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P300 SPELLER WITH ENHANCED ACCURACY IN BRAIN COMPUTER INTERFACE

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ABSTRACT

Communication channel connecting the brain to a computer or other electronic devices is nothing but brain computer interface (BCI). The information extraction from brain is a very demanding task. Brain signals are mixed with other signals or noises coming from a finite set of brain activities that overlap in both time and space. Electroencephalogram (EEG) has been the most popular signal that is used in developing BCI systems because of its low cost and convenience of use. Such systems may provide a complementary or alternative way for individuals with severe neuromuscular disorders to drive applications to extend their scope of mobility and, thus, improve their quality of life and independence. P300 wave is an event related potential which evoked in the process of decision making of human brain which can be generated using oddball paradigm. In this paper we are discussing a system for improving accuracy in P300 potentials. The main idea is to capture the signals from the brain for P300 BCI and after processing signals desired output can get with higher accuracy. The accuracy can be increased by filtering and classification algorithms such as Linear Discriminant Algorithm (LDA) and special filters.

Keywords: Accuracy, Brain Computer Interface (BCI), Electroencephalogram (EEG), P300, X-Dawn,

I. INTRODUCTION

Brain computer interface are software and hardware system which connects the human brain waves to external devices that is computer assigning people without muscles activity to control and communicate their environment. BCI i.e. Brain computer interface is the straightway communication between the human brain and computer or an electronic device. A BCI can provide a new way of communications for special users who cannot communicate via normal pathways. BCI substitutes conventional communication pathways as nerves and muscles with EEG signals and the hardware and software that translate those signals into actions. Advantages of this BCI are, it does not require extensive training so that their control signals can be easily and quickly set-up. Over the last two decades BCI has made significant progress and substantial research is going on to communicate with the human brain. Brain computer interface is one of the human-computer interfaces which allow as the direct communication between human brain and computer by examine electroencephalographic activities which reflect the functions of the brain [32].

1.1 Brain Computer Interface

BCI systems acquire EEG data from the human brain, then recognize and translate the specific brain signal patterns into the device control command through the signal processing algorithm. The control commands may be used for a computer application or a neuroprosthesis. BCI systems provide a communication channel between the human brain and the external device for people with severe motor disabilities. So that external devices can be controlled by translating the EEG data into a control command. Patients suffering from severe motor disabilities, such as ALS, SCA and other paralyzed patients, may have limited movement while constrained on a hospital bed. Therefore, the BCI system is suited for patients with severe disabilities; it not only reduces the nursing labor load, but also facilitates patient autonomy. A typical architecture of the BCI system we consider which includes: 1) EEG electrodes, 2) EEG signal acquisition, 3) EEG signal processing, 4) Feature Extraction, 5) EEG signal classification and 6) Applications.

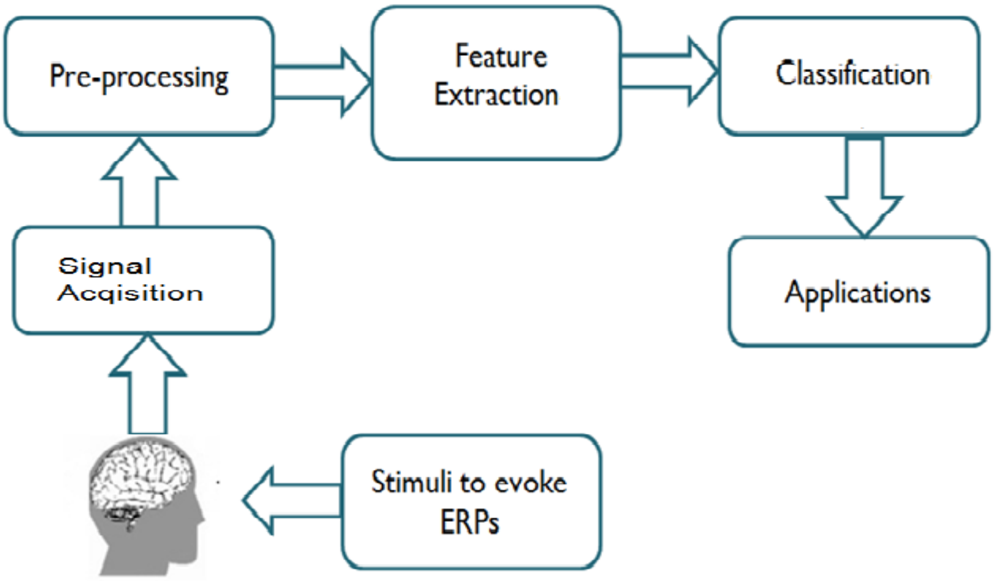

Fig. 1 – Architecture of Brain Computer Interface using P300 Potentials

1.2 Types of BCIs

According to the type of input signals, BCI can be categorized into two approaches, 1) Exogenous BCI and 2) Endogenous BCI.

Exogenous BCI uses the neuron activity elicited in the brain by an external stimulus such as VEPs or auditory evoked potentials (i.e. P300 and SSVEP), which does not require any intensive training [14]. Endogenous BCI is based on self-regulation of brain rhythms and potentials without external stimuli. Through neurofeedback training, users learn to generate specific rhythms or the SCPs [14]. In an Endogenous BCI, electrodes are only placed on the patient's scalp and used in this study. This system based on the electro physical activity.

1.3 P300

P300 is the largest ERP among all the ERP components. P300 is an event related potentials which evoked the process of decision making. P300-based Brain–computer interfaces (BCIs) are based on the P300 brainwave, which was first introduced by Sutton, Braren, Zubin, & John in 1965[3]. It can be evoked by either a visual or

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auditory stimulus that a user has to concentrate upon while different non-target stimuli are also presented [23]. In (Picton, 1992) the characteristics of the P300 signal are described more nearly [3]. Usually P300 is occurred when an occasional target stimulus is detected from the several non-target stimuli by the user. This is called an "oddball paradigm" [23]. Advantage of P300-based BCI (P300 BCI) system is that it does not require any time consuming or specific training.

Now-a-days P300 is very popular than the other BCI system and Researchers attracted towards a number of P300 BCI paradigms due to several conclusions: (1) the P300 response is easy to calculate, (2) no user training require, (3) it working with the various subjects also consider which are related to neurological disease, and (4) gives a destination oriented control signal which is specially suited for spelling and power of direction applications [25]. Various methods of using P300 interface have been proposed i.e. for moving the cursor, robot and writing text. The drawback of this interface (P300) is that they require the user to move his eyes but it is difficult or not possible for a completely paralyzed person.

P300 based BCIs gives a very low rate of information transmission because the classifier based on an average is very simple and the accuracy of P300 potential found is too low [14]. Subsequently, so many trials are required to select only single symbol in the given matrix. Accuracy of the P300 based BCIs can be improved, while using more difficult classifier than a simple average to ensure that the several repetition remain unaffected [14]. Performance reduces when matrix with smaller symbols are used, instead of grey and black one [23].

This study introduces a technique for classifying different frequencies separately so that accuracy is high. The xDawn filtering technique is used in this system. We are using a P300 speller so that we can check out our accuracy and running of the system.

II. THEORETICAL BACKGROUND

2.1 xDAWN Algorithm

Despite other spatial filters, xDAWN focuses on the signal-to-noise ratio (SNR) rather than on the overall classification accuracy which is believed to be a useful procedure for EEG sensor selection. SNR is a measurement used to compare the meaningful information (desired signals) to the background noise (unwanted signals). The xDAWN algorithm is based on the following assumption:

The data consists of two characteristic reactions, one is generated by the flashing targets and one is generated by all stimuli (target and non-target). Suppose: $X = D_1A_1 + D_2N_2 + N$, where $X \in R^{Nt}$ N_s is the recorded data, Nt is the number of samples, Ns is the number of channels/sensors. $A_1 \in R^{N1\times Ns}$ are the signals synchronized with the target stimuli and $A_2 \in R^{N2\times Ns}$ are the responses associated with the non-target stimuli. $D_1 \in R^{Nt\times N1}$ and $D_2 \in R^{Nt\times N2}$ are Toeplitz matrices in which the first column entries are zero with the exception of the ones corresponding to the target stimuli time indexes, respectively. N_1 and N_2 represent the samples quantity for A_1 and A_2, and N_f is the residual noise. xDAWN assumes that the reactions generated by the target stimuli can be enhanced by spatial filtering, and accordingly aims to estimate Nf spatial filters $U_1 \in R^{Ns\times Nf}$ to maximize the SNR that can be defined by:

$$g(U)=\frac{T_r(U^T\hat{\Sigma}_1 U)}{T_r(U^T\hat{\Sigma}_x U)}\ ,\quad \hat{U}_1=\arg\max_x g(U_1)$$

where Tr (.) is the detection driver and , $\sum_1\hat{}=A_1\hat{}^T D_1^T D_1 A_1\hat{}$, $\sum_X\hat{}= X^TX$. $A_1\hat{}$ is the lowest mean square estimated of the not known target evoked reactions A_1. A_s D_1 A_1 and D_2 A_2 may overlap, $A_1\hat{}$ is calculated from:

$$\begin{pmatrix}\hat{A}_1\\ \hat{A}_2\end{pmatrix}=(D^TD)^{-1}D^TX$$

in which D= [D_1, D_2] the spatial filters $U_1\hat{}$ are estimated from $U_1\hat{}$ =R_X^{-1} $\Psi_{1:Nf}$ after computing the QR decompositions X= Q_X R_X and D1 = Q_1R_1 . $\Psi_{1:Nf}$ is the sequence of the N_f individual vectors $\Psi_Z\hat{}$ that are correlated with the N_f highest individual values $\lambda_Z\hat{}$ given by the individual value factors of $R_1B_1^T Q_X = \Phi\Lambda\Psi^T$, where Λ is a diagonal matrix, Φ and Ψ represent the unitary matrices and $A_1\hat{}$ = B_1^T X . In this case, the enhanced signals are specified by the following formula in the final stage:

$$\hat{S}_1 \stackrel{\Delta}{=} X\hat{U}_1 = D_1A_1\hat{U}_1 + D_2A_2\hat{U}_1 = N\hat{U}_1$$

2.2 Linear Discriminant Analysis (LDA) Algorithm

LDA is a well-known data mining algorithm. It has been widely applied in numerous different classification problems. It is simple to use and requires a very low computational time. It has achieved high classification performance in different BCI applications: the P300 Speller (Bostanov, 2004), asynchronous (Scherer, Muller, Neuper, Graimann & Pfurtscheller, 2004), and multiclass (Garrett, Peterson, Anderson & Thaut, 2003).

According to Yoon, Roberts, Dyson and Gan (2011), the LDA classifier aims to separate the dataset into two classes using hyperplanes. The class of a sample is determined by the side of the hyperplane in which a sample, or as it is also called, a feature vector is placed on, as shown in Figure

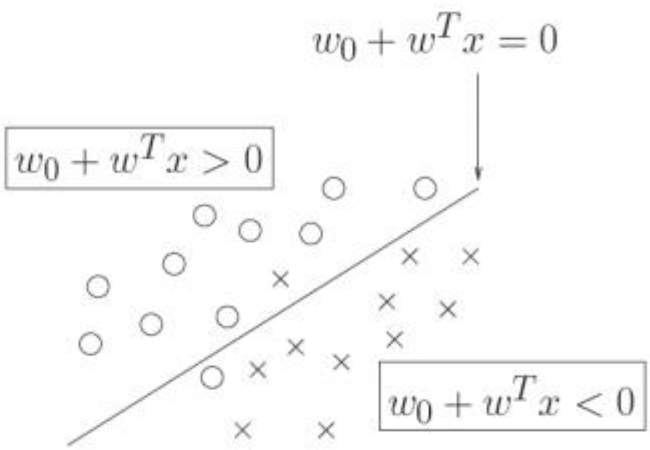

Figure 2 – A Hyperplane Created By The LDA Algorithm To Split The Data Into 2 Classes (Yoon Et Al.,2011)

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This algorithm assumes normal distribution of the conditional probability density functions P(X│y=0) , and mean of P(X│y=1). Based on that, samples are associated with the second class if the long-likelihoods ratio is smaller than scalar T:

$$\vec{X}-\vec{M}_o{}^{T}\sum_{y=0}^{-1}(\vec{X}-\vec{M}_o)+In\left|\sum_{y=0}1-(\vec{X}-\vec{M}_1)^{T}\sum_{y=1}^{-1}(\vec{X}-\vec{M}_1)-In\right|\sum_{y=1}\ \Big|<T$$

III. PROPOSED FRAMEWORK

In this project we developed the framework and describe the techniques used for improving accuracy in BCI using P300 speller. The experimental setup was the following: Participants were seated in front of the system i.e. computer screen which presenting the 6✕6 matrixes and concentrate over there. Our Proposed methodology consists of 6 modules: - (1) Signal Monitoring, (2) Acquisition, (3) Training x-DAWN, (4) Training classifier, (5) Online testing and (6) Replay Testing

3.1 Signal Monitoring

This scenario should be always used prior to anything and in background to check the signal quantity of the acquisition device. Once you are sure that the EEG acquisition runs correctly, you can go on to the next step. Temporal filter and signal decimation boxes transform the signal so you can see what is actually used online. This scenario can be used in order to check the quality of signals before starting an experiment. We should definitely check the quality of the signals and ensure that:

- Eye blinks are visible
- Jaw clenching
- Alpha waves are visible when closing eyes.

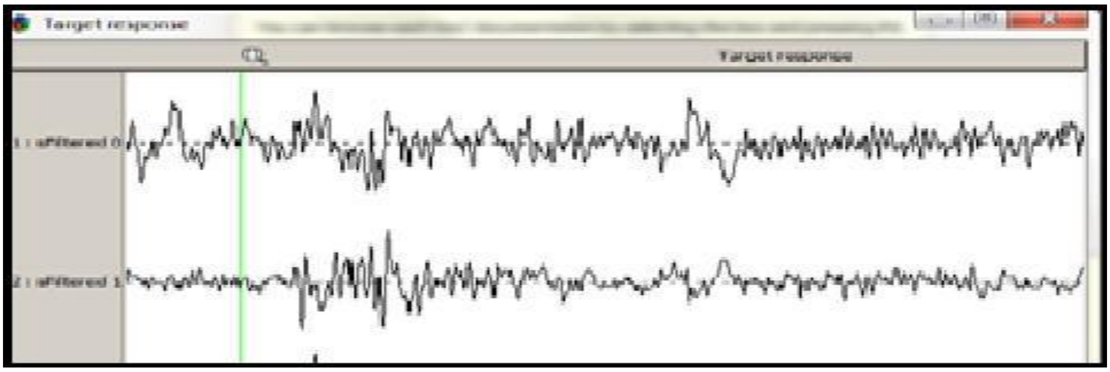

Fig 3- Target Response

3.2 Training Data Acquisition

First step is to acquire some data in order to train the LDA classifier that will detect the P300 brainwaves. The default training session is made of 10 trials. Each time the user is instructed to focus on a particular letter (instruction in blue). After 12 repetitions (12 flashes of each row and column, so 24 flashes for each letter on the grid) we move on to the next letter. Change the Lua stimulator settings to configure the number of letters, the timings, the colors etc. Overview- this scenario can be used as a first step to collect some training data. Those data will later be used to train a spatial filter and a classifier for online use. You will then be presented a blue letter that you have to focus on, followed by a 12 times flashing sequence (24 flashes of each letter i.e. 12 for row and 12 for column) of the whole grid. This will be repeated 10 times.

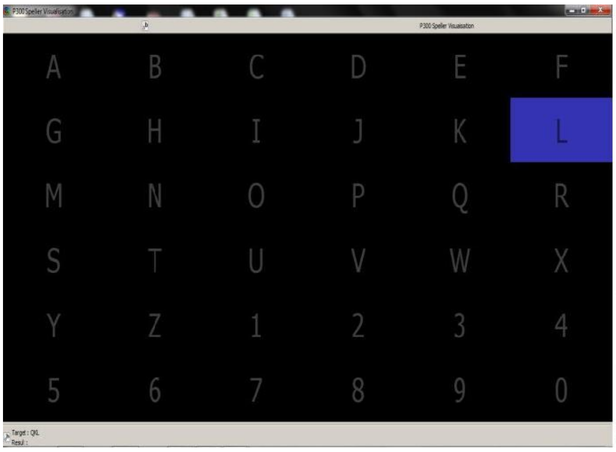

Fig 4- Instructing letter in blue

Fig 5- Flashing row after instructing letter

3.3 Training X-Dawn

This scenario should be used to train the spatial filter using the x DAWN algorithm. Just configure the Generic stream Reader box to point to the last file you recorded with scenario I-acquisition and fast forward this scenario. At the end of the training, you will have line in the console about Eigen values. Using a Player Controller the scenario will automatically pause at the end of the training. The preprocessing of the signal is performed here.

3.4 Training Classifier

This scenario trains LDA classifiers that try to discriminate the two classes P300 or not and uses after x-DAWN filter has been trained. Just configure the Generic stream Reader box to point to the last file you recorded with scenario 1-acquisition and forward this scenario. At the end of the training, you will have an estimate of the classifier performance printed in the console. If this performance is lower than 70%. Just run a new 4-online session to have better results.

3.5 Online Testing

This scenario allows the user to spell some text. User can choose to spell the designated letters (in blue) or any other letter. However it is advised to follow the instructions as a well-formed online session can be used to train again the classifier if the results are not good enough. After the 12 repetitions, the system displays the letter it chooses as the best candidate (in green). Change the Lua stimulator settings to configure the number of letter, the timings, the colors, etc.

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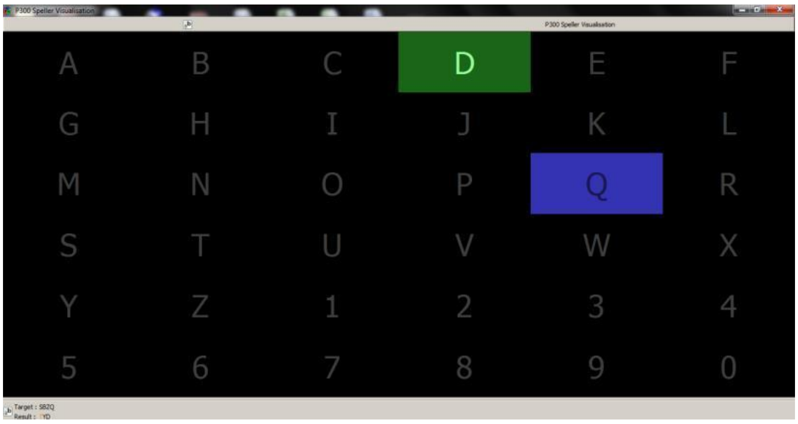


Fig 6- Target and result letter shown in blue and green respectively

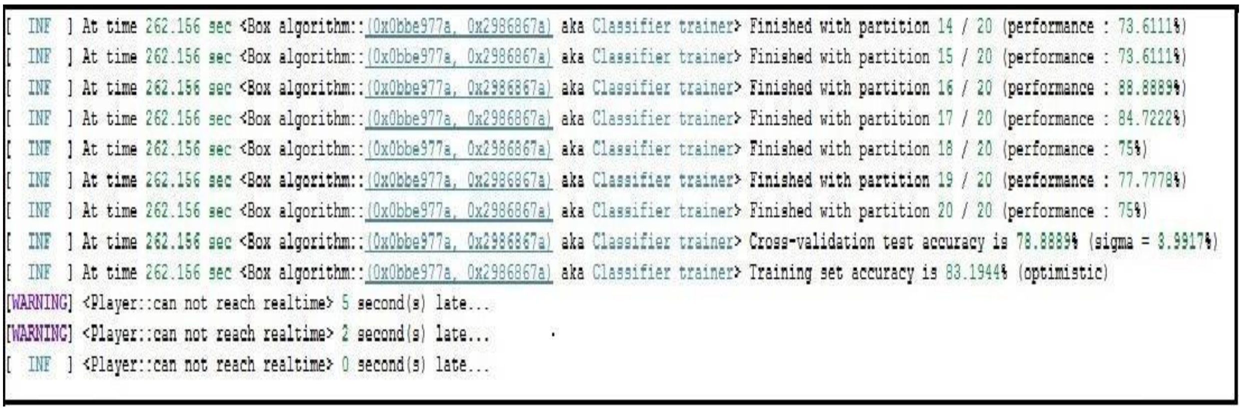
3.6 Replay

After performing all methods one by one, scenario generates the final result which was show in the green block whatever we got in the previous modules without showing the target letters.

Fig 7- Result shows after performing online testing without instructing target

IV. RESULT

After performing many trials all the procedure successfully, we get the improved accuracy in BCI by using P300 speller near about 80% to 90%.



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[  INF  ] At time 262.156 sec <Box algorithm::(0x0bbe977a, 0x2986867a) aka Classifier trainer> Finished with partition 14 / 20 (performance : 73.6111%)
[  INF  ] At time 262.156 sec <Box algorithm::(0x0bbe977a, 0x2986867a) aka Classifier trainer> Finished with partition 15 / 20 (performance : 73.6111%)
[  INF  ] At time 262.156 sec <Box algorithm::(0x0bbe977a, 0x2986867a) aka Classifier trainer> Finished with partition 16 / 20 (performance : 88.8889%)
[  INF  ] At time 262.156 sec <Box algorithm::(0x0bbe977a, 0x2986867a) aka Classifier trainer> Finished with partition 17 / 20 (performance : 84.7222%)
[  INF  ] At time 262.156 sec <Box algorithm::(0x0bbe977a, 0x2986867a) aka Classifier trainer> Finished with partition 18 / 20 (performance : 75%)
[  INF  ] At time 262.156 sec <Box algorithm::(0x0bbe977a, 0x2986867a) aka Classifier trainer> Finished with partition 19 / 20 (performance : 77.7778%)
[  INF  ] At time 262.156 sec <Box algorithm::(0x0bbe977a, 0x2986867a) aka Classifier trainer> Finished with partition 20 / 20 (performance : 75%)
[  INF  ] At time 262.156 sec <Box algorithm::(0x0bbe977a, 0x2986867a) aka Classifier trainer> Cross-validation test accuracy is 78.8889% (sigma = 3.9917%)
[  INF  ] At time 262.156 sec <Box algorithm::(0x0bbe977a, 0x2986867a) aka Classifier trainer> Training set accuracy is 83.1944% (optimistic)
[WARNING] <Player::can not reach realtime> 5 second(s) late...
[WARNING] <Player::can not reach realtime> 2 second(s) late...
[  INF  ] <Player::can not reach realtime> 0 second(s) late...
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Fig 8- Improved Accuracy Shown after Performing all Modules

V. CONCLUSION

From all the various systems of BCIs P300 BCI is used in various system because of its popularity and hence it is very famous. Now-a-days there are various BCI applications which based on P300 BCI system used by paralyzed patients (locked-in patients) in their daily life. Various techniques are used to improve accuracy and flexibility of P300 based BCI, but we use the modest technique to increase the efficiency of the system. The drawback of existing P300 based BCI system provide a very low rate of information transmission and low accuracy. Due to continuous flickering of light sources it is difficult for user to concentrate and also leads to fatigue. In this project we overcome this problem by improving accuracy in the brain computer interface system with P300 potentials.

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