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**RESEARCH ARTICLE**

# Hybrid Visual BCI Combining SSVEP and P300 with High ITR and Accuracy

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***Abstract:** The working of the brain computer interface depends on the EEG signals quality and the processing method used for that of the signals. The BCI system have their disadvantages with respect to their signals quality and they can be improve with new concept i.e. hybrid brain computer interface. Recent the signals processing is the very new trend in the recent years for EEG. Due to the non linear characteristics of EEG signals it is very difficult to extract exact pattern and accuracy. Due to these characteristic of the EEG signals we cannot achieve similar accuracy at all time. The need of hybrid BCI is to improve the use of the BCI very easily and effectively.*

***Keywords: EEG, BCI***

## I. Introduction

Brain Computer Interface is the way of communication between the brain and the computer. It takes signals from human brain and transfers it into the digitized form. In BCI so many researchers have work for the effective utilization of the system to the end users. For the effective utilization the proposed system is the Hybrid Brain Computer Interface [1]. Several different signals can be used in the BCI system. P300 event related potentials (ERP), Steady state visually evoked potentials (SSVEP), and Motor Imaginary (MI).

A BCI system can send commands, controlled by brain activity and distinguished by EEG signal processing. There are many features which can be extracted from EEG, for example, six brain rhythms can be distinguished in EEG based on the differences in frequency ranges; delta (1- 4 Hz), theta (4-7 Hz), alpha (8-12 Hz), mu (8-13 Hz), beta (12-30 Hz), and gamma (25-100 Hz). The delta and theta rhythms occur in high emotional conditions or in a sleep stage. The alpha rhythm happens in awake and eyes closed relax condition. The oscillation in alpha rhythm has smooth pattern. The beta rhythm pattern is desynchronized and the condition is the normal awake open eyes. The gamma rhythm can be acquired from somatosensory cortex and mu rhythm from sensorimotor cortex.

 

A brain-computer interface (BCI) system can provide a communication procedure to convey brain messages independent from the brain's normal output pathway. Brain activity can be analysis using different approaches that include standard scalp-recording electroencephalogram (EEG), magnetoencephalogram (MEG), functional magnetic resonance imaging (fMRI), electrocorticogram (ECoG), and near infrared spectroscopy (NIRS). However, EEG signals are considered as the input in most BCI systems. BCI systems are categorized based on the brain activity patterns such as event-related desynchronization/ synchronization (ERD/ERS), steady-state visual evoked potentials (SSVEPs)[3], P300[2] component of event related potentials (ERPs), and slow cortical potentials (SCPs).

THE goal of brain–computer interfaces (BCIs) is to translate the signals produced by brain activity into control signals and to use these signals to control external devices without the participation of peripheral nerves and muscles. EEG-based BCIs are relatively convenient and inexpensive; therefore, they have attracted a great deal of attention for research. The brain signals often used by EEG-based BCIs include P300 potentials, steady-state visual evoked potentials (SSVEP), slow cortical potentials, and event-related desynchronization/ synchronization (ERD/ERS) produced by motor imageries.

The BCI control may be asynchronous or synchronous. In asynchronous BCIs, an important problem is to distinguish the control and idle states promptly and accurately based on ongoing EEG Signals [2]. Many studies have addressed the issue of asynchronous BCIs based on MI, SSVEP, and P300 potential. Many studies have addressed the issue of asynchronous BCIs based on MI, SSVEP, and P300 potential.

To utilize the advantages of different types of BCIs, different approaches are combined, called hybrid BCIs. In a hybrid BCI, two BCI systems can be combined. In recent years, there has been more attention to hybrid BCI systems. In general, in a hybrid BCI, two systems can be merge or utilized sequentially or simultaneously [1][4]. In a simultaneous hybrid BCI, both systems are processed in parallel. Input signals used in simultaneous hybrid BCIs can be two different brain signals, one brain signal, or one brain signal and another input. In sequential hybrid BCIs, the output of one system is used as the input of the other system. Hybrid EEG-based BCI can be any combination of electric brain activity patterns such as ERD-SSVEP, ERS-SSVEP, P300-SSVEP and SSVEP-SCP [5, 6 and 7].

This paper conducts comprehensive work on hybrid BCI's system. It focuses on data preprocessing, feature extraction, accuracy and ITR. This paper can be organized as follows: section II depicts as a signal processing and their components like preprocessing, feature extraction and signal processing, and also survey of classification algorithms. Section III introduces methodology, under section IV Experiment are Describes and under section V the result are describes.

## II. Signal Processing

The general structure of the signal processing is described in the give figure 1. The signal acquisition system acquires the signals. Then pre processing system can do some pre processing function in order to remove some noise and artifacts. Then the feature can be extracted from that pre processed signals .theses feature can be then given to the classifiers and it may classify it according to their characteristics

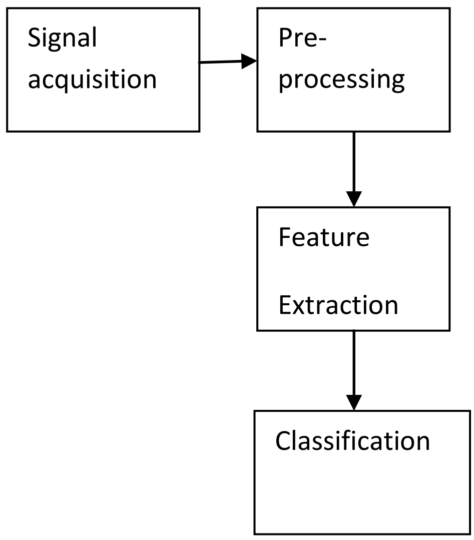


Fig1. Block Diagram of the EEG Processing

## III. Methodology

### A. Data Selection

The data used in this study were collected using the following procedure using OPEN Vibe system. The subjects are placed in the room and electrode position are Fz, Cz, Pz,P3,P4,Oz, O1, O2, POz, PO7, PO8 and two grounded electrodes. The data can be filtered using Notch filter at 60Hz and also using Bandpasss filter 1 50 HZ. Subjects are continuously focusing on the training visually. The data were collected from the 5 subjects having different age, all male.

### B. Experimental procedure

Data collected using Open VIBE[8] can be used to perform different operation on the dataset. For the effective and efficient performance of the Brain computer interface Needs to perform some actions that may reduce noises, artifacts in data in order to give more accurate signals , because eeg signals are non stationary and non linear.

## IV. Experiment

To evaluation of our approach offline analysis were performed on the 5 healthy subjects. These data may be further used for the experiments.

Data collected using that subjects were used for the training classifier and calculate the accuracy with that classifier training time. We are using simulator to evoke the event. We perform the Filtering process on the collected data first. In that process filter the filter gives input signal its process s it and gives output as a processed signals. Filter signals put on to next steps i.e Epoching which in terms select signals on particular event which event created by the simulator. The result of this epoching will be discontinued. After that epoch average performed on these signals. Then output of the epoch average gives to the feature aggregater function which aggregates the input signals into feature vector. Finally the training performed using classifier training functions. It trains models to classify data it collects the input as a feature vectors. It starts training on the specific simulator is triggered. And it calculates the accuracy of the training data.

As per the above mentioned procedure we have to perform it on the five subjects the results are vary depending on the condition of the subjects.

 

## V. Result and Discussion

The results found in the offline system are very good expecting one subject. Training accuracy was very high as compared to system we have worked. With the help of accuracy we Calculated the ITR (Information Transfer Rate) manually which is not possibly to calculate automatically [9]. Results which are coming out from our experiment are helpful to improve BCI systems. The figure shows the calculated accuracy and ITR.
Comparing to the BCI system hybrid system may performed better results but due to the non stationary characteristics of the eeg signals it may vary results. The ITR was calculated with the help of following formula as stated.

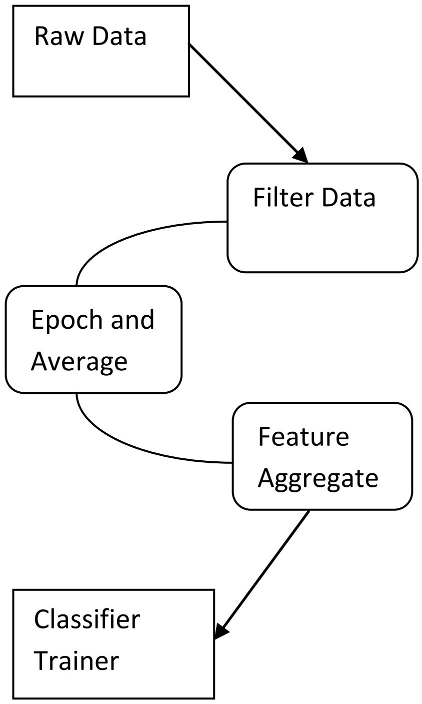


Fig2. Processing Module of Raw Data

$$B = \log_2 N + \ Acc \ \log_2 Acc + (1 - Acc) \log 2 \left(\frac{1 - Acc}{N - 1}\right)$$

$$\text{ITR} = \text{B} \times 60/\text{t}$$

N= No of choices

Acc =accuracy of the classifiers.

B =ITR for each Sections

T= time required fir identify each target.

ITR calculation may be vary from system to system.

 

| Subjects | Accuracy |
|---|---|
| S1 | 85.72 |
| S2 | 81.92 |
| S3 | 76.29 |
| S4 | 87.22 |
| S5 | 83.51 |

Table 1
Results of offline analysis

## VI. Conclusion

These study measure the eeg signals brain activity and uses the different functions to improve the accuracy and information transfer rate. As the study of the system performs visual hybrid bci the accuracy we have calculated during the training time is better and information transfer rate also good. These systems demonstrate very good detections of the accuracy for five subjects and having average accuracy is 82.93. thes study make a conclusion that use of hybrid brain computer interface proves very effective. During that many problems are arrived so it proves that there are needs of processing segment in order to improve quality of the eeg signals.

Hybrid BCI helps in future to enhance the quality of the BCI system. It help people with disabilities' to overcome them.

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