P300 Detection using Ensemble of SVM for Brain-Computer Interface Application

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***Abstract*—This study provides a novel brain-computer interface (BCI) approach for character recognition. The character recognition task is a two class classification problem. The key objective of the character recognition is to detect the P300 signal from the set of electroencephalogram (EEG) signals. The character is predicted from the detected P300 signal and row/column information of the oddball paradigm. The signal-to-noise ratio (SNR) of the electroencephalogram (EEG) signal is low. Ensemble of classifier is used to reduce the classifier variability and enhance the SNR of the acquired signal. Here ensemble of SVMs (ESVMs) is used a classifier. The distribution of dataset is imbalanced due to its paradigm. A novel approach is applied in this work to balance the dataset. The proposed algorithm is evaluated on dataset IIb of BCI Competition II and dataset II of the BCI Competition III. The experimental results show that the proposed method outperforms the state-of-the-art character recognition performance.**

***Index Terms*—Brain-computer interface (BCI), electroencephalogram (EEG), ensemble of SVMs (ESVMs), P300.**

I. Introduction

Brain-computer interface (BCI) is a hardware and software based system for the patients who suffer from amyotrophic lateral sclerosis (ALS), Parkinson's disease, spinal cord injuries or other motor disabilities [1]. These types of patients require a direct and easy access communication medium for their daily work. Over the past decade, research on BCI system is a fast growing field and several electroencephalogram (EEG) based methods are proposed for BCI applications. The BCI systems are developed based on different types of brain signal like P300, steady-state visually evoked potential (SSVEP), electrocorticography (ECoG), event-related desynchronization/synchronization (ERD/ERS) [2], [3] produced by motor imageries etc. A P300 speller used to spell characters on a computer screen through visual stimuli. In this work a BCI framework based on P300 is proposed. P300 is typical response of the brain signal for the predefine audio/visual stimulus. The signal is defined as P300 as a significant peak is appeared about 300 ms after the stimulus. P300 signal is a common response of the brain to any stimuli, so it does not need any type of training for the good performance.

Over the last few years, several P300 feature extraction and classification algorithms are developed for character recognition. In [1] a recursive channel elimination method is proposed for channel selection, which is a time consuming task. Also an ensemble of support vector machine (ESVMs) is proposed for the classification. In [4], wavelet based feature extraction is proposed and ensemble of fisher's liner discriminant analysis is applied as a classifier. A score normalization technique with ESVMs is proposed in [5] for P300 classification. In [6] a multi-resolution approximation based feature selection is done and linear discriminant analysis (LDA) is used as a classifier. A regularied discriminative frame work is proposed in [7]. Convolutional neural networks (CNN) based deep-feature extraction and classification technique is reported for P300 detection in [8]. CNN extract the important feature from the signal and it does not need any prior information about the signal. A semi-supervised classifier based on least squares support vector machine (LS-SVM) is proposed in [9]. Here less number of data is used to train the model. An efficient feature generation and ensemble support vector machines (ESVMs) [10] is used for P300 detection. A novel distance coupled hidden markov models (HMM) classifier is proposed in [11]. In [12] genetic algorithm is used for channel selection and Bayesian linear discriminant analysis (BLDA) as a classifier. In [13], the group-Lasso model based on sparse Bayesian linear discriminant analysis is proposed for P300 classification.

The distribution of P300 and not-P300 signals are not equal due to its oddball paradigm. The number of not-P300 signals is five times more compared to the P300 signals. Under this unbalanced condition, the classifier is biased towards the not-P300 signals. To overcome this, the P300 signal is repeated four times. Then, the training data is divided into five equal parts in our algorithm. In each part, there is equal number of P300 and not-P300 signals. The signal-to-noise ratio (SNR) of the EEG is low. Signal averaging is a way to enhance the SNR of the EEG. Ensemble of classifier is the another way to reduce the signal variability and enhance the SNR of the EEG signal. Support vector machine (SVM) is a good classifier for binary class problem. Here ensemble of SVMs is used as a P300 classifier.

The rest of the paper is organized as follows: Section II briefly describes about the data set which is provided by the BCI competition and the description on speller paradigm. In Section III, the details about SVM classifier is mentioned. The proposed method is explained in Section IV. Finally, Section V represents the experimental results and comparisons with earlier reported works and conclusions of the work is given in Section VI.

II. The Data Set

The data sets are available in the BCI competition site. Both the datasets are provided by the Wadsworth Center, New York State Department of Health.

A. BCI Paradigm

Fig. 1. P300 speller Paradigm [14]

Farwell and Donchin [15] first proposed a visual speller paradigm for P300 speller. The BCI speller paradigm used for data acquisition is shown in Fig. 1. The speller paradigm consists of 36 characters in the 6×6 matrix. To spelled any character, user has to focus his/her attention on the desired character. The rows and columns of the speller flashed randomly. The intensification rate of the speller is 5.7 Hz. The speller is on for 100 ms and off for 75 ms. When flashed row/column contains the desired character, a P300 signal appears. The responses evoked by these infrequent stimuli are different from those evoked by the stimuli that did not contain the desired character. In one round there are 12 flashing, out of which only 2 flashing contain the desired character.

B. Database Used

Two publicly available datasets, IIb of BCI Competition II [16] and dataset II of the BCI Competition III [14] are used here. The data is collected using standard 10-20 electrode placement system, which acquire the data continuously from all 64 channel. Dataset IIb of BCI Competition II contains a single subject data. It consists of 42 training and 31 testing characters. Out of 42 training characters, only 39 characters are used for training as the last set of data contained an error in event cue information. Dataset II of BCI competition III [14] consists of two different subject's data. The database is composed of 85 training and 100 test characters of each subject. Five different sessions are used to collect the data. There are several runs in each session. In each run the subject focused his/her attention on a single character. In one round there is 12 flashing, 6 for the rows and 6 for the columns. These sets of 12 intensifications are repeated 15 times (i.e., each row/column is intensified 15 times and thus there are $12 \times 15 = 180$ total intensifications for a single character). Each repetition is called epoch. So, each character data consist of fifteen epochs. The signal is filtered with a bandpass filter with the cut-off frequency 0.1 - 60 Hz. Then the filtered signal is digitized at a sample rate of 240 Hz.

III. Support Vector Machine (SVM)

For binary classification problem SVM is an good classifier. Vapnik [17] designed this classifier for binary class problem. Let considered a training data set of N points $(x_i, y_i)_{i=1}^{N}$, where $x_i \in \mathbb{R}^m$ is ith input pattern and $y_i \in \{-1, 1\}$ is ith output pattern. For the construction of an optimal separating hyperplane with maximum margin and minimize the classification error, one solves the following quadratic programming (QP) problem which is represented as follows :

$$\min_{w,\xi} \left[\frac{1}{2} \|w\|^2 + C \sum_{i=1}^{N} \xi_i \right] \tag{1}$$

where, w is weight vector, C is the regularization parameter and ξ_i is the slack variable. C has an important role in the performance of classifier [18]. The main objective of SVM to find a hyperplane with maximum margin. If the valu of C is chosen small, then it ignores the points near to margin and increases the margin boundary, whereas the larger value of C considered all the points and to do so it is reduced the margin boundary. The above function can be represented in term of Lagrangian as follows :

$$\begin{aligned} &\max_{\alpha} \left[\sum_{i=1}^{N} \alpha_i - \tfrac{1}{2} \sum_{i,j=1}^{N} \alpha_i \alpha_j \, y_i y_j k(x_i, x_j) \right] \\ &w = \sum_{i=1}^{N} y_i \alpha_i \Phi(x_i) \\ &\sum_{i=1}^{N} \alpha_i y_i = 0, \qquad 0 \le \alpha_i \le C, \ \forall i \end{aligned} \tag{2}$$

where α_is are Lagrange multipliers related to each training point, $k(x, x_i)$ represent the kernel function. The constructed SVM decision function is

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i k(x, x_i) + b \tag{3}$$

where bias b is a real constant.

IV. Proposed framework

Preprocessing, feature extraction and classification are the three successive stages for the P300 based character recognition. The basic block diagram of the proposed BCI system is shown in Fig. 2.

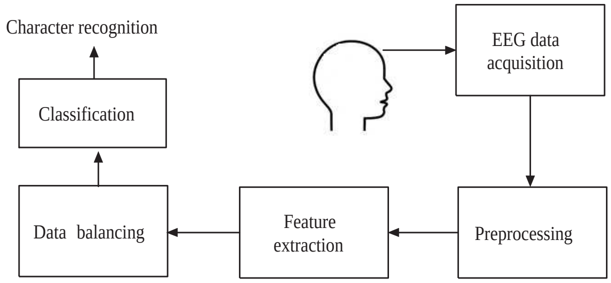

Fig. 2. Proposed block diagram of BCI system

A. Preprocessing and Feature Extraction

The preprocessing step consists of the following stages [1] : (i) it is postulated that a 667 ms of data after the stimulus can capture the P300 information from the signal. So, a 0-667 ms window which consist of 160 samples are taken from each channel for classification. These windows are overlapping windows. (ii) After extracted the signal from each channel the signal is filtered by a 8^{th} order bandpass Chebyshev filter of Type I. The cut-off frequency of the filter lies between 0.1 and 20 Hz. (iii) Then these filtered signals are decimated according to the sampling rate and highest cut-off frequency. After decimation, 14 samples are taken for a single channel. (iv) Then the decimated samples are transformed into a vector by concatenation of all 64 channels. Thus, for a single subject of BCI III data set, the training set is composed of $15300 = 12 \times 15 \times 85$ post-stimulus vectors x_i of dimension $896 = 14 \times 64$ and for BCI II data set, the training set is composed of $7020 = 12 \times 15 \times 39$ post-stimulus vectors x_i of same dimension.

At the time of training, the distribution of P300 and not-P300 signals are not equal. The number of not-P300 signals is five times more compared to P300. To solve the issue, P300 signals are repeated four times, as the classification performance of an unbalanced training dataset is biased towards the class, which has more number of samples. Then the training data is divided into five equal parts. In each part, there is all the P300 signals and one fifth of not-P300 signals.

B. Ensemble of Support Vector Machines (ESVMs)

In ESVMs the classifiers score are averaged out as its reduced the classifier variability [19]. Now if the number of classifiers are K and numbers of sequences are J, then the ESVMs decision function is written as follows:

$$f_{avg}(x) = \frac{1}{K}\frac{1}{J}\sum_{k=1}^{K}\sum_{j=1}^{J} f_k(x) \tag{4}$$

$$f_{avg}(x) = \frac{1}{K}\sum_{k=1}^{K}\sum_{i=1}^{N}\alpha_i y_i k(\frac{1}{J}\sum_{j=1}^{J} x, x_i) + b \tag{5}$$

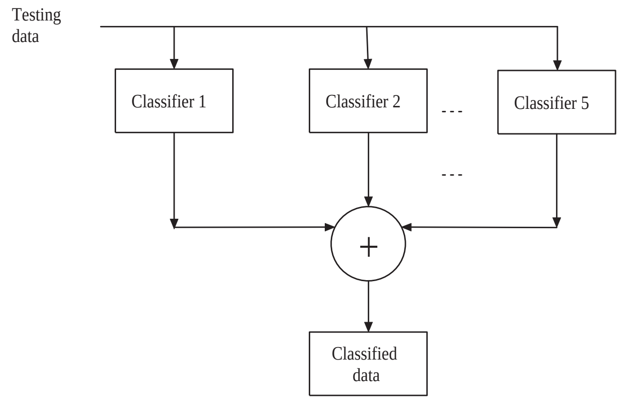

Fig. 3. Flowchart of proposed classification algorithm

where x represents the post stimuli vector and $f_{avg}(x)$ is the score of row or column. After each epoch, the row and column are predicted as follows:

$$\begin{aligned} c &= \arg\max_{1\leq i\leq 6}\ f_{avg}(i) \\ r &= \arg\max_{7\leq i\leq 12}\ f_{avg}(i) \end{aligned} \tag{6}$$

where c and r are the predicted column and row, respectively. The character is predicted from the intersection of this row and column.

V. Results and Discussion

The proposed method is executed on two publicly available standard databases and the result is discussed in this section. In SVM, the regularization parameter $(C = 0.01)$ and linear kernal is used for classification. In BCI competition III dataset, there is 85 training character for each subject. Number of P300 signal is $85 \times 30 = 2550$ for each subject. The training data is divided into five equal parts, which consists of all the P300 data and one fifth of the not-P300 data. The result of the proposed method is shown in Table I. It is observed from the table as the number of epochs is increased the the classification accuracy increased. For subject A the proposed technique recognizes 99 character after 15 epochs. A comparision with the proposed method with the earlier reported techniques [1], [4], [8], [13], [21], [22] is shown in Table II for the first 5, 10 and all 15 epochs. It is observed from the table that the proposed method provides better or competitive result compared to the earlier reported methods. In [1] a channel selection algorithm and ESVMs are used for p300 classification, but the training data is not balanced as balance data train the model in better way compare to the unbalance data. CNN is used for classification in [8], [21]. In [13], group-Lasso model based on sparse Bayesian linear discriminant analysis is proposed, but for binary classification SVM perform better compared to the LDA. The proposed method achieve an average accuracy of 74.5%, 92.0% and 98.0% after first 5 , 10 and all 15 epochs.

TABLE I
NUMBER OF CORRECTLY CLASSIFIED SYMBOLS FOR BCI COMPETITION III DATA SET

	Epochs														
Subject	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
A	17	34	55	64	69	80	74	79	85	89	92	94	96	98	99
B	42	62	70	71	80	83	87	90	94	95	95	97	96	96	97
Mean	29.5	48.0	62.5	67.5	74.5	81.5	80.5	84.5	89.5	92.0	93.5	95.5	96.0	97.0	98.0

TABLE II
PERFORMANCE COMPARISON OF THE PROPOSED TECHNIQUES WITH EARLIER REPORTED TECHNIQUES FOR BCI COMPETITION III DATASET

Method	Epoch		
	5	10	15
ESVM [1]	73.5	87.5	96.5
CNN-1 [8]	70.0	88.5	94.5
MCNN-1 [8]	69.0	87.0	95.5
WT-EFLD [4]	71.5	87.5	95.0
gsBLDA [13]	74.5	89.5	97.0
EWSVM [20]	72.0	87.5	98.0
BN^3 [21]	74.5	90.5	96.5
LDA [22]	60.5	85.0	92.0
Proposed	74.5	92.0	98.0

Result for the dataset IIb of BCI Competition II is shown in Table III. The result is shown upto 5th epochs as after 5th epochs all the words are correctly classified. In last column of the table, actual words are shown and it is observed from the table that most of the misclassified character belong to same row/column of the desired character. It means one row/column is correctly classified through the proposed method.

TABLE III
THE WORDS PREDICTED (WITH 1, 2, 3, 4 AND 5 EPOCHS) USING THE PROPOSED SAE TECHNIQUE AND ACTUAL WORDS FOR BCI COMPETITION II DATASET

Run Number	Word Predicted After					Actual Word
	1 epochs	2 epochs	3 epochs	4 epochs	5 epochs	
1	FOOD	FOOD	EOOD	EOOD	FOOD	FOOD
2	MOOT	MOOT	MOOT	MOOT	MOOT	MOOT
3	HBM	HAM	HAM	HAM	HAM	HAM
4	JIE	PIE	PIE	PIE	PIE	PIE
5	CAHE	CALE	CAKE	CAKE	CAKE	CAKE
6	ZUNA	TUNA	TUNA	TUNA	TUNA	TUNA
7	ZYBOT	ZYAON	ZYSON	ZYGOT	ZYGOT	ZYGOT
8	45Z7	4567	4567	4567	4567	4567

TABLE IV
COMPARISON OF THE PROPOSED TECHNIQUE WITH EARLIER REPORTED TECHNIQUES FOR BCI COMPETITION II DATASET IN TERMS OF NUMBER OF CORRECTLY CLASSIFIED SYMBOLS

	Epochs					
Method	1	2	3	4	5	6
Kaper *et al.* [23]	20	22	26	30	31	31
BN^3 [21]	24	23	27	28	29	30
Chaurasiya *et al.* [10]	-	18	25	-	31	31
Proposed	25	29	28	30	31	31

Result of the proposed method with the earlier reported techniques [10], [21], [23] is shown in Table IV. It is observed that after 1st epoch the proposed method correctly recognize 25 characters out of 31 characters. So the error is only about 19%, which is better compared to the other methods.

VI. CONCLUSION

In this paper, a novel data balancing method is proposed for unbalance data set. The P300 speller paradigm create unbalance data set of P300 and not-P300 signal. The number not-P300 signal is five times more compare to the P300 signal. Here the performance of character recognition accuracy in P300 speller is discussed after the data is balanced. Feature extraction and selection play an important role in the P300 classification. The SNR of the EEG signal is low. To enhance the SNR signal averaging or classifier averaging can be performed. Ensemble of classifier is used for classification as it reduce the classifier variability. The performance of the above method is evaluated on dataset IIb of BCI Competition II and dataset II of BCI competition III, which are the benchmark data available on-line. The proposed method provides better result compared to previously reported techniques for first 5, 10 and all 15 epochs. The algorithm will not work if the environmental noise level is high as SNR of the EEG signal is low.

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