Implementation of advanced detection intentional control for event related potential technique using spelling BCI Interface

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Abstract: A brain-computer interface (BCI) is a tool to communicate with a computer via brain signals without the user making any physical movements, thus enabling disabled people to communicate with their environment and with others. P300-based ERP spellers are a widely used spelling visual BCI using the P300 component of event-related potential (ERP). However, they have a technical problem in that at least $\sqrt{2}N$ flashes are required to present $N$ characters. This prevents the improvement of accuracy and restricts the typing speed. To address this issue, we propose a method that uses N100 in addition to P300. We utilize novel stimulus images to detect the user’s gazing position by using N100. By using both P300 and N100, the proposed visual BCI reduces the number of flashes and improves the accuracy of the P300 speller. We also propose using N100 to classify non-control (NC) and intentional control (IC) states. In our experiments, the detection accuracy of N100 was significantly higher than that of P300 and the proposed method exhibited a higher information transfer rate (ITR) than the P300 speller.

Keywords: visual evoked potentials (VEP); N100; P300; brain computer interface (BCI); intentional-control (IC); self-paced BCI; P300 speller

Introduction

The brain-computer interface (BCI) is an alternative communication pathway to communicate with and control devices by discriminating brain signals without the user making any physical movements. The major goal of BCI research is to develop applications that enable disabled or elderly users to communicate with others and control their limbs and/or the environment [1]. Various types of event related potentials (ERPs) have been utilized to realize BCI, such as P300 based BCI, steady state visual evoked potential (SSVEP), auditory steady state response (ASSR), and $\mu$-rhythms from the sensorimotor cortex [2], and various systems have been used to measure it, including electroencephalography (EEG), magnetoencephalography (MEG), and functional magnetic resonance imaging (fMRI). In this paper, we focus on an EEG-based BCI system.

EEG-based ERP spellers have been extensively used because of their simplicity and high accuracy. Most of ERP spellers use P300 evoked by counting the number of times the target is intensified to detect the desired target command [3,4]. The P300 speller proposed by Farwell and Donchin is a well-known BCI system using P300 [3]. A $6 \times 6$ matrix containing target characters is used for stimulation. Each row and column of the matrix is flashed in random order and the user silently counts the number of times the desired character is presented. The desired character is determined by detecting P300 evoked by the mental task. In [4], early ERP components such as P1, N1, and P2 are used in addition to P300 as the features to detect the target command. GeoSpell (a geometric speller) is an alternative visual ERP-based spelling system. In the GeoSpell interface, each $N$ character is assigned to two $N$ groups arranged in a circle.

Existing ERP spellers have several drawbacks: (i) at least $\sqrt{2}N$ flashes are required to present $N$ commands; (ii) since the stimuli containing a group (e.g., row or column) of the characters flash randomly, at least one character containing a group in a row in some ERP spellers (including the P300 speller); and (iii) at least two counting tasks are required to type one character, which is like counting row and column in a matrix in the P300 speller. In Section 2, we discuss these drawbacks in detail.

1. ERP Speller

P300 is a positive deflection in ERP that appears 300 ms after the onset of stimuli. The oddball paradigm is used to observe P300 [18]. P300 is elicited if a user isactively trying to detect the targets. Themental task of counting thenumber of targetsstimulus isoften used for BCI. P300 is evoked by not only visual but also auditory [19] or tactile [20] stimuli.
The P300 speller is a classical spelling BCI proposed by Farwell and Donchin in 1988. It features a $6 \times 6$ matrix containing alphanumeric characters arranged on a display as shown in Figure 1. Each row and column having six characters is flashed in a random order. The user performs a mental task such as counting how many times the desired character is presented.

P300 evoked by the counting task is detected by the system and the target character is determined by detecting P300 from the target row and column [3]. An example of the detection process of the desired character “K” is given in Figure 2. GeoSpellandHex-o-Spell are improved versions of the ERP speller. They do not require eye-gaze control.

![Figure 1. Examples of stimulus of P300-speller. (a) The first row is intensified; (b) the first column is intensified.](image1)

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![Figure 2. Stimulus and operating principle of P300-speller. When the subject counts the number of flashes of the character “K”, P300 is elicited by the user’s response.](image2)

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The performance of BCIs is usually evaluated by the information transfer rate (ITR) as well as the classification accuracy of discriminating the target character. Such measurements depend upon three factors: typing speed, classification accuracy, and the number of commands [21],

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

where $T$ (s) is the time of one session, $P$ is the classification accuracy, and $N$ is the number of commands.

Although ERP spellers are widely used because of their simplicity and high ITR, they have several technical problems, as stated in the Introduction. The first is that ERP spellers require at least $\sqrt{2}N$ flashes to present $N$ commands. Suppose that the classification accuracy is $P = 0.9$ and the stimulus onset asynchrony (SOA) is $T_0 = 187.5$ ms, that is, it takes $T = t_0 \times \sqrt{2}N$ ms to present all commands. Figure 3 shows the relationship between $N$ and ITR obtained by Equation (1).

This figure suggests that making the matrix larger than $3 \times 3$ (nine commands) does not improve the ITR. Moreover, the accuracy $P$ is expected to be lower for large $N$ because the number of classes increases with $N$. This is the main limitation of the ERP speller.

![Figure 3. Relationship between no. of commands $N$ and the information transfer rate (ITR) \( \text{(p}=0.9, \ T=187.5 \times \sqrt{2}N) \)](image3)

Figure 3. Relationship between no. of commands $N$ and the information transfer rate (ITR) \( \text{(p}=0.9, \ T=187.5 \times \sqrt{2}N) \)

Most ERP spellers require the target stimuli to be counted at least two times because of the two-stage selection process. Moreover, if we use...
averaging to improve accuracy, the number of counting times increases, which increases the risk of the users becoming fatigued.

If we use a large matrix in the P300 speller, all characters are small and close together. This causes users to make mistakes and is not user-friendly, especially for the elderly.

2. N100 and Its Discriminability

The visual N100 (also referred to as N1) is a negative deflection in the transient VEP that appears 100 ms after the onset of a stimulus. P1 and P2 are also observed around N100, and they would also be useful features for BCI. In a previous study, it was investigated that P1, N100, and P2 components were found to have amplitudes large enough to discriminate the target intensity.

Unlike P300, N100 is not related to the reaction to a specific target, e.g., a counting task to low-frequency stimuli. When a user pays attention to a stimulus area, N100 is evoked by any stimulus. Thus, it is difficult to use N100 solely for BCI. N100 has larger amplitude when the user focuses on or pays attention to the target position. We confirm this in our experiment in Section 5.1.

3. Proposed Method

N100-P300 Speller

In a similar manner to the standard 6×6 P300 speller, we consider a BCI that has 36 commands: 26 letters (A–Z) and ten numbers (0–9). Since N100 is evoked without any counting task, we propose an efficient stimulus presentation based on rapid visual presentation (RVP) in order to utilize N100 for BCI.

The 36 characters and several blanks are arranged in the stimulus images. Figures 4 and 5 show examples of the proposed images. The positions of characters are fixed, and a user is assumed to know the target position beforehand. The proposed system detects the target characters as follows:

(i) The user pays attention to the target position and counts how many times the target characters are presented; (ii) the system detects P300 evoked by the counting task and determines the target stimulus image; (iii) the system also detects absent or weak N100 caused by blanks in the stimulus images and determines the position of the target character; and finally (iv) the desired character is determined by the combination of the detected image and position.

![Figure 4. Examples of stimulus images of the proposed method (2 × 2 matrix).](image-url)
Figure 5. Examples of stimulus images of the proposed method (2 × 3 matrix).

Figure 6 shows an example of this detection process. Suppose the target character is “K”. In this case, the user focuses on the top-right part evoked by the user’s counting task after thesecond stimulus image is presented. The system detects the target position and image from N100 and P300, respectively.

In our study, we developed two BCI systems, one with 2 × 2 matrices (Figure 4), and the other with 2 × 3 matrices (Figure 5). In the case of the 2 × 2 matrix, we used 12 stimulus images. To perform averaging for the N100 absence signals, we arranged three blanks for each position. In this case, the number of stimulations is twelve, which is the same as that of the 6 × 6 P300-speller matrix. The arrangement of the characters is listed in Table 1. For the 2 × 3 matrix, we also arranged three blanks for each position and used nine stimulus images. Examples of stimulus images are shown in Figure 5. The arrangement of the characters is listed in Table 2.

Table 1. Character arrangement of 2 × 2 matrix, “-” denotes the blank. “T”, “B”, “L”, and “R” respectively mean top, bottom, left, and right.

<table>
<thead>
<tr>
<th>No.</th>
<th>TL</th>
<th>TR</th>
<th>BL</th>
<th>BR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>J</td>
<td>S</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>A</td>
<td>T</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>B</td>
<td>K</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>C</td>
<td>L</td>
<td>U</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>M</td>
<td>V</td>
<td>4</td>
</tr>
<tr>
<td>6</td>
<td>D</td>
<td>W</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>E</td>
<td>N</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>F</td>
<td>O</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td></td>
<td>P</td>
<td>Y</td>
<td>7</td>
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<tr>
<td>10</td>
<td>G</td>
<td>Z</td>
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<td></td>
</tr>
<tr>
<td>11</td>
<td>H</td>
<td>Q</td>
<td>9</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>I</td>
<td>R</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Character arrangement of 2 × 3 matrix, “-” denotes the blank. “T”, “B”, “L”, “C”, and “R” respectively mean top, bottom, left, center, and right.

<table>
<thead>
<tr>
<th>No.</th>
<th>TL</th>
<th>TC</th>
<th>TR</th>
<th>BL</th>
<th>BC</th>
<th>BR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>G</td>
<td>M</td>
<td>Y</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>A</td>
<td>N</td>
<td>Z</td>
<td>6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>B</td>
<td>H</td>
<td>1</td>
<td>7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>I</td>
<td>O</td>
<td>S</td>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>C</td>
<td>P</td>
<td>T</td>
<td>9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>D</td>
<td>J</td>
<td>U</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>K</td>
<td>Q</td>
<td>V</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>E</td>
<td>R</td>
<td>W</td>
<td>3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>F</td>
<td>L</td>
<td>X</td>
<td>4</td>
<td></td>
<td></td>
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</tbody>
</table>
In a similar manner, SVM1n is also binary classifier trained by the EEG responses of the blank positions (positive samples) and the non-blank positions (negative samples). For each position, the feature vector of SVM1n is made by averaging the EEG responses of the blank. For blank, and so forth. Thus we obtain four or six feature vectors from one trial. In the training stage, since we use labeled samples, we obtain one positive sample, and three (or five) negative samples from one trial. In the testing stage, four or six feature vectors are input to SVM1n, and the position having the maximum output is taken as the estimated position. These outputs of four or six responses are also used in the next NC/IC classification.

**Discrimination of NC/IC States:**

When individuals use the BCI system, they are not constantly typing characters or control tools in practice. To realize a practical BCI, a function must be developed to distinguish whether the user intends to spell characters or not. The previous study proposed a stopping criterion whereby the maximum amplitude of VEPs such as P1 and N1 is thresholded. In this method, however, we have to tune the threshold depending on experimental environment and condition each time [15].

![Figure 7. Classification procedure of the proposed method.](image)

4. **Experiments**

We describe three experiments in this section. All participants signed a consent form approved by the research ethics committee of The University of Electro-Communications.

**Preliminary Experiment for N100:**

**Purpose and Method**

To show the discriminability of N100 and clarify the effect of eye movement, we conducted a preliminary experiment. Although the amplitude of N100 is significantly different between the attended and non-attended conditions [12], sufficient averaging number is unclear. Moreover, in the proposed system and in the P300 speller, users may move their eyes while typing. However, some seriously ill patients, such as those in the final stages of amyotrophic lateral sclerosis (ALS), cannot move their eyes [26]. The relationship between the P300 speller and eye movement has previously been reported [27]. We also investigated the effect of eye movement on the N100-based BCI.

![Figure 8. Stimulus images of the preliminary experiment.](image)

The EEG was recorded using an active EEG (Guger Technologies) at a 512 Hz sampling rate and an abio-signal amplifier (Digitec) with a 0.5 Hz analogue high-pass filter and a 100 Hz analogue low-pass filter. FCz,
FC2, FC1, Cz, CP1, CP2, Pz, POz, P3, P4, POz, PO3, PO4, O1, O2, and Iz were used. AFz and A2 were used as the ground and the reference, respectively (Figure 9). The locations of electrodes were based on the extended international 10–20 system.

Figure 9. Electrode locations of the preliminary experiment based on the extended international 10–20 system.

For the recorded EEG, we used a second-order Butterworth band pass filter (1–13 Hz) and a third-order Butterworth band stop filter (49–51 Hz) to remove the hum noise. The signal was down-sampled from 512 to 64 Hz. A linear SVM was used to classify the participant’s attention. We extracted the EEG signal from the specific range after the onset of stimulus and averaged six responses for each stimulus. A 160-dimensional feature vector was made by concatenating ten samplepoints and 16 channels. The soft margin parameter C was selected from \{0.1, 1, 10, 100, 1000\}. All signal processing tools were implemented on MATLAB, and LibSVM was used [28]. The mean accuracies of five-fold cross-validation were compared.

Results

The averaged waveforms of participant 1 are shown in Figure 10. The left side of the figure shows the case in which the participant gazes at the stimulus circle. From the responses for the stimulus intensification, a negative peak is observed around 175 ms to 200 ms after the onset of the stimulus. Two positive peaks, P1 and P2, around the N100 peak are also observed. In contrast, from the responses for the blank stimulus, N100 is not observed.

Figure 10. Grand averaged waveform over all subjects for N100 on FC1, FC2, P3 and P4. The number of averaging is 360. Left side of figures obtained when the subject gazes at the stimulus circle. Rightside of each signal is obtained when the subject gazes at the center circle and pays attention to the stimulus.
The right side of Figure 10 shows the case in which the participant gazes at the center and pays attention to the stimulus. In this case, the difference between the two conditions is small. However, P2 around 270 ms after the onset can be observed. Table 3 shows the mean classification accuracy and standard deviation. The classification accuracy of the gazing case is higher than that of the attention case. However, in the attention case, the range 150–300 ms shows a classification performance significantly better than chance (50%).

The accuracy is expected to be higher if we average more signals.

### Table 3. Classification accuracy and standard deviation (%) of VEP detection.

<table>
<thead>
<tr>
<th>Range (ms)</th>
<th>Gazing</th>
<th>Attention</th>
</tr>
</thead>
<tbody>
<tr>
<td>50–200</td>
<td>100.0 ± 0.0</td>
<td>93.3 ± 14.9</td>
</tr>
<tr>
<td>100–250</td>
<td>100.0 ± 0.0</td>
<td>93.3 ± 14.9</td>
</tr>
<tr>
<td>150–300</td>
<td>100.0 ± 0.0</td>
<td>96.7 ± 7.5</td>
</tr>
<tr>
<td>200–350</td>
<td>100.0 ± 0.0</td>
<td>100.0 ± 0.0</td>
</tr>
</tbody>
</table>

We compared the proposed BCI using the 2 × 2 matrix and 6 × 6 P300-speller. Eleven healthy 22-24-year-old males participated in this experiment. They performed 50 trials each for the P300 speller and the proposed method alternately. In the proposed method, 12 stimulus images are presented twice in one trial in random order, thus the total number of flashes is 24 per trial. In the P300speller,12flashesarepresentedtwiconeinoneteriali

Figure 11. Electrode locations of experiment of the proposed BCI based on the extended international 10–20 system.

P300 and N100 were respectively extracted from 125 to 625 ms and from 100 to 250 ms after the onset of the stimulus. P300 was averaged for each stimulus image in both methods, and then a 512-dimensional feature vector for SVM1p was made by arranging a 32-sample-point signal and 16 electrodes. N100 was averaged for each position, and then a 160-dimensional feature vector was made by arranging a 10-sample-point signal and 16 electrodes for SVM1n.

### Results

The grand averaged waveforms over P300 are
shown in Figure 12. The waveform of a target is averaged over the responses when the subject responds to the target character. From the target response waveform, P300 is observed around 400-500ms after the onset of the stimulus. The P300 latency of the proposed speller is larger than that of the P300 speller. The left side of Figure 13 shows the averaged waveforms of N100. The waveform of the stimulus is averaged over the responses when a character is presented in the target position. The waveform of the blank is averaged over the responses when no character is presented in the target position. N100 is observed around 150ms after the onset of the stimulus. The negative peak amplitude of the blank around 150 ms is smaller than that of the stimulus in P3 and P4. The significance of the difference over the N100 peak of P3 was confirmed by the t-testing \( p < 0.01 \). Negative peaks around 340ms in Figure 13 are caused by the subsequent stimuli because the SOA is 187.5 ms. The positive peak amplitude of the stimulus around 150 ms is much larger than that of the blank in FC1 and FC2. The significance of the difference over the P1 peak of FC2 was also confirmed by the t-testing \( p < 0.01 \).

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**Figure 12.** Grand averaged waveform over all subjects of P300 on FCz and Pz. The signal for the target (non-target) stimulus is averaged 1100 (12,100) times for 2 × 2 matrix N100-P300 speller. The signal for the target (non-target) is averaged 2200 (11,000) times for P300-speller.
Figure 13. Grand averaged waveform over all subjects for N100 on FC1, FC2, P3 and P4. The signal for the target (non-target) stimulus is averaged 9900 (3300) times for 2 × 2 matrix N100-P300 speller. The signal for the target (non-target) stimulus is averaged 6600 (3300) times for 2 × 3 matrix N100-P300 speller.
5. Conclusions

We have proposed a spelling BCI using both P300 and N100 to reduce the number of flashes and increase the ITR. To utilize N100 in a BCI, we have arranged uniquely designed stimulus images containing both characters and blanks. The blanks are arranged not to elicit N100. Hence, the proposed system can detect the gazing position by using N100. The advantages of the proposed method are that (i) the classification accuracy of N100 is higher than that of P300; (ii) the proposed method takes less time to type one character since the number of flashes can be reduced to nine in the case of the 2 x 3 matrix; (iii) the number of counting tasks can be reduced because N100 is elicited by visual stimulation without counting tasks, thus reducing user fatigue; and (iv) no characters flash twice in a row, whereas at least one character flashes twice in a row in most other ERP spellers. Therefore, the SOA may be shorter than that for the P300 speller. These advantages have been confirmed by our experiment.

References
