A P300-Based Word Typing Brain Computer Interface System Using a Smart Dictionary and Random Forest Classifier

Faraz Akram, Hee-Sok Han, and Tae-Seong Kim
Department of Biomedical Engineering
Kyung Hee University,
Yongin-si, Republic of Korea
farsun@gmail.com, hshan@khu.ac.kr, tskim@khu.ac.kr

Abstract— **The conventional P300 brain computer interface (BCI) system for character spelling is typically composed of a paradigm that displays flashing rows or columns of characters and a P300 classifier from which a target character gets recognized. One significant drawback of this system in practice is its typing speed which could take a few minutes to type each character of a target word. In this work, we propose a novel BCI system through which a whole word can be typed with much higher word typing speed and accuracy. In our presented system, we have integrated a custom-built smart dictionary to give word suggestions upon few key characters initially typed by the user. Upon the suggested words, the user can select one out of the given suggestions to complete word typing. Our novel paradigm significantly reduces the word typing time and makes words typing more convenient. In the classification part, we have also adopted a new classifier, Random Forest (RF) instead of a commonly used Support Vector Machine (SVM). Our results with four subjects using the presented word typing system demonstrate an average typing time of 1.66 minutes per word, whereas the conventional took 2.9 minutes, improving the typing time by 42.75%. Also RF improves the P300 classification accuracy significantly, outperforming SVM. Our presented system could be useful for practical human computer interaction applications.**

Keywords-P300; Brain Computer Interface; Word Typing; Human Computer Interaction

I. INTRODUCTION

Brain Computer Interface (BCI) is a system that provides a way of communication between a computer or device and the brain. The primary goal of a BCI is to enable severely disabled peoples to communicate and control their external environment without relying on peripheral nerves and muscles. Yet it is not restricted to disabled peoples only, many applications for normal peoples are emerging. A BCI system that utilizes P300 event related potentials of the brain is known as P300 BCI. One application of P300 BCI was first demonstrated for character spelling by Farwell and Donchin [1]. Since then Farwell and Donchin (FD) paradigm has been most widely used for P300-based character spelling [2,3]. Most of the later research followed the same scheme and was focused on improving the classification accuracy and speed.

To improve the classification accuracy, many techniques have been suggested for P300 classification such as support vector machine (SVM) [4], linear discriminant analysis (LDA) [5], and neural network [6] and lately for P300 extraction such as independent component analysis (ICA) [3] and constrained ICA [7]. Recently, there is a growing interest in designing efficient paradigms. Various attempts have been made to modify the FD paradigm. For instance, in [8] Salvaris and Sepulveda made various changes to the visual aspects of the FD paradigm. In [9], Allison and Pineda tried three different matrix sizes such as 4×4, 8×8, and 12×12 to investigate the effect of matrix size on the amplitude of P300. In [10], Guan et al. used a single character flipping instead of row and column intensifications to improve classification accuracy. Single character flipping reduced the target probability, hence increasing the amplitude of P300. In [11], Townsend et al. used an 8×9 checkerboard paradigm to eliminate this double flash problem, improving accuracy.

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 typing a single word. A new paradigm is in need by which a user can type a whole word in less typing time and effort. Some attempts have been made in this regards. In [12], 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 [13], Ryan et al. proposed a predictive spelling scheme with words suggestions, but in their work, classification accuracy was decreased due to a higher workload in their displays. In [14], Kaufmann et al. used a German language predictive speller with some commonly used German words. They obtained the similar results due to the required high attentions.

In this paper, we propose an improved BCI system in the words suggestions and selection paradigms by reducing the workload to the user and by employing a better classifier. In this work, we have implemented a smart dictionary to give words suggestions to the user in order to reduce the typing time. In our proposed scheme, a user only needs to spell few initial characters of a word. Then possible words matching the typed initials will be suggested to the user. Finally, the user only needs to select one of the suggestions. This scheme reduces the spelling time and thereby increases information transfer rate. Our proposed scheme also reduces the visual fatigue by reducing the number of characters required to type a word, hence a user can better concentrate on typing in longer trials. We have tested our P300 words typing BCI and

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have increased the typing speed by 42.75% in comparison to the conventional character typing under the same conditions. Also, we have adopted a new RF classifier for P300 classification to improve the accuracy of typing. Our results, in comparison to a commonly used classifier in BCI, show that RF outperforms SVM in the typing accuracy. Our presented system should be useful as a practical P300 BCI spellers. Also it could be used in the application areas of human computer interaction for word typing.

The paper is organized as follows: Section II describes the conventional speller and our proposed word typing methodology with classification. The results are presented in Section III, followed by a conclusion in Section IV.

II. METHODOLOGY

A. *The Conventional P300 Speller*

The conventional P300 speller consists of a 6x6 matrix of characters and numbers (much similar to Fig. 1 (a)) in which each row and column flashes randomly. A user is asked to focus on a target character. P300 is elicited when a row or column containing the target character flashes. The target character is detected by identifying the row and column containing P300s. The user completes word typing by spelling every character of the target word.

B. *Overview of Our Proposed P300-based Word Typing System*

In our proposed system, we have added a words suggestion mechanism with a smart dictionary to the conventional character spelling paradigm. Our system consists of two paradigms: the first paradigm is a matrix of 6×5 with characters, as shown in Fig. 1(a). When a session starts, the first paradigm is shown to a user and the user spells few initial characters of a desired word. The typed initial characters get in to the dictionary module and the dictionary searches for the words matching the initial characters. When the number of suggested words is less than a pre-specified threshold (in our case of nine), the searched words are displayed as suggestions. Finally, the user is asked to select one out of those suggestions as shown in Fig. 1(b). The user selects the target word using the second paradigm.

C. *Initial Character Spelling Paradigm*

In the implementation of the initial character spelling paradigm as shown in Fig. 1 (a), we have used a 6×5 matrix of characters similar to the FD paradigm in which each row and column gets intensified randomly. Intensifications are block randomized and in each block of eleven intensifications, each row or column gets intensified exactly once in a random order. For one character epoch, this block of intensifications is repeated fifteen times. After each character epoch, there is a 2.5s blank time before starting for the next character. This blank time indicates a user that one character is completed and the user must spell the next character of a word to be typed. Intensification time is 100ms with a 75ms blank time between the intensifications according to the standard P300 BCI data of BCI competition III [2].

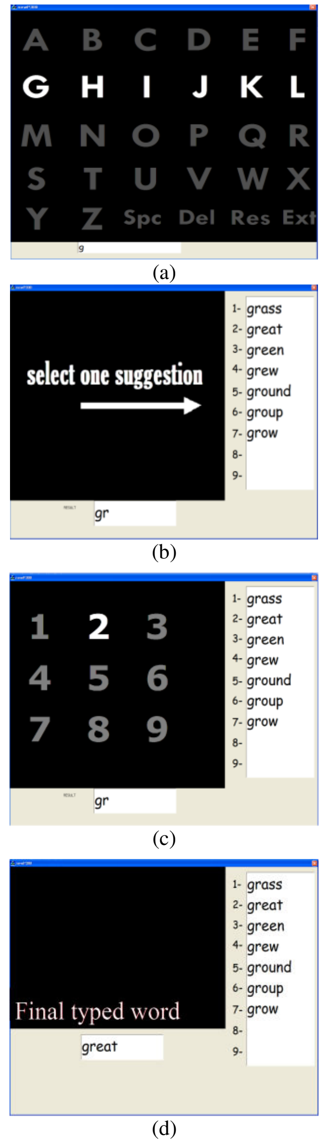

Figure 1. Our word typing paradigms. (a) The first paradigm for spelling initial characters, (b) a words suggestion screen, (c) the second word selection paradigm, and (d) a display showing the final typed word

A randomly chosen target word is displayed before the start of intensifications. The user focuses on a target character and silently counts the number of times of each row or column containing the target character intensified. P300 potentials are elicited when the row or column containing each target character gets flashed.

D. *Dictionary Module*

The dictionary module is implemented in the form of a Ternary Search Tree (TST). TST is a special prefix tree ('Trie') data structure that can find all key words having a given prefix. Partial matches can easily be searched. The advantage of using the prefix tree is its fast searching, but it has a disadvantage of its high storage requirements [15]. TST handles the storage requirement by combining prefix tree with the binary search tree [16]. For an online system, a

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method is needed to search the dictionary with less access time. TST can perform this very efficiently with less storage requirements. Implementation of TST was done based on the work of Bentley and Sedgewick [16]. Our dictionary consists of 2,000 most commonly used English words.

E. The Second Word Selection paradigm

The second paradigm is a matrix of 3×3 used to select a word out of the suggested words given by the dictionary as shown in Fig. 1(c). Since it is known that the row or column-wise intensifications with the 3x3 matrix size decrease P300 amplitude and the P300 amplitude has an inverse relationship with a priori probability of target stimulus [9], in the second paradigm, we used a single number intensification, instead of intensifying rows and columns, to decrease the priori probability of the target stimulus. After the word selection, the final word gets typed as shown in Fig. 1(d). Table I shows the timing specification for both paradigms.

TABLE I. TIMING INFORMATTION OF BOTH PARADIGMS

	First Paradigm	Second paradigm
Intensification time	100ms	100ms
Blank time between intensifications	75ms	75ms
Total stimuli	11	9
Character repeat	15	15
Blank time between characters	2.5s	2.5s

Timings of both the paradigms are same except the total number of stimuli: the first paradigm has 11 stimuli (i.e., 6×5 matrix) whereas the second paradigm only 9 (i.e., 3×3 matrix).

F. Classification

In this study, we adopted the RF classifier, an ensemble learning technique introduced by Breiman [17]. It is a powerful classifier that has been used efficiently in other areas of classification but is relatively unknown in the field of BCI. The main idea of RF is to combine multiple independent decision trees and let them vote for the popular class. We have compared the performance of RF against SVM. Each subject participated in training and testing sessions. In the training session, each subject was instructed to spell ten randomly selected characters. We applied a band-pass filter with the cutoff frequencies of 0.1Hz and 25Hz. Then epochs of 600ms after the stimulus onset were extracted. One character data contains two targets and 9 non-target epochs (i.e., two out of eleven rows and columns contain P300s). To balance the training data, only two randomly chosen non-targets and two targets are used. Segments of data are concatenated over the channels to create a single feature vector. A total of six channels was used for classification. Both classifiers were trained using the same features.

III. RESULTS

We conducted the word typing experiments with four healthy subjects. The consent forms were obtained from each subject. The EEG data was acquired through a 32-channel BrainAmp MR amplifier [18] with a sampling frequency 250Hz. Electrodes were placed according to the 10-20 international standards. Six channels out of 32: namely Cz, Pz, P3, P4, O1, and O2, were used in typing words with the proposed system. There were ten test sessions and in each session, each subject typed one word, totaling ten words per subject. Table II shows the accuracy of four subjects in terms of words using SVM and RF.

TABLE II. ONLINE ACCURACY

Subject	Accuracy (%)	
	SVM	*RF*
S1	60	70
S2	80	90
S3	80	80
S4	90	100
Mean	**77.5**	**85**

Based on the timing information given in Table I, we have computed the time required to spell one character using both the paradigms. For the conventional and our first paradigm, the total number of intensification is 165 (i.e., 11 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 31.375s (i.e., [165×175] ms + 2.5s blank time between characters). In the same way, this comes out to be 26.125s for the second paradigm.

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 III shows the time required to spell these words using the conventional paradigm with 100% accuracy.

TABLE III. WORD TYPING TIME USING THE CONVENTIONAL SCHEME

Word Number	Word Typing Time Using the Conventional Scheme (minutes)			
	S1	*S2*	*S3*	*S4*
1	2.61	2.09	2.09	4.18
2	2.61	2.61	3.13	2.09
3	3.13	2.61	2.09	3.66
4	2.09	2.61	2.61	4.18
5	4.71	4.18	4.18	2.09
6	3.13	3.66	3.13	2.09
7	3.13	2.61	3.66	3.13
8	2.61	2.61	2.61	2.61
9	2.09	3.13	2.61	2.09
10	2.61	4.18	2.61	2.09
Mean	**2.87**	**3.03**	**2.88**	**2.82**
Grand mean	2.9			

Table IV shows the time taken by the proposed scheme to spell the same words. The conventional spelling required an average time of 2.9 minutes per word while with the proposed took an average typing time of 1.66 minutes per word, decreasing the typing time by 42.75 %. Note that in this study, we have used the standard timings as used in the conventional spellers to compare the performance of the proposed against the conventional paradigm. Typing speed can be improved by reducing the number of stimulus repetitions and stimulation rate.

TABLE IV. WORD TYPING TIME USING THE PROPOSED SCHEME

Word Number	Word Typing Time Using the Proposed Scheme (minutes)			
	S1	*S2*	*S3*	*S4*
1	1.48	1.48	2.00	1.48
2	1.48	2.00	0.96	1.48
3	2.00	1.48	1.48	2.00
4	0.96	2.00	2.00	2.00
5	1.48	2.00	2.00	1.48
6	2.00	2.00	2.00	1.48
7	1.48	2.00	1.48	2.00
8	1.48	1.48	1.48	1.48
9	1.48	2.00	2.00	1.48
10	1.48	0.96	2.00	1.48
Mean	**1.53**	**1.74**	**1.74**	**1.64**
Grand mean	**1.66**			

We also compared the offline classification results of RF against SVM for different number of stimulus repetitions. Fig. 2 shows the grand mean classification accuracy vs. the number of stimulus repetitions for both SVM and RF over all subjects.

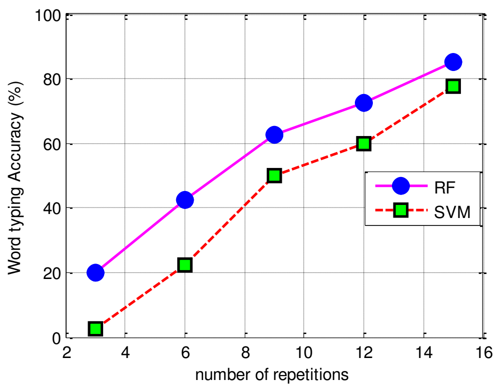

Figure 2. Grand averaged classification results over four subjects for RF vs. SVM with different number of repetitions

Our results show that the RF classifier gives a better performance on P300 classification even under lesser repetitions.

IV. CONCLUSION

This study is aimed at developing an efficient and convenient P300-based word typing BCI. The word typing will be enhanced in terms of speed and accuracy through the proposed word typing paradigm, a smart dictionary, and RF classifier. Our results show that the proposed method of P300 word typing system not only increases the speed of typing but also makes the spelling task easier for users with less fatigue. This could be one important advantage to become a practical BCI.

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