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A Novel Weighted Edit Distance-Based Spelling Correction Approach for Improving the Reliability of Devanagari Script-Based P300 Speller System

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ABSTRACT P300 speller-based brain–computer interface is a direct communication from human-brain to computer machine without any muscular movements. In conventional P300 speller, a display paradigm is used to present alphanumeric characters to users and a classification system is used to detect the target character from the acquired electroencephalographic signals. In this paper, we present an 8 × 8 matrix consisting of Devanagari characters, digits, and special characters as Devanagari script (DS)-based display paradigm. The larger size of the display paradigm as compared with conventional 6 × 6 English row/column (RC) paradigm, involvement of *matras* and *ardha-aksharas* and similar looking characters in DS increase the adjacency problem, crowding effect, fatigue, and task difficulty. This results in deteriorated performance at the classification stage. Binary differential evolution algorithm was employed for optimal channel selection and support vector machine was used to classify target verses non target stimuli for the data set collected from ten healthy subjects using the DS-based paradigm. In order to further improve the system reliability in terms of higher accuracy at word prediction level, this paper proposes a novel spelling correction approach based on weighted edit distance (WED). A custom-built dictionary was incorporated and each misspelled word was replaced by a correct word of minimum WED from it. The proposed work is based on the validation of hypothesis that most of the target-error pairs lie in the same RC. Using the proposed spelling correction approach with optimal channel selection, an average accuracy of 99% was achieved at the word prediction level. The statistical analysis carried out in this paper shows that the proposed WED-based method improves the system reliability by significantly increasing in the accuracy of word prediction. This paper also validates that the proposed method performs better as compared to the conventional edit distance-based spelling correction approach.

INDEX TERMS P300 speller, brain-computer interface, edit distance, EEG, SVM, spelling correction, binary DE, optimization, Devanagari, channel selection.

I. INTRODUCTION

P300 speller-based Brain-Computer Interface (BCI) is a direct communication from human-brain to computer machine. This communication does not require any muscular movements [1]. P300 speller imitates a computer-keyboard and is a possible medium of communication for patients suffering from severe motor disabilities but having cognitive abilities [2]. P300 spellers work on the principle of generation and decoding of P300 Event Related Potentials (ERP) in the brain responses recorded as electroencephalographic (EEG) signals. P300 ERPs can be generated using an *oddball* paradigm-based experiment [1], [3]. In oddball experiment, subjects are randomly presented with two types of stimuli, one of which rarely occurs. The rare (infrequent) stimuli generate a P300 (positive peak after around 300 ms of its presentation to the subject).

The first P300 speller (that was developed by Farwell and Donchin) was also based on the oddball paradigm & is commonly referred to as Row/Colum (RC) display paradigm-based speller [3]. The oddball paradigm is reliable and several classification methods such as Support Vector Machines (SVM), Step-wise Liner Discriminant Analysis (SWLDA) and Baysian-LDA (BLDA) have successfully classified the brain responses [4]–[9]. A comparison of the performance of different linear and non-linear classification techniques for P300 spellers for healthy and disabled subjects has been dealt in [10] and [11], respectively. The low signal-to-noise ratio (SNR) of the acquired EEG signals results in poor classification accuracy. Hence, a reliable system requires classifiers to work with more than one instance of same response. The repetition of experiments extends the duration of signal recording, which results in low information transfer rate (ITR) and increased subject fatigue. Several methods have been studied to further improve the ITR and reliability of P300 spellers. The methods include trying different matrix sizes [12]–[14], font size, font styles, background color, display area and inter-stimulus interval [15]–[17]. Different dimension reduction [18]–[20] and 0 signal processing [21], [22] methods have also been applied to increase the ITR. Although most of the display paradigms designed so far include English alphabetic scripts, numeric digits and special characters; P300 spellers for other languages, such Chinese [23], [24], Japanese [25], and Arabic [26] have also been developed.

For better user convenience and ITR and to reduce cost and complexity, a practical P300 speller system should use the optimal number of electrodes, so as to avoid redundant data arising from larger number of electrodes. In this regard, several channel selection method have been proposed in recent years. The channel selection methods try to improve the classification accuracy by selecting the most relevant channels. Recursive channel elimination [27], Gibbs sampling method [28], and jump-wise regression [29] have been used for channel selection. Evolutionary optimization algorithms such as Genetic Algorithm (GA) [30], Particle Swarm Optimization (PSO) [23], and binary Differential Evolution (DE) [9] have also been applied for optimal channel selection.

Several (online and offline) word prediction and spelling correction methods have been proposed for P300 spellers [31]–[36]. Kaufmann et al. [33] and Akram et al. [32] used predictive spellers with in-built dictionaries as an online P300 speller. In both the spellers, the dictionary unit suggests a list of words based on the detection of initial few characters. In [32], the suggestion of words starts when the number of possible words is less than a threshold, whereas in [33], the dictionary of words suggest 6 most probable words (The probability of words was calculated by counting the number of occurrences of words on German internet pages). Both the studies indicated that the spelling time can be significantly reduced as user will not have to spell out each character of a word. However, in real-world situation, the methods may not be advantageous as reported. In [32], only 1000 commonly used English words were added to the custom built dictionary. If all the words from an English corpus would have been added to their dictionary (which is more than 100 million) then the user would end up spelling all the characters of a word. In the study of Kaufmann et al. (which used around 80 thousand words), the suggested six most probable words might not be the one that user wants to select, as the probability assigned to the words would have been influenced by internet specific contents. Also, in the speller, the user does not have access to all possible German words. The study of Ryan et al. [37] suggest that though the spelling prediction-based P300 spellers may increase the ITR, the amplitude of the P300 and hence the classification accuracy in non-predictive spellers is significantly larger than the spelling prediction-based P300 spellers. Ahi et al. [31] have used a dictionary driven word correction approach in P300 speller. Although they conducted the experiments with only four character words, the study suggested that the accuracy can be increased by including a dictionary unit into a P300 speller system. The probabilistic approach of Kindermans et al. [34] for offline spelling correction has also improved the accuracy of classification. The method of Ceballos and Hernández [35] stressed on the responses of characters adjacent to the target character for extracting useful information. Hence, they have proposed a classifier system that combines the information of just-adjacent rows/columns with standard classifier that is used for target verses non-target classification. However, the validation of the hypothesis tested in [35] (which is also in-line with [31], [38], and [39]), suggest that all (and not the just-adjacent) characters of the rows and columns of the target character must be considered for taking the advantage of adjacency error-patterns. In [36], Mainsah et al. proposed a dictionary driven spelling correction approach. Though, a simple edit distance (ED)-based string matching algorithm is used in addition to Baysian correction algorithm, a significance increment in accuracy of word prediction was achieved. In addition to utilizing the findings of [31] and [35]–[37], the method proposed by us, try to remove aforementioned drawbacks of various word correction approaches.

In our previous work on P300 spellers, we have proposed a novel Devanagari Script (DS)-based speller system [9]. DS-based paradigm can be used input text from *Hindi, Marathi, Sanskrit, Nepali, Pali, Konkani, Bodo, Sindhi* and *Maithili* etc. languages. The selection of DS-based paradigm was motivated by the fact that the DS-based languages jointly serve as the third most speaking language in the world [40]. A 64 character sized display paradigm containing 60 Devanagari characters & numbers and 4 special characters is used to input text. The main aim of the study was to achieve maximum classification accuracy at character detection level. Due to its better generalization capability, SVM was used to classify the target verses non-target stimuli. The selection of optimal sets of channels (with the objective of maximizing the classification accuracy) was carried out using binary DE algorithm. The use of binary DE algorithm is motivated by the fact that it requires tuning of lesser number of algorithm specific parameters and possesses better convergence as compared to other evolutionary algorithms [41]. This article extends the work of [9] by proposing a novel spelling correction approach for improving the accuracy at word prediction level.

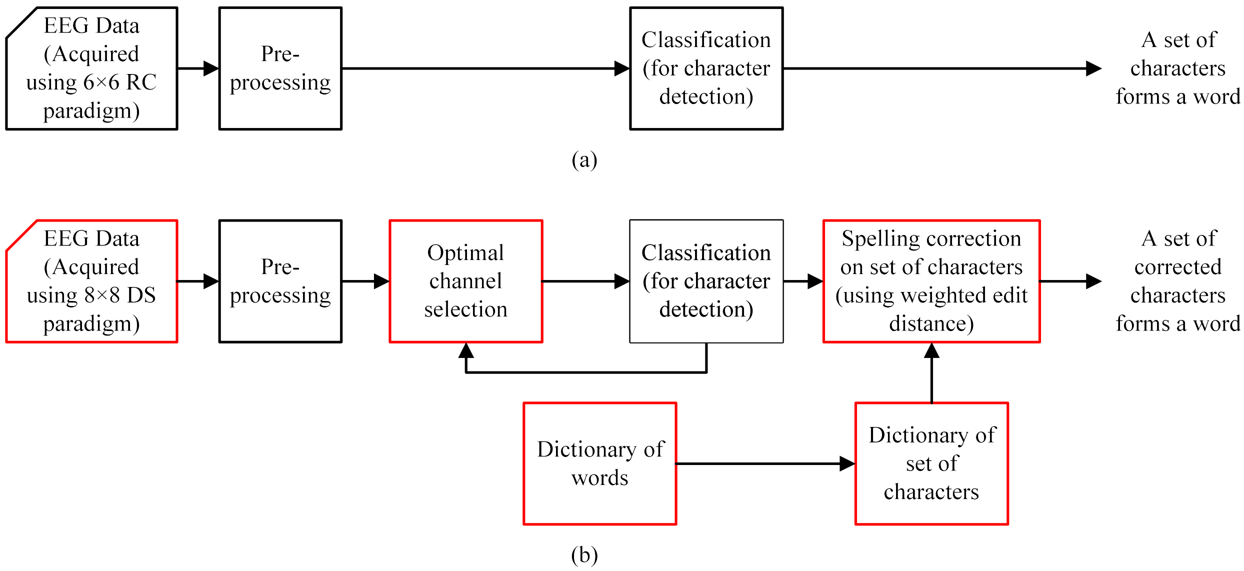

FIGURE 1. (a) Flowchart of a conventional P300 seller system. EEG data acquired through 6 × 6 English RC display paradigm are pre-processed and classified for character detection. The detected set of characters forms a word. (b) Flowchart for the proposed system: The EEG data are acquired using 8 × 8 DS-based display paradigm. A channel selection method is applied with classification method to achieve maximum accuracy for character detection by selecting the optimal channel set. A customized dictionary is created by converting meaningful Hindi words to the set of characters as per the rules given in table 1. The final word is formed after WED-based spelling correction approach is applied on the detected set of characters.

Fazel-Rezai has shown in [38] that with increase in the number of characters on the display matrix, similar looking characters and time extended trials deteriorates the quality of generated P300. It has also been shown that due to crowding effect and adjacency problem, a non-target character near target character may also elicit a P300. The larger size of the display paradigm as compared to conventional 6 × 6 English RC paradigm, involvement of *matras* and *ardha-aksharas* and similar looking characters in DS increase the problems related to crowding effect, adjacency problem, and fatigue and task difficulty, thus resulting in poor performance at classification stage. After observing the error patterns in character detection by SVM, we have also validated the hypothesis that most of the target-error pairs lie in the same row/column. Hence, in order to further improve the system reliability at word prediction level, a novel weighted edit distance (WED)-based spelling correction approach has been proposed. A custom-built dictionary was incorporated and each misspelled word was replaced by a correct word of minimum WED from it. The weights for *character substitution* in ED calculation are based on the analysis of the error pattern in target-error pairs. Figure 1(a) depicts the flow chart of a conventional P300 speller system; the proposed DS-based system with optimal channel selection and a spelling correction model is shown on fig. 1(b).

The rest of the paper is organized as follows: section II introduces the DS-based display paradigm and describes the challenges associated with it. Experimental setup for data acquisition, dataset, signal preprocessing for feature extraction, classification and optimal channel selection are also described in the next section. Section III validates the hypothesis that most of the target-error pairs lie in same row/column. WED-based spelling correction approach is also proposed in section III. Section IV is dedicated to results and discussion is provided in section V. Finally, the paper is concluded in section VI.

II. MATERIALS AND METHODS

A. DS-BASED DISPLAY PARADIGM

The 8 × 8 DS-based display paradigm consists of 50 commonly used Devanagari characters (13 vowels (*swaras*), and 37 consonants (*vyanjanas*)), 10 Devanagari digits and 4 special characters. The proposed display paradigm is a similar to an RC paradigm and shown in fig. 2. All 8 rows and 8 columns of the display matrix are intensified in a random fashion and the subject is asked to attend the character which he wants to spell (target character). The classification task involves the detection of one row and one column that could contain the target character.

Words written in DS consist of *aksharas, matras* and *ardha-aksharas*. The special characters in the paradigm are used to write a proper word by converting the functionality of a character from *akshar* to *ardha-akshar* or *matra* using a predefined rule. Table 1 shows the functionality of each special character. Few sample examples of writing a word using special characters are depicted in table 1.

B. CHALLENGES ASSOCIATED WITH DS-BASED DISPLAY PARADIGM

The concept of proposed DS-based paradigm is similar to conventional RC paradigm. Different phenomena such as adjacency problem [16], [38], crowding-effect [42], [43],

TABLE 1. **The functionality of special characters (Spl. Ch.) in DS-based display paradigm with sample examples for writing a proper words.**

Spl. Ch.	Name	Functionality	Example word		Remark
			Set of target characters	Actually spelled word	
#	*Hash*	A *hash* (#) character followed by a consonant will spell an *ardha-akshara* for that consonant. Whereas, *hash* followed by a vowel will spell that vowel. A vowel without a preceding *hash* will be considered as a *matra* for the previous consonant.	ह इ # न द ई	हिन्दी	'#न' spelles न् (ardha-akshara for 'न')
			ब ई स ई # आ # ई	बीसीआई	'ई' without a preceding *hash* is spelled as the *matra* for it, whereas '# आ' and '# ई' spell actual vowels
			# उ प ल # ब ध	उपलब्ध	'# उ' is उ and '# ब' is ब्
—	*Space*	To insert space between two words	भ आ र त — द ए श	भारत देश	'—' introduces space between two words
«	*Back-space*	To delete the previous target character	क ख «	क	'ख «' delets 'ख'
?	*Question-mark*	Question mark symbol	क ऐ स ए ?	कैसे ?	Usage of '?' reduces the need of more words to make a meaningful sentence.

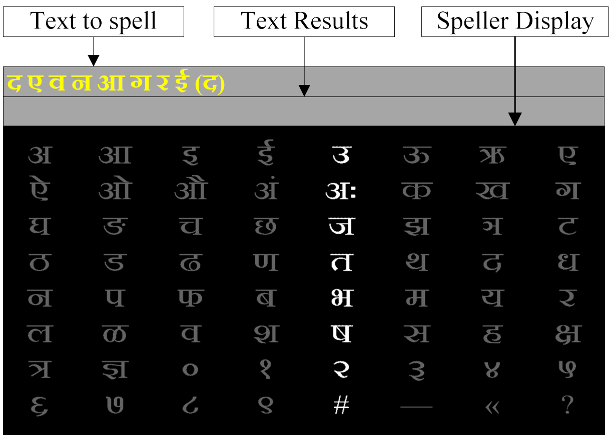

FIGURE 2. **The proposed DS-based display paradigm consists of 50 commonly used Devanagari characters (13 vowels (*swaras*), and 37 consonants (*vyanjanas*)), 10 Devanagari digits and 4 special characters.**

and fatigue [1], [39] can degrade the quality (amplitude and latency of generated P300 using RC paradigm. This subsection describes about the effect of these factors on the P300 generated using the RC paradigm. It is also described that how the problems related to crowding effect, adjacency problem, and fatigue and task difficulty are increased when a DS-based paradigm is used.

Adjacency error occurs due to flashing of non-target characters near target character. The error further increases with decrease in the gap between the characters [16]. It has also been observed that the false generation of P300 due to flashing of characters in the row/column adjacent to the target character is the major source of error in P300-based BCI [38]. Adjacency error can be reduced by increasing the gap between the characters, which can be achieved either by decreasing the number of characters or by decreasing the size of characters on the screen. However, reduced character size leads to poorer classification performance [16]. In DS-based paradigm, the increased number of characters leads to decreased gap between them. This causes more severe adjacency problem and results in error in character detection at classification stage.

Crowding-effect occurs when the target character is surrounded by similar looking characters or by increased number of characters on the screen. This leads to generation of low amplitude P300 and hence results in error in character detection [42], [43]. In Devanagari alphabet, most of the similar looking characters are placed together (e.g. अ and आ, भ and म, ए and ऐ etc.). The number of characters (64) in DS-based paradigm are also comparatively more than the English RC speller which has 36 characters. The increased number of characters and similar looking characters increases the problem of crowding-effect in DS-based paradigm and hence reduces the performance in terms of classification accuracy.

Subject fatigue due to time extended trials and habituation also leads to low amplitude P300 [1], [39]. Flashing of 16 rows/columns in DS-based paradigm requires 33% extra time for each character as compared to flashing of 12 rows/columns in English RC paradigm. The extended time trials increase the probability of habituation and subject fatigue, ultimately leading to reduced classifier performance.

Several paradigms such as Single-Character (SC) [44], Region-Based (RB) [45], and Check-Board (CB) [39], paradigm have been introduced to reduce the errors related to adjacency, crowding effect and fatigue. In SC paradigm, instead of a row/column, only a single character is flashed at a time. The paradigm is based on the concept that the amplitude of the generated P300 is inversely proportional to the probability of the infrequent event in the odd-ball paradigm experiment [46]. SC speller results in larger P300 amplitudes compared to the RC speller. However, RC paradigm is about two times faster than the SC paradigm [47]. CB paradigm was designed to overcome the problem of adjacency-error and double flashes-error (caused due flashing of target twice in immediate succession). It is shown in [39] that the CB produced significant improvements in accuracy (by reducing adjacency and double flash errors) and ITR, as compared to the RC paradigm. However, the error pattern in the CB speller is random and a spatial relationship cannot be established between the target-error pairs. Similar to CB paradigm, the

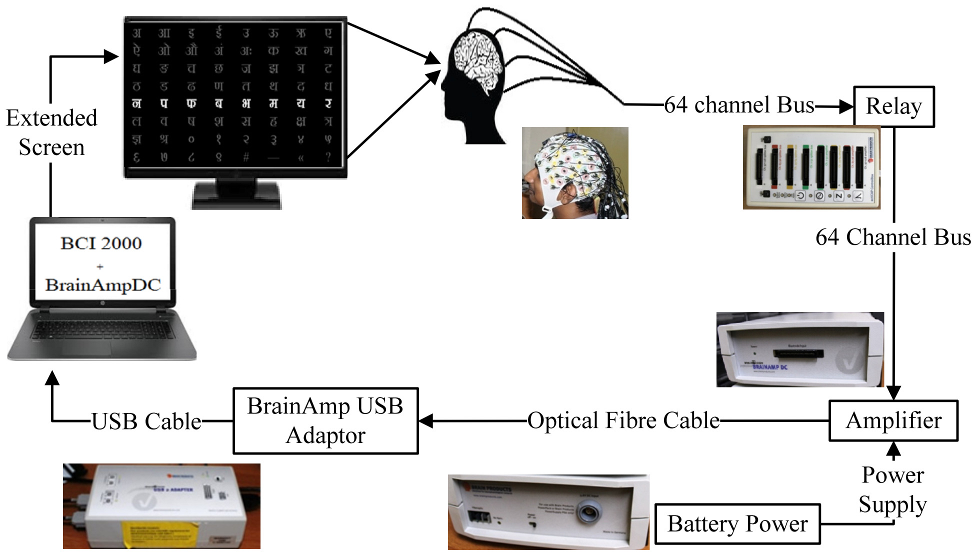

FIGURE 3. **The block diagram of experimental setup used for EEG acquisition.**

errors-pattern in RB paradigm-based speller is also random. Hence, though the RC speller produces more errors, a proper exploitation of the error pattern (caused due to adjacency and crowding effect) can help to produce significant improvement in accuracy by reducing the errors at spelling correction level. This motivates to design the DS-based paradigm similar to RC paradigm. With the knowledge of the possible sources of error, we have analysed the pattern to validate a hypothesis relating adjacency-error and crowding-effect with misspelled characters. Further, a WED-based spelling correction approach is designed by taking the advantage of the hypothesis and the same is described in section III.

C. THE DATASET

The data were recorded at primate research lab, Indian Institute of Science (IISc), Bangalore, India. We conducted the experiments on 10 healthy subjects (7 male and 3 female) with a mean age of 26.5 (std. = 2.46, range = 21-29). The subjects were not having any previous experience with BCI systems and were having normal or corrected to normal eye vision. All subjects were familiar with the characters of Devanagari Script. A 64-channel actiCAP with BrainAmp DC (Brain Vision, UK) EEG recording equipment was used for EEG acquisition. The recorded data was sampled at 500 Hz and a digital band-pass filter between 1 to 250 Hz was applied at the time of recording. The block diagram of the recording setup is shown in fig. 3. The channel configuration used for recording EEG data is shown in fig. 4. Total 64 channels were used for recording the EEG responses in addition to two electrodes (AFz and FCz) as ground and reference, respectively.

General purpose BCI2000 software was used to display DS paradigm [48]. For each subject total 100 characters were presented in 20 runs. The same set of 100 targets was used

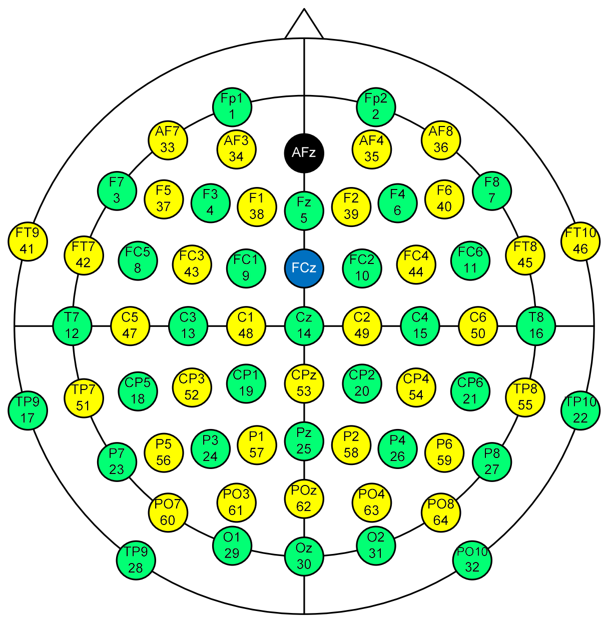

FIGURE 4. **The channel configuration used for recording EEG data.**

for all the subjects. Only the 50 Devanagari letters, *hash* and *back-space* were set as target. The digits and two other special characters (*space* and *question-mark*) were never assigned to be target characters. The set of characters that were used in each run spelled meaningful words of Hindi language. The smallest set of characters was composed of four and the longest one was composed of ten characters. The user's task was to silently count the number of flashes of the target character. For each run, the display matrix was left blank for first 10s. Afterwards, for each target character, all 16 rows/columns were successively and randomly flashed for 120ms, followed by 80ms blank. By repeating this sequence of experiments for 15 times, total 15 trials per character were recorded. With a gap of 10s, the experiment was repeated for next character. The 10s gap in the beginning and between the recording of two characters is more than the usual 2.5s in English RC paradigm. This is because in general any English speaker perfectly remembers the positions of characters in the alphabet. However, such is not the case with DS. For each target character, it may take a while for users to search for where it's placed on the screen. However, as suggested in [49], the workload and task difficulty decreases with practice. Hence, the gap can be reduced to 2.5 seconds for a trained user. For increasing the ITR, the flashing time and the blank time (currently 120ms and 80ms, respectively) can also be reduced for an individual having sufficient practice of P300-based BCI.

For a particular character, responses from 240 flashes were acquired (15 trials $\times$ 16 rows/columns). Out of 240 flashes, 30 were supposed to contain the P300 (1 row and 1 column in each sequence). The classification task aimed at detecting one row and one column (and hence the target character) that could contain the P300. The set of target characters detected for one run are used to form one word by the rule mentioned in Table 1.

D. PREPROCESSING AND FEATURE EXTRACTION

For each channel, EEG signals from 0 to 600 ms posterior to each flashing of row/column were extracted (total 300 samples at 500 Hz sampling rate). The time window of 600 ms is large enough to capture the P300, but short to contain the irrelevant information. Afterwards, the signal samples were passed through a 1-10 Hz band-pass filter and were decimated according to high-cut of frequency of band-pass filer (i.e. 10 Hz). The decimated signals were having 50 times (500Hz/10Hz) lesser data points than the original signals. At this point, the extracted signals were composed of 6 samples per flashing per channel. For each character, the preprocessed dataset is composed of 240 feature vectors each of dimension 384 (6 samples $\times$ 64 channels). Thus, we have total 2400 feature vectors for each subject; 300 of which are supposed to contain P300 (Class $+1$) and rest are supposed to be class -1 vectors. Figure 5 depicts examples of sample variations of EEG signals (averaged over the recordings of one characters) of class $+1$ and class -1 for all ten subjects for channel Cz. A positive going peak at around 300 ms can be observed in the class $+1$ signals, which indicate the presence of P300 ERP in the class $+1$ signals.

E. CLASSIFICATION

The actual classification task in P300 speller is to detect a particular character; the detection of row/column containing the P300 is a binary classification Problem. In this study, SVM is employed as classification algorithm. Because of its better generalization capability, SVM was preferred over other pattern classification algorithms [50]. For each subject, the training and testing of the classifier was done separately. The main goal of this study was to formulate a WED-based spelling correction approach by observing the error patterns that arise by different phenomenon influencing the generation of P300 during EEG acquisition process; more sophisticated and complex learning algorithms (such as ensemble of classifiers) were deliberately avoided.

The dataset for each subject consists of 100 characters (corresponding to 20 words). The selection of these 20 words was done in such a way that all the first and last 10 words consisted of 50 characters. This allows the dataset for each subject to be divided into two equal subsets. For 5 out of 10 subjects, the dataset of first 10 words was used for training and the rest was used for testing. For the remaining 5 subjects the dataset of last 10 words was used for training and rest was used for testing. The division of subjects into two groups was carried out randomly. In this way, we get all 20 words in training as well as in test data set.

For nonlinearly separable data points as in the present problem, SVM learns a hyper-plane which maximizes the separation margin between two classes while controlling the number of errors that are allowed in the process. This classification task can be formulated as an optimization problem and further solved using Lagrange's theorem [50]. If we have training data points $\boldsymbol{x}_i, i = 1, 2 \ldots N$ with respective class labels $y_i = -1 or + 1, i = 1, 2 \ldots N$, then for a novel data point $\boldsymbol{x}$, the separating hyper-plane (or discriminant function) is learned as

$$f(\boldsymbol{x}) = \sum_{i=1}^{N} y_i \lambda_i (\boldsymbol{x} \cdot \boldsymbol{x}_i) + b \tag{1}$$

Here, $\lambda_i, i = 1, 2 \ldots N$ are the Lagrange's multipliers. The λ_is are zero for all the data points that are not support vectors.

For character detection, only one row and one column has to be detected by using all the test vectors corresponding to the recording of one character. SVM assigns a score $f\left(\boldsymbol{x}_{r|c}\right)$ to a test data point $\boldsymbol{x}_{r|c}$ associated to a given row (r) or column (c). After a number of trials J (varying 1 to 15), the detected row and column is the one that maximizes the score

$$S_{r|c} = \frac{1}{J} \sum_{j=1}^{J} f\left(\boldsymbol{x}_{r|c}^{(j)}\right) \tag{2}$$

Here $S_{r|c}$ is the score for the test vector $\boldsymbol{x}_{r|c}^{(j)}$ associated to a given row or column during the j^{th} trial. The target character is the intersection of the detected row and the detected column.

F. OPTIMAL CHANNEL SELECTION

The problem of selecting the best channel configuration for maximizing the classification accuracy has been formulated as an optimization problem and solved using binary DE algorithm. DE is a population based evolutionary optimization algorithm which uses mutation, crossover, and selection operation for updating the target vectors of the population for the next generation [51]. For solving the problems defined in discrete space, several binary versions of DE have been proposed [52], [53]. The binary DE-based optimal channel

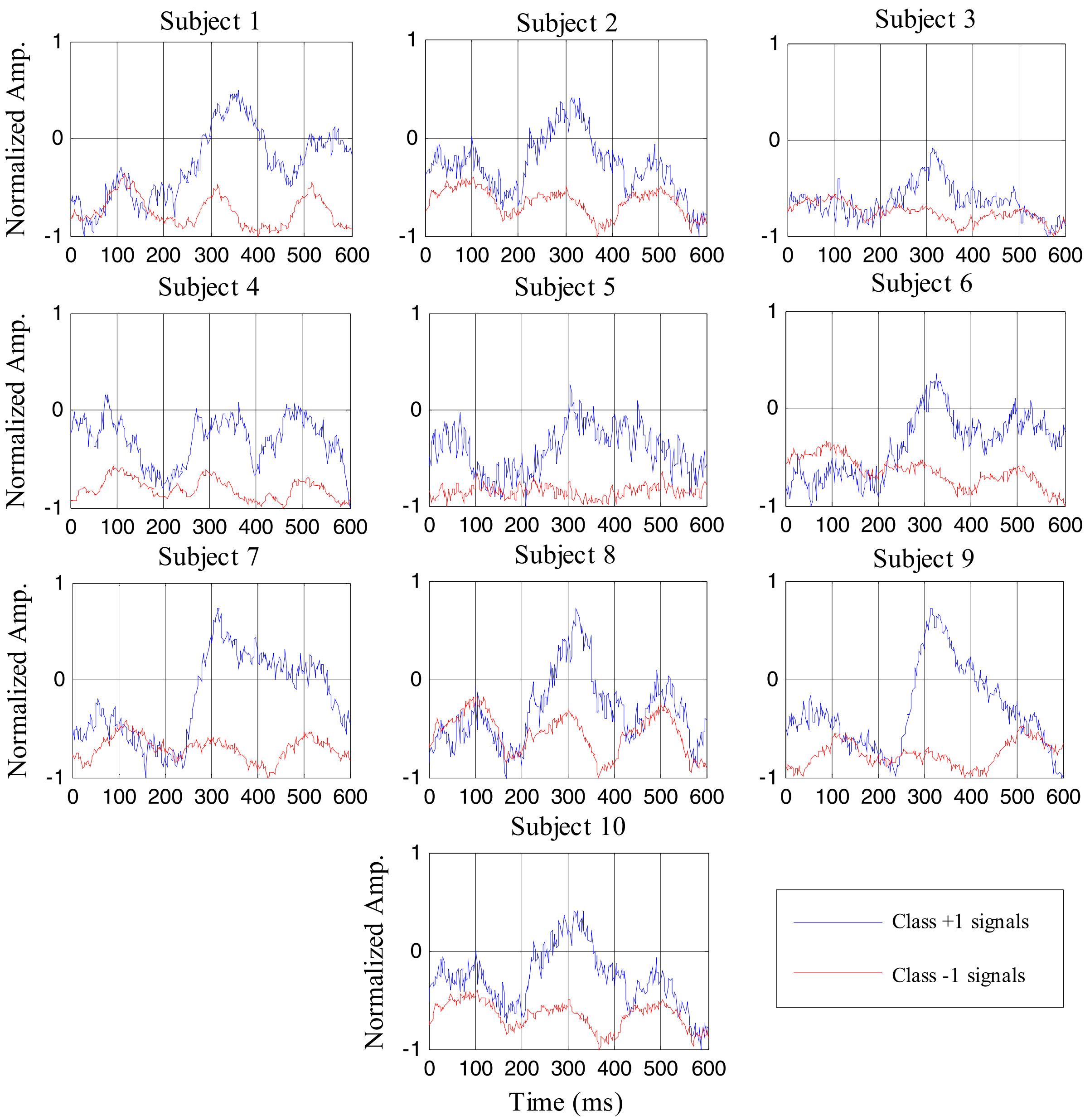

FIGURE 5. Sample EEG signals (averaged over the recordings of one characters) for Subjects 1–10 for channel Cz. The signals corresponding to the class +1 (supposed to contain P300s) are shown by blue and samples from class −1 (not supposed to contain P300s) are shown by dotted red. A positive going peak at around 300 ms (sample number 150) can be observed in the class +1 signals, which indicates that the P300 ERPs are present in class +1 signals.

selection process [9] can be stated as:

$$\begin{aligned} &max\ A(x_i) \\ &s.t.\ x_i \subseteq x \end{aligned} \tag{3}$$

Here $x_i = \left\{x_{i,1}, x_{i,2}, \ldots, x_{i,64}\right\}$, is a 64 dimensional i-th target vector of population such that $x_{i,j} \in \{0, 1\}\, \forall j = 1$ to 64. In i-th particle, channel number j $(1 \leq j \leq 64)$ is selected for feature extraction only if $x_{i,j}$ holds a value '1'. $A(x_i)$ is the accuracy of character detection obtained while selecting the features corresponding to the channel set of target vector x_i. In Eq. (3), vector x is a 64-dimensional vector of all 1s (i.e. it contains all channels). The constraint "$x_i \subseteq x$" indicates that all target vectors x_is must contain a subset of these 64 channels. The detailed description about the updating mechanism of binary DE, algorithm specific parameters, population size , and number of iterations can be seen from [9]. The effectiveness of the binary DE-based approach in improving the classification accuracy has been described in section IV and section V.

III. SPELLING CORRECTION USING WED-BASED APPROACH

A. VALIDATION OF HYPOTHESIS FOR ERROR-PATTERN

As discussed in section II-B, different phenomenon can affect the generation of the P300, leading to error in

Target row \ Target column	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	Total errors
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
3	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
2	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	2
1	0	0	0	0	0	0	0	5	2	1	0	0	0	0	0	8
0	0	1	1	0	0	2	6	436	6	4	3	1	1	1	0	26
-1	0	0	0	0	0	0	2	9	3	0	1	0	0	0	0	15
-2	0	0	0	0	0	1	0	5	0	0	0	0	0	0	0	6
-3	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	2
-4	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
-5	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
-6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
-7	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
Total errors	0	1	1	0	0	3	8	28	11	5	4	1	1	1	0	64

FIGURE 6. The number of times and the locations of detected characters with respect to actual target characters as row and column difference. In this figure the target row and column are considered at (0, 0).

detection of targets. We have analysed the error-patterns of target character detection after classification stage. The results of character detection obtained using SVM (with all 64 channels) has been used for the hypothesis testing as we wanted to have more number of misclassified character to analyse the error pattern. Out of total 500 test characters across all subjects, 436 (87.2%) were detected correctly using 15 trials. Because of wrong detection of row or column (or both), 64 characters were misclassified. Figure 6 represents the number of times and the locations of detected characters with respect to actual target characters in terms of row and column difference. In the figure, location (0, 0) is for actual target character which shows that the target characters were detected 436 times correctly. Any other nonzero number at any other location relates to error in character detection. For example, the entry 9 at $(0, -1)$ shows that nine times the detected row was one row below target row, while there was no error in column detection. Similarly, entry 1 at location (2, 1) depicts that once the detected row was one row above the target row and two columns right to the target column.

For analysis of error patterns, the misclassified characters having either same row or same column as of target cheaters were placed in one group and characters with misclassification in both row and column locations were placed in second group. Figure 7(a) shows that 84% (54 out of 64) misclassified characters were having either same row or column as of target characters. In order to further analyse the error pattern, misclassified characters lying on the target row or column were grouped based on their Chebyshev distance from the target characters, where the Chebyshev distance D between points $p(x_p, y_p)$ and $q(x_q, y_q)$ is given by

$$D = \max\left(\left|x_q - x_p\right|, \left|y_q - y_p\right|\right) \tag{4}$$

Percentage of the error cases for different values of Chebyshev distance D is depicted in fig. 7(b). For example, total characters with $D = 1$ and having either same row or column as of target characters are 26/64, which shares 40% area in figure 7(b).

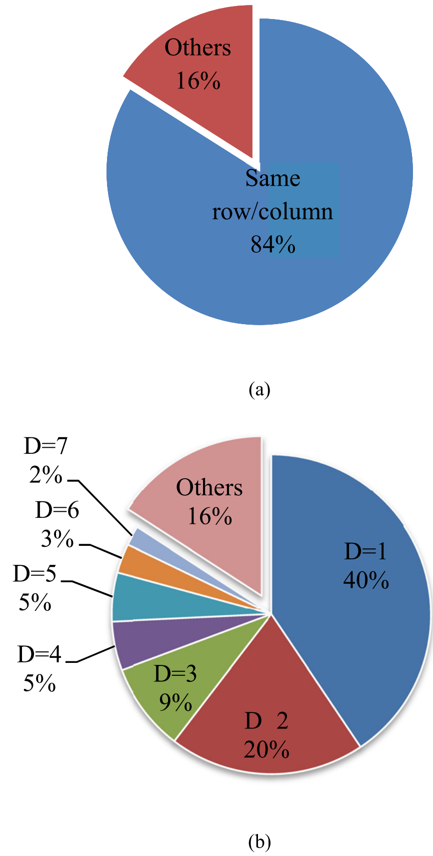

FIGURE 7. (a) The misclassified characters lying on the row or column of target cheaters verses the rest. (b) Error distribution in terms of Chebyshev distance from the target character.

From the error distribution patterns, we can observe that 84% of total target-error pairs have either the same row or column number. This validates the hypothesis that most of the target-error pairs lie on the same row or column. The error pattern also validates the fact the adjacency causes the error in P300 spellers.

It can also be observed from fig. 6 and fig. 7 that 16% of total target-error pairs neither have the same row nor the column number. Additionally, the number of target-error pairs decreases with increase in Chebyshev distance D between the pairs. This error pattern can be linked to the crowding effect, which causes errors when the target character is surrounded by similar looking characters or where are too many characters in the screen.

B. WED-BASED SPELLING CORRECTION

The validation of the hypothesis that the most of the target-error pairs lie in the same row or column is also in line with phenomenon described in [31] and [38]. Another reason for such an error distribution is attributed to the fact that the target character is decided to be the intersection point of the predicted row and predicted column. After validating the phenomenon, a spelling correction approach is proposed where different weights are assigned to different substitutions in computation of ED.

In order to utilize the error-pattern analysis, the spelling correction algorithm should be implemented on the set of detected characters and not on the final words. Hence we developed a customized dictionary by converting meaningful Hindi words to the set of characters as per the rules of table 1. For example word 'बिंदी' was added as set of words 'ब इ # न द ई'. We selected total 600 words *similar* to the words that were used by us for training and testing purpose. Popularly used Rajpal's Hindi dictionary was used for selection of words [54]. The selected words were then converted to the set of words and were added to the customized dictionary.

Our proposal for spelling correction approach is based on two assumptions: Firstly, subject does not make any mistakes in spelling a word, and all the misspellings are due to insufficient performance of the classifier. Secondly, only Devanagari letters and *hash* are set as targets. Numbers, *space*, *question-mark* and *back-space* are not used. The first assumption can later be relaxed by incorporating an adaptive spelling correction mechanism. The second assumption can also be bypassed by separating numbers from letters and by integrating different number based dictionary (such as phone book etc.). Special characters such as *question-mark* and *space* can be handled by natural language processing (NLP)-based algorithms. Additionally, after online implementation of the work, *back-space* character may also be utilized.

ED allows measuring the dissimilarities between two words (or strings). The widely used *Levenshtein edit distance* is computed by counting the minimum number of substitution, insertion and deletion operations required to transform one word into the other [55]. For example, one substitution is required to convert '*him*' to '*ham*', one insertion is required to convert '*beuty*' to '*beauty*' and one deletion is required to convert '*sppell*' to '*spell*'. Mathematically, given two words (or strings) A and B, the ED between them is minimum total number of substitution S, insertion I and deletion R operations required to change word A into word B,

$$D_L(A,B) = \min_{j}[S(j) + I(j) + R(j)] \tag{5}$$

In the original version of Levenshtein edit distance scheme, each operation is given a unit weight. However, weight functions are definitely required to better address the problems rising in various applications. For example, for spelling correction in the words typed by QWERTY keyboard, it is reasonable to assume that changing a '*q*' to an '*a*' results in lower cost than changing a '*q*' to a '*p*'. This is because in typing the letters, '*q*' and '*a*' are typed using same finger and are placed closed to each other whereas '*q*' and '*p*' are not typed by same finger and are also not placed close to each other.

Depending upon the applications, several WED-based schemes have been proposed [56]–[59]. Based on the analysis of the error-pattern in the proposed P300 speller, we have also proposed a WED-based word correction approach. Since it is assumed that subjects perform perfect spelling and the misspellings are due to faulty performance of the classifier, insertion and deletion operations are not required for spelling correction. Only weighed substitution operations are used for computing the distance between misspelled words from the words in dictionary. As only substitution operations are performed, misspelled words were compared with other words of same length (i.e. number of characters) for computing WED. For substituting character a with coordinates (r_a, c_a) by character b with coordinates (r_b, c_b) the cost of substitution (for computing WED) is given by

	1	2	3	4	5	6	7	8
1	अ	आ	इ	ई	उ	ऊ	ऋ	ए
2	ऐ	ओ	औ	अं	अः	क	ख	ग
3	घ	ङ	च	छ	ज	झ	ञ	ट
4	ठ	ड	ढ	ण	त	थ	द	ध
5	न	प	फ	ब	भ	म	य	र
6	ल	ळ	व	श	ष	स	ह	क्ष
7	त्र	ज्ञ	०	१	२	३	४	५
8	६	७	८	९	#	—	«	?

FIGURE 8. Coordinates for different characters for computation of cost of substitution in WED-based approach. For a given character, first coordinate is its row number and second coordinate is its column number.

$$cost(a,b) = \begin{cases} \dfrac{1}{D_{max}} max\left(|r_b - r_a|, |c_b - c_a|\right); \\ \qquad\qquad if \ \ (r_b = r_a) \ or \ (c_b = c_a) \\ 1 + \dfrac{1}{D_{max}} max\left(|r_b - r_a|, |c_b - c_a|\right); \\ \qquad\qquad otherwise \end{cases} \tag{6}$$

The coordinates to be used for a character are represented in fig. 8. In Eq. (6), the cost of substitution is directly proportional to the Chebyshev distance between the two characters if they lie in same row/column. An additional cost of one unit is added in the total cost for the character pairs with different row as well as column number. This formulation for cost calculation reflects the fact that the most target-error pairs lie in the same/row column and the chances of getting target-error pairs decreases with increase in Chebyshev distance D between the pairs. Division by factor D_{max} is to make sure that the cost varies between 0 to 1. Please note that D_{max} for the proposed speller is 7 and $D(a,b) = max\left(|r_b - r_a|, |c_b - c_a|\right)$ may vary between 0 to 7 for any character pair (a, b). For example, given two characters 'अ' (1, 1) and 'इ' (3, 1), then the cost of replacement of 'अ' by 'इ' is 2/7. Similarly cost of replacement of 'अ' by 'औ' (2, 3) is 9/7 and cost of replacement of 'अ' by 'च' (3, 3) is also 9/7, but cost of replacement of 'अ' by 'ढ' (4, 3) is 10/7.

For the given word, if the two different cost values of substitution are the same, then the replacement is done with the word requiring minimum number of substitution operations. In the very rare case, when the numbers of substitutions are

TABLE 2. The percentage classification accuracies of character detection using SVM classifier with increasing number of trials for the dataset collected from all 64 channels (channel selection method not applied).

Subject No.	Accuracy of character detection with increasing number of trials														
	1	2	3	4	**5**	6	7	8	9	**10**	11	12	13	14	**15**
1	10	26	48	64	**70**	74	78	82	82	**84**	84	84	86	86	**88**
2	8	12	26	54	**66**	70	70	74	78	**80**	80	82	84	86	**86**
3	8	20	44	64	**76**	76	76	74	82	**86**	86	86	86	88	**88**
4	12	22	32	58	**68**	68	70	76	78	**82**	80	82	84	84	**88**
5	14	18	38	42	**64**	68	72	76	80	**86**	86	84	86	86	**86**
6	16	30	52	76	**82**	82	84	88	90	**90**	92	92	92	92	**92**
7	12	28	42	56	**70**	72	76	78	80	**84**	84	84	84	84	**84**
8	14	32	46	64	**74**	74	74	76	80	**82**	84	84	84	86	**86**
9	16	24	40	58	**66**	78	80	80	82	**82**	82	82	84	84	**84**
10	20	32	48	60	**70**	76	80	86	88	**90**	90	90	90	90	**90**
Average	13.0	24.4	41.6	59.6	**70.6**	73.8	76.0	79.0	82.0	**84.6**	84.8	85.0	86.0	86.6	**87.2**

TABLE 3. Average number of channels selected (N_c) and average accuracy (A) obtained (averaged over 10 executions of the optimization) using SVM classifier, applied with binary DE-based channel selection method.

Subject No.	Averaged number of channels selected (N_c) and corresponding average accuracy of character detection (A) with different number of trials					
	5		10		15	
	N_c	A	N_c	A	N_c	A
1	24.4	75.2	28.2	92.6	23.7	92.8
2	36.2	67.4	34.4	83.4	28.6	89.2
3	23.5	80.8	25.6	92.4	28.6	93.4
4	36.3	74.4	37.3	86.0	32.6	91.6
5	38.4	70.6	34.7	88.4	31.3	92.6
6	22.2	85.8	26.4	92.2	21.4	94.4
7	29.4	76.4	27.5	87.8	24.9	92.4
8	23.3	82.2	22.2	84.6	22.8	89.8
9	32.3	69.8	31.3	86.4	30.9	89.4
10	21.4	75.2	21.2	93.2	22.0	96.0
Average	**28.7**	**75.8**	**28.9**	**88.7**	**26.7**	**92.2**

also equal, the incorrect word is replaced with any of those words, randomly.

C. COMPARISON OF WED-BASED APPROACH WITH CONVENTIONAL ED-BASED APPROACH

In order to check the effectiveness of WED-based spelling correction approach, the performance of it has been compared with conventional ED-based word correction approach. While using the conventional approach, the detected sets of characters were first converted to words and then they were compared with the words in dictionary of words (not of set of characters). Minimum number of required substitution, insertion and deletion operation were counted for converting a misspelled word into a correct word. Each misspelled word was replaced with the word with minimum ED from it.

IV. RESULTS

The effectiveness of the proposed WED-based word correction approach has been evaluated using an offline analysis procedure in this section. The section has been subdivided into three subsections: The first subsection presents the classification results for character detection. Second subsection presents the results for word prediction obtained by the proposed spelling correction approach. The statistical analyses of the results obtained with different methods are dealt in third subsection.

A. RESULTS FOR CHARACTER DETECTION

This subsection presents the classification results for character detected when SVM was applied to detect the target characters. As mentioned earlier, 50 characters (10 words) were used for training and 50 characters (10 words) for testing for each subject. Table 2 presents the classification accuracies of correctly detected characters when SVM was used with the dataset collected form all 64 channels. The results are presented for increasing number of trials (1 to 15) for all the subjects. Results presented in Table 3 were obtained by applying SVM with binary DE-based channel selection method. The binary DE algorithm was applied with SVM classifier for channel selection with 5, 10 and 15 trials of each character. In order to ensure that the optimization algorithm does not converge to the local minima, the experiment of selecting the optimal channels was executed 10 times. Table 3 shows the average accuracy of character detection along with the corresponding average number of channels selected (averaged over 10 executions) for each subject. For each subject, the topological plots of the frequency of selected channels (in 10 executions) are shown in fig. 9.

B. RESULTS FOR SPELLING CORRECTION

Table 4 depicts the accuracy obtained for word prediction. The comparison was performed word-by-word and even a partially corrected word is regarded as full mistake.

TABLE 4. The accuracy of word prediction for 10 subjects with 5,10 and 15 trials using (1) Conventional P300 speller system without CS and without spelling correction, (2) P300 speller-with CS (without spelling correction), (3) conventional ED-based spelling correction approach with CS, (4) The proposed WED-based approach with CS. CS here stands for channel-selection.

Subject	(1) P3 speller (without CS and without spelling correction)			(2) P3 speller-CS (without spelling correction)			(3) ED-CS-based spelling correction approach			(4) WED-CS-based spelling correction approach		
	Number of trials			Number of trials			Number of trials			Number of trials		
	5	**10**	**15**	**5**	**10**	**15**	**5**	**10**	**15**	**5**	**10**	**15**
1	10	40	50	20	60	60	50	90	90	80	100	100
2	0	30	50	0	30	60	40	70	90	80	90	100
3	20	50	60	30	70	80	80	90	100	90	100	100
4	30	40	60	30	40	60	50	70	90	80	100	100
5	20	40	40	30	40	60	50	70	70	80	90	100
6	50	70	80	50	80	80	80	90	90	100	100	100
7	30	50	50	40	50	60	70	80	80	80	90	90
8	20	30	60	30	40	60	60	70	80	80	100	100
9	10	30	40	10	50	40	70	80	80	70	100	100
10	20	70	70	30	70	90	80	100	100	90	100	100
Average	21	45	56	27	53	65	63	81	87	83	97	99

The results for four different methods are presented in table 4 i.e. first, conventional P300 speller system without channel selection and without any spelling correction, P300 speller system with channel selection and without spelling correction, conventional ED-based spelling correction approach with channel selection, and finally the proposed WED-based approach with channel selection.

C. STATISTICAL ANALYSIS

In order to check the statistical significance of binary DE-based channel selection method for character detection and WED-based spelling correction method for word prediction, the Friedman test was employed. Friedman test was preferred over other paired tests (such as paired t-test or repeated-measure ANOVA), as the Friedman test along with a post-hoc Nemenyi test can provide a multiple comparison analyses [60]. The Friedman test ranks different methods according to their performance on datasets. The best method gets rank 1, the second best gets rank 2 and so on. Friedman test statistics is calculated on the average ranks obtained by different methods. A null hypothesis is then tested for confidence level α (=0.05 in our test). If calculated *p-value* is less than α, then the null hypothesis (no significant difference between the individual methods) is rejected.

Further, a post-hoc Nemenyi test is used to observe any significant difference between the individual methods [61]. If the ranks of a pair of methods differ by the critical difference (CD), then the performance of the pair of methods is considered to be significantly different at confidence level α.

To check the statistical significance of binary-DE-based channel selection method, the test was applied for six different cases i.e. SVM (without channel selection) for 5, 10, and 15 trials and SVM (with binary DE) for 5, 10, and 15 trials. The computed *p-value* (3.1×10^{-9}) was less than 0.05 and the null hypothesis was rejected. Further, a post-hoc Nemenyi test computed a critical difference (CD) of 2.384. The results of the individual comparisons among the different methods are visualized in fig. 10(a). The average rank for each method is illustrated in ascending order on horizontal axis, where different lines (below the horizontal axis) indicate that the post-hoc test shows no significant difference between the methods connected by one line. From fig. 10(a), it can be observed that though there were no significant improvement; the average ranks of SVM (with binary DE) were better than the corresponding ranks of SVM (with no channel selection) for all trial values (5, 10 and 15).

Further, to check the statistical significance of WED-based spelling correction method, the Friedman test was applied on the results of table 4. As the results of P300 speller (with and without channel selection) were not very impressive for 5 and 10 trials, they were not used for statistical analysis (another reason was that the visualization of too many results would have looked very complex). The eight methods used here were the P300 speller (15 trials), P300 speller-with channel selection (CS) (15 trials), conventional ED-based method-with CS (5, 10 and 15 trials) and proposed WED-based method-with CS (5, 10 and 15 trials). The computed *p-value* (3.57×10^{11}) suggested rejection of the null hypothesis. The post-hoc test computed a CD of 3.32. The results of the individual comparisons among the different word correction methods with different trials are visualized in fig. 10(b). Figure 10(b) indicates the effectiveness of the proposed method as the WED-based spelling correction method with only 5 trials (WED-CS(15)) produced significantly better results than a P300 speller with 15 trials (P3(15)). Though there was no significant difference, the proposed spelling correction method with only 10 trials (WED-CS(10)) was ranked better than the conventional ED-based method with even 15 trials (ED-CS(15)) with a very convincing margin in the rank difference. In fact, conventional ED-based method (ED-CS(15)) requires 10 extra trials to perform better than the proposed method with 5 trials (WED-CS(5)).

V. DISCUSSIONS

The results presented in table 2 shows that the accuracy of character detection increases with increase in number

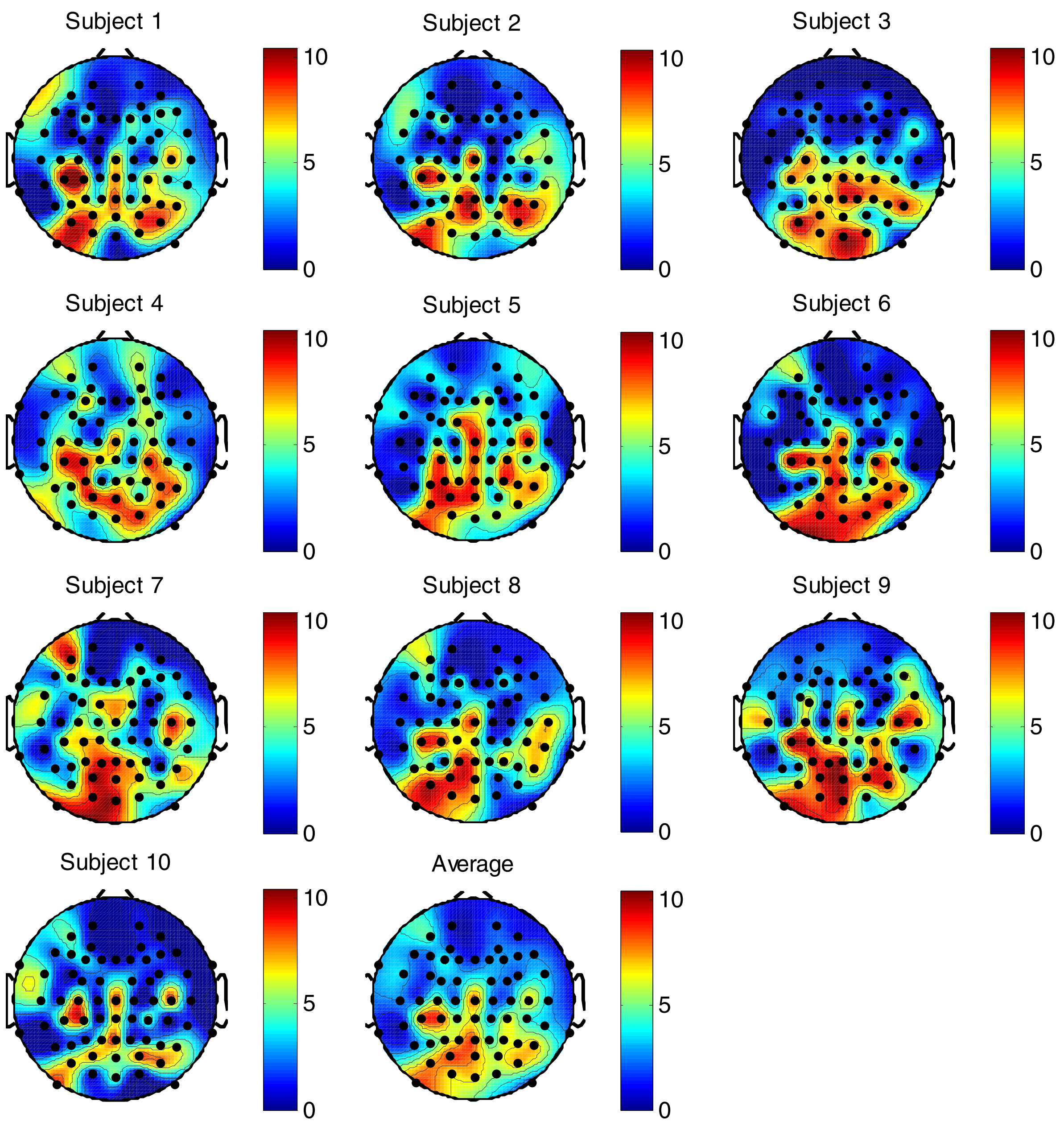

FIGURE 9. **The topographical maps showing the frequency of channels selection in 10 executions of binary DE-based optimal channel selection algorithm, applied with SVM classifier for 15 trials of recording for each subject. The average plot is shown by taking the average over all 10 subjects.**

of sequences. Considering an average over all the subjects, accuracy of 70.6%, 84.6% and 87.2% is achieved for 5, 10 and 15 sequences respectively. This improvement can be mathematically justified by Eq. (2), which involves averaging over multiple trials using parameter $j = 1$ *to* J. The averaging increases the signal to noise ratio and supresses the artifacts due to movement of subjects/eye-blinks etc. However, the rate of increment of accuracy with respect to number of trials is not linear and beyond a certain number of trials, an insignificant improvement is observed in the accuracy value. Further, more number of trials results in poorer ITR and lesser user-convenience. Hence, a reliable BCI system should not be solely dependent on only a classifier system for achieving higher accuracy and ITR. The results presented in table 3 shows that a channel selection method can further improve the classification accuracy only the most relevant channels are used for classification. Further, the channel selection method reduces the cost and complexity of the system and provides a better user convenience.

In order to further improve the system reliability by increasing the accuracy of word prediction, the spellings were corrected using the WED-based approach. From table 4,

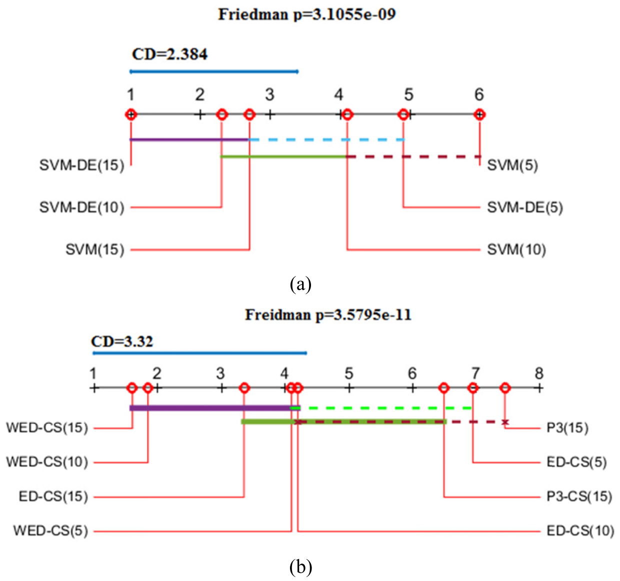

FIGURE 10. (a) The visualization of post-hoc Nemenyi test that was applied to check the effectiveness of the channel selection method for character detection. (b) The visualization for the test that was applied to provide the statistical significance of the proposed WED-based spelling correction method. The proposed method with only 5 trials performed significantly better than a P300 speller with 15 trials.

it can be observed that the proposed approach correctly recognized at-least four more words (out of total ten) with only 5 trials as compared to the P300 speller system with channel selection. The proposed method achieved 83% accuracy with only 5 trials, whereas the maximum accuracy achieved without spelling correction was only 65%, that too with 15 trials. From the analysis, it can be concluded that the spelling correction in P300 speller not only increases the accuracy, but also increases the ITR and speed of communication by reducing the number of trials required for communication. It can also be observed from table 4 that with only 10 trials, an average accuracy of 97% was achieved. The results also suggest that the contribution of proposed spelling correction approach is more effective with lesser number of trials.

Though DS is used to write several languages with lakhs of possible words, in the present study, we have included only 600 Hindi words in our customized dictionary. By imposing such a limitation, we were able to show the contribution of the proposed spelling correction approach in a simpler way. Obviously, using more number of words will decrease the accuracy. However, this will not change the fact that the reliability of the system is increased and number of required trials is decreased by using the proposed spelling correction approach.

Though the conventional ED-based spelling correction approach also increases the classification accuracy; the statistical analysis suggests that the performance of the proposed approach is better than it. In fact, the proposed method with only 10 trials produced better results than the ED-based method with 15 trials. This is because the conventional approach does exploit the fact that most of the target-error pairs lie in the same row or column. Additionally, the speed of word correction using conventional approach was much slower than the proposed scheme, as each misspelled word was compared with all the words in dictionary using all three ED operations (i.e. substitution, insertion and deletion). Whereas in the proposed approach, the misspelled words are compared with the words of same length in the dictionary and only substitution operation is used for computing ED. However, in the proposed approach, each word has to be converted to a set of characters before adding to the dictionary. At current stage, the proposed method is only designed to correct the mistakes made by classifier system and the misspelling performed by users are not handled. As the proposed WED-based spelling correction approach helps in reducing the errors caused by adjacency and crowding effects, the concept can be used for spelling correction for any RC paradigm-based speller which suffers from similar errors.

VI. CONCLUSION

This paper presents a BCI for Devanagari script using P300 speller. The selection of Devanagari script is motivated by the fact that the languages written using the script jointly serve as the third most used languages in the world. Using SVM classifier with binary DE-based optimal channel selection method, on the dataset collected from 10 healthy subjects, we achieved an average accuracy of 92.2% for character detection and 65% for word prediction.

In order to further improve the reliability of the system in terms of classification accuracy, a novel WD-based spelling correction approach has been proposed. The approach is based on the validation of the hypothesis that most of the target-error pairs share same row or column number. Using the proposed approach, an accuracy of 99% was achieved for word prediction. The statistical analysis presented in the study shows that for the DE-based speller system, the proposed spelling correction method with only 5 trials produced significantly better results than a conventional P300 speller system with 15 trials. The analysis also reflects the superior performance of the proposed approach as compared to the conventional ED-based spelling correction approach. Hence, it can be concluded that the WED-based spelling correction approach not only increases the reliability by increasing the accuracy, but also increases the ITR by reducing the number of trials.

The method proposed in this paper is validated using an offline analysis procedure. Extending the concept of the proposed 'spelling correction approach' to a 'word suggestion approach' for an online BCI will be the part of our future work. Work is also planned on the incorporation of natural language processing for achieving sentence level accuracy and accurate handling of numbers during spelling correction.

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