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# A novel EEG-based spelling system using N100 and P300

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**Abstract.** P300-speller is one of the most popular EEG-based spelling systems proposed by Farwell and Donchin. P300-speller has a 6×6 character matrix and requires at least 12 flashes to input one character. This restricts increasing of the information transfer rate (ITR) by decreasing the number of flashes. In this paper, a novel spelling system is proposed to reduce the number of flashes by sequential stimulation of images. In order to determine the command, the proposed system utilizes two kinds of the event-related brain potentials (ERP), N100 and P300 whereas P300-speller utilizes only P300. Thanks to using both N100 and P300, the proposed system achieves higher accuracy and faster spelling speed than P300-speller. Our experiment by ten subjects showed that ITR of the proposed system is an average of 0.25bit/sec improved compared to P300-speller.

**Keywords.** EEG; Brain-Computer Interfaces; Visual Evoked Potentials; Event-Related Potentials; P300.

## Introduction

Brain-Computer Interface (BCI) is a direct communication pathway to command devices by discriminating brain signals. The major goal of BCI research is to develop systems that make it possible for disabled users to communicate with the other people and control their limbs or the environment [1, 2]. To this end, many aspects of BCI systems have been investigated. Especially BCI systems using Event-Related Potential (ERP) are friendly for disabled users because ERP is reliable and stable for almost all people. In addition, users do not have to train to control the BCI. Electroencephalography (EEG) is often used for BCI since EEG is relatively low-cost, fast, and safe device to observe brain signals such as ERP in different area on the scalp. P300, which is a kind of ERP, is elicited roughly 250ms to 500ms after the target stimulus in the process of the oddball task [3]. In this oddball paradigm, when a user conducts experiment presenting two discriminative stimuli (one is target and another is non-target), P300 is elicited by user's response such as counting the incidences of the target stimuli.

P300-speller proposed by Farwell and Donchin is well-known and the first BCI system using P300 [3]. A 6×6 matrix containing commands such as the letters of alphabets or numerals is displayed on a screen. Each row and column of the matrix is flashed in random order. The user silently counts the number of times that the desired

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command is flashed. The flash containing the desired character evokes P300. The system detects evoked P300, and sends the command.

P300-speller can be extended by enlarging the size of the stimuli matrix to deal with many commands, however, such extension would require more time to present the stimuli and hence the information transfer rate (ITR) may not be improved. Several methods to improve the classification accuracy and ITR of P300-speller or P300-based BCI have been investigated such as signal processing methods [4], classification algorithms [5], and error correcting codes [6]. However, these methods focus more on the signal analysis and less on the reduction of the number of the stimulations. Decreasing the number of stimulations enables us to increase the spelling speed and reduce the user's fatigue.

In this paper, a novel BCI system using N100, which is a kind of visual evoked potential (VEP), in addition to P300, is proposed to reduce the number of the stimulations. In the proposed method, nine kinds of stimulus images including a 2×3 matrix containing four commands are used and only nine flashes per a trial are required (Fig. 1). 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. Our experiment by ten subjects shows that N100 and P300 can be detected by the proposed stimulation scheme, and averaged ITR of the proposed method is 0.25bit/sec higher than that of P300-speller.

## 1. Methods

### *1.1. P300-speller*

P300-speller has a 6×6 matrix containing alphabets and numerals. Each row and column is flashed in random order. The user can type the desired character by counting the number of times it is flashed. The desired character is detected by using P300, which is evoked by the flash of the row and column containing the desired character.

### *1.2. Proposed method*

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. In order to reduce the number of the stimulations, the proposed method detects the desired character by the following two steps: (1) the image containing the desired character is detected by using P300, (2) the position that the user gazes on is detected by using N100. In order to detect the user's gazing position by using N100, we arrange blank positions in the stimulus images. Since N100 is elicited by any visual stimulus without a mental task [7,8], we can detect the position that the user gazes on by comparing N100 responses for the blank and non-blank positions. P300 is elicited by counting the number of times that the desired character is flashed as well as P300-speller.

In our study, nine pattern images are used. Four characters and two blanks are assigned in the 2×3 matrix as shown in Fig. 1. Each position presents six characters and three blanks in a trial. The position on which the desired character is presented, is informed to the user before the experiment.

An example of the detection process of the desired character ‘K’ is shown in Fig.1-(b). The position that the user gazes on is detected by N100, and the image that the user responds is detected by P300. The desired character is detected by the combination of the target position and the target image.

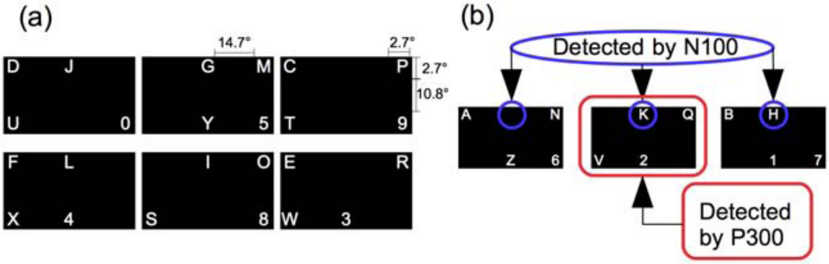


**Figure 1**. Examples of (a) stimulus images and (b) the method to detect the desired character in the proposed system

### *1.3. Experimental condition and procedures*

Ten healthy subjects (22-24 years old males) participated in our study. They conducted experiments of P300-speller and the proposed system 40 times alternately. P300-speller flashes 24 times (= 12 flashes × two trials), on the other hand, the proposed system flashes 18 times (= nine flashes × two trials) in one session. 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. The flash has 125ms duration and the inter stimulus interval (ISI) is 62.5ms. The proposed system takes 3.375s to input a character per one session, whereas P300-speller takes 4.5s.

The EEG was recorded using an active EEG (Guger technologies) and a bio-signal amplifier (Digitec) with 0.5Hz analogue high-pass filter and 100Hz 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 [3,8]. AFz was used as the ground and A2 was used as the reference.

### *1.4. Feature extraction and classification scheme*

The second-order Butterworth band pass filter (1-13Hz) is used to filter the EEG and the third-order Butterworth band stop filter (49-51Hz) is used to remove the hum noise. The signal is downsampled from 512Hz to 64Hz. P300 and N100 components are respectively extracted from 125ms to 625ms and from 100ms to 250ms after the stimulus. P300 signals are averaged for each stimulus image in both methods. N100 signals are averaged for each position. For P300, 512-dimensional feature vectors are made by arranging 32 points signal and 16 electrodes. For N100, 160-dimensional feature vectors are made by arranging 10 points signal and 16 electrodes.

The linear SVM is used to classify the signal. The soft margin parameter $C$ is selected to from {0.1, 1, 10, 100, 1000}.

ITR [bit/sec] is used as the performance index since the length of one session is different. ITR is calculated by

$$B = \frac{1}{T}\left\{\log_2 N + P\log_2 P + (1-P)\log_2 \frac{1-P}{N-1}\right\} \text{ [bit/sec]},$$

where $T$ [sec] is the time of one session, $P$ is the classification accuracy, and $N$ is the number of commands [10].

## 2. Results

Averaged waveforms over the target and non-target stimuli of electrode Cz are shown in the left of Fig. 2. Averaged waveforms over the attended and unattended stimuli of electrode FCz is shown in the right of Fig. 2.

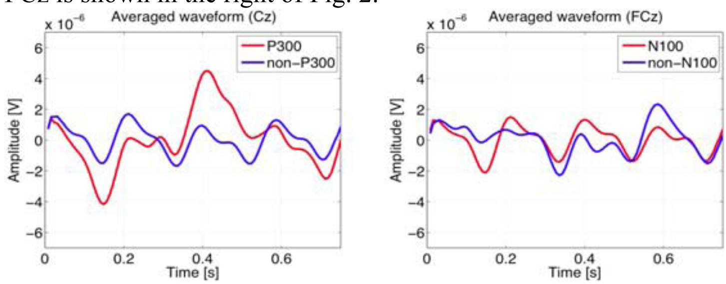


**Figure 2.** Averaged waveforms of electrode on which the largest amplitude of P300 (N100) is observed.

Table 1 shows the averaged classification accuracies and the standard deviations over ten subjects.

**Table 1.** Classification accuracy [%] and standard deviation of ERP components (P300,N100).

| | P300-speller | | Proposed system | |
|---|---|---|---|---|
| | P300 (row) | P300 (column) | P300 | N100 |
| **Average** | 81.3 ± 13.9 | 80.5 ± 13.2 | 74.0 ± 18.4 | 88.5 ± 10.4 |

Table 2 shows the classification accuracies and ITR. The significance of ITR of the proposed system was confirmed by the F-test at level $\alpha=0.05$ and the unilateral Welch's t-test at level $\alpha=0.05$.

**Table 2.** Classification accuracy and information transfer rate (ITR).

| Subject | Classification Accuracy [%] | | ITR [bit/sec] | |
|---|---|---|---|---|
| | P300-speller | Proposed | P300-speller | Proposed |
| **1** | 75.0 ± 21.7 | 70.0 ± 14.3 | 0.713 ± 0.287 | 0.832 ± 0.267 |
| **2** | 67.5 ± 16.8 | 60.0 ± 32.4 | 0.593 ± 0.231 | 0.728 ± 0.598 |
| **3** | 85.0 ± 13.7 | 70.0 ± 19.0 | 0.870 ± 0.255 | 0.855 ± 0.408 |
| **4** | 70.0 ± 11.2 | 77.5 ± 18.5 | 0.619 ± 0.167 | 1.002 ± 0.389 |
| **5** | 60.0 ± 5.6 | 62.5 ± 12.5 | 0.479 ± 0.068 | 0.691 ± 0.218 |
| **6** | 72.5 ± 10.5 | 67.5 ± 11.2 | 0.654 ± 0.156 | 0.778 ± 0.197 |
| **7** | 70.0 ± 14.3 | 85.0 ± 10.5 | 0.624 ± 0.200 | 1.143 ± 0.256 |
| **8** | 65.0 ± 16.3 | 57.5 ± 6.8 | 0.558 ± 0.227 | 0.598 ± 0.111 |
| **9** | 47.5 ± 10.5 | 80.0 ± 14.3 | 0.334 ± 0.118 | 1.043 ± 0.326 |
| **10** | 65.0 ± 10.5 | 72.5 ± 10.5 | 0.549 ± 0.138 | 0.872 ± 0.208 |
| **Average** | 67.8 ± 15.6 | 70.3 ± 17.1 | 0.599 ± 0.222 | 0.854 ± 0.336 |

## 3. Discussion and Conclusion

From the right of Fig. 2, there is a significant difference around 150ms between signals containing N100 and non-N100. The periodic negative peaks (340ms, 530ms, and 720ms) are due to the response of the other stimulations. The difference of N100 around 150ms is caused by utilizing the stimulus images containing the blank positions in the proposed method. Thus, the proposed method can detect the position that the user gazes on by using N100 component.

From Table 1, the classification accuracy of P300 in the proposed system is an average of 6.9% lower than that in P300-speller. The reasons are as follows: i) the number of the training data for P300 of the proposed system is a half of that in P300-speller since the proposed system evokes P300 only once in a trial, whereas P300-speller evokes twice, that are the row and column; ii) the number of the classes for P300 in the proposed system is larger than that in P300-speller since the proposed system has to classify to nine classes in order to detect the desired image, whereas P300-speller classifies to six classes to detect the desired row and column.

The ITR of the proposed system is an average of 0.25bit/sec higher than that of P300-speller. Moreover, the averaged accuracy of N100 is 7.6% higher than that of P300 in both methods. This is due to the fact that the performance of feature extraction of N100 is better than that of P300 since N100 signal is averaged six times, on the other hand, P300 signal is averaged two times.

We proposed a novel design for a spelling system using P300 and N100 to reduce the number of flashes per trial and increase ITR. The advantages of our system are i) the classification accuracy of N100 is better than that of P300 since the number of averaging for N100 is greater than that for P300; ii) it takes shorter time to input one command since the number of flashes can be reduced to nine flashes; iii) N100 is elicited by the visual stimulation without a mental task, such as counting the number of flashes, hence the user's fatigue can be reduced; iv) each character never flashes in a row whereas at least one character flashes in a row in P300-speller; v) the user has to respond the desired character only once per one trial in the proposed system, whereas in P300-speller the user has to respond it twice, that are the row and column containing the desired character.

In future work, we extend the proposed method to improve ITR by extending the size of matrix. The optimal selection of electrode positions should also be investigated.

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