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A P300-based brain computer interface system for words typing

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ABSTRACT

P300 is an event related potential of the brain in response to oddball events. Brain Computer Interface (BCI) utilizing P300 is known as a P300 BCI system. A conventional P300 BCI system for character spelling is composed of a paradigm that displays flashing characters and a classification scheme which identifies target characters. To type a word a user has to spell each character of the word: this spelling process is slow and it can take several minutes to type a word. In this study, we propose a new word typing scheme by integrating a word suggestion mechanism with a dictionary search into the conventional P300-based speller. Our new P300-based word typing system consists of an initial character spelling paradigm, a dictionary unit to give suggestions of possible words and the second word selection paradigm to select a word out of the suggestions. Our proposed methodology reduces typing time significantly and makes word typing easy via a P300 BCI system. We have tested our system with ten subjects and our results demonstrate an average word typing time of 1.91 min whereas the conventional took 3.36 min for the same words.

1. Introduction

Brain Computer Interface (BCI) is a system which can be used for direct communication between a computer and the brain without actual muscular movements. The primary goal of a BCI is to enable the normal and disabled people to communicate and control their external environment with the neural signals of the brain. An event-related brain signal called P300 which is generally elicited by oddball paradigm and appears as a positive potential with a delay of 300 ms after stimulation, is one of frequently used EEG signals for BCI. The first application of P300 for a character spelling was first demonstrated by Farwell and Donchin in 1988 [1]. Their paradigm consisted of displaying a 6×6 matrix of characters and numbers in which each row and column is successively intensified. The user is asked to focus on each target character and P300 is elicited when the row or column containing the target character is intensified which is detected using some classification procedures. Since then Farwell and Donchin paradigm (FD paradigm) has been a benchmark paradigm for P300-based character spelling and most of the later works followed the same scheme [2–4]. Typical P300 based BCI spellers can be divided in two parts: (a) stimulus presentation paradigm and (b) signal processing and classification. So far, most relevant research works focus on classification, but recently there is a growing interest in designing efficient paradigms.

Various attempts have been made by modifying the Farwell and Donchin (FD) paradigm to improve the accuracy and typing speed. For instances, Allison and Pineda [5] 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 and concluded that the amplitude of P300 gets higher in larger matrix sizes and the amplitude of P300 has an inverse relationship with target probability. Guan et al., [6] used a single character flipping instead of row and column intensifications to improve classification accuracy. Single character flipping reduced the target probability, hence increased the amplitude of P300. Salvaris and Sepulveda [7] made various changes to the visual aspects of FD paradigm such as symbol dimensions, distance between the symbols, and colors to determine the effect of these changes on character typing accuracy. Their results demonstrated that no single paradigm was best for everybody and there was only a small variation between visual protocols. Takano et al., [8] compared a green/blue flicker matrix with the conventional white/grey matrix. To increase the accuracy they combined luminance and chromatic information and concluded that the green/blue matrix with luminance and chromatic flicker produced some improved results. Guger et al., [9] compared a paradigm of each character intensification (SC speller) against the row or column intensification of the FD paradigm (RC speller). The SC speller required more spelling time. Generally the RC speller is about two times faster than the SC speller. In the RC speller, sometimes, target character can flash consecutively because intensifications are random. This double flashing of a target character can

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cause errors in two ways: (a) the second flash may go unobserved and (b) P300 response from both flashes may overlap. Townsend et al., [10] used an 8×9 checkerboard paradigm to eliminate this double flash problem, improving accuracy. However for each character spelling the checkerboard paradigm took 41% more flashes compared with RC speller of the same matrix size, therefore spelling time was increased. Fazel and Abhari [11] used region-based flashing paradigm instead of FD paradigm, character spelling was done in two steps: in first step, the users selected a region containing a target character and then in the second step, the target character was selected from that region. Region-based flashing reduced the error rate but spelling time is expected to increase. Furthermore this scheme is more tiring to subjects to go through two levels in order to spell a single character. Since fatigue is one of the important factors of error in BCI as it becomes difficult for users to concentrate for a prolonged time, it is highly desirable to have a paradigm that is user friendly and produce less fatigue. Pires et al., [12] proposed a new lateral single-character speller by dividing the paradigm into two regions and compared it with RC speller. Characters flashed alternatively between the two regions and inter-symbol interval was eliminated. The lateral single-character speller produced marginally better results than RC speller. Shi et al., [13] proposed a submatrix based paradigm by dividing the conventional 6×6 matrix into several submatrices to remove adjacency-distraction and double flash errors. They used the single character flashing independently in each submatrix.

Most of these paradigm studies were intended to modify the size of matrix and characters, intensification ordering and timing, or colors of characters. Some works go beyond the matrix display using either single character flashing or region-based flashing. These modifications slightly improved the performance either in terms of accuracy or spelling time but the difference was not substantial. All these conventional methods of P300-based single-character spelling share the same drawback: to type a word, a user has to spell a word by each character. As P300 detection requires averaging over several trials, this spelling process tends to be slow and could take several minutes to type a word. Moreover the spelling process is tiring for user which in turn increases error. A new paradigm is needed that can help users to type a whole word using less character spelling.

In this study, we propose a new scheme to type a whole word. This scheme utilized a words suggestion mechanism with a dictionary search according to some pre-spelled key characters to give word suggestions to users. The proposed methodology consists of two paradigms. The first paradigm uses the conventional spelling paradigm with a 6×5 matrix of characters. In this step, initial characters of a target word are spelled using the conventional FD paradigm. Then based on these initial characters, the dictionary suggests some possible words. The second paradigm uses a 3×3 matrix of numbers to select the target word from suggestions. It is expected that our proposed methodology speeds up the communication rate and makes word typing easier to the user.

Ryan et al. [14] proposed a similar work in which a predictive spelling scheme was implemented with words suggestions. In their work, predictive spelling increased the typing speed, but, classification accuracy was decreased due to a higher workload in their displays. Also, Kaufmann et al. [15] used a German language predictive speller with some commonly used German words. They presented six most likely suggestion words in the first column of the flashing matrix. Their results also showed that predictive spelling could significantly decrease spelling time. Ahi et al., [16] integrated a custom built dictionary of 942 four-letter words in to the classification system of P300-based speller. The dictionary was used to correct the word in the case the user makes a mistake. The dictionary unit receives the word spelled by the user and searches for the same word in employed dictionary. If a spelled word is not found in the dictionary, dictionary searches for the words that have coincident letters and attempts to correct the word. Their aim of integrating a dictionary was to detect misspelling occurred and to correct the mistake automatically. Their interface was similar to the standard FD paradigm with the modification that they rearranged the placement of letters in a 6×5 paradigm to reduce the chances of error because mostly errors occur in neighborhood of target letter. Kindermans et al. [17] used a unified probabilistic model to detect event related potentials combined with language information to increase the accuracy and a dynamic stopping strategy that reduces number of iterations.

In this work however, we integrate a dictionary with two paradigm interface to give suggestions to the users during word typing to make typing process faster and to make typing easier to the users. The aim of integrating dictionary is to provide word suggestions to the user so that instead of writing complete words the user will be able to type words by spelling only few characters of each word and then by selecting a correct word from the suggestions. Moreover our proposed methodology 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-based words typing BCI system with ten subjects: each subject was given a task to type ten words through the proposed system. Our results demonstrate significant improvement in the typing speed, decreasing the typing time by 43%.

2. Materials and methods

2.1. Conventional P300 speller

The conventional P300-based character speller consists of a flashing paradigm with a classification unit. The flashing paradigm displays a matrix (usually 6×6) of characters and numbers in which each row and column is randomly intensified. The user is asked to focus on each character that is to be spelled from the flashing matrix while silently counting the number of times the target character gets flashed. P300 is elicited when the target row or column is intensified. The classification unit detects one row and one column containing P300s which leads to identify the target character. Each detected character is given to the user as a feedback. This conventional scheme is shown in the shaded box of Fig. 1.

2.2. Overview of the proposed P300-based word typing BCI system

In our proposed word typing BCI system, we have added a words suggestion mechanism with a dictionary search to the conventional character spelling paradigm as an initial speller of a word as the overall flow given in Fig. 1. The proposed word typing scheme consists of two paradigms. The first paradigm is the conventional character spelling paradigm which is used to spell initial characters of a word. With the initially typed characters, the dictionary module performs a prefix search to find some corresponding words that start with the typed characters. If total words starting with the spelled prefix are less than a threshold (in our case of nine), then these words are displayed as suggestions and the user gets asked to select one out of these suggestions. The second word selection paradigm is used to select one word from the suggestions. If the numbers of the suggested words are greater than the threshold then the user continues to write the next character of the desired word using the first paradigm.

2.3. Initial character spelling paradigm

In the implementation of the initial character spelling paradigm as shown in Fig. 2(a), we have used a 6×5 matrix of characters

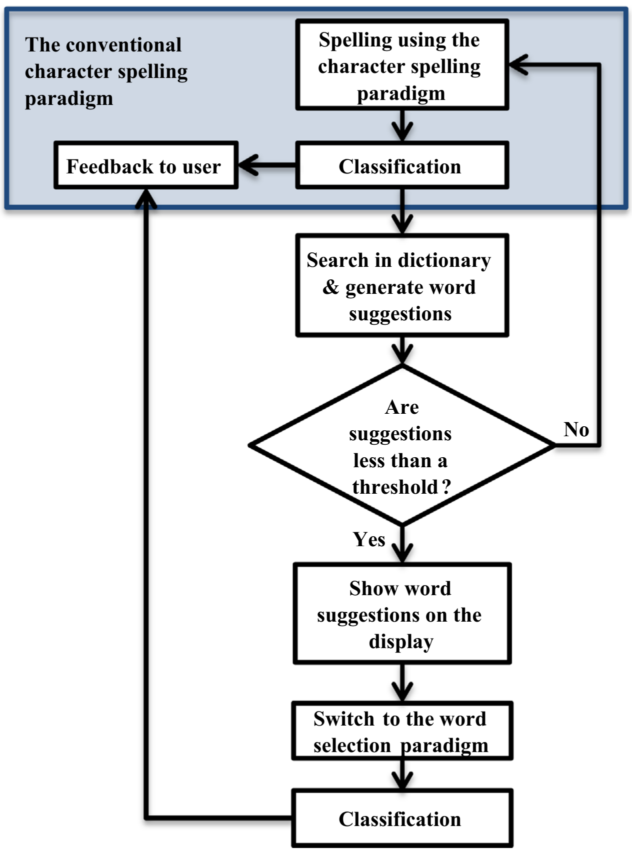

Fig. 1. A flow diagram of the proposed P300-based word typing system.

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 15 times. After each character epoch, there is a 2.5 s 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 100 ms with a 75 ms blank time between the intensifications according to the standard P300 BCI data of BCI competition III [2]. 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 evoked potentials are elicited when the row or column containing each target character gets flashed.

The extracted epochs for each row or column are used by the classifier to detect the presence or absence of P300. Detection of a pair of one row and one column containing P300s leads to identify the spelled character. The classification result is fed into the dictionary module described in the next section. The dictionary module performs prefix search and finds the words that start with the spelled prefix. The user keeps on spelling the target word using the same paradigm until the number of word suggestions becomes less than the specified threshold.

2.4. 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 [18]. TST handles the storage requirement by combining prefix tree with the binary search tree [19]. For an online system, a method is needed to search the dictionary with less access time. TST can perform this very efficiently with less storage requirements. TST does not store complete string at each node, but it stores a single character and all descendants of a node having common prefix.

Implementation of TST was done based on the work of Bentley and Sedgewick [19]. Our dictionary consists of 2000 most commonly used English words [20]. Fig. 3 shows the data structure of a simple prefix tree to hold five words that are 'has', 'had', 'held', 'help,' and 'hi'.

The dictionary provides words suggestion based on the initial characters that a user has spelled according to the initial character spelling paradigm. The user continues to spell a prefix of the target word until the numbers of suggestions become less than a given threshold. When they become less, the user gets to examine words suggestions and asked to select one of them, as shown in Fig. 2(b). The suggestion screen is shown for 2.5 s and then automatically switched to the second word selection paradigm.

2.5. Word selection paradigm

The word selection paradigm displays a matrix of 3×3 to select a word out of nine suggested words (according the specified threshold) given by the dictionary as shown in Fig. 2(c). Since it is known that the row or column-wise intensifications with the 3×3 matrix size decrease P300 amplitude and the P300 amplitude has an inverse relationship with a priori probability of target stimulus [5,21]. In a 3×3 matrix of row and column intensifications, the probability of target intensification is two out of six (1/3) while with single character intensifications, it is one out of nine (1/9). Therefore we used a single number intensification scheme, instead of intensifying rows or columns as in the first paradigm. Intensification and blank time are 100 ms and 75 ms respectively. Intensifications are block randomized in the blocks of nine.

In the word selection paradigm, one out of nine intensifications contains P300. All intensifications represent one of the nine numbers. Detection of single intensification containing P300s leads to identify the target word. All numbers on the word selection paradigm corresponds to one suggestion word. The selected word from the suggestion list gets typed.

2.6. Classification of P300s

A classifier is required to detect the presence of P300 in both the paradigms. In this study, Support Vector Machine (SVM) is implemented as a classifier [22]. SVM is one of the frequently used classifiers in the field of BCI. We use SVM to detect the absence or presence of P300 component in both the paradigms.

Six channels: namely Cz, Pz, P3, P4, O1, and O2, are used in typing words with the proposed system. The EEG data is first band-pass filtered with a cutoff frequency of 0.1 Hz and 25 Hz then epochs of 600 ms are extracted after the stimulus onset for each channel. Segments of data are concatenated over the channels to create a single feature vector. SVM is trained for binary classification of the presence of P300s. A set of data for 10 characters is used to train the SVM classifier: one character data contains two targets and nine 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.

Classification results are used by the dictionary module to generate word suggestions and are also shown to the users as a feedback. After the word selection using the second paradigm, a final word gets typed as shown in Fig. 2(d).

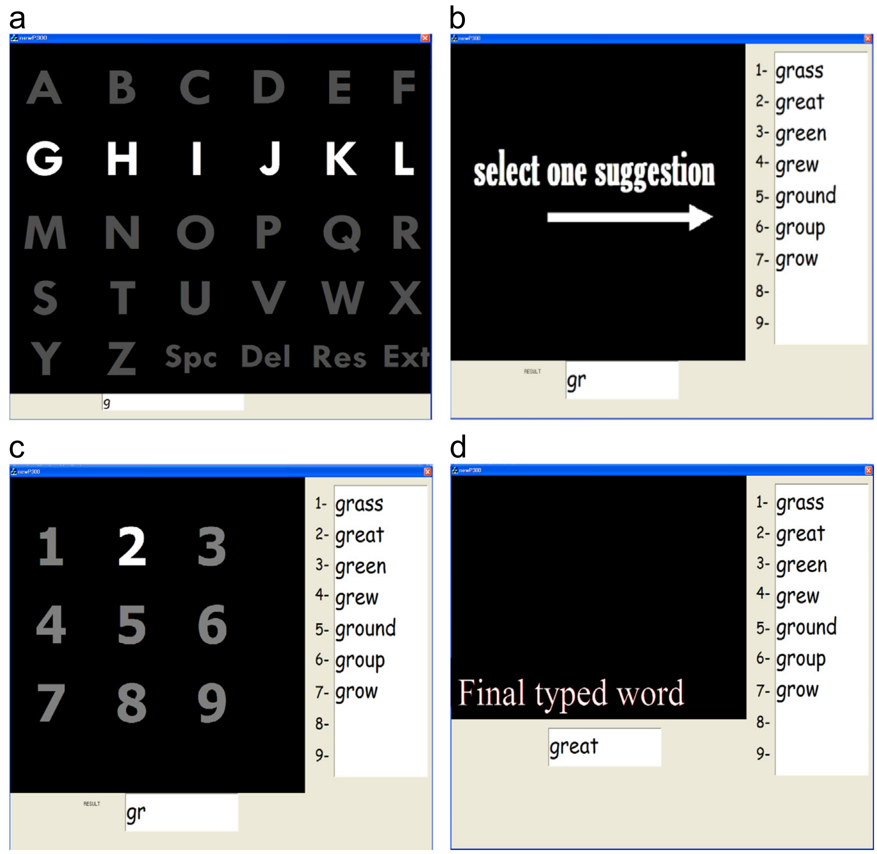

Fig. 2. Our word typing paradigms (a) the first paradigm for initial character spelling, (b) the words suggestion screen, (c) the second paradigm for a word selection, and (d) the display showing the final typed word.

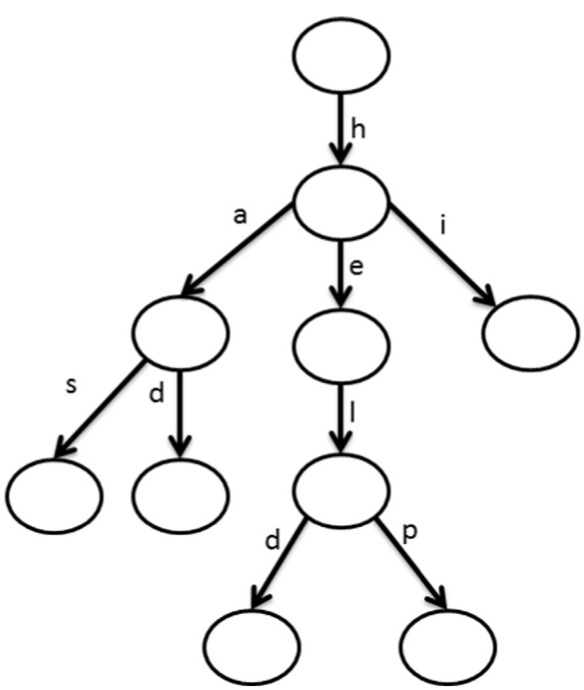

Fig. 3. A simple tree containing five strings.

Table 1
Timing information for both our paradigms.

	Initial character spelling paradigm	Word selection paradigm
Intensification time	100 ms	100 ms
Blank time between intensifications	75 ms	75 ms
Total stimuli	11	9
Character repeat	15	15
Blank time between characters	2.5 s	2.5 s

2.7. Subjects

We conducted word typing experiments using our proposed system on 10 male subjects with an age range between 20 and 27. Subjects had no record of any neurological brain diseases and had normal or corrected vision. Subjects had no previous experience with any brain computer interface. All subjects in the study provided written informed consent in accordance with the Institutional Review Board of Kyung Hee University. Out of 10 subjects, three subjects were not able to use the speller and were marked as BCI illiterates. These results are consistent with the previous studies as discussed in [23,24]. Results from other seven subjects are presented in the results section.

2.8. Data acquisition

EEG data was acquired on a 32-channel BrainAmp EEG system [25] with a sampling frequency of 250 Hz. A 10–20 international electrode cap was used. The users sat on a chair in front of a LCD monitor were asked to focus on target characters of the matrix and count the number of times the target character flashed.

Each subject attended two sessions, training and testing. In the training session, each subject was asked to spell 10 randomly shown characters and numbers. The test session consisted of

10 runs; in each run a randomly chosen word was shown to the users and the task was to type each word. During word typing the classification results were shown to the user below the main flashing paradigm as shown in Fig. 2(a) and(c).

Table 1 shows the timing specification for both the paradigms. Our character spelling paradigm was implemented according to the timing of the conventional paradigm used in the BCI competition III dataset II [2] except for the number of stimuli: the conventional paradigm uses 12 stimuli (i.e., 6×6 matrix of characters and numbers) whereas our character spelling paradigm has 11 (i.e., 6×5 matrix of characters).

3. Results

In the test session, each subject typed 10 randomly shown words. The words typed by the users are listed in Table 2.

3.1. Waveform morphologies

The averaged P300s for target stimuli across subjects are shown in Fig. 4 along with the averaged waveforms for non-target stimuli. Our analysis focused only on six used channels (i.e., Cz, Pz, P3, P4, O1, and O2.) P300s are clearly discernible against the waveforms of non-target stimuli.

3.2. Theoretical timing comparison

We computed the processing time required to spell the target words in Table 2 using the conventional FD (i.e., character by character typing without word suggestion) and the proposed paradigms. For a fair comparison we used the same flashing rate as in Table 1. For the character spelling paradigm, the total number of intensifications per character were 165 (i.e., 11 stimuli $\times$ 15 repetitions) and one intensification time was 175 ms (i.e., flash time + blank time). Therefore time required to spell one character comes out to be 31.38 s (i.e., [165×175] ms + 2.5 s blank time between characters). The conventional paradigm has the same spelling time of 31.38 s per character. In the second word selection paradigm, the total number of intensifications per character were 135 (i.e., 9 stimuli $\times$ 15 repetitions) and one intensification time was 175 ms. Therefore the required time to spell one character became 26.13 s (i.e., 135 ms $\times$ 175 ms + 2.5 s blank time). The time required to type the same words as given in Table 2 using both paradigms are shown in Table 3.

Table 2
Target words.

Word number	S1	S2	S3	S4	S5	S6	S7
1	Smell	Same	Make	Plant	Language	Young	Please
2	Table	Story	Yellow	Subject	Rain	Summer	Talk
3	Summer	Happy	Bank	Fruit	Thought	Complete	Game
4	Kind	Smell	Movement	Page	Complete	Answer	Past
5	Scientist	Complete	Signal	Understand	Name	Town	Use
6	Design	Capital	Subject	Snow	Ball	Write	Suppose
7	Answer	Party	Great	Yes	Window	Information	Winter
8	Happy	Write	Plant	Property	Wrong	Same	Remember
9	Ball	Inside	Party	Bank	Time	Story	Both
10	Built	Question	Property	Temperature	Smell	Radio	This

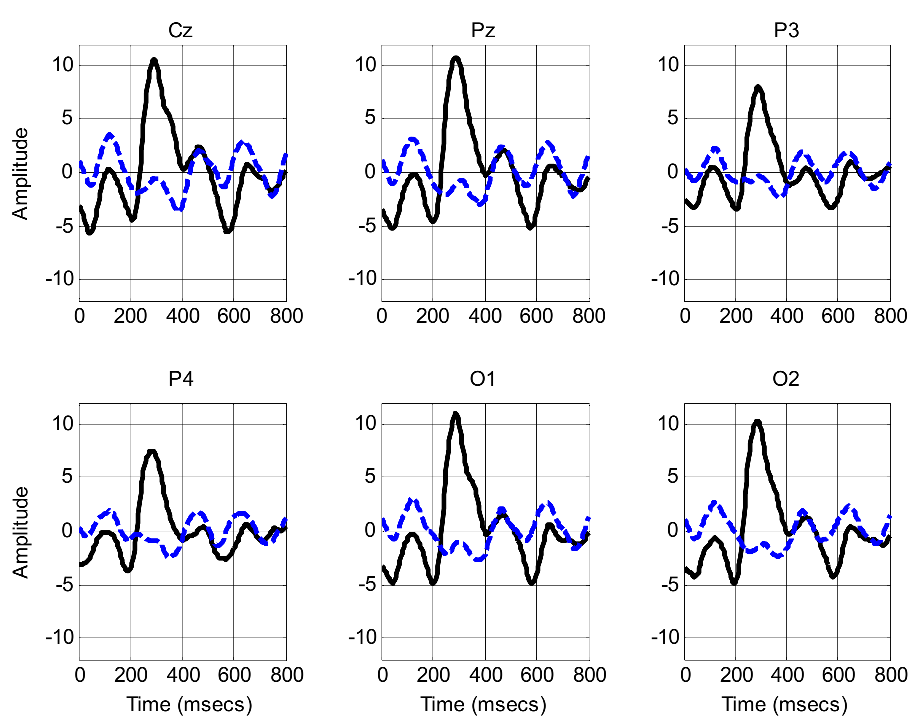

Fig. 4. Grand averaged P300s for target (solid) and the waveforms for non-target (dashed) are shown for the six used electrodes.

Considering no mistakes while assuming the same experimental settings, our proposed paradigm required an average time of 1.67 min per word in comparison to the conventional which required 2.96 min per word. The proposed paradigm significantly reduces the word typing time.

Table 3
Comparison of the time required by the conventional FD speller and our proposed word typing paradigm.

Word set	Typing time (min)	
	Conventional	*Proposed*
S1	2.87 ± 0.75	1.53 ± 0.30
S2	3.03 ± 0.73	1.74 ± 0.37
S3	3.03 ± 0.77	1.74 ± 0.37
S4	3.19 ± 1.45	1.58 ± 0.33
S5	2.88 ± 0.86	1.64 ± 0.25
S6	3.09 ± 1.11	1.69 ± 0.36
S7	2.61 ± 0.85	1.79 ± 0.27
Mean	**2.96 ± 0.94**	**1.67 ± 0.32**
OCM	**1.91**	**3.92**

We also computed the output characters per minute (OCM) for both the systems. OCM was computed by dividing total characters in the target words and total time required by each method to type those words as done in [14]. The OCM of the proposed method (i.e., 3.92) was significantly higher than the conventional (i.e., 1.91).

3.3. Experimental results

In real experiments misspelling can occur and it takes an extra time for correction. In case of spelling mistakes, the time required to correct the mistake by the proposed method is less than or equal to the conventional method. In the conventional paradigm, if a spelling mistake occurs a user should spend one character epoch (31.38 s) for the delete key and then the user should spell the target character again costing 31.38 s more. In total the cost of one mistake becomes 62.75 s. As we have two paradigms in the proposed system and misspelling can occur in any of the paradigms.

Table 4
Comparison of the elapsed time by the conventional FD speller and our proposed word typing system.

Word number	Elapsed time using the conventional scheme (min)							Elapsed time using the proposed scheme (min)						
	S1	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S1*	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*
1	3.7	2.1	3.1	2.6	4.2	2.6	4.2	1.5	1.5	2	1.5	1.5	1	1.5
2	2.6	2.6	3.1	3.7	2.1	3.1	2.1	2.5	2	1	2	1.5	2	2.5
3	3.1	3.7	2.1	3.7	3.7	5.2	3.1	2	2.5	1.5	2.5	2	3.1	1.5
4	2.1	2.6	5.2	2.1	5.2	3.1	2.1	2	2	2	2	2	1.5	2
5	5.8	5.2	3.1	6.3	2.1	2.1	2.6	1.5	2	2.5	1.5	2.5	2	1.5
6	4.2	3.7	4.7	2.1	2.1	2.6	3.7	2	3	2	1.5	1.5	1.5	3.1
7	3.1	2.6	2.6	1.6	4.2	6.8	3.1	2.5	2	1.5	1	2	2	2
8	3.7	3.7	2.6	5.2	2.6	2.1	5.2	1.5	1.5	1.5	3.1	1.5	2.5	2
9	3.1	3.1	2.6	2.1	3.1	3.7	2.1	1.5	2	2.5	1.5	1.5	2	3.1
10	3.7	4.2	5.2	6.8	2.6	2.6	2.1	2.4	1	2	1.5	1.5	1.5	2
Mean ± SD	**3.5 ± 1.0**	**3.4 ± 0.9**	**3.4 ± 1.2**	**3.6 ± 1.9**	**3.2 ± 1.1**	**3.4 ± 1.5**	**3.0 ± 1.1**	**1.9 ± 0.4**	**2.0 ± 0.6**	**1.9 ± 0.5**	**1.8 ± 0.6**	**1.8 ± 0.4**	**1.9 ± 0.6**	**2.1 ± ± 0.6**
Grand Mean ± SD	**3.36 ± 1.23**							**1.91 ± 0.52**						
OCM	**1.68**							**3.46**						

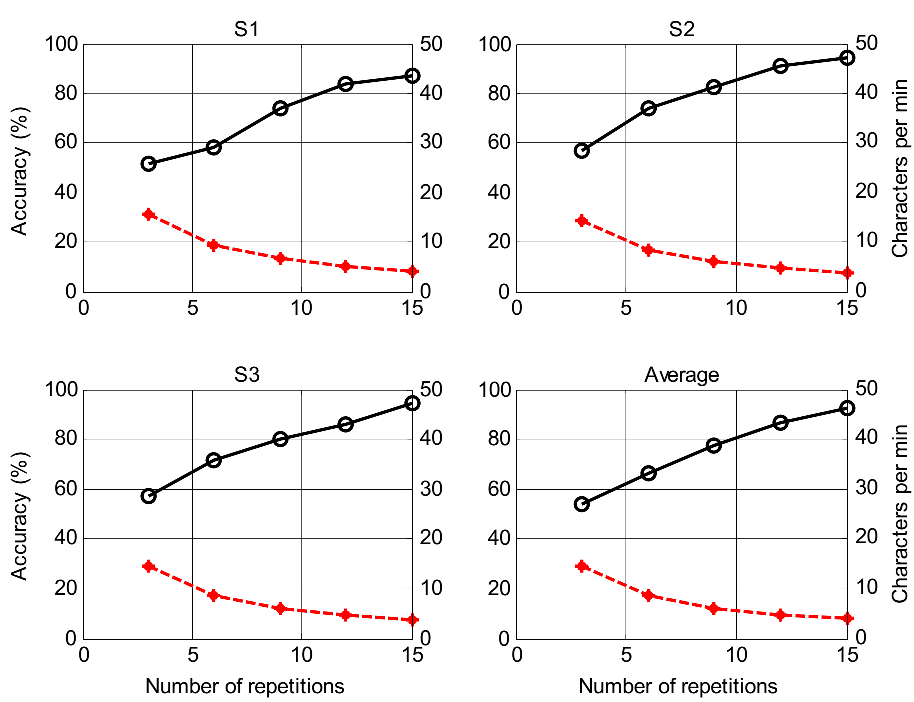

Fig. 5. Characters classification accuracy (Solid) and OCM (dashed) plotted against the number of repetitions for three subjects (S1-S3) and the grand average results of all seven subjects.

If a mistake occurs in the first paradigm, its correction is exactly same as the conventional paradigm costing 62.75 s. However if the mistake happens in the word selection paradigm, after word selection the user is automatically switched to the first paradigm so the user will have to take the delete key on the first paradigm costing 31.38 s. Selecting the delete key switches the paradigm back to the suggestion screen and the user can reselect from one of the suggestions that will cost a time of 26.12 s. Therefore the total time required to correct a mistake comes out to be 57.5 s which is less than the time required in the conventional.

In the experiments, using the proposed paradigm the users were able to type 77.14% words correctly without any mistake and the other words required error correction. Table 4 shows the word typing time of seven subjects using the conventional FD and our proposed paradigms. This word typing time includes the error correction time therefore this time is higher than that of theoretical time of Table 3. Similarly OCM was reduced to 3.46 from the theoretical value of 3.92.

The character classification accuracy and OCM with respect to the number of repetitions for three subjects (S1–S3) and the grand average results of all seven subjects are shown in Fig. 5.

4. Discussion and conclusion

This study is aimed at developing an efficient P300 based words typing BCI system. The proposed system could help to solve one of the major problems in BCI, speeding up the typing time. Our presented results, demonstrate that the proposed word typing system could reduce the word typing time in BCI.

In this study, the proposed system achieved a word typing time of 1.91 min per word. One should note that however, this is not the maximum speed that one can get using the proposed scheme. In this study, we had used the standard settings for flashing rate and number of repetitions. Word typing time can be reduced by reducing the number of repetitions and an efficient classification scheme will be able to classify P300 evoked potentials in lesser repetitions.

As there are fewer characters to type using the proposed method, therefore there are less chances of making mistakes. For instance to write a word ‘property’, a user must spell eight character using the conventional paradigm and a ‘space’ after each word is also required. However, in the proposed system, the user needs to spell only some initial characters such as ‘pro’ and then select one of the suggested words. In total, the user will have to spell only four characters instead of nine in the conventional to type the same word. In the proposed system there is no need to spell ‘space’ after the word because the system knows about word completion and switches automatically to the first paradigm for writing next word. Therefore there are less chances of making mistakes using the proposed system.

Our proposed method also reduces fatigue by reducing the number of characters to type the same word. Fatigue is one of the important factors causing errors in BCI. Spelling process induces visual fatigue and after few character spellings it becomes difficult to users to concentrate. Our proposed method reduces the task of users by giving spelling suggestions and the spelling process becomes less tiring. In the predictive spelling proposed by Ryan et al., [14] the accuracy was significantly decreased because of the increased workload as it required more attention than the conventional method: the user had to focus on many things at a time. Our methodology reduces the workload of the user and guarantees an improved performance of words spelling through BCI. This could be one of the important advantages as a practical BCI application especially for the disabled.

In [14], Ryan et al. used the 8×9 checkerboard paradigm which requires more number of intensifications in a single trial: our paradigm requires 11 flashes in a single trial whereas the paradigm of Ryan et al. requires 24 flashes because their 8×9 display is virtually divided into two 6×6 sub-matrices and each virtual row/column of both sub-matrices should flash in each sequence. This could slow the spelling time. If we compare the typing speed of our system to that of the paradigm of Ryan et al. under the same flash rate and repetitions, the time required to spell a single character by the paradigm of Ryan et al. comes out to be 65.5 s considering no mistake, whereas our proposed method takes 31.38 s to spell one character. Furthermore to select one suggestion word, the paradigm of Ryan et al. needs 65.5 s whereas our method takes 26.13 s. Thus our paradigm could offer faster typing speed, but this requires experimental validation under exact same conditions. In this work, we have used a custom-built dictionary of 2000 words taken from the most commonly used English words, but a bigger sized dictionary could also be used. TST can handle larger size dictionaries efficiently, as it has been used for several years to represent dictionaries in commercial optical character recognition systems [19].

Conflict of interest

None declared.

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