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EEG Character Identification using Stimulus Sequences Designed to Maximize Mimimal Hamming Distance.

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Abstract— **In this study, we have improved upon the P300 speller Brain-Computer Interface paradigm by introducing a new character encoding method. Our concept in detection of the intended character is not based on a classification of target and nontarget responses, but based on an identifaction of the character which maximize the difference between P300 amplitudes in target and nontarget stimuli.**

Each bit included in the code corresponds to flashing character, '1', and non-flashing, '0'. Here, the codes were constructed in order to maximize the minimum hamming distance between the characters. Electroencephalography was used to identify the characters using a waveform calculated by adding and subtracting the response of the target and non-target stimulus according the codes respectively. This stimulus presentation method was applied to a 3×3 character matrix, and the results were compared with that of a conventional P300 speller of the same size. Our method reduced the time until the correct character was obtained by 24%.

I. INTRODUCTION

In recent years, many researchers have been developing Brain-Computer Interfaces (BCI), which create an interface from the brain to a computer using information obtained from biological signals such as electroencephalograms (EEG). This technique allows a person to control a machine just by thinking. This technology is expected to yield exciting new communication tools and interfaces.

The P300 speller is well known as a representative BCI paradigm for inputing characters to a computer. P300's are considered to be related to human judgment and recognition. The speller utilizes P300's evoked by a subject's attention to the intended (target) character to input when it flashed.

A number of research studies regarding the P300 speller have been performed and various aspects of the P300 speller have been examined. Various character presentation methods, such as matrix element dimensions, flash patterns including inter-stimulus interval [1], feature extraction [2],[3] and classifiers for character identification [4],[5] have been reported.

In a conventional speller, characters light up with one row or one column randomly. A minimal trial consists of 12 flash stimuli to find the intended character when 36 candidate characters are arranged in a 6×6 matrix.

In this study, we propose a simple method to shorten the time before character identification by changing the method of presenting the stimuli.

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II. METHODS

Our concept in detection of the intended character is not based on a classification of target and nontarget responses, but based on an identifaction of the character which maximize the difference between P300 amplitudes in response to target and nontarget stimuli.

A. Assigning codes (Encoding)

First, we assign a code to each character by expressing flashing and non-flashing characters as '1' and '0' respectively. In a typical odd-ball paradigm, a P300 appears more prominently when target stimulus occurs than when non-target stimulus occurs. In principle, the intended character for input requires that a P300 corresponding to the target and non-target stimuli perfectly match with flashing '1' and non-flashing '0' respectively. Since, in this paper, a target stimulus corresponds with the character that a subject would like to input, we can identify the intended character by evaluating the degree of a straightforward matching score.

Next, assume that all characters are flashing with the same frequency in one measurement trial. This means that the number of times each character is flashed is constant and a constant number of bits with '1' are included in a fixed code. In this study, we also set the flashing rate of a character set to 50%, i.e., a character is flashing and non-flashing an equal number of times. Namely, the same number of binary digits '0' and '1' are included in the code. When m is the number of flashes, the code length is $2m$ bits and ${}_{2m}C_m$ kinds of characters can be identified by the combinations of '0' (non-flashing) and '1' (flashing).

Therefore, following equation should be satisfied,

$$ {}_{2m}C_m \geq N, \tag{1} $$

where N is the number of candidate input characters.

For example, in the case of a typical P300 speller, consisting of a 6×6 character matrix, m should be more than 4 and the code length becomes 8 because ${}_6C_3$ = 20 and ${}_8C_4$ = 70. Accordingly, 8 bits are needed to identify 36 different characters.

Ideally, if we can discriminate between the P300 for target stimuli from that for non-target stimuli using a single trial response, it will be easy to specify the intended character. Realistically, however, a technique such as averaging a large number of responses is required in order to suppress spontaneous EEG, noise and various other artifacts. We claim that, due to these difficult conditions, a longer hamming distance between two codes will yield a higher accuracy for identification. In order to identify the intended character from among more than 3 candidate characters, it is preferable to choose the combination of codes to maximize the minimum hamming distance because maximization of minimum hamming distance corresponds to increase the gap between P300 amplitudes in target and nontarget responses. .

In our study, we compared our stimulus presentation method to that of a conventional P300 speller with matrix having small number of characters, 3×3, as shown in Figure 1. In Figure 2(a), we see the six stimuli patterns that are used in the conventional P300 speller and in Figure 2(b) we see the eight stimuli patterns used to construct our enhanced P300 speller. Assuming that the patterns are presented in the same order shown in Figure 2, the codes for each character are shown in Table I. Table II shows the hamming distance between each pair of codes, with the hamming distances for the conventional method below the diagonal and the hamming distances for our method above the diagonal. Notice that the minimum hamming distance between any two codes in using the conventional method is 2 while the minimum hamming distance between any two codes is 4 when using our enhanced method.

As mentioned above, the average of a large number of responses is typically used for P300 estimation. However, the codes for our method, shown in Table I, include only 8 stimulus presentations consisting of 4 target and 4 non-target flashes. Therefore, this procedure should be repeated in order to measure enough responses for averaging. However, repetition of the same stimulus sequence may cause habituation, potentially reducing the P300 amplitude. One potential solution to this problem is to introduce a level of randomness into the stimulus sequence. For example, one might exchange among the codes used to express the 9 characters, although this may change the hamming distance in Table II. Another potential solution is to simply change the presentation order in Figure 2. This solution does not change the minimum hamming distance, although the codes shown in Table I may vary between repetitions.

In this study, we choose to only vary the sequence of stimulus presentations in order to examine the relationship between hamming distance and the score for character identification, as described by Equation 3 in the following section.

TABLE I

EXAMPLE OF ASSIGNED CODE FOR EACH CHARACTER.

character	P300 speller	our method
A	100100	00111100
B	100010	01010101
C	100001	01011010
D	010100	01100110
E	010010	01101001
F	010001	10010110
G	001100	10100101
H	001010	11000011
I	001001	11110000

TABLE II

HAMMING DISTANCE BETWEEN TWO CODES IN TABLE I.

	A	B	C	D	E	F	G	H	I
A	-	4	4	4	4	4	4	8	4
B	2	-	4	4	4	4	4	4	4
C	2	2	-	4	4	4	8	4	4
D	2	4	4	-	4	4	4	4	4
E	4	2	4	2	-	8	4	4	4
F	4	4	2	2	2	-	4	4	4
G	2	4	4	2	4	4	-	4	4
H	4	2	4	4	2	4	2	-	4
I	4	4	2	4	4	2	2	2	-

Entries below the diagonal are distances for the conventional P300 speller while entries above the diagonal are distances for our method.

B. Character identification (Decoding)

In order to suppress signal components other than the desired evoked potentials and in order to identify the intended character, we first find

$$
\begin{aligned}
\overline{y}(t) &= \frac{1}{2m}\sum_{i=1}^{2m}(-1)^{1-k}x(t) \\
k &= \begin{cases} 1 & \text{flashing} \\ 0 & \text{non-flashing} \end{cases}
\end{aligned}
\tag{2}
$$

for each character according to the assigned codes. Ideally, a P300 appears more prominent in the response for target stimulus than in the response for a non-target stimulus. When an intended (target) character flashes, a P300 appears with a large positive amplitude, driving $\overline{y}(t)$ in the positive direction. The other hand, when an unintended (non-target) character flashes, $\overline{y}(t)$ is driven in the negative direction. Since this method uses both target and non-target responses, the signal to noise ratio is improved by increasing the number of averaged responses.

The intended character can then be identified by calculating the score

$$
\begin{aligned}
s &= \overline{y}(t') \\
t' &= \max_{t}\ \overline{y}(t), \\
& \quad (200ms \leq t \leq 500ms)
\end{aligned}
\tag{3}
$$

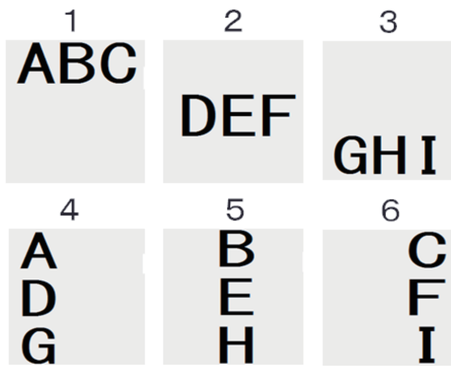
where the parameter, t, is the time from the stimulus onset. The score, s, should be the largest for the intended character because P300 for target stimulus contributes to an increase of the score to positive direction.

Although this method requires the scores to be generated for all characters before identifying the target character, real-time computation is easily achieved since Equation 2 consists only of simple addition and subtraction. Moreover, processing can be terminated when the intended character is found because the averaged waveforms, i.e., $\overline{y}(t)$, can be updated after each stimulus.

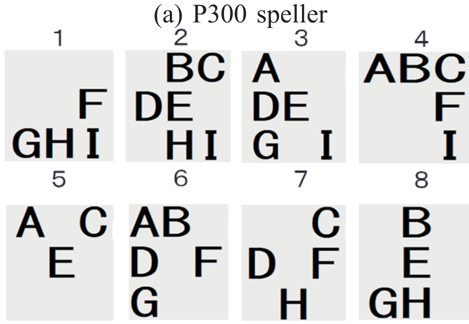
C. EEG Measurement

A multichannel EEG signal was acquired using a Comet (Grass Technology) with a 0.3s time constant and a 60Hz high cut filter. The EEG signals used for the analysis were

Fig. 1. 3×3 character matrix.



(a) P300 speller



(b) proposed method

Fig. 2. An example of character presentations. Printed characters are flashing.

measured at P_z 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 400Hz. The subject is a healthy male whose age is 22.

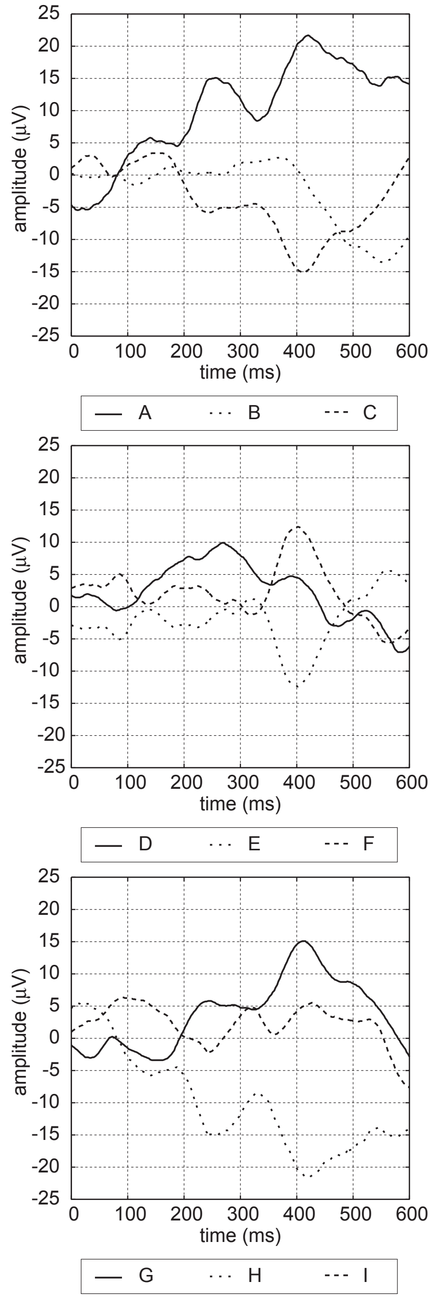


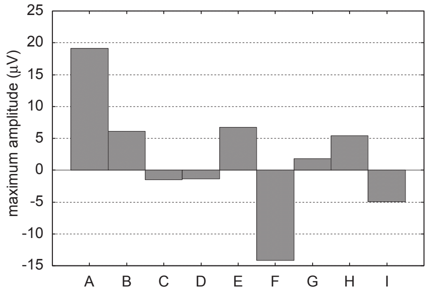
Fig. 3. Waveforms of $\overline{y}(t)$ for each character in the case of 8×4 stimuli using our method.

III. RESULTS

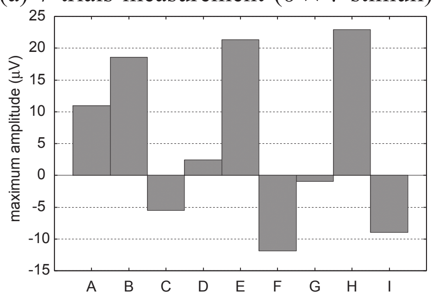
In this study, we show the results when the subject intends to input the character, 'A'. The averaged waveforms, $\overline{y}(t)$, from stimulus onset to 600ms after the onset are shown in Figure 3. In order to simplify our analysis, we separated 9 waveforms for 9 characters into three graphs by three waveforms. The score, that is maximum amplitude within the section from 200 to 500ms from the stimulus onset corresponding the appearance time of P300, is calculated for each character. Figure 4 and Figure 5 show the results for the conventional P300 speller and for our method respectively.

Figure 4(a) was the score obtained from the waveform by averaging the responses from all 7 trials of (6×7) stimuli by the stimulus presentation of conventional P300 speller. The correct character could be estimated because the character with maximum score is 'A'. On the other hand, in the case of 6 trials (6×6) stimuli, estimated character having maximum score is 'B'. It appears that the correct answer could be obtained using more than 7 trials. Therefore, it is thought that less than 6 trials does not give a correct result due to the limited number of averaged responses.

Using our method, the correct result could be obtained with more than 4 trials (8×4) stimuli, as shown in Figure 5.

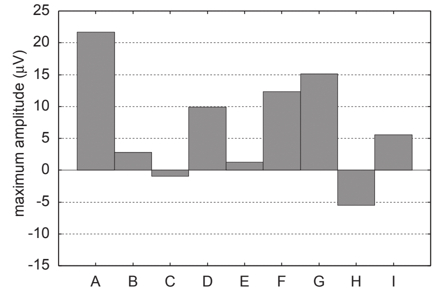


(a) 7 trials measurement (6×7 stimuli)

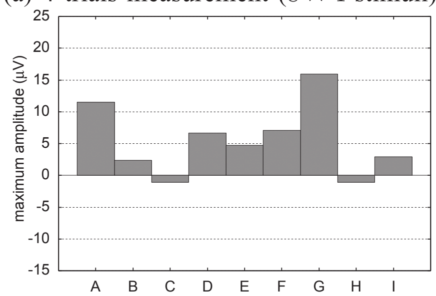


(b) 6 trials measurement (6×6 stimuli)

Fig. 4. Scores, s, on the stimulus presentation of a conventional P300 speller.



(a) 4 trials measurement (8×4 stimuli)



(b) 3 trials measurement (8×3 stimuli)

Fig. 5. Scores, s, on the stimulus presentation of our method.

IV. DISCUSSION

Our method of maximizing the minimum hamming distance between stimulus presentations outperformed the conventional P300 speller by correctly identifying the intended character in a shorter time, i.e., using fewer stimulus repetitions. With a 3×3 characters matrix, more than 32 (8×4) stimuli were needed when using our method. On the other hand, a conventional P300 speller needed at least 42 (7×6) stimuli. This is about a 24% reduction in the required number of stimuli.

Our method mistook the correct character, 'A', for 'G' in 6 trials of stimuli. The hamming distance between 'A' and 'G' is 4, and the distance was minimum. However, the difference in score was maximum between 'A' and 'H' whose the distance is 8. This result supports our claim that maximizing the minimum hamming distance make it easier to detect the intended character. However, there are variabilities among characters even when the distances are the same. Therefore, more investigation into parameters other than the distance should continue to be examined. In this study, we used EEG recorded from only a single electrode, P_z. Moreover, we have not applied any filters, dimensionality reduction techniques, such as principal component analysis (PCA), or supervised classification techniques. These results will likely be further improved by applying such techniques. 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]. We should examine the influence of irrelevant stimuli to our results in the future research.

V. CONCLUSIONS

In this study, we proposed a novel stimulus presentation technique that assigns a code for each character. Each bit included in the code corresponds to flashing a character, '1', and non-flashing a character, '0'. Here, the codes were constructed to maximize the minimum hamming distance between character codes. We then applied this stimulus presentation method to character identification using a 3×3 matrix and compared the results to that of a conventional P300 speller. Our method reduced the time until the correct character was identified by 24%.

In this method, identification was performed using a relatively simple calculation. Since no filtering or sophisticated classification algorithms were applied, there is still room for improvement in our method. Moreover, the measurement of EEG from a large number of subjects is required in order to ascertain the effectiveness of our method statistically.

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