Appliance of Genetic Algorithm for Empirical Diminution in Electrode numbers for VEP based Single Trial BCI.

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Abstract: In this research work, we explored to find the means selecting minimal electrode channel set for a Brain Computer Interface (BCI) for the classification of Target and Non-Target signals without compromising on the efficiency. The dataset used in this research work was from: http://bci.epfl.ch/efficientp300bci.html. These Visual Evoked Potential (VEP) signals were recorded with the P300 features extracted in single trials using a picture based BCI paradigm. The benefits of choosing the best scalp electrode combination are essential to every single trial BCI. The experimental evaluations were done using different electrode configurations against the configuration that is selected with the aid of Genetic Algorithm. The performances of these configurations were calculated using their ability to do the correct matching and rejection percentages. The recommendations for optimal electrode channels are given with valid performance evaluations. Therefore, it is proposed that for future experiments, the GA based selection of optimal channels could be considered for applications that involve classification of Target and Non target signals in BCI.

Keywords: Visual Evoked Potential, Single trial, Genetic Algorithm, Brain Computer Interface

1 Introduction

The Visual Evoked Potential (VEP) generated by the Brain in response to a visual stimulation is captured using the multiple electrodes spread over the scalp area of a subject. The utilization of VEP signals are under intense focus due to their usefulness for neuropsychological studies, clinical purposes and non conventional means of communication including BCI [1,5,6,9]. Traditionally the method of signal averaging from a number of trials is used to reduce noise contamination from background electroencephalogram (EEG) activity. However, signal averaging requires numerous trials that increase the system complexity and higher computational time which is not suitable for real time applications like BCI as compared to single trial analysis.

In this piece of work, we considered single trial analysis of VEP signals that are used for an efficient BCI using different combination of electrode sets [2]. The classification of Target and non target signals were carried out using a combination of Singular Value Decomposition (SVD) [3] and a k-NN classifier to group the classes. This method is more efficient than methods requiring peak picking algorithms where the latency and other criteria are also needs to be considered. The optimization of the BCI performance nowadays is extended to electrode channel reduction methods too.

The problem in this case is to identify the most predominant channels that carry significant information for classification purposes from a huge number of electrodes so that the reduced number of electrodes yields the benefit of lesser volume of
operational data and freedom of movement to the subject wearing the electrode [3].

Although modern VEP capturing instruments like electrode caps, provide numerous electrodes for measuring data, in general not all of them are essential to pick up the component of interest like P300. Different tasks such as auditory or visual may require different channel configurations to capture the information from the brain. Prior knowledge of the configuration of these channels will allow a reduction in the required hardware and computation time. Therefore, methods of identifying these channels should be formulated.

In this study, we intend to show the benefits of using fewer selected channels of different configurations and perform the identical procedure of experiments to analyse their fitness to be the channel of choice. We then compared the performances of the different configurations with another electrode configuration selected by Genetic Algorithm proposed for this purpose. The method specified by other researchers [8] to select the optimal channel configuration that maximize classification of target and non-Target VEP signals using GA is adopted here but with different and easier fitness function techniques.

This method can also be applied in any classification problem where feature set reduction is necessary without losing performance, for example, in selecting optimal features for image classification. Although our work concentrated on offline optimal channel selection and classification, the selected optimal channels can also be used in an online classification system to reduce classification time on the specific subjects.

2 Methods

2.1 The Data

The EEG datasets provided by Ulrich Hoffman in http://bci.epfl.ch/efficientp300bci.html has eight files and each file has a size of about 270M. A MATLAB software program was also provided to extract the signals from the packed datasets.[10]. The EEG signals used in this research 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 Subjects

The single trial signals employed in this work are extorted from four able bodied subjects and four disabled subjects in four sessions each. Among the four, subjects 1 and 2 were able to produce simple, slow arm and hand movements. Subject 3 can do restricted movement using his left hand only and spoken communication with him is impossible. The patient can only answer Yes or No using the eye blinks. Subject 4 has little control over arm and hand movement and spoken communication also possible in spite of the mild dysarthria. Subject 5 suffers from severe hypo phonny and movements of limbs and arms are restricted. Subjects 6 to 9 are healthy PhD students of age group 30 to 33 and not having any neurological deficits. The experiment was conducted on two different dates with two sessions of extractions per day. The EEG signals captured using thirty two electrodes fixed on the scalp of subjects were used to extract single trial signals for one second. An inter stimulus interval (ISI) of 400 milliseconds is overlapping in between trials [10]. This experiment of Channel selection by GA was carried out for all the eight subjects and found that the electrode configuration varies from subject to subject in giving the best performance.

2.3 The Paradigm

Six complete and simple pictures similar to the pictures shown in figure 1 were used as the display paradigm, and were displayed randomly only once in each run. The pictures provided are plain and distinct from each other with the expectancy of escalating the accuracy of identification and reducing the response time.
The data captured for this experiment were obtained from four able bodied subjects and five disabled subjects with four sessions for each subject. The experiment was organized on two different days with two recording sessions per day. Six simple but complete pictures (as shown in Figure 1) like television, radio etc. were used in the display paradigm. This paradigm prevents the occurrence of repetitive blindness (RB) phenomena by displaying the pictures in random order but each picture shown only once per trial.

2.4 The Electrode Configurations

The electrode configuration in which the recording took place is shown in Figure 2. The sampling frequency of signal acquisition was 2048Hz. Apart from the 32 electrodes on the scalp two more electrodes are fixed to be the reference electrode with arbitrary referencing schemes to obtain a good signal to noise ratio. The data matrix is now formed for every single trial signal in 32X2048 dimensions. The down sampling is used to reduce the 2048 data points into 32Hz but all the 32 electrodes are used for the preliminary classification experiment. The second part of the classification experiment is carried out with other electrode configurations as shown in figure 3. In which the number of electrodes are drastically reduced to 4 – 6 in order to achieve the freedom of movement and hardware. The final part of the classification was carried out with the Genetic Algorithm proposed configuration ‘G’ shown in figure 4 where 8 electrodes are selected using GA similar to the process in [8]. Genetic Algorithms (GA) is a family of computational models inspired by evolution and is based on genetic processes like selection and processes of biological organisms. In a nutshell, a genetic algorithm is a search or optimization technique based on natural selection model. Consecutive generations develop more robust individuals based on survival of the fittest theory. The computer simulation of such evolution leads to genetic algorithms where the user pre defines the environment (function) in which the population must evolve. [4]

2.5 Feature Extraction

The signals captured are categorised in to two, based on the presence of P300 component [6] that was invoked as a result of target stimuli flash. This P300 is the element of interest in the captured signals and gives a skewed difference between the non target signals those do not have the P300 component inside. The characterizations of the signals were done by the Singular Value Decomposition (SVD) effectively.
The dimension of each signal, $A$ was $n$ by $m$, where $n$ was the number of electrodes and $m$ was the number of sequential samples in one second. In this experiment, $n$ varies as the number of electrodes changes and $m$ was fixed as 32 sampling points.

To represent the signal $A$ and to reduce its dimensionality of representation as a feature vector subjected for classification, SVD approach was applied to matrix $A$ (both target and non-target signals). The SVD of matrix $A$ is given by

$$A = USV^T,$$ (2.1)

where $U(m \times m)$ and $V(n \times n)$ are orthogonal matrices and $S(m \times n)$ is a diagonal matrix. The columns, $u_i$ and $v_j$ of $U$ and $V$ are the left and right singular vectors respectively, and the diagonal elements of $S$ are called the singular values.

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

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

We used only the $l$-largest singular values of $A$ as feature contents representing every single trial VEP signal. Therefore, the entire signal $A$ is now represented by a highly discriminate feature vector of length $l$. These $l$-largest singular value features reflects the presence of P300 component in the VEP signal that discriminates the target from non-target signals. To make the classification function precise, we set $l$ value to 5 after subjecting it for preliminary simulations and it revealed good performance in classification.

### 2.6 Classification

Given ‘n’ SVD feature sets as input, a cross validation method is used to compute the classifier reference from ‘n-1’ feature sets by averaging and test it on the individual signals in the left out feature set which is not included in the averaging process. Here in this experiment the same method was followed for all the four sessions of data provided in the data set by leaving out every session’s data in the run as a left out file once and calculated the reference from the other three sessions. We found this inter session referencing method as a better aid for classification than other referencing methods. The reference formed out of the Target signals ‘d’ and non target signals formed a reference ‘D’. The test signals having smallest distance with d are considered as targets. Adapting the well known strategy of ‘simple methods first’, a Euclidean distance $d_1$ and $d_2$ from the d and D references were calculated for the arrived singular value features of every target and non target signals respectively. The calculated distance between the test signal and each pair of reference is used to categorize the signal. In general, the distance between points $f$ and $r$ in Euclidian distance ‘Ed’ is specified as

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

The classification procedure mentioned above was done on the signals extracted from all the eight subjects using different electrode configurations shown in figure three and with the GA selected configuration.
Step 1: Initialize a current generation G = 0;
Step 2: Generate an initial population of individual channels.
Step 3. Repeat
(i) Evaluate the fitness of each individual channel in the population
(ii) Select the parents from the population, based on the fitness values.
(iii) Allow recombination (Crossover) on the selected parents.
(iv) Allow Mutation (to a certain level) to the new subject of the population from (iii)
(v) Replace the parents of the older generation by the offspring of the younger generation
(vi) Increment the generation ‘G’ by 1.
Step 4: Go to Step 3 unless the termination point is achieved.

Figure 5: GA method to identify VEP predominant channels

3. Results

Table 1: Subject wise Configuration Performance

<table>
<thead>
<tr>
<th>Subjects</th>
<th>Trials</th>
<th>Best performing configurations</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>1-3</td>
<td>ABCG</td>
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<tr>
<td></td>
<td>4</td>
<td>A</td>
</tr>
<tr>
<td>S2</td>
<td>1-3</td>
<td>ABCG</td>
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<td></td>
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<td>S3</td>
<td>1-3</td>
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<td>S6</td>
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The performance results of configuration with respect to the trials for every subject are given in Table 1. The total of best performance by every configuration is given as the bar chart in Figure 6.

Figure 6: Session Performance of electrode configurations

4 Discussion

The performance score of configuration G selected using GA method is higher than all the other configurations. The reason for performance was not solely depends on the increase in number of electrodes, since the six electrode configuration C was not able to perform better than the 4 electrode configurations of A and B. The GA based selection of electrodes was found to be the best method since other numerical based analysis like ranking and covariant coefficient methods. Since the electrodes selected by GA varies from subject to subject, the electrodes that are repeatedly selected for many subjects were considered as the most predominant channels for P300 based BCI systems.

5 Conclusion

It is found that GA is working well for every subject and the possibility of applying GA to find the optimum electrodes is considered as the best method of electrode optimization. Some common electrode like Pz, Cz, and Fz were present in seven of the configurations out of eight subjects and are considered as the most predominant channels. Channel Po4 was found in only one configuration selected by GA and can be considered as the least dominant channel. Channel P3 and P4 were seen in six electrode configurations and are considered as moderately dominant channels. This confirms the existing neuroscience knowledge of ocular response in parietal and occipital lobes.
Acknowledgement

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References


