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STEADY STATE VISUALLY EVOKED POTENTIALS FRAMEWORK IN BRAIN COMPUTER INTERFACE

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ABSTRACT

Development of framework for steady state evoked potentials (SSVEP) using electroencephalogram (EEG) signals has been discussed in this paper. Signals from the brain for SSVEP application are captured and then after processing signals we can get desired output. Using classification algorithms k-fold cross validation test and Common spatial filter (CSP) we tried to increase information transfer rate. This study introduces a technique for classifying different frequencies separately so that accuracy is high. We can get more ITR if we get more accuracy as ITR is dependent on ITR. Using Wolpaw's Method ITR can be calculated. The focus of this paper is proposing the development of framework that can capture the EEG signals classify them in the SSVEP signals. These SSVEP signals then are used to train the user and application can be used by will of the user.

Keywords: Brain Computer Interface (BCI), Electroencephalogram (EEG), Information Transfer Rate(ITR), Steady state visually evoked Potentials(SSVEP).

I. INTRODUCTION

Brain computer Interface uses an uncommon way of communication between brain and computer. Even though it is uncommon way it is most direct as intentions are directly sent to the computer from human brain. With Brain Computer Interface subjects ideally need not to use common output pathways like peripheral nerves or muscles, which is the main function of a BCI system. With the help of electroencephalography (EEG), Cerebro-electrical brainwaves can be measured. These brainwaves in the past used for the clinical purposes, with amplification and fed into a system. Under certain circumstances and with proper algorithms we can process these waves to satisfy application needs [1].

We can categorize brain computer interface in two parts depending on the input given to the system as synchronous BCI and asynchronous BCI. This categorization can be done on the basis of the time intervals. There is time window defined in the system for synchronous BCI for time variant. If any of the signals are generated from the brain outside this time interval, it gets ignored or rejected. This means that application must be used by user in a specific time window specified by the BCI system. The main advantage for the synchronous BCI is only predefined signals are allowed in the system no other artifacts can be generated because of the user's fault. This makes the system more simple and reliable.

Asynchronous BCI on other hand is more demanding and complex. Asynchronous BCI needs continuous processing of the data. Even though user action is not a proper command system will continue the process [2]. Because of this asynchronous mode is more natural way of interaction for the human to computers.

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To collect data from the brain we need to use headsets. These headsets use electrodes to sense the brain waves and collect them. There are generally two types of headsets are used for collections of data. They are 10-10 and 10-20 headsets [3]. The name is given to these headsets according to their separation of the electrodes. Electrodes in 10-10 system are having distance among them as that of 10% of the total headset while 10-20 system is having distance between electrodes as 10% for boundary electrodes and 20% for other electrodes of the headset. 10-10 system may have 31-38 electrodes while 10-20 system may have up to 21 electrodes. We use less power for electrodes in 10-20 headsets, as they are having more no of the electrodes. Most of the 10-10 system electrodes are covered by the 10-20 headsets by heir functionalities. 10-10 system is more complex compared to 10-20 system. Because of these attributes generally 10-20 system is most commonly used [4][5].

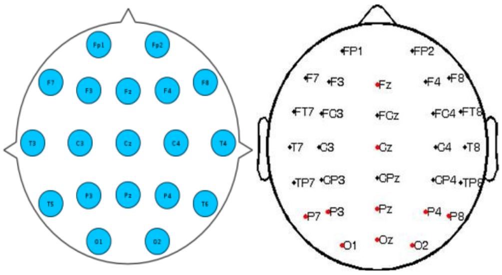

Fig. 1 10-20 and 10-10 electrode positions

SSVEP-BCI offers the classification of a large number of symbols simultaneously and hence we can say that SSVEP BCI is multiclass in nature and provides high performance. Visual evoked potentials (VEPs) are electrical potential differences; those can be derived from the scalps after a visual stimulus, for example a flash-light [6].

There is a very high possibility of information transfer rate with minimal training time to the subject and very low requirements in SSVEP base BCI. Secondly if the system is carefully designed then it can be relatively robust with respect to noise and artifacts. The very important advantage is that we can easily extend the commands of the system because of the input process and short timing phase. The aim is to detect the reliably of frequency with the high accuracy. Furthermore the aim is to detect when the frequency do not appear, hence when the person or subject does not look at the stimulus.

Open-Vibe is software which is used for interfacing computer and EEG capturing device. We are using Open vibe to capturing and storing the EEG signals. These signals are processed by the framework and then final application can run after the training is provided to the subject. We have used different modules to create the framework for example configuration of signals, training, classification and final application.

II. METHODOLOGY

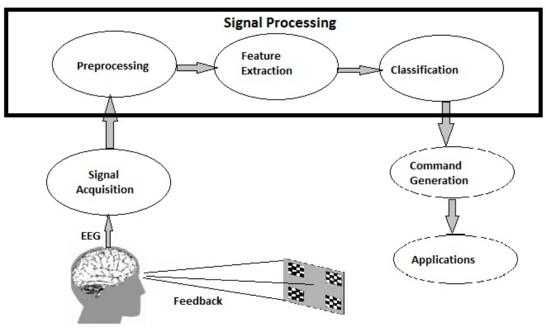

Fig. 2 Steps in generation of SSVEP signals.

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2.1 Preprocessing

After the signal acquisition from the headset, signals will be processed to identify the SSVEP response. However, before processing there are several things needed to be done to isolate the occipital channels and sanitize the signal to preprocess the data. The SSVEP response should appear in all the channels and averaging to eliminate some of the noise and non-important differences between all the channels. This common average reference is an average number for all used electrodes of the required headset over the course of the signals for time. This eliminates the unimportant signals from the needed signal by expressing lobe signal as variation from the in general EEG activity [7].

Artifacts are unwanted signals present in BCI. Artifacts have various origins, which include the utility frequency like noise, body and eye movements, or attention blinks. We can handle artifacts by three main approaches: avoidance, rejection and removal. By artifact avoidance the user should not execute any movement which may result in EEG artifacts. This can reduce artifacts, but obviously we cannot stop eye movements and blinks, so sometimes these artifacts may occur. Because of constant restraining from blinking by user can cause fatigue. Another approach is the rejection of all trials which are introduced by artifacts. This can be done in any way manually or automatically. By a manual artifact rejection procedure, we determine which of the trials are introduced through visual examination and in automatic artifact rejection an algorithm may be implemented which is able to determine contamination of artifacts. Artifact rejection may reduce the size of the training set; this can lead to consequences in the classification accuracy [8].

High-pass filtering of the signal is the simplest method for artifact removal. The eye artifacts generally occur in the low frequency range of 0–4 Hz, we may reduce the EOG artifacts by filtering these components out.

There are two types of signal processing methods can be used in the SSVEP generation according to filtering types for preprocessing. Those are frequency filtering and spatial filtering. We can use any of these in our second step of preprocessing.

2.1.1 Frequency Filtering

The signals are filtered according to the characteristics of the frequencies related signals. We have two types frequency filtering we can use for the preprocessing of the SSVEP signals. They are Band pass filter and Notch filter.

Band pass Filter: In Band pass filter frequency range is designed according to the frequency harmonics or to the simulation frequencies. Band pass filter is relatively simple to implement but the drawback is that it may be very stringent for explaining the time-varying signals [9].

Notch Filter : Usually notch filter is used for removing the power line interference.

2.1.2 Spatial Filtering

In spatial filtering there is combination of signals from different channels to magnify the SSVEP responses. This can be done with the reduction of the interference of the noise. Signals from multiple channels are less affected by noise. The most affected signals are either unipolar or bipolar systems. This technique also can be used for the feature extraction techniques. Spatial filtering is classified techniques those are explained below:

i) Maximum contrast combinations (MCC): MCC is most frequently used method for spatial filtering. MCC tries to maximize ration between SSVEP and background signals. The computation for MCC is complex.

ii) Principle component analysis (PCA): For the decomposition of signals into components of SSVEP signals and brain activity we need to use PCA. The dimension of the original data can be reduced by the help of PCA.

iii) A common spatial pattern method based on the (ACSP): ACSP method is based on the analytical representation of signals. Based on CSP method ACSP reflects amplitude as well as phase information of SSVEPs.

iv) Component average filter (CAR): The average values of all the electrodes is subtracted from the channel of interest to make EEG recording nearly reference free.

v) Canonical correlation analysis (CCA): The relation between two multivariable data sets are computed by CCA after linear combinations of linear data. Other methods are KCCA, Multiway CCA and p-CCA. KCCA is used for the high dimension data sets. Multiway CCA uses optimal reference signals while p-CCA uses the phase information in reference signals.

2.2 Feature Extraction

Feature extraction is an important step in getting emotion assessment, because features with very high discriminative power are very crucial for efficient in pattern recognition. These are the most often used features which are computed from the signal's power spectrum [10]. The power of the EEG signals is used by the researchers at several frequency bands which may often range from 2 Hz to 45 Hz or a combination of the energy to different frequency bands, as it may be done by computing the ratio of energies with the help of left and right lobes to obtain indexes. ERP is only moderately using for a BCI as it is necessary to take the average of the signals over several trials of the same emotional class for obtaining reliable ERP [11],[12].

Feature extraction is key issue in the signal processing. A variety of feature extraction methods can be used for the system. Some of the newer feature extractions filters other than band pass filters can be used in the designing of the framework are standard moving average filter (MA) and Savitzky-Golay filter. MA is used to analyze data points by creating calculations of a series of averages of different subsets of data sets. MA is also called a moving mean (MM). A Savitzky–Golay filter is a digital filter. This filter can be applied to a set of digital data points. This can be done for the purpose of smoothing the data by doing this, there is increase the SNR without greatly distorting the signal.

2.3 Classification

There are many classification algorithms can be used for the SSVEP generation process, but most effective are LDA, SVM and ANN. Linear discriminant analysis (LDA) is method used in pattern recognition and machine learning to find linear combinations of features those are characterized or separated by two or more classes of events or objects. The result may be used as a linear classifying combination or for dimensionality reduction before later classification [13].

Support vector machines (SVMs) supervise learning models along with associated learning algorithms in machine learning those analyze data and recognize patterns which used for classification and regression analysis. Within the given set of training examples, each marked as belongings to one of given categories [14]. SVM training algorithms build models those assign new examples into one of the category by making it as a non-probabilistic binary linear classifier [15].

In artificial neural network algorithm with the help of Supervised Learning the perception can be trained. It can be done by adjusting the weights of the inputs. In this learning technique, the patterns to be recognized are known in advance by subjects, and a training set of input values is already classified with the desired output [16],[17].

III. THEORETICAL BACKGROUND

3.1 Information Transfer Rate

BCI performance might affected by two important task parameters. First is the number of targets. A large no. of targets may increase system performance, as more targets provide more information. Alternatively, a greater no. of targets may decrease system performance by decreasing its accuracy. The other is the rapidity of frequency change. Because of this user may feel tired after continuously watching at the screen. Jonathon Wolpaw proposed a formula to calculate the ITR

$$ITR = s \cdot \left[\log_2 N + P \log_2 P + (1-P) \log_2 \left(\frac{1-P}{N-1}\right) \right]$$

where N is the no. of possible targets. P is the probability that the target hit (accuracy). Bit rate can be calculated by dividing S by the trial . In case of this project N=3. Accuracy and S is varying.

Electrode Positions: This is the important aspect in any BCI system. The positions of the electrodes play an important role in the capturing the signals accurately. It means the quality of signals depend on the placement of electrodes [18]. The positions used in this project are CPz, POz, Oz, Iz, O1,O2. The signals individually can be captured and then processed individually for each frequency.

K-fold Cross Validation Test : k-fold cross validation is a common technique for estimating the performance of a classifier. a single run of k-fold cross validation proceeds as follows:

1. Arrange the training examples in a random order.
2. Divide the training examples into k folds. (k chunks of approximately m/k examples each.)
3. For i = 1, . . . , k:

• Train the classifier using all the examples that do not belong to Fold i.
• Test the classifier on all the examples in Fold i.
• Compute ni , the number of examples in Fold i that were wrongly classified.

4. Return the following estimate to the classifier error.

IV. PROPOSED SYSTEM

The Project is developed in Open-Vibe software. The EEG signals are captured by the OpenBCI headset V-3 32 bit kit. There are different modules say scenarios are used in the system are Acquisition of signals, Training to user, CSP filtering and Classification, Online testing.

Acquisition of signals and configuration: Signals are tested in this module. Continuity of signals and quality of signals are checked using this module. We can check individual signals using this module.

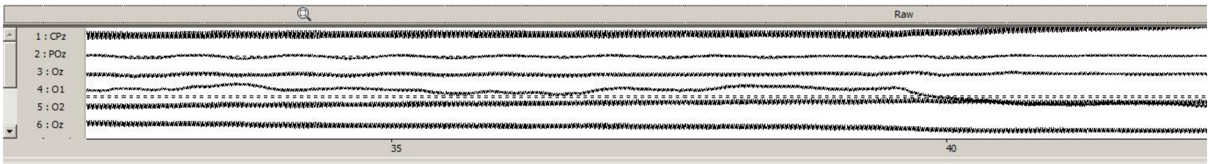

Fig 3 Signal Display of various electrode positions on brain.

This module contains FFT of average of all the signals and various boxes like acquisition client, temporal filter spatial filter for averaging, spectral analysis and signal display. Configuration of the framework can be configured SSVEP experiment [19]. There are two boxes of configuration parameters for peripheral and experimental settings. These settings are for stimulus and refresh rate of the screen.

Training of user: This SSVEP module uses Common Spatial Pattern (CSP) spatial filter which automatically selects the best characteristics. This means that user can place the electrodes on the occipital area's any part of the scalp [20]. This module is used for acquisition of the training data necessary to train the SSVEP classifiers. In order to run correctly it has to be configured by the SSVEP Training Controller. Boxes used in this module are SSVEP training controller, stimulation control, acquisition client, and stream writer to write the data captured by the headset.

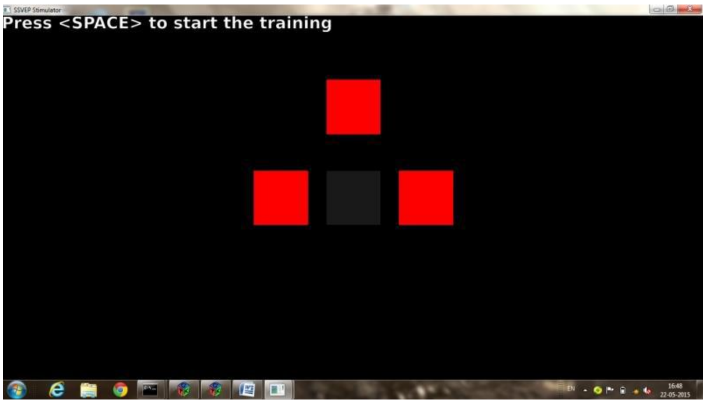

Figure 4 Flickering Stimuli for training the user.

CSP Training and Classification: CSP training is used for training of the Common Spatial Pattern filters. These enable user to use any set of electrodes and will automatically select the best combination of them for user. Signal processing is done on 3 different stimulation frequencies separately. Boxes used in the module are temporal filter, stimulation based epoching CSP spatial filter training, player controller and generic stream reader which loads the data written in previous module. Classification process contains boxes as generic stream reader, spatial filter, Target stimulator for different frequencies, time based epoching, DSP, Signal Average and classifier trainer. This module calculates the accuracy of the system which is useful for the calculation of ITR.

Online Testing: This module is used for the online testing of the framework. The trained data is used for scenario control of the system. This is in form of a game in which a ship is designed. It is having two wings which are flickering in two different frequencies which are used to rotate the ship in clockwise or anticlockwise. It also has a cannon which is used to fire the target. The cannon flicker with different frequency with respect to the two wings. The ship works in a way user concentrates on the flickering stimuli. This scenario contains boxes as SSVEP shooter controller, Scenario control, Button simplifier, player controller, Stimulator control, Spatial filter for three different frequencies, Time based epoching, Simple DSP, Signal average, Feature aggregator, classifier processor,SSVEp voter , VRPN ship control and Acquisition client.

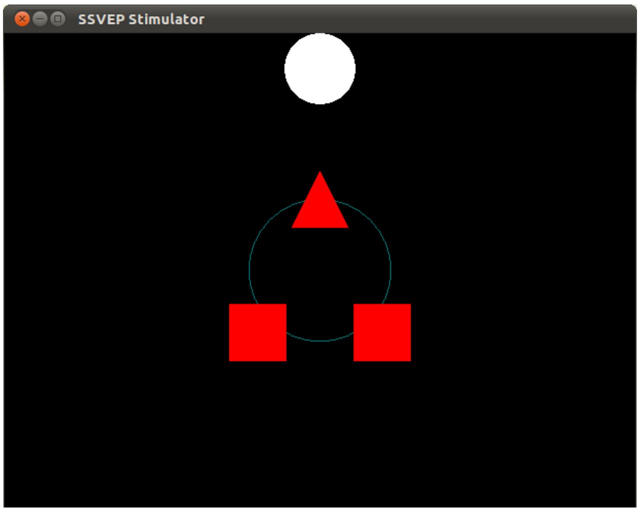

Fig 5 SSVEP stimulator online game

V. RESULTS

After running all the modules explained above we get the accuracy ranging from 78% to 92%. Which leads to calculation of ITR.ITR is calculated manually and we get it from 24 bits/min to 40 bits/min with the feedback. The signals captured from the EEG headset are unstable with the software we used but most of the times signals captured were continuous and having great quality. The SSVEP stimulation is an online shoot game which is use for the testing of the system. It is running accurately with OpenBCI headsets. If user concentrates at right wing the ship rotates in clockwise direction. If user concentrates at right wing the ship rotates in anticlockwise direction. If user concentrates at cannon ship fires. After one target is vanished other target appears. There are total 8 targets to be vanished to finish the game.

VI. CONCLUSIONS

In BCI mostly there is preference to the SSVEP system. As it is Exogenous BCI and it requires very low training to use, it is possible for user to perform actions on the system by their convenience. Furthermore SSVEP gives high information transfer rate so it is possible to use in real life also. Control signals can set up very easily so it is possible to use many options in one system using SSVEP. In this project ITR is increased then many of other frameworks used in past. There are some disadvantages for the system; flickering visual stimuli may cause some tiredness or fatigue to the subject if used for a long time. If the subject is having some neurological disorders like color blindness or similar disorder, it is not appropriate for a person to identify the color, frequency or pattern in the system.. There is possibility of combining SSVEP signals with other Exogenous or Endogenous BCI signals. This can be done for the better performance, reliability of the system, robustness and more options to user.

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