35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Character Identification by Maximizing the Difference between Target and Non-target Responses in EEG without Sophisticated Classifiers

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***Abstract*— We propose a simple character identification method demonstrated by using an electroencephalogram (EEG) with a stimulus presentation technique. The method assigns a code maximizing the minimum Hamming distance between character codes. Character identification is achieved by increasing the difference between target and non-target responses without sophisticated classifiers such as neural network or support vector machine. Here, we introduce two kinds of scores reflecting the existence of the P300 component from the point of time and frequency domains.**

We then applied this method to character identification using a 3×3 matrix and compared the results to that of a conventional P300 speller. The accuracy of character identification with our method indicated a performance of 100% character identification from five subjects. In contrast, the correct character was detected in two subjects and a wrong one was detected for one subject. For the remaining two subjects, no character was detected within ten trials. Our method required 4.8 trials on average to detect the correct character.

I. Introduction

A Brain-Computer Interface (BCI) is an interface from the brain to a computer using information obtained from biological signals. In recent years, much research related to BCI has been done. In this paper, we used an electroencephalogram (EEG) as the biological signal, which is widely available because it requires a low cost device and compact measurement system.

In the field of character input interface, the P300 speller is well known as a representative BCI paradigm. In a conventional speller, characters randomly light up with one row or column. A minimal trial consists of 12 flash stimuli to find the intended character when 36 candidate characters are arranged in a 6×6 matrix. P300 is one component of the evoked potentials that are generated by sensory stimuli with the task associated with human judgment and recognition. The speller utilizes the P300s that are evoked by a subject's attention to the intended (target) character to input when it was flashed. A number of research studies regarding the P300 speller have been performed.

Various character presentation methods, such as matrix element dimensions, flash patterns including inter-stimulus interval [1], feature extraction [2], [3] and sophisticated classifiers such as support vector machine for character identification [4], [5] have been reported. Gupta et al. investigated the influence of irrelevant stimuli during a task in the popular Rapid Serial Visual Paradigm (RSVP) and reported that RSVP showed high classification accuracies and bit rates because of the absence of irrelevant stimuli [6].

To shorten the time before character identification, we previously proposed a simple character presentation by stimulus sequences designed to maximize the Hamming distance and difference between target and non-target responses [7]. Regarding an assignment of code to the character considering the Hamming distance, we can find some reports in the literature [8]. They are based on the concept of error-correcting code whereby character identification is performed by correcting erroneous bits after classification of target and non-target responses. However, from this we inferred that a time-consuming classification technique is not needed to only identify an intended character. We therefore utilized the scores reflecting the difference between target and non-target responses by only using the characteristic that target responses have larger amplitudes than non-target responses. In our approach, the Hamming distance is not used for error-correction of code but to increase the difference between target and non-target responses. In a previous report [7], we showed that for one subject, our method reduced the time until the correct character was obtained. In this study, we improve upon our method by adding a frequency filter to obtain more stable results. Additionally, we increase the number of subjects and ascertain the effectiveness of the method by considering individual differences.

II. Methods

In this section, we describe the key aspects of our method. More details can be found in a previous publication [7]. Our concept for the detection of the intended character is not based on a classification of target (intended) and non-target (unintended) responses, but on the detection of the most appropriate of candidate characters, that is, an identification of the character that maximizes the difference between P300 amplitudes in response to target and non-target stimuli.

A. Character Presentation

We first assign a code to each character by expressing flashing and non-flashing characters as '1' and '0', respectively. We can then assign a unique code for each character. Generally, a P300 appears more prominently when the target stimulus occurs than when the non-target stimulus occurs in an oddball paradigm. Distinguishing between target and non-target responses perfectly, we can identify the intended character. However, it is very difficult to distinguish between target and non-target responses because P300 is easily affected by various factors such as spontaneous EEG overlapping with the P300, the subject's condition and

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motivation, and stimulus characteristics. In general, an averaging technique to sum up a large number of responses is widely used. However, to reduce the measurement time, a smaller number of stimuli are preferable. In this study, we focused on the way that characters are presented so that we could reduce the measurement time before detecting an intended character. We did this by introducing the Hamming distance as a metric for defining the distance between two different codes. This is based on the concept that two stimulation patterns having a longer Hamming distance will enable easier distinguishing of two different characters. In the case of character identification from among more than 3 candidate characters, it is preferable to choose the combination of codes that maximizes the minimum Hamming distance because maximization of the distance corresponds to an increase in the gap between P300 amplitudes in target and non-target responses.

In our study, we compared our character presentation method to that of a conventional P300 speller with a matrix having a small number of characters, 3×3. The six stimuli patterns that are used in the conventional P300 speller are shown in Figure 1. In Figure 2, the eight stimuli patterns used in our method are shown. Note that the minimum Hamming distance between any two codes is 2 when using the conventional method while the minimum Hamming distance between any two codes is 4 when using our enhanced method. Naturally, these stimuli patterns are randomly presented one at a time.

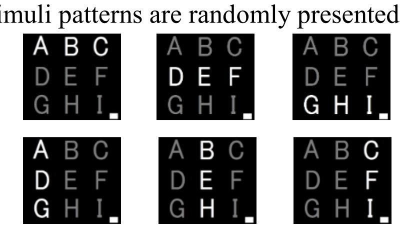

Figure 1. Character presentation patterns in the conventional P300 speller

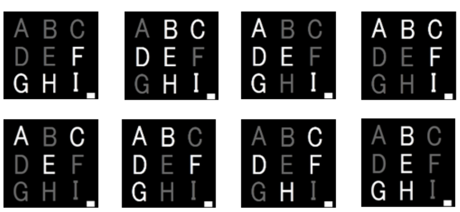

Figure 2. Character presentation patterns in our method

As previously mentioned the average of a large number of responses is typically used for P300 estimation and is a requisite processing step. However, as shown in Figure 2, the sequence includes only 8 stimulus presentations consisting of 4 target and 4 non-target flashes. Therefore, this procedure should be repeated so that enough responses are measured for averaging.

B. *Character identification*

To identify the intended character, we introduce two kinds of scores. The first is a score expressing the maximum amplitude of P300. If $x_{i,j}(t)$ is the EEG response to the i-th stimulus pattern of the j-th trial, we calculate

$$\bar{y}(t) = \frac{1}{MN}\sum_{j=1}^{N}\sum_{i=1}^{M}(-1)^{1-k}x_{i,j}(t) \tag{1}$$

$$k = \begin{cases} 1 & \textit{flashing} \\ 0 & \textit{non-flashing} \end{cases}$$

for each character according to the assigned codes. Here, M and N indicates the number of stimuli in one trial and the number of trials, that is, M is the length of a code, and is 8 in our method. Moreover, $x_{i,j}(t)$ is the signal processed with a 1-7 Hz band pass filter. The frequency range is set for eliminating alpha waves (8-13 Hz) and also by many reports that delta (0.5-4 Hz) and theta (4-7 Hz) frequency components contribute to the composition of P300 [9], [10].

In Equation (1), when an intended character flashes, a P300 appears with large positive amplitude, driving $\bar{y}(t)$ in the positive direction. When an unintended character flashes (and the intended character is non-flashing), $\bar{y}(t)$ is driven in the negative direction. The most appropriate choice of intended character will take the largest positive value because a P300 for the target stimulus contributes to an increase of the score in a positive direction. Therefore, we define a first score, s_1, by the following equation,

$$s_1 = \max_{200 \le t \le 500ms} \bar{y}(t) \tag{2}$$

where the parameter, t, is the time from the stimulus onset.

Next, we define the other index in terms of frequency. This index is obtained based on $\bar{Y}(f)$, which is the frequency power spectrum of the EEG signal, $\bar{y}(t)$. In this study, we obtained the power spectrum by Fourier transform of EEG signals from the time of stimulus onset to a time 1,000 ms after onset. Then, the second index is given by the following equation.

$$s_2 = \sum_{1 \le f \le 7Hz} \bar{Y}(f) \tag{3}$$

This index shows that the total power ranges from 1 to 7 Hz. By using the two kinds of score described above, we judged a character that had maximum scores at both s_1 and s_2 as an intended character. Although this method requires that the scores be generated for all characters before identifying the target character, real-time computation is easily achieved since these scores can be obtained with low computational cost.

C. *EEG Measurement*

A multichannel EEG signal was acquired using a Comet (Grass Technologies) with a 0.3s time constant and a 60 Hz high cut filter. The EEG signals used for the analysis were measured at Pz according to the International 10/20 system. Here, a monopolar derivation with bilateral references to the corresponding earlobes was used. The EEG signals were digitized at a sampling frequency of 400 Hz. Five subjects participated in this study. They were all male and the average age was 21.8 ± 0.45. Ten trials for one character detection were performed.

III. RESULTS

We show present the results when the subject intends to input the character,, ‘A’, among 9 characters. Final detection results are tabulated in Table 1. In this paper, because of space limitations, we show the results for one of five subjects (Subject No.2 in Table 1). In the case of Subject No. 2, the correct character was detected at the fourth trials (4×8 stimuli) for of our method and at the tenth trials (6×10 stimuli) for the conventional P300 speller. The averaged waveforms for the conventional P300 speller after 10 trials and our character presentation method after 4 trials, $\bar{y}(t)$, from stimulus onset to 1,000 ms after the onset are shown in Figures 3 and 4, respectively. We can see the maximum amplitude for character 'A'. Note that in our method, the positive and negative are inverted in the waveforms for character 'A' and 'H' (Figure 2) because their assigned codes have a bit inversion relationship. This means that one is flashing when the other is non-flashing and vice versa. This phenomenon can also be seen in the relationship between 'C' and 'G', and 'E' and 'F'. From these figures, the score, s_1, that is the maximum amplitude within the section from 200 to 500 ms from the stimulus onset corresponding to the appearance time of P300, is calculated for each character. Figures 5 and 6 show the relationship between scores and the number of trials for the conventional P300 speller and for our method, respectively. Moreover, in addition to s_1, the s_2 corresponding power in the range of frequency that includes P300 can also be obtained. Shown in Figures 7 and 8 are the results for the conventional P300 speller and for our method, respectively.

We then tabulated the detected character and number of trials to detect the character in Table 1. In all subjects, the correct character, 'A', could be detected by using our method. However, in only two of five subjects could the character be detected correctly. In the other three subjects, the wrong character was detected or the intended character could not be detected within ten trials.

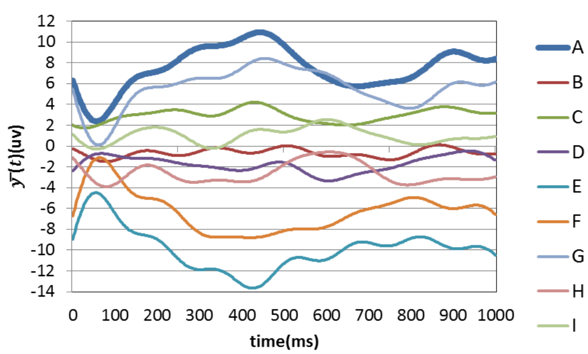

Figure 3. Averaged waveforms, $\bar{y}(t)$, measured by character presentation of the conventional P300 speller

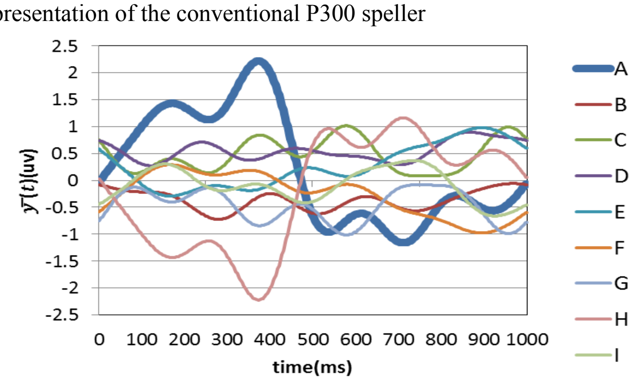

Figure 4. Averaged waveforms, $\bar{y}(t)$, measured by character presentation of our method

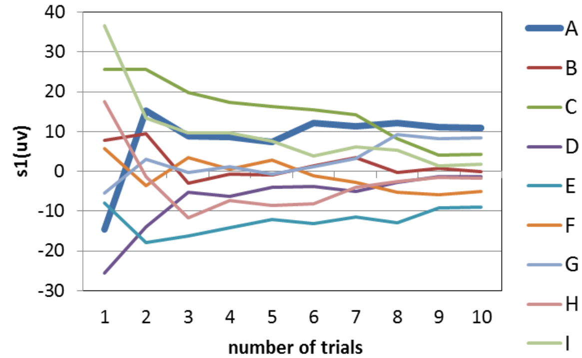

Figure 5. Temporal change of the score, s_1, obtained from $\bar{y}(t)$ measured by character presentation of the conventional P300 speller

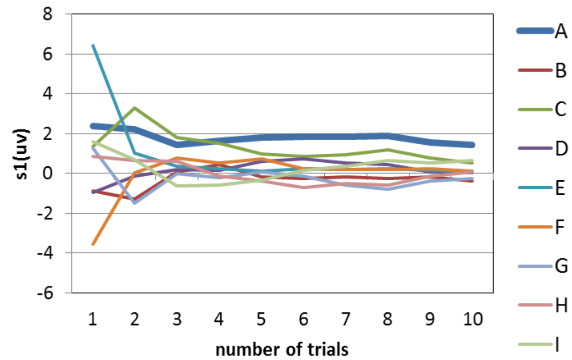

Figure 6. Temporal change of the score, s_1, obtained from $\bar{y}(t)$ measured by character presentation of our method

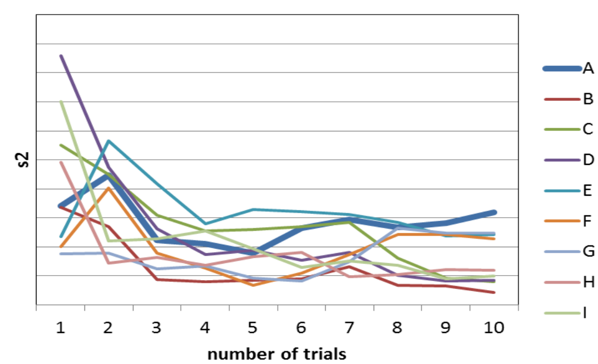

Figure 7. Temporal change of the score, s_2, obtained from $\bar{y}(t)$ measured by character presentation of the conventional P300 speller

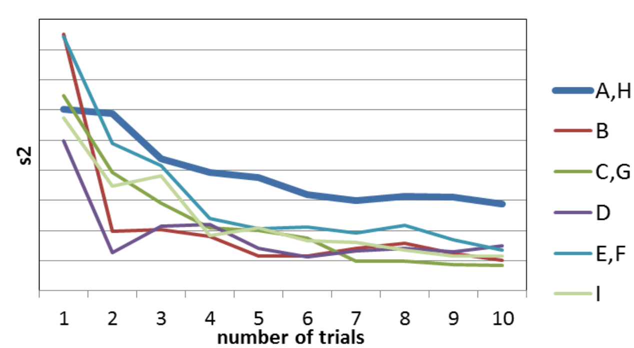

Figure 8. Temporal change of the score, s_2, obtained from $\bar{y}(t)$ measured by character presentation of our method

Table 1. Detected character and number of trials to detect the character

Subject	Conventional P300 speller		Our method	
	Detected character	Number of trials	Detected character	Number of trials
1	‘A’	10	‘A’	2
2	‘A’	9	‘A’	4
3	‘B’	2	‘A’	6
4	Not detected	-	‘A’	6
5	Not detected	-	‘A’	6

IV. Discussion

Our method maximizes the minimum Hamming distance between stimulus presentations and utilizes two kinds of indices considering the existence of P300 in the time and frequency domains. We found that our method outperformed the conventional P300 speller by correctly identifying the intended character in a shorter time.

Our purpose was to pick up the most appropriate character without identifying target and non-target responses because classification between target and non-target responses is difficult from a small number of recorded responses because of spontaneous EEG and various artifacts. Specifically, we increased the averaging number by combining target and non-target responses, and eliminated the classification process by using the difference between target and non-target responses.

In a previous report, we defined the one score, s_1, which is the maximum amplitude of the averaged waveform, $\bar{y}(t)$. However, the threshold is needed as a termination condition in character detection. By using two kinds of scores, we can give a termination condition such that when one character shows a maximum in two scores we can define the character as detected or estimated. In Figures 6 and 8, the intended character, ‘A’, shows the maximal value at s_1 at the fourth trial and at s_2 at the second trial for the first time. We consider that the score, s_2, has information regarding frequency, including P300 detected earlier than s_2. Although these scores are very simple indices, our method correctly detected and identified characters with 100% accuracy in five subjects.

The time required for detection is not sufficiently short; therefore additional processing is necessary to reduce the time. However, in this study, we used EEG recorded from only a single electrode, Pz. Moreover, we did not apply any filters, dimensionality reduction techniques such as principal component analysis (PCA), or supervised classification techniques. Although the use of simple signal processing on the EEG measurements is an advantage of our method, it is possible that these results will be further improved by applying such advanced processing techniques.

V. Conclusion

In this study, we proposed a simple character identification method with a stimulus presentation technique that assigns a code constructed to maximize the minimum Hamming distance between character codes and character identification without sophisticated classifier such as neural network or support vector machine. This is done by using two kinds of scores, s_1 and s_2, considering the existence of P300 in both time and frequency. The score, s_1, is the maximum amplitude within the section from 200 to 500 ms from the stimulus onset corresponding to the appearance time of P300. The other score, s_2, is the total power range from 1 to 7 Hz in the frequency domain. These scores are calculated for each character and the character having maximum scores at both s_1 and s_2 is detected.

We then applied this method to character identification using a 3×3 matrix and compared the results to that of a conventional P300 speller. We set the character, ‘A’, located at the left top corner in the matrix as an intended character. Results indicated that the proposed method showed a 100% character identification performance when applied to five subjects. In contrast, the correct character was detected in two subjects and the wrong character was detected for one subject. For the remaining two subjects, no character was detected within ten trials. As for the time needed to detect the correct character, our method required 4.8 trials on average. This value is insufficient when compared with other reports. An advantage of the method is that identification was performed using a relatively simple calculation on data from a single EEG channel. Moreover, no sophisticated classification algorithms or data training were applied.

In future, the measurement of EEG signals from a larger number of subjects is required to allow a statistical evaluation of the effectiveness of the proposed method.

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