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

An Efficient Words Typing P300-BCI System Using a Modified T9 Interface and Random Forest Classifier

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Abstract— **The conventional P300-based character spelling BCI system consists of a character presentation paradigm and a classification system. In this paper, we propose modifications to both in order to increase the word typing speed and accuracy. In the paradigm part, we have modified the T9 (Text on Nine keys) interface which is similar to the keypad of mobile phones being used for text messaging. Then we have integrated a custom-built dictionary to give word suggestions to a user while typing. The user can select one out of the given suggestions to complete word typing. Our proposed paradigms significantly reduce the word typing time and make words typing more convenient by typing complete words with only few initial character spellings. In the classification part we have adopted a Random Forest (RF) classifier. The RF improves classification accuracy by combining multiple decision trees. We conducted experiments with five subjects using the proposed BCI system. Our results demonstrate that our system increases typing speed significantly: our proposed system took an average time of 1.83 minutes per word, while typing ten random words, whereas the conventional spelling required 3.35 minutes for the same words under the same conditions, decreasing the typing time by 45.37%.**

I. Introduction

Brain Computer interface (BCI) is a system that provides direct communication with a computer through signals generated by the brain. P300 evoked potentials are one of the commonly used EEG signals for BCI known as a P300 BCI. A typical P300-based character spelling BCI system consists of a stimulus presenting paradigm and a classifier. The most widely adopted paradigm for character spelling was first introduced by Farwell and Donchin [1]. Their speller paradigm involved a 6×6 matrix of characters and numbers in which each row or column is randomly intensified. A user looks at a target character and intensification of either a row or column containing the target character evokes P300. Classification of a set of row and column containing the evoked P300 leads to the recognition of the target character. Most of the later research followed the same scheme and was focused on improving classification accuracy and speed.

To improve classification accuracy, many techniques for P300 extraction and classification have been used such as support vector machine (SVM) [2], [3], linear discriminant analysis (LDA) [4], neural network [5], independent component analysis (ICA) [6], and lately constrained independent component analysis cICA [7]. Recently there is a growing interest in designing efficient paradigms. Various attempts have been made to modify the Farwell and Donchin (FD) paradigm. These modifications include using different matrix sizes [8], changing visual aspects such as color, symbol dimensions, and distance between the symbols [9], [10], single character flipping instead of the row and column intensification [11], and using a checkerboard paradigm [12]. Some works suggested the region-based [13] or submatrix-based [14] paradigms.

A common drawback of all these conventional P300 spelling systems is that to type a word a user has to spell each character of a word one at a time. This spelling process is slow and can take several minutes to finish a single word. A new paradigm is in needs by which a user can type a whole word in less typing and time.

Some attempts have been made in this regards. In [15], Ahi et al used a dictionary driven P300 speller. They integrated a custom-built dictionary of 942 four-lettered words into the classification system of P300 speller for automatic correction of misspellings. However, the dictionary was used only for word correction and the user had to spell all the characters of a target word. In [16], Höhne et al used a German language T9 system with an auditory event related potential based speller. The user spelled on a 3×3 scheme with audio stimuli and suggestions are shown after the user spelled a complete word. Words typing using their system was slow because to write a five-letter word, the user must go through 5-character spellings, then the user further needed to go through at least two extra spellings: one for switching to the control mode and the other for the selection of a target word.

In this study, we propose a modified T9 (Text on Nine keys) interface with a dictionary to give words suggestions to the user while typing. In the mobile text messaging system, the T9 is used to write text messages at high speed using a keypad with twelve keys. Eight keys are associated with several characters and a dictionary is used to suggest words according to the sequence of keys a user presses. Four other keys are used for other functions. In this study, we have modified it to be used only with nine keys: eight keys are associated with characters and one key for a delete function in case of error. Word typing is done in two steps. A user needs to spell only few characters of a target word using a 3×3 matrix of the modified T9 keys, and then the dictionary module suggests some words starting with the spelled combination of keys. Finally, the user can select one out of the given suggestions using the same 3×3 matrix. The suggested paradigm reduces the typing time significantly. Furthermore to improve the accuracy of typing, we have adopted a Random Forest (RF) classifier for P300 detection. The RF, an ensemble learning technique introduced by Breiman [17], is a powerful classifier

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and has been used efficiently in many fields but is relatively unknown in the field of BCI.

We have tested our P300 words typing BCI with five healthy subjects and each subject was instructed to write ten randomly shown words. Our results show that the proposed P300 word typing paradigm took an average of 1.83 minutes to write a word whereas the conventional paradigm required 3.35 minutes for the same words. The proposed scheme reduces the word typing time by 45.37%, thereby increasing the information transfer rate consequently.

II. Methodology

A. The Conventional P300 Speller

The conventional P300 speller consists of a 6x6 matrix of characters and numbers in which each row or column flashes randomly. A user is asked to focus on a target character and silently count the number of times the flashed target character. P300 is elicited when the row or column containing the target character is flashed. A classifier detects one row and one column with P300 which leads to identify the target character. The user completes word typing by spelling every character of the target word.

B. Overview of Our Proposed P300-based Word Typing

In our word typing BCI system, we have added a word suggestion mechanism to reduce typing time. Word typing is done in two steps: spelling initial characters for words suggestions and a word selection from the suggestions. When a session starts, a user starts to spell initial characters of a target word using a 3×3 matrix of keys in which each key is associated with several characters and each key is randomly intensified. The user focuses on the key containing the target character. The classification results are fed into the dictionary module. The dictionary module searches for the words starting with prefixes made by the classified combinations of the keys. If the number of those words are less than a threshold (in our case of nine), a suggestion screen is shown to the user and is asked to select one out of those suggestions. If the number of suggestions is greater than the threshold, the user continues to write the next character of the target word.

C. Word Typing Paradigm

Our modified T9 word typing paradigm is a 3×3 matrix of nine keys. The eight keys contain three or four characters and the ninth key is for a 'delete' function used to delete the last spelled character in case of a spelling mistake as shown in Fig. 1(a). The interface is similar to the keypad of a mobile phone where text messages are written on a keypad with 12 keys and a T9 predictive dictionary is used for faster typing. We used only nine keys and each of nine keys flashes randomly with intensification time 100ms and 75ms blank time between intensifications. A user focuses on the key containing the target character and keeps on counting the number of times the target key flashes. Detection of one key containing P300 leads to identify the target key. Each key contains three or four characters. The dictionary module generates a list of words starting with the characters in the spelled key. The user continues to write next characters of the word until the word in the suggestion list become less than the threshold. When they become less, the word suggestion screen is shown to the user as shown in Fig. 1(b) and the user is asked to select one out of the suggestions. The user spells the number from 1 to 9 according to the target word as shown in Fig. 1(c) to complete typing the word.

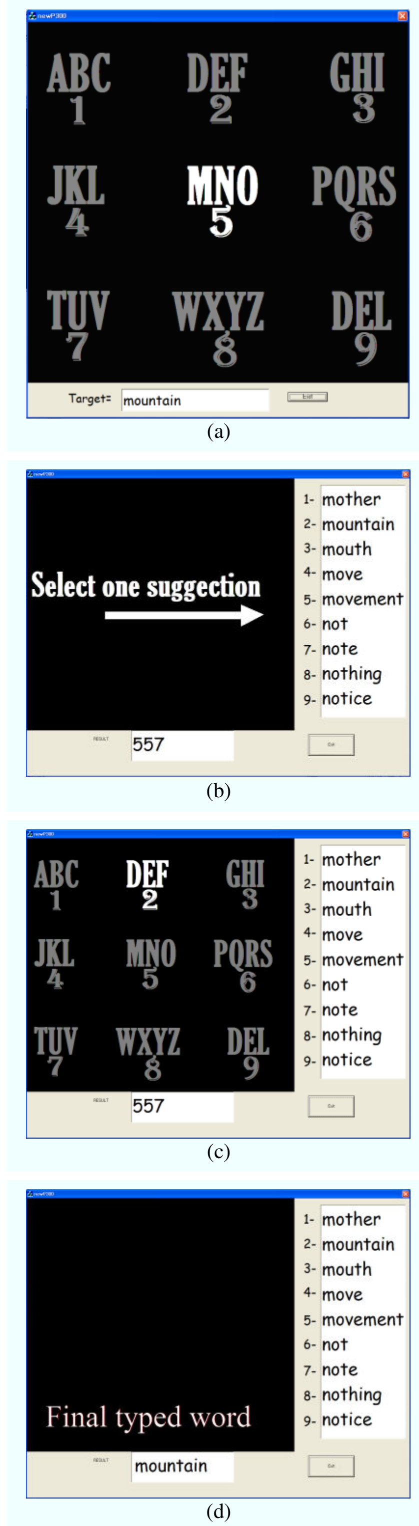

Figure 1. Our word typing paradigm. (a) The first step for spelling initial characters, (b) a words suggestion screen, (c) the second word selection step, and (d) a display showing the final typed word

The final typed word is shown to the user as shown in Fig. 1(d) and then switched back to the main paradigm to type the next word. If a spelling mistake occurs during the word selection step, the user can select the 'delete' key and start typing again from word selection step.

Table I shows the time specification of the conventional paradigm as used in the BCI competition III dataset II [18] and the proposed paradigm.

TABLE I. TIMING INFORMATION FOR THE PARADIGMS

	Conventional paradigm	Proposed Paradigm
Intensification time	100ms	100ms
Blank time between intensifications	75ms	75ms
Total stimuli	12	9
Character repeat	15	15
Blank time between characters	2.5s	2.5s

D. *Dictionary Module*

We used a custom-built dictionary of 1,000 most commonly used English words. The dictionary is implemented in the form of Ternary Search Tree (TST). TST is a kind of prefix tree data structure that can be used to find words having a given prefix. The dictionary gives suggestions based on the combinations of prefixes that are formed by the user typed keys. For example, if a user selects the Key-5 while typing the first character of a target word, the Key-5 contains three characters (M, N, and O): the dictionary will suggest all words starting with these three characters. Afterwards, if the user selects the Key-5 again for the second character, there can be a total of nine prefixes (MM, MN, MO, NM, NN, NO, OM, ON, and OO). Then the dictionary module filters out only those words that start with these prefixes. The number of words decreases in the suggestion list after the user types each character and as the number falls below the threshold a suggestion screen is shown to the user. The user needs to choose one out of the suggestions to complete word typing.

E. *Classification*

We applied a band-pass filter with cutoff frequencies of 0.1Hz and 25Hz. Then epochs of 600ms after the stimulus onset were extracted. A total of eight channels were used for classification. To detect P300s, we have adopted a RF classifier. The main idea of RF is to combine multiple independent decision trees and let them vote for the popular class. RF can improve accuracy significantly and we have compared the performance of RF against the widely used SVM.

F. *Experiments*

This study was conducted using five healthy male subjects. Subjects had no record of any neurological brain diseases and had normal or corrected vision. All participants in our study were provided the written informed consent.

The EEG data was acquired through a 32-channel BrainAmp MR amplifier with a sampling frequency 250Hz. Electrodes were placed according to the 10-20 international standard. Each subject participated in training and testing sessions. In the training session, each subject was instructed to spell ten randomly selected characters. This data was used to train the classifier. In the test session each subject typed ten randomly selected words from the dictionary. A set of exemplary target words includes "window," "beautiful," "poem," "stone," "wings," "understand," "smell," "answer," "statement," and "piece."

III. RESULTS

Based on the information given in Table I, we have computed the time required to spell one character using both the conventional and proposed paradigms. For the conventional paradigm, the total number of intensification is 180 (i.e., 12 stimuli×15 repetitions) and 175 ms (i.e., intensification time+blank time between intensifications) is the time for one intensification. Therefore the time required to spell a single character using the conventional paradigm comes out to be 34s (i.e., [180×175]ms+2.5s blank time between characters.) Similarly for the proposed paradigm, this comes out to be 26.125s per character. With these numbers, we computed the time required by the conventional paradigm to spell the target words and compared it with the actual time taken by the proposed paradigm for the same words. Table II shows the time required to spell these words using the conventional paradigm with 100% accuracy.

TABLE II. WORD TYPING TIME USING THE CONVENTIONAL PARADIGM

Word Number	**Word typing time using the conventional scheme (minutes)**				
	S1	***S2***	***S3***	***S4***	***S5***
1	3.4	3.4	4.53	2.83	2.83
2	2.83	2.83	4.53	2.83	2.27
3	5.1	4.53	2.27	2.83	3.4
4	5.1	2.27	3.4	5.1	2.83
5	5.67	6.23	2.83	3.4	2.83
6	2.27	3.4	2.83	2.83	3.4
7	2.83	2.27	3.4	3.97	3.4
8	2.83	3.97	2.83	2.83	4.53
9	2.83	3.4	2.83	3.97	3.4
10	3.4	2.27	2.83	2.83	2.27
Mean	**3.63**	**3.46**	**3.23**	**3.34**	**3.12**
Grand mean	**3.35**				

Table III shows the actual time taken by the proposed scheme to spell the same words. The conventional spelling required an average time of 3.35 minutes per word while the proposed word typing scheme took only an average typing time of 1.83 minutes per word, decreasing the typing time by 45.37 %. Note that the lapsed time for the proposed scheme includes error correction time.

TABLE III. WORD TYPING TIME USING THE PROPOSED PARADIGM

Word Number	**Word typing time using the proposed scheme (minutes)**				
	S1	***S2***	***S3***	***S4***	***S5***
1	1.74	1.74	1.74	1.74	1.74
2	1.74	2.61	2.61	1.74	1.74
3	1.74	1.74	1.31	1.74	2.61
4	1.74	1.31	1.74	2.18	1.74
5	1.74	1.74	1.74	2.61	1.74
6	1.74	1.74	1.74	1.74	2.61
7	1.74	1.31	1.74	1.31	2.61
8	1.74	2.61	1.31	2.18	1.74
9	1.74	1.74	1.74	1.74	1.74
10	1.74	1.74	1.31	1.74	1.74
Mean	**1.74**	**1.83**	**1.7**	**1.87**	**2**
Grand mean	**1.83**				

We also compared the offline classification results of RF against SVM for different number of stimulus repetitions. Our results show that the RF classifier can better classify P300's even with lesser repetitions. Fig. 2 shows the grand mean classification accuracy for both SVM and RF over all subjects.

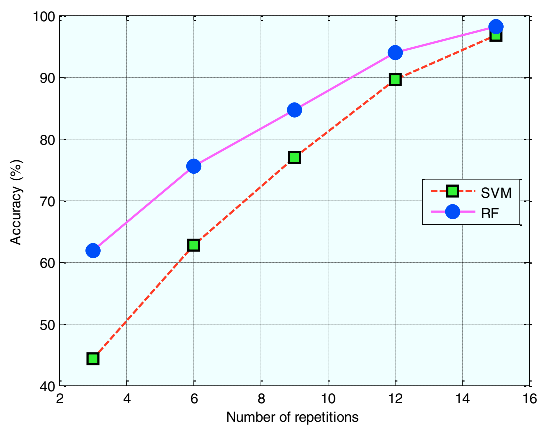

Figure 2. Grand averaged classification results over five subjects for SVM vs. Random Forest with different number of repetitions

IV. Discussion

The proposed method has a significant advantage in terms of accuracy over the conventional spelling because in the proposed paradigm prior probability of target is less and accuracy is inversely proportional to the prior probability of the target [8]. The conventional paradigm uses a 6×6 matrix with flashing rows or columns. Two targets out of 12 intensifications give the probability of the target equals 1/6, whereas the proposed paradigm has a prior probability of the target equal to 1/9.

Also, in the proposed paradigm, there are less chances of making mistakes because a user has to spell only few characters to type a word. In case a spelling mistake, the user can spell a 'delete' key and then write the correct character again. This error correction time is also less in the proposed paradigm compared with the conventional paradigm.

V. Conclusion

In this study, we proposed an efficient dictionary based P300 word typing BCI paradigm using the modified T9, a dictionary, and RF. Our results show that the proposed method of P300 word typing system not only increases the speed of typing with higher accuracy but also makes the spelling task easier for users with less fatigue. This could be one of the important advantages to become a practical BCI especially for the disabled.

Acknowledgments

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MEST) (2011-0029485). This research was supported by the MKE (The Ministry of Knowledge Economy), Korea, under the ITRC (Information Technology Research Center) support program supervised by the NIPA (National IT Industry Promotion Agency) (NIPA-2013-(H0301-13-2001)).

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