Singular Value Decomposition Based Feature Classification for Single Trial Brain-Computer Interface Design

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Abstract:-The performance of any brain-computer interface (BCI) highly depends on being artifact free. In this study, we propose a mathematical modelling approach to design an efficient non-invasive BCI based on P300 component found in single trial visual evoked potential (VEP) signals. Since the brain processes multiple functions simultaneously the extracted VEP results are in a complex pattern. Further, the characteristics of the P300 component are difficult to be determined a priori especially when the signals are analysed on single trial basis. However, the data used by BCI systems have high dimensionality due to the recording from multiple electrode locations and this high dimensionality could be exploited for reducing the effects from artifacts, using specific pre-processing techniques. In this research study, we propose a mathematical framework for noise reduction and a two-step classification using dynamic methods that results in an enhanced BCI design. The application of singular value decomposition (SVD) to the discrete single trial VEP data facilitates reduction of noise and operational data dimension. Frequency specific filtering further reduces noise and a computationally simple distance based measure with novel method of using two thresholds was utilised for classification. The experimental results give a very low false accept rate (FAR) and false reject rate (FRR) and a near negligible equal error rate (EER) of 2.91%. The high accuracy obtained validates our proposed single trial based approach.

Key -Words:- Brain-computer interface; P300 component; Singular value decomposition; Single trial analysis; Visual evoked potential

1. Introduction

The aim of visual evoked Potential (VEP) based brain-computer interface (BCI) using P300 component is to utilise the evoked component of electroencephalogram (EEG) signal around 300 ms after a visual stimulus onset to establish a communication protocol that bypasses the conventional peripheral muscles and limbs. This would have many applications; the prime one being able to help the disabled community to communicate with their environment.

The EEG used for this purpose measures the electrical activity of the brain from electrodes placed on the scalp and the recorded EEG pattern varies according to the experimental paradigm. The non-invasive method (such as EEG rather than implanted electrodes) is desirable to prevent surgical risks. Out of the four major BCI categories of the non-invasive method based on EEG [14], P300-VEP based BCI is advantageous due to

its ease of use without prior training [6, 7,10,12].

Significant growth using this P300-VEP based BCI have taken place since 1988 [6] and in recent years, many different variants of the oddball paradigm (to evoke P300) [3] have been developed where P300 features could be classified into necessary codes for BCI designs. However, to obtain this P300 component from VEP signals is not a straightforward task. This is because of the effect of the unrelated background EEG artifact that is many times higher in amplitude as compared to P300 component in VEP. Standard approach to solve this problem is through ensemble averaging but this would be requiring many trials of recording and therefore, low response rates for BCI designs. EEG signals are always recorded from multiple electrode sites and this result in multi-channel data and cause an increase in the computational complexity. Channel reduction would reduce this complexity but also serves to degrade the classification accuracy [8,12,14]. However, multi-channel data allows methods such as principal component analysis (PCA) to be used for feature and noise reduction [1]. Nevertheless, it has been shown that classification of features using general principals could result in poor discrimination [5].

In this present work, data from a relatively new BCI paradigm constructed with six choices of simple pictures is used [13]. Frequency specific filtering is used to separate the narrowband P300 components from the wider spectral band background EEG. The singular value decomposition (SVD) method is used to reduce the overlapping spectral EEG and other noise artifacts. The use of SVD also reduces the feature size and simple distance based classifier (with two thresholds) is capable of availing this reduced feature set.

The rest of the paper is organised as follows. In section 2, we describe in detail about the data utilized and our proposed approach while the results from our approach are given in section 3. A brief discussion and conclusion follows in the subsequent final section.

2. Problem formulation

2.1 Signal acquisition

The EEG signals were recorded using 32 electrodes fixed on the scalp of subjects (using extension of the 10-20 electrode system) and measurements were taken for one second from stimulus onset. Two additional mastoid electrodes were used as reference channels. There were nine subjects selected for this experiment, where five of them were disabled. The recorded signals were amplified and the data was sampled at 2048 Hz.

2.2 Experimental paradigm and subjects

The data used in this work were obtained from four able bodied subjects and five disabled subjects with four sessions for each subject. The experiment was conducted on two different days with two recording sessions per day. Six simple but complete pictures (as shown in Figure 1) were used in the display paradigm, and were displayed in random order (but each picture shown only once per trial). This paradigm prevents the occurrence of repetitive blindness (RB) phenomena. The RB occurs when two identical targets are presented consecutively with an interval of less than 500 milliseconds and RB causes the second picture to be missed [11].

The pictures provided were distinct from each other which are important to increase the accuracy of identification and reduction of the response time through minimal number of trials [4,7]. One session consisted of six trials of complete set of picture presentation in which one selected picture acted as the target picture, while the rest of the pictures served as non-targets. Subjects were asked to concentrate on the target picture by counting the number of times it flashed. EEG data were recorded for 1 s after each picture presentation. As mentioned earlier, the pictures were flash displayed randomly and flashing of all the six pictures will be completed in every trial. Each picture was flashed from 100 ms and the time taken to complete one run of six trials (i.e. six picture blocks with 36 picture flashes) was approximately one minute which included an ISI of 400 milliseconds between the flashes [2]. On average, a session consisted of 22.5 runs and there were four sessions per subject. The probability of rare occurrence i.e. the target picture flash was 16.6%. The age of the disabled subjects participants ranged from 33

to 56 years, while age of the able bodied subjects was 30± 2.3 years.

Figure 1: The six picture paradigms used to evoke the P300-VEP

2.3 Pre processing

The raw EEG data were recorded from 32 electrodes using a referencing procedure that used the average of two mastoid electrodes. Next, frequency specific filtering was used to extract P300-VEP using a 6th order forward-reverse[1] Butterworth band pass filter with cut off frequencies of 1 to 12 Hz. Next, the data was down sampled to an effective sampling frequency of 32 Hz. The other artefacts like eye blinks and muscle movements were eliminated using data elimination in 0 to 10 and 90 to 100 percentile amplitude values of the signal. The data were then normalised from -1 to +1.

2.4 Signal decomposition and feature selection

The average number of blocks of six flashes for one run was about 22.5. So the number of target flashes in average per run was equal to 22.5 and non-target flashes were 112.5. The signals from every session were grouped into two separate groups as target and non-target signals.

The dimension of each signal, $\boldsymbol{A}$ was n by m, where n was the number of electrodes and m was the number of sequential samples in one second. Throughout the experiment, n and m were fixed as 32.

To reduce the dimensionality and to reduce the effects of overlapping spectral information between EEG and P300-VEP, SVD approach was applied to matrix $\boldsymbol{A}$ (both target and non-target signals). The SVD of matrix $\boldsymbol{A}$ is given by

$$\mathbf{A} = \mathbf{USV}^{\mathbf{T}}, \tag{2.1}$$

where $\boldsymbol{U}$(m by m) and $\boldsymbol{V}$(n by n) are orthogonal matrices and $\boldsymbol{S}$ (m x n) is a diagonal matrix. The columns, u_i and v_i of $\boldsymbol{U}$ and $\boldsymbol{V}$ are the left and right singular vectors respectively, and the diagonal elements of σ_i of $\boldsymbol{S}$ are called the singular values.

Next, the singular values are arranged on the main diagonal in such an order:

$$\sigma_1 \geq \sigma_2 \geq \sigma_3 \cdots \geq \sigma_{r+1} = \cdots = \sigma_p = 0\,. \tag{2.2}$$

We propose to use the l-largest singular values of $\boldsymbol{A}$ as feature contents representing every single trial VEP signal. Therefore, the entire signal $\boldsymbol{A}$ is now represented by a highly discriminate feature vector of length l. These l-largest singular value features contain P300 component in VEP that discriminates the target from non-target signals. To minimise

[1] To remove phase distortion effects.

computational complexity, we chose *l* value to be 5 after it revealed good performance during our preliminary simulations.

2.5 Classification

As mentioned earlier, *l*-largest singular value features were formed from each signal and distance of every test data were computed from training data prototypes. A template computed out of the average of training prototypes would be necessary to determine if the computed distances of the test data were from target class or non-target class. A distance value higher than a certain threshold would denote the non-target class and the distance value lesser than the threshold would denote the target class.

Two different methods could be used to obtain this template. In the *intra-session reference method,* the target signals within a particular session were collected and the average was considered as the target reference template for all the individual signals in that session. Similarly all the non-target signals within the session were averaged to obtain the non-target reference.

In the *inter-session reference method,* four fold cross validation method was used here where three out of the four sessions of data subsets were used as training data to obtain the classifier template and the remaining session data was used as testing data. This was repeated with different subsets four times and the averaged classification performance is reported.

Through preliminary experiments, we found that the inter-session referencing method produced better results than the intra-session referencing and we followed use the earlier throughout our experiments.

In our work, Euclidean distance measure was used. Euclidean distances of the SVD features were calculated for every test data from two inter-session reference templates: target and non-target class. Euclidean distances, *d1* and *d2* of the test signal with the reference templates were used to categorise the signal into target and non-target category. The Euclidean distance, *d* between data *x* and *y* is computed as

$$d = \sqrt{\sum_{i=1}^{l} (x_i - y_i)^2} \qquad (2.3)$$

The signals having a smaller distance with target reference template less than the *threshold1* were considered as targets and the signals having smaller distance with non-target reference less than *threshold2* were considered as non-targets. Similarly, the signals with target reference distances large than *threshold1* were considered non-targets and the signals with non-target reference distances larger than *threshold2* were considered as target signals. These two threshold values were chosen after some preliminary simulations. We used only one target and one non-target reference template signals here to minimise computationally complexity but this method could be expanded to include more than one reference template for each target and non-target class.

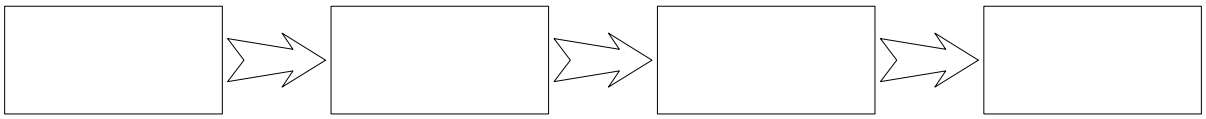

Figure 2: Block diagram showing the steps in our proposed approach

During classification, the False Accept Rate (FAR) is calculated by

$$FAR = \frac{\sum_{1}^{n} NT}{\sum_{1}^{t} NT} .(100) \qquad (2.4)$$

Where NT_1^n = Total number of falsely accepted non-targets, and NT_1^t is the total number of tested non-targets .

while the False Reject Rate (FRR) is calculated by

$$FRR = \frac{\sum_{1}^{n} RT}{\sum_{1}^{t} TT} .(100) \quad (2.5)$$

Where RT = Total number of falsely rejected targets , and TT =Total number of tested targets

and both the FAR and FRR values are tabulated in Table 1. The Equal Error Rate (EER) is calculated by the intersection of FAR and FRR curves and is plotted in Figure 3.

3. Solutions and discussion

All the trial data available were considered for every subject since we focused on single trials rather than averaging. Furthermore, we did not perform any specific multi-trial analysis as in the study by Ulrich Hoffmann and his team, where blocks of only 12 or more trials were analysed for their results [13]. The average value of 723 target distances taken from all the subjects from every session was higher than the average value of 3615 non-target distances. But some individual sessions vary due to the reasons specified by the authors in [13]. It was found that the ratio of non-target distances and target distances when considering all the subjects was 1:3.3.

Table 1: FAR and FRR values for subject 1

Threshold	FAR%	FRR%
0.1	70	0.7
0.2	51	1.9
0.3	43	2.66
0.4	29	3.9
0.5	12	11
0.6	9	31
0.7	6	46
0.8	2	57
0.9	0.88	74

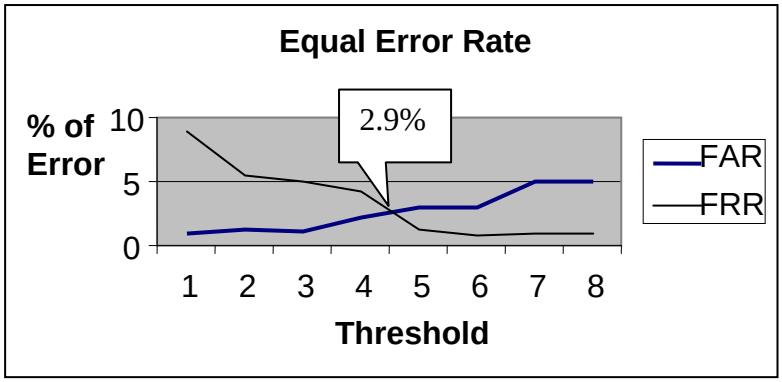

Figure 3: Equal Error Rate for Subject 1

Table 2: EER values for all the subjects

	EER (%)
Subject 1	2.9
Subject 2	3.7
Subject 3	5.4
Subject 4	4.1
Subject 6	3.6
Subject 7	2.5
Subject 8	3.3
Subject 9	4.9

Table 3: Grand average of P300 latency for able and disabled subjects

Able subjects (ms)		Disabled subjects (ms)	
Target	Non-target	Target	Non-target
290	210	510	510

We also performed an analysis on P300 amplitudes of signals obtained from the subjects. The P300 amplitude was found using the method described elsewhere [1]. The results indicated shorter P300 latencies (when using grand averaging) for healthy subjects as compared to disabled subjects (for both target and non-target signals) as shown in Table 2. The P300 latency timings were found to be better for healthy subjects here as compared to than healthy youngsters of the same age group 30± 2.3 from the previous studies [9,10]. The reason could be because of one very highly motivated subject who contributed to this group.

The average P300 latencies of disabled subjects from all the four sessions were found to be slower than the able bodied subjects.

In addition to the above classifications, we performed a separate analysis in comparing the distances of able bodied subjects from target and non-target reference templates. The results are shown in Table 3 where one of the very highly motivated subject is differentiated from other able bodied subjects. The average distances of the target responses of motivated subject 8 were very close to the target reference template. Similarly the average distances of non-target responses of subject 8 were very far from the target reference template as compared to the same distances with subjects 6, 7 and 9 with their corresponding reference templates. This corroborates the earlier studies [4, 13].

Table 3: Distance measures of able subjects (including the 'motivated' subject 8)

	Average distance from the reference template	
Reference	Subject 8	Subjects 6, 7, & 9
Target	8.25	10
Non-target	62.5	32.6

Even though the averages of target distances were higher than the non-target distances, there were some odd individual cases which others have also mentioned [14], which could be caused by lack on concentration by the individual subjects.

The presence of FAR and FRR for subject 8 is limited to three trials only, i.e. the FAR and FRR values were zero in all the other trials. So, omitting these three trials would produce a 100% classification result for subject 8. The presence of errors in three trials could be due to over enthusiasm displayed by the subject or due to the occurrence of fake P300 patterns that is similar to P300 wave forms [4,10].

4. Conclusion

We developed and presented a new approach for single trial P300-VEP based BCI technology with an enhanced performance by using the *l*-largest singular values of the signal data matrix which is helpful in reducing the operational data and ease of classification.

The features were classified using a simple distance measure with two thresholds. Overall, the results indicate the validity of our proposed approach. Our future focus is to increase the accuracy further without any compromise on response time.

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