experiments; iii) each character never flashes in a row whereas at least one character flashes twice in a row in P300-speller; iv) the number of response times can be reduced. That is because the user only has to respond the desired character only two times per trial in the proposed system, whereas in P300-speller the user has to respond it four times, that are the row and column corresponding to the desired character. Hence, the user's fatigue caused by mental task can be reduced in the proposed system.

In future work, we extend the proposed method to improve ITR by extending the size of matrix. The selection of electrode positions should also be investigated. The comparison between the proposed BCI and other P300-BCIs needs to be done.

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