Enhanced Accuracy for Six Commands BCI System Using Hybrid ERPs/SSVEP Based Paradigm

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Copyright Statement

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I am thankful to my Creator Allah Subhana-Watala to have guided me throughout this work at every step and for every new thought which You setup in my mind to improve it. Indeed, I could have done nothing without Your priceless help and guidance. Whosoever helped me throughout the course of my thesis, whether my parents or any other individual was Your will, so indeed none be worthy of praise but You.

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ABSTRACT

This study presents a hybrid brain computer interface (BCI) system that achieves better accuracy based on event related potential signals. Following system based on the P300-SSVEP hybrid sequential BCI system to decode six reactive brain commands using ensemble classifier. The device which we are using for the record of EEG data only displays the signal on the computer screen and does not decode the signal into some readable file. So in order to get EEG readable signal, we convert signal images into digital form using image processing techniques. Based on the proposed algorithm of signal conversion, we have evaluated on previous EEG dataset and results are encouraging. P300 signal is evoked by oddball paradigm using stimuli of images flicker in random order. For P300 we have used already recorded six images stimulus dataset. The feature vector is extracted from the denoised waves after filtered through least mean square (LMS) filters. Extracted feature samples are fed into ensemble classifier model for classification. To achieve high accuracy, output from ensemble classifier trigger respective SSVEP frequency stimulus. On computer screen, triggered SSVEP stimulus begin to flash. A person is asked to focus on the stimulus for several seconds. EEG signal on occipital region is recorded. After classification of SSVEP signal command is sent to drive quadcopter. For BCI application, a virtual quadcopter environment is created and controlled by proposed hybrid BCI system.

Key Words: *SSVEP, P300, Hybrid BCI, Ensemble classifier*

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CHAPTER 1: INTRODUCTION

The development of a control channel and communication between the human brain and robots has evolved into one of the rapidly growing regions of scientific speculation. People's activities, expressions to surroundings are controlled by signals in the brain. Some people can't do the muscular activity but their brains are still generating signals like a normal person. Brain-computer interface (BCI) gives a way to control one's environment without using the normal neuromuscular output pathways. A BCI acquires the electrophysiological or other signals of the brain, interpret them, and translate them into commands that accomplish the intent of the user. The most common use of such technology is to perform a useful function for disabled people having neuromuscular disorders. Its future achievements will depend on the convenience of hardware i.e. portable and able to function in all environments and real-time reliability of natural muscle-based function. This emerging field of BCI technology brings hope to people by restoring basic communication capabilities. In short, the dream of controlling one's surroundings through thoughts has become true.

BCI technology is the tool of communication, which can be categorized into non-invasive, invasive, and semi-invasive. In invasive BCI, electrodes are directly placed into the cortex. In the case of semi-invasive electrodes are placed on the exposed surface of brain tissue whereas in non-invasive, electrodes are attached to the patient scalp. Most researches focus on non-invasive electroencephalography (EEG) signals due to better temporal resolution as compared to other non-invasive methods.

1.1 Electroencephalography (EEG)

EEG is the electrical activity recorded as a result of ionic current flows within neurons and correlated with the mental process. A reactive BCI is a subtype of BCI which generates output form brain activity in response to external stimulation. There are several mental processes and stimulations fulfill the requirements of corresponding strategies of brain signals. The most commonly used design for the creation of the BCI system is event-related potentials (ERP). The technique of extracting evoked potentials signals such as visual, auditory, or somatosensory is one of the oldest applications of BCI. Practically most applications use visual evoked potentials to decode brain activity. It is initiated by visual stimuli, display on the screen and the signal is recorded from the occipital cortex of the brain.

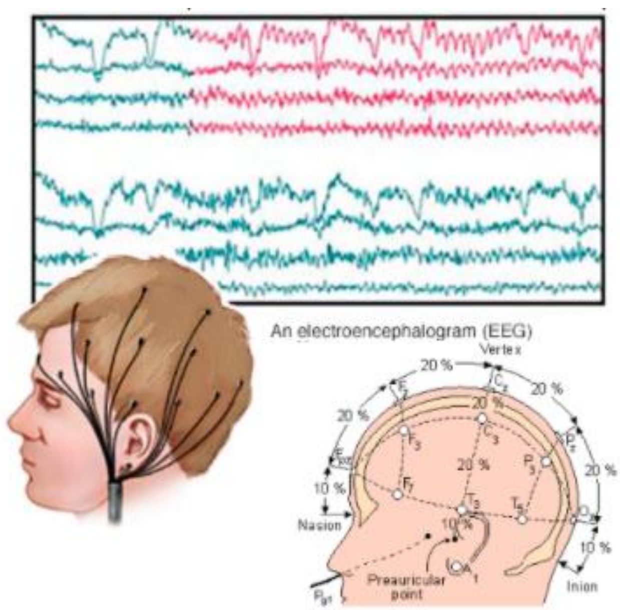

Figure 1 : EEG Electrode placement

1.2 Steady-State Evoked Potential (SSVEP)

In SSVEP based evoke potential subjects are allowed to choose a target command using eye gaze. For capturing SSVEP, target stimuli are flickered at some distinctive frequency. When subject gaze at target stimuli, a series of potential waves are observed which is of the same frequency as that of the target stimuli. So that response frequency content is determined from the stimulus frequency. A reliable SSVEP signal requires a continuous-time window of few seconds as SSVEP response is periodic. SSVEP is confined to a set of specific frequencies, so it is extracted by analyzing the EEG signal in the frequency domain instead of the time domain. SSVEP-based BCI system provides reliable responses by achieving a high information transfer rate.

1.3 P300

P300 is the form of event-related potential, which is elicited by the occurrence of some surprising event. It is usually evoked by using an oddball paradigm when subjects recognize unusual stimuli from a normal chain of standard stimuli. As a result of this activity, positive deflection occurs about 300ms in the EEG signal after a target stimulus is delivered. Its latency varies within the range of 250 to 750ms. The prominent P300 responses are observed over the parietal region of a brain.

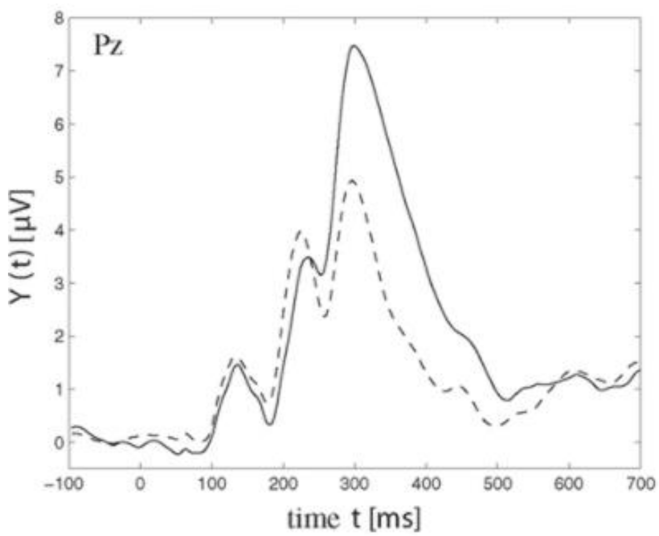

Figure 2: P300 Wave

1.4 Hybrid BCI

Conventional BCI systems have their pros and cons. Due to the unavailability of high accuracy and low information transfer rate, two systems can be worked in series or parallel to improve the performance of BCI systems [1]. This new approach increasing advantages and reducing disadvantages from different brain signals by combining the advantage of each system with different brain activity patterns [2]. A hybrid BCI is categorized into two types: In sequential hybrid BCI, two systems are connected in series such that the output of one systems is used as the input to drive the other system. To increase number of commands then systems are processed in parallel, it is known as simultaneously hybrid BCI.

1.5 Current problems and solutions

In recent years, research in BCI has undergone explosive growth. Nowadays, the spectrum of research and technology in the BCI field is broad by using a variety of brain signals, signal extraction signal features, translational algorithm, and classification model. P300 based BCI is one of the widely used system to increase the number of commands. New advances in P300 based paradigm designs are the source of reliability as they could give us a way to communicate by evoking potential in the brain. The conventional P300 based speller was introduced by Farwell and Donchin in 1988, which is known as the Row-Column (RC) paradigm. It consists of a 6x6 matrix that randomly flickering the row/column. The subject is asked to focus on the number of flashes of the target character [3]. Recent trends have focused on the improvement of the standard oddball paradigm by introducing new ways of flickering stimulus, changing colors, and characters to enhance the signal response [4] [5]. Other poplar spellers are Single-Character (SC), Checkerboard (CB) speller, and Region-based (RB) speller. These above paradigms only evoke a P300 signal. In RC and CB spellers, the user has to pay attention to the number of flashing of character by counting them. Moreover, due to continuously flickering of columns and rows may causing vision tiredness. To overcome this problem we are using an oddball paradigm of inverted and rotating image stimuli to evoke ERP components P300, N170, and vertex positive potential (VPP). N170 and VPP components are generated due to the configuration of the face image.

To improve the accuracy of the BCI system, we are creating P300-SSVEP based hybrid sequential BCI system [6] [7]. In most existing BCI, the decoding of output from EEG relies on the classification algorithm. These algorithms estimate the class of data by using a feature vector extracted from the signal. Recently used classifiers are Linear Discriminant Analysis (LDA), Baysian Linear Discriminant Analysis (BLDA), Logistic Regression, Support Vector Machine (SVM), and Artificial Neural Networks (ANN). Several Hybrid EEG modalities have been implemented in the BCI field to improve accuracy by using simple machine learning algorithms. Research on the classification of hybrid ERP/SSEVP with ensemble method is limited Ensemble classifier is also used in BCI domain to identify the class of output. It is used to improve accuracy by combining multiple models. It has better accuracy, higher consistency, and reduce bias and variance errors. For P300 detection we need a strong classifier and more training. The problem with a single classifier is that it may cause over-fitting over extra training. So we used ensemble classifiers to reduce overfitting [8].

The extraction of the EEG signal is a cumbersome task. The device which we are using for the record of P300 only displays the signal on the computer screen and does not decode the signal into some readable file. So we also decode the EEG signal display on the computer screen into tabulated form. Using image processing techniques, signals form images are translated into digits.

1.6 Objectives

The overall research objective is to design and develop the Hybrid ERP/SSVEP system that will generate four commands accurately and improve classification accuracy by using ensemble machine learning.

1.7 Expected Outcomes

This research will increase the recall rate of algorithm and improve BCI system efficiency which is designed for assisting people with disabilities in their daily house life. The Oddball paradigm of inverted and moving image stimuli can generate a strong ERP signal as compared to the conventional speller.

1.8 Applications

In our country, individuals who are severely disabled by disorders such as spinal cord injuries, brainstem stroke, and muscular dystrophies might benefit from BCI. This technology allows paralyzed people to control prosthetic limbs with their brains [9]. Improvement in such a system improves the quality of life for a person who is unable to perform body movements [10]. Other applications include the control of BCI smart home, Wheelchair control, Prosthetics, Quadcopter control, Robotic Augmentation [11].

CHAPTER 2: LITERATURE REVIEW

2.1 Hybrid Reactive BCI (P300/SSVEP)

A BCI enables a direct pathway for communication for those special users who cannot function their peripheral parts via normal communicating channels. A BCI equipped system can send a direct command that can be govern by performing some the brain activity and distinguished by an electroencephalography EEG features [12].

Based on the patterns of EEG brain activity, BCIs can be further sub divide into four distinguished groups: event–related desynchronization/synchronization (ERD/ERS) which is elicited by some reactive stimulus [7], P300 component of event related potentials (ERPs) evoked by oddball event [13], Slow cortical potentials (SCPs) , steady state visual evoke potentials (SSVEP) generated as a result of flickering stimlus [14]. Each modality has its own embedded advantages over others, but disadvantages are also incorporated in their functionality. Such as SSVEP-based systems have higher information transfer rate (ITR) and better accuracy than SCP and P300-based BCI systems which have advantages in other applications where SSVEP BCI not implementable. SSVEP BCI produces better results where training time is short and fewer EEG channels available [15]. In recent times, SSVEP systems faced several challenges while implementing in current application. Besides these pros and cons, required training time and information transfer rate are the two main features of all BCI modalities.

One of the main approaches for BCI systems is based on Event related potentials (ERPs). Capturing and interpreting the externally evoked brain responses to specific cognitive, sensory, or motor events are classified as Event Related Potentials (ERPs) [16]. P200, P300 and P700 are the most used components of ERP as they are the prominent peaks in entire signal. The target stimulus in an oddball paradigm can produce a positive deflection at the occipital region in the EEG, 300ms after onset of the stimulus. The reactive stimulus can be provided either auditory, somatosensory, or visual medium. The evoked response at 300msec classified as P300 ERP component [17]. Temporally, the typical range of P300 amplitude in the range of 2 to 5 μV in the signal while its duration of 150 to 200ms in time domain as shown in Figure.

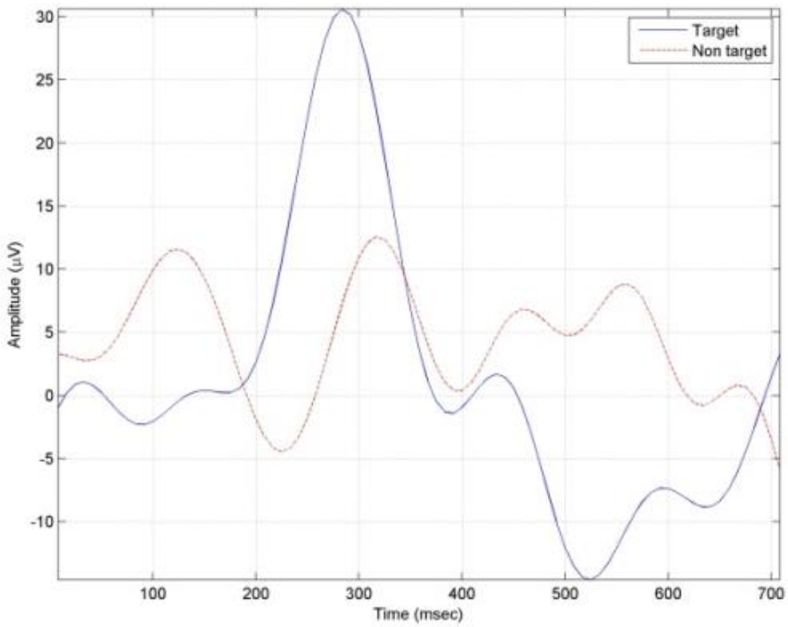

Figure 3: Temporal pattern of P300 component [17]

This modality has been widely used in BCI systems since 1988. Better accuracy, higher portability, inexpensive hardware manufacturing and new advancements in these systems make it possible to carry this technology outside the laboratory and implement in real-life applications. P300 based BCI system have the potential to enhance the quality of life as it can assist the specially enabled persons to maneuver by controlling wheelchair, creating commands for virtual keyboard to spell and type and interact with computers.

Besides other types of external stimulus, increase in neural activity elicited by gazing at a stimulus as demonstrated by various Electrophysiological and neurophysiological studies. Visual evoked potentials are evoked when some reactive visual stimuli is given. If reactive stimulus is repetitive visual stimuli would lead to same stimulus frequency voltage harmonics pattern in EEG that is called SSVEP [18]. Although, the fundamental mechanism of how SSVEP function is still unknown, generally SSVEP is considered as a continuous visual cortical response produced as a result of repetitive stimuli flickering with a constant frequency on the central retina. SSVEP contains as same fundamental frequency as external stimulus when waveform oscillates sinusoidal, having some harmonics of fundamental frequency [19].

SSVEP regarded as the basis for BCI systems. It has found its applications for the diagnosis of visual pathway and brain mapping impairments in clinical systems. In recent times, SSVEP BCI gained much attention in BCI paradigms continuum because of the newly discovered possibilities of its implementation in various domains, especially in those application areas where some major necessities are required to perform functionality. Some examples are as follow:

- BCI commands are required in large numbers
- Highly reliable and accurate recognition is compulsory
- Very limited scale of training available
- An enhancing performance is required

Irrespective of the advancement in this technology, still number of obstacles limits its implementation in routine life. Some of the hurdles are BCI illiteracy, uneven and unsatisfactory accuracies for different subjects, and low information Transfer Rate (ITR). The elimination of these factors can develop a sustainable implementation environment and they can be eliminated by removing their disadvantages and enhancing the existing capabilities. One way is to combine the various modalities in one system and an extensive amount of work in BCI has been done based on combination of different types of BCI systems in series or parallel in order to improve the system performance, or BCI and non-BCI, called hybrid BCI systems. Hybrid BCI has the capability to overcome the disadvantages and limitations of conventional individual BCIs. In recent year, hybrid BCI becomes the main potential in this field.

Among all EEG-based BCI modalities, SSVEP and P300-based BCIs have many clinical applications because of their conveniently high information transfer rates (ITRs) [20]. In P300-based BCI, a speller board presents the instruction commands on display screen and randomly intensifies the commands. The rare intensifications of the user’s intent commands will elicit P300 responses of the brain. The evoked potentials at 300 ms are identifies by the BCI system and translate these potentials to commands [21]. SSVEP has been extensively studied in the fields of engineering and neurosciences [1]. SSVEP is a response elicited by the visual stimulus modulated at a constant repetitive rate, normally higher than 6 Hz, and is characterized as a stationary periodic oscillation with a dominant spectral content, consistent with the stimulus temporal frequency [22].

SSVEP-based BCI systems has developed by the researchers that can achieve the ITR of 124 bits min−1 at peak.

Hybrid BCI seems a potent approach to improve the performance of the system. Several studies also reported about the combination of features of P300 with the features of SSVEP [23]. An synchronous system has been developed by Panicker et al which utilized P300 for command selection while simultaneous recognition of control state has done with SSVEP module. In current pure hybrid BCI systems, potentials at multiple EEG channels translates into multiple commands in such a way that different channels produce different commands wholly used in one system as one unit. This phenomenon uses the specific channels to generate associated commands via that modality which ensures the better performance [24]. This will enhance the overall performance of entire system with better accuracy. Compatible modalities can combine in one system for hybrid BCI. P300 and SSVEP modalities are two outstanding candidates to combine in one system for mental control tasks. Higher efficiency can be achieved by combining them. The combination may demand some elaborated design of the system to detect same brain activity due to the different characteristics of both BCIs. Time-locked P300 BCI has a temporal response of only few hundred milliseconds while phase-locked SSVEP signal needs several seconds to find its specified spectral response.

2.2 Available Data Sets

Data sets which are available are of three different types which are used in BCI competition [25]. The data set of P300 spelleer was developed by Farewell and Donchin which are of character recognition. It contains 36 characters which are in a 6x6 matrix, whose columns and rows are arranged randomly. Since this data set consists of two data subjects which are classified as subject A and subject B which involves 85 training and 100 testing characters respectively. These are the arrangement for Dataset BCI Competition III. For Dataset BCI Competition II, they have 42 training and 31 testing characters in database. The task of these dataset is to have full attention on desired characters as indicated by investigator. The flashing rate for this is 5.7 Hz. The paradigm is on the 100 ms and it will show blabkness till 75ms. Signals are collected from 64 channels with a filter cut-off frequency 0.1-64Hz and digitized at 240 Hz.

Another dataset which is used for SSVEP is presented in [26] . The most recent for this is going on unmanned vehicle where this is controlled by brain activity. Brain data is get by using the BioSemi Active two EEG system with a desired sampling rate at 512 Hz. Signals are recorded by locating it at over nine different positions. Two reference electrodes are connected at the left and right mastoids. This whole system is operated by ROS with wireless network control. The data from nine channels were preprocessed by using two electrodes at left and right.

In another research Hybird model of EOG and EEG is presented. It works in two modes: an EOG for eye movements such as blinks, and an EEG mode detects oddball signals like P300. In this study, they designed an algorithm that could detect four types of eye movements including blinking, blinking, looking, and blurring. An oddball paradigm with stimuli of inverted faces is used to evoke P300, N170, and VPP [27] [28].

2.3 Features Extraction Methods

From the past experiments it is observed that the peak for P300 will appear after 300 ms of the visual stimuli [29]. The assumption taken for it is 667ms, which is adequate for P300 classification. The chebyshev Type 1 band pass filter is deployed which has a cut-off frequency from 0.1-10Hz. Which will be further used to down sample in accordance with high cut-off frequency of filter [30]. After visualizing it, a single channel consist of 14 samples. For BCI Competition II and III there are 64 channels, the data are gathered according to the channels available. Due to the difference in design, the database is not homogeneous. It compromises of five times more P300 signals as compared to the P300 signals [31]. Due to this reason, classifier may not perform well as expected. For the classifier to perform the data should be homogeneous [32].

For the process of feature extraction the auto encoder is used. This process does not require any label data to construct the model. According to study, it requires two layers one is input layer other is hidden layer. The input layer dimension should be equal to feature dimension of input data whose feature are to be extracted. It also includes the reconstruction layer. To get the minimum error, the input layer replicate the reconstruction layer.

There are many different things that have been tried to design BCI such as EEG signal amplitude values, Band Powers (BP), Power Spectral Density (PSD), Autoregressive (AR) and Adaptive Autoregressive (AAR) parameter, Time-frequency features and inverse features for the model.

A lot of other techniques are used for feature extraction and artifact removal [33] such as time-frequency image fusion, adaptive filtering, kalman filtering, linear regression, independent component analysis (ICA), canonical correlation analysis (CCA), independent vector analysis (IVA), surface laplacian transform (SLT), morphological component analysis (MCA), wavelet decomposition (WD), empirical mode decomposition (EMD), multivariate empirical mode decomposition (MEMD), singular spectrum analysis (SSA) and other variants of them.

2.4 Classification Algorithms

The accuracy for the discussed data sets which we considered above show two types of features which are presented here [34]. One consists of feature extraction with feature set of SAE features combined with temporal features. The other consist of SSAE features along with temporal features. In this experiment two layers of SSAE features are chosen empirically for SSAE model. All the models are implemented in MATLAB platform. In BCI Competition III, the hidden layer nodes are chosen 450 and 460 for the two subjects A and B [35]. They are along with the deep features of classification. The character recognition of these two combined features are calculated with SVM and ESVM [36]. Single SVM model is trained and the character recognition are extracted from SVM and ESVM. The presented SVM models give accuracy of 74.5% , 90% and 97.5% after 5, 10 and 15 epoch respectively. The combined effect of SAE-ESVM with the feature trained gives the accuracy of 92% , 99% , 75% after the 5 , 10 and 15 epoch respectively. The proposed SAE-SVM and the proposed SSAE-SVM provide better performance. They helped to balance the training database and classifier integration to reduce variant variability. In Linear analysis discriminant (LDA) was used to distinguish the main focus of the topic. Other approaches are Bayesian Linear Discriminant Analysis (BLDA) used to prevent overfitting to high dimensional , ANN [37] [38], SVM, Logistic Regression etc [39].

2.5 Applications

P300 is suitable for the purpose of selection applications. In our country, individuals who are severely disabled by disorders such as spinal cord injuries, brainstem stroke, and muscular dystrophies might benefit from BCI. This technology allows paralyzed people to control prosthetic limbs with their brains. Other than this, it has the most common application in smart home controlling. BCI modalities are also used to control the wheelchair [40], navigation of robot, flight of quadcopter [41]etc.

CHAPTER 3: METHODOLOGY

3.1 Experimental Setup and Procedure

3.1.1 P300 Dataset

The following dataset of P300 was recorded by Hoffmann [28]. In this experiment user were asked to focus on the screen containing six images stimulus. The stimulus were images of a television, a lamp, a window, a telephone, a door and a radio. The images were flashed in random order such that one image at a time. Stimulus flashed for 100ms and in next 300ms none of the images was flashed. The total inter stimulus interval (ISI) was 400ms. The data was recorded at 4048 Hz sampling frequency from 32 electrodes according to 10-20 system.

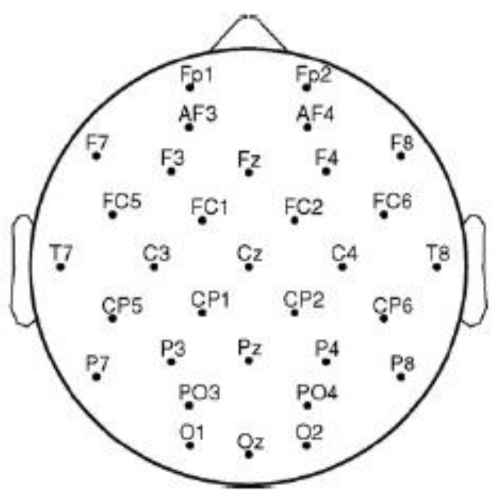

Figure 4: 32 electrodes placement for P300 detection using 10-20 system.[1]

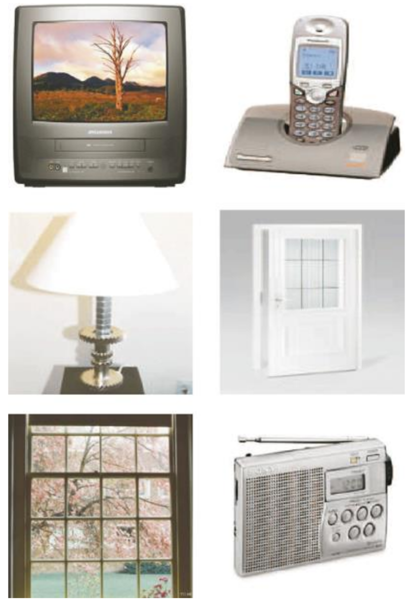

Figure 5: Six object images stimulus [1]

A. Subjects

The experiment was performed with four disabled and four healthy. The disables subjects had limb muscle control abilities and all were wheelchair bound. Some disabled subjects had varying communication and some are suffered from dysarthria. The healthy subjects were Ph.D. students and none of them had any neurological deficits.

B. Experimental Procedure

The dataset contained four session for each subjects. Each sessions was consist of six runs such that one run for each of the six stimulus. The following steps are followed:

- Subject was asked to focus on one image and count how often a focused image was flashed.
- After four seconds a warning tone was issued and a random sequence of flashes was started such that every image was flashed.
- The flashed sequence after warning tone was block-randomized which means that after six flashes each image was flashed once.
- The number of blocks was randomly chosen between 20 to 25. Each block represented one target trial of P300.

- In each run there are 20 to 25 target trial and 100 to 125 non-target trial.
- EEG was recorded when block stimulus sequence was started to flash.
- The time duration of one run was one minute. One session comprised of total 810 trials and for one subject, the whole data consisted on average of 3240 trials.

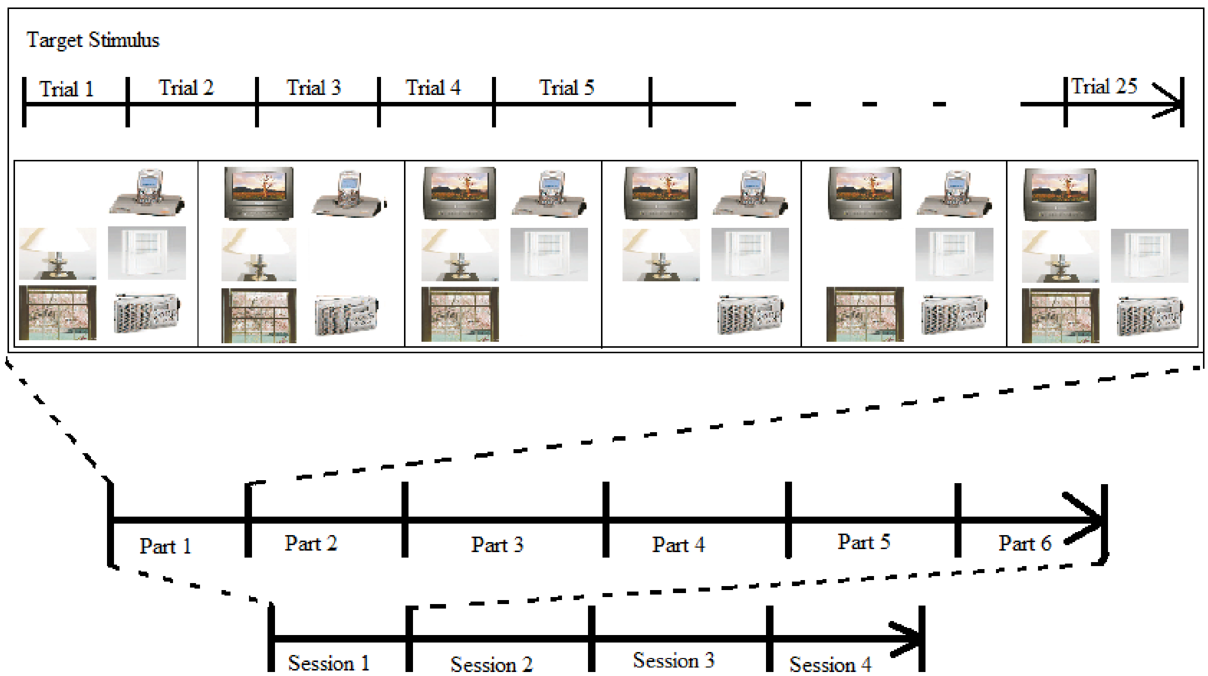

Figure 6: P300 data recording

3.1.2 SSVEP Dataset

The dataset which we are using for SSVEP classification is AVI SSVEP dataset recorded by Vilic [42]. The data was taken on six flickering stimulus and recorded by placing electrodes at Oz for signal, Fz as reference and Fpz as ground using the 10-20 system. The hardware setup was consist of LCD monitor and BenQ XL2420T, with refresh rate of 120 Hz.

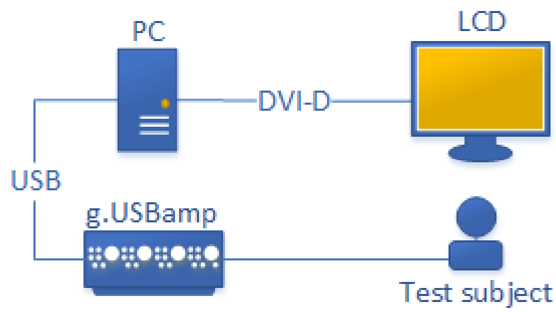

Figure 7 : Hardware Setup [2]

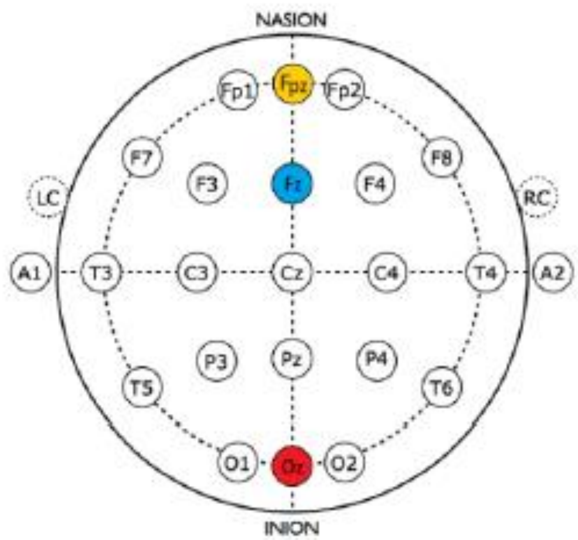

Figure 8 : Electrode placement on the scalp of SSVEP dataset[2]

A. Subjects

The experiment was performed with five subjects, two are females and three are males. All the subjects were healthy and did not have any neurological issue.

B. *Experiment Procedure*

Six choice flickering stimulus panel was used for collection of dataset. Each stimulus flash with multiple frequencies of 6Hz, 6.5Hz, 7Hz, 7.5Hz, 8.2Hz, 9.3Hz. Following protocol was followed for experiment:

- A subject was seated at the distance of 60cm from the stimulus screen.

- Six stimulus with different frequencies were starting to flash.
- A subject was asked to focus at one of the flickering target, which changes color quickly from black to white.
- The data was recorded in two sessions for each of the subjects.
- Each session had ten trials of sixteen seconds.

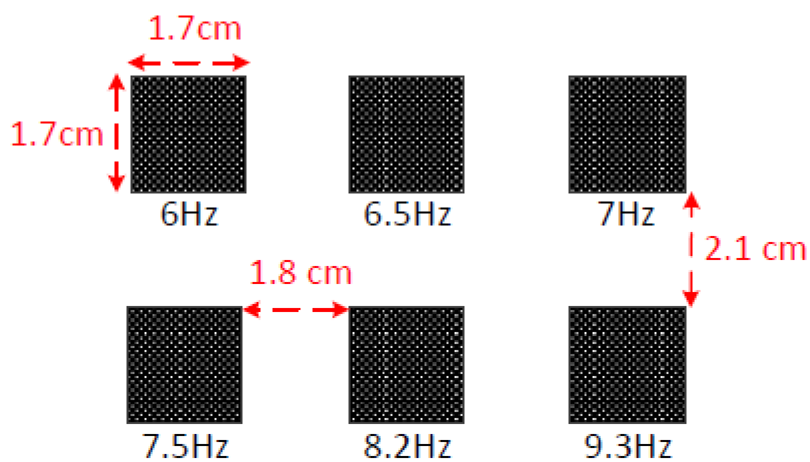

Figure 9: SSVEP flickering stimulus paradigm

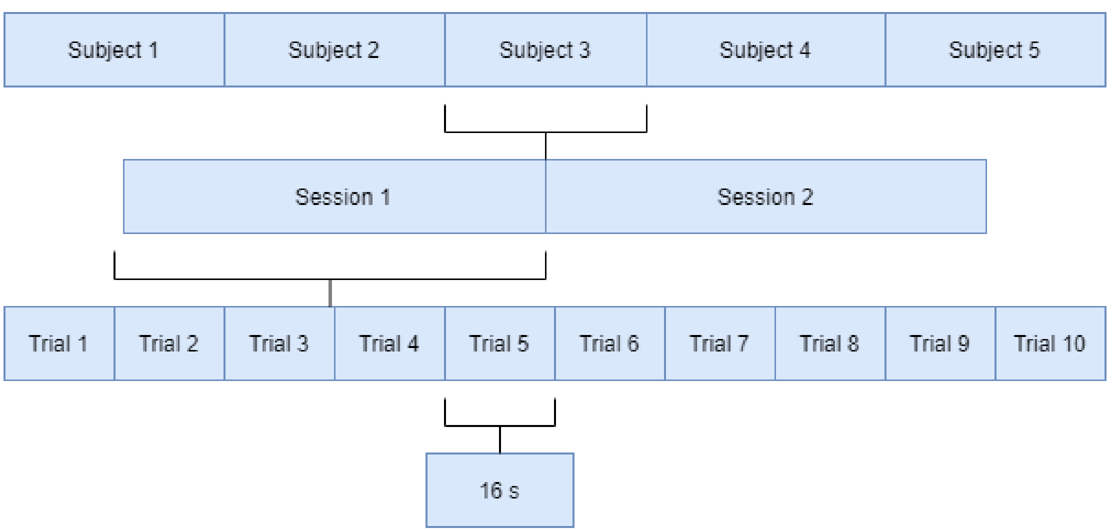

Figure 10 : SSVEP data recording scenario

3.2 Signal Acquisition and Preprocessing

3.2.1 Signal Acquisition of P300 and SSVEP

P300 signals generated as a result of tasks performed by the subjects were acquired by the electrodes placed on the scalp of the subjects using 10-20 system. The amplification and analog to digital conversion of the EEG signals was done by Biosemi Active Two amplifier. EEG data was sampled at 2048Hz sampling rate. Whereas for SSVEP was recorded on BenQ XL2420T, with refresh rate of 120 Hz.

3.2.2 Preprocessing of P300 and SSVEP Signal

Before features extraction, several preprocessing operations are applied on the raw EEG signal. For P300, dataset of 32 electrode is given. Channel T7 and T8 are used as a reference. In our experiment we are using four electrodes as a signal electrodes Fz, Cz, Pz, and Oz. Data is down sampled from 2048Hz to 265Hz. To reduce noise from the raw data, channels are filtered by Butterworth bandpass filtered with the cut-off frequencies are 1Hz to 20Hz [43]. Signal is recorded at the starting of flicker of an image and excuted at 1000ms. As P300 is detected in 300ms after the onset of stimulus so 1 sec of window is extracted for a single trial. To reduce the effect of possibly artifacts which act as outliers such as eye blink, heartbeat, respiratory and other motion artifacts, the bandpass data from each channel is windsorized. In windsorizing method, for each trials the 10^{th} percentile and 90^{th} percentile are calculated. Amplitude values lying out of the mentioned range of percentile are replaced by the respective percentiles. The samples are further normalized to the interval [-1, 1].

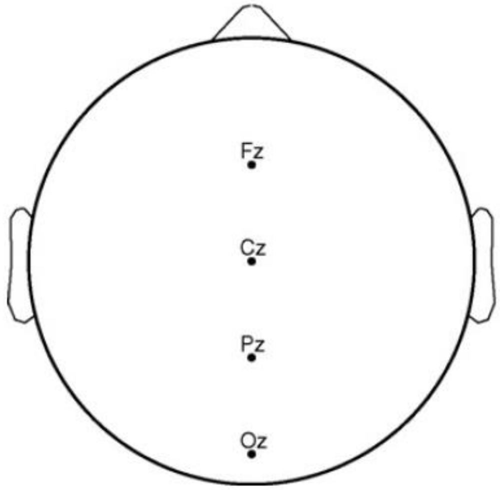

Figure 11: four electrode placement for P300 signal [2]

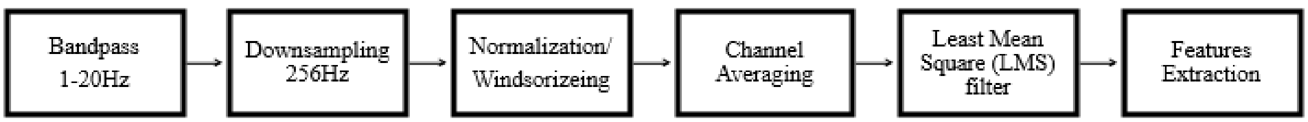

Figure 12: Preprocessing steps of P300

Preprocessing of SSVEP is quite simple as compared to P300. SSVEP is detected in frequency domain and range of stimulus frequencies are known. According to stimulus frequencies value, the EEG raw signal is filtered by bandpass filters between 4Hz to 11Hz. The filtered output which is in time domain signal is converted into frequency domain by taking Fast Fourier Transform (FFT). By analyzing the power spectrum of the FFT signal, the dominant frequency having maximum amplitude is consider as the frequency of the stimulus on which the subject has focused on.

Figure 13: Preprocessing steps for SSVEP

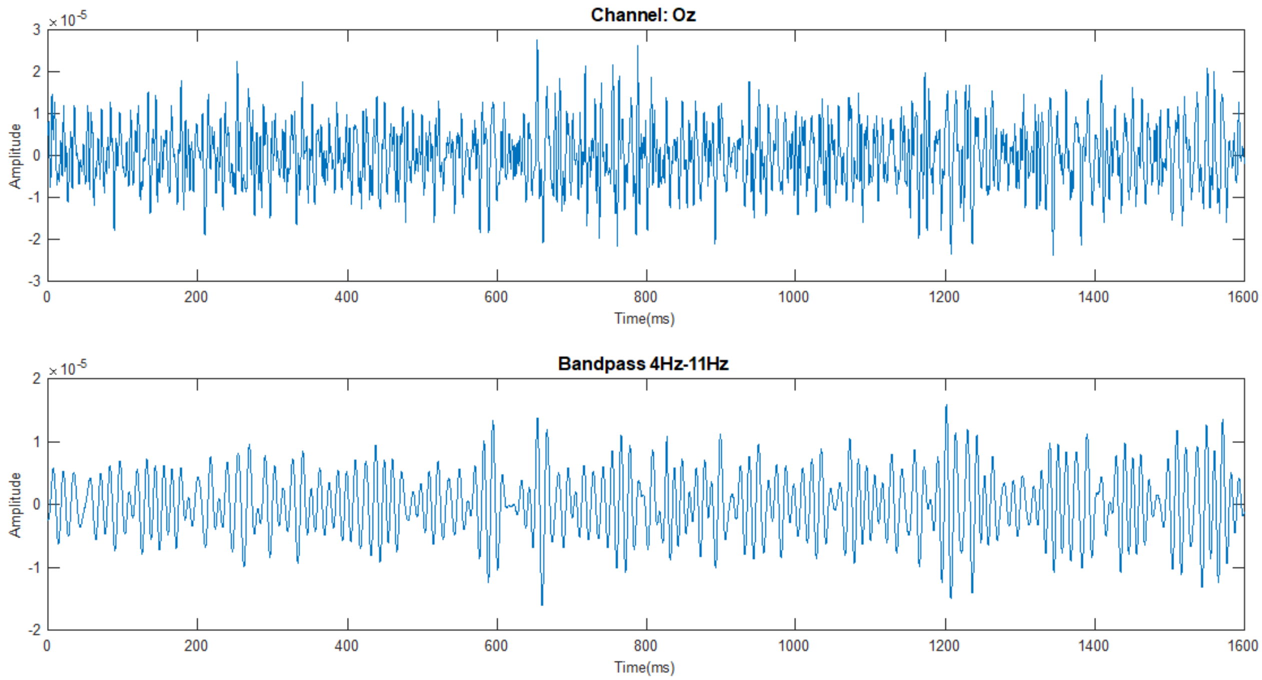

Figure 14: Bandpass signal result for SSVEP detection

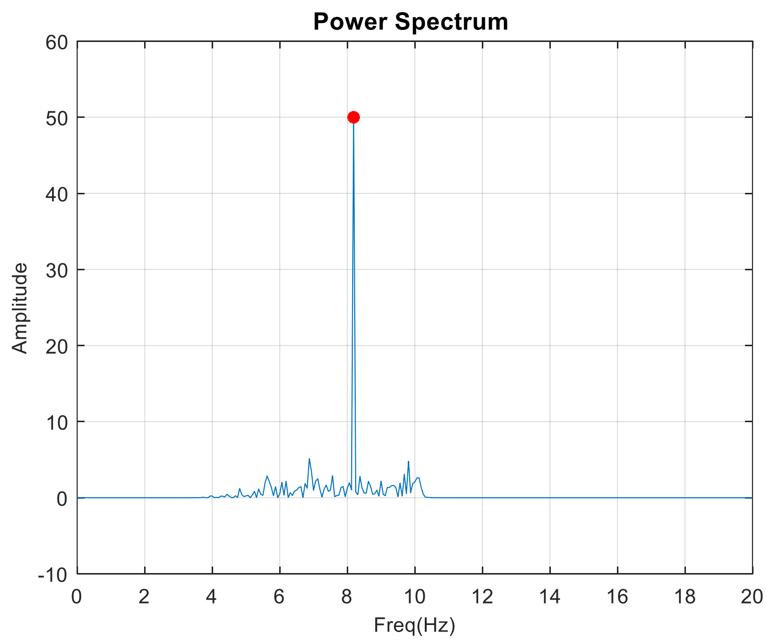

Figure 15: Power Spectrum of the signal followed by FFT

3.3Feature Extraction

3.3.1 P300 Features

The feature extractions intends to extract the important information from brain signals. The statistical measurement should decode the desired commands related to the specific task according to mental activity. Features should not contain any noisy factor that can manipulate the results of classification. P300 preprocessed signal is used to extract the relevant information. We have used Adaptive Least Means Square (LMS) filters to extract the P300 features [44]. By using preprocessed signal, LMS changes its filter coefficient based on the desired or reference signal by reducing the least mean square error. In our case desired reference signal is known noise signal. This delayed version of the noisy signal is extracted by finding common signal between target and non-target signal of P300. The algorithm tries to find the common noise in both the reference signal and filter output signal, estimates the error between the two. In Fig. x(k) is the one trial signal of 1000ms, y(k) is the filtered output, d(k) represent the reference signal. The whole process is repeated for M channels and N trails.

$$y = w \times x \tag{1}$$

$$e = d - y \tag{2}$$

$$w = w + (\mu \times e \times x) \tag{3}$$

Where y = output

x = input

e = error

μ = learning rate

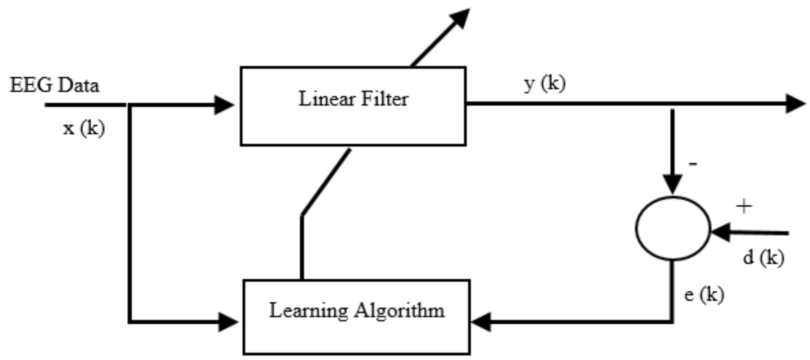

Figure 16: Least Means Square filter

When error gets minimized output y, which is noisy signal is subtracted from the initial input signal. The LMS filtered signal then analysis by statistical methods. Following statistical measurement are computed:

- Positive Peak
- Positive Peak Latency
- Negative Peak
- Negative Peak Latency
- Peak to Peak
- Peak to Peak latency
- RMS

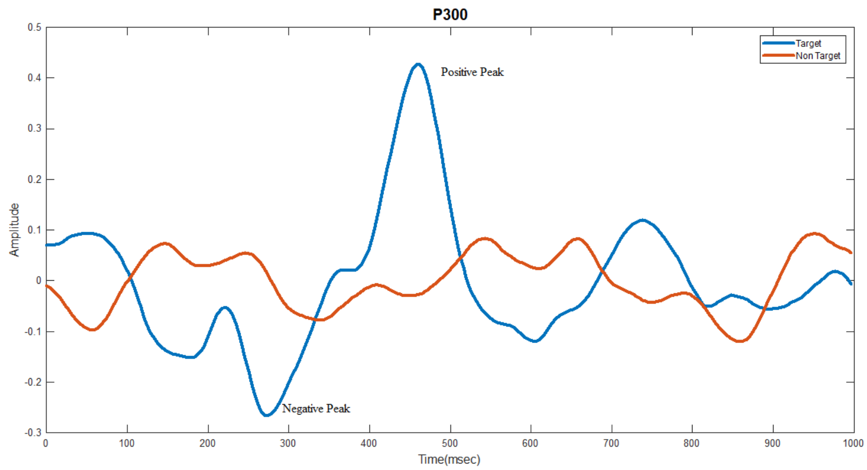

Figure 17 : Filtered output form LMS filter for target and non-target P300

3.3.2 SSVEP Features

As SSVEP is a periodic response generated when subject has focused on some repetitive stimulus. It is confined to a specific set of stimulus frequencies, so instead of time domain it is analyze in frequency domain. So power spectrum of a signal is taken followed by FFT. The frequency having highest power respective to their amplitude is consider as a feature for classification process.

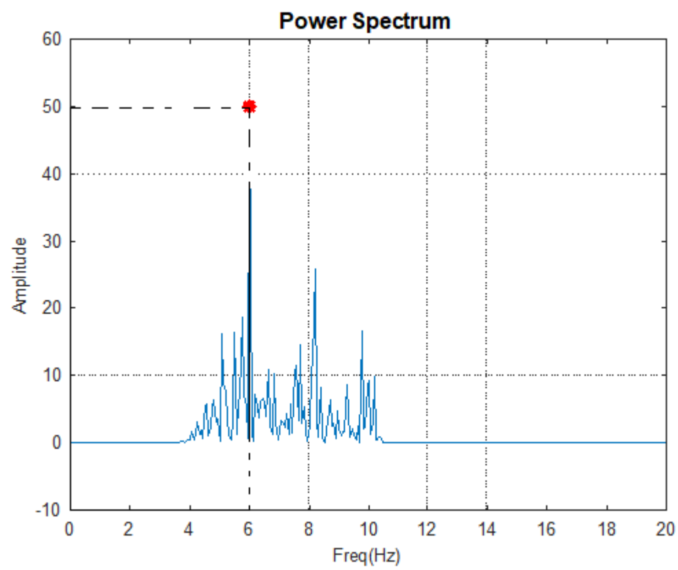

Figure 18: SSVEP Feature

3.4 Work flow

We have implemented sequential hybrid P300/SSVEP system that generates six commands. Six images stimulus oddball paradigm is used to generate the P300 signal. After filtration followed by preprocessing, features are extracted and feed into ensemble SVM model. Classified output trigger the SSVEP paradigm and frequency respective to ensemble output starts to flicker. EEG signal for SSVEP detection is recorded. After signal acquisition and filtering, extracted features are classify by simple LDA algorithm. Generated output is used to control the virtual quadcopter on MATLAB simulation.

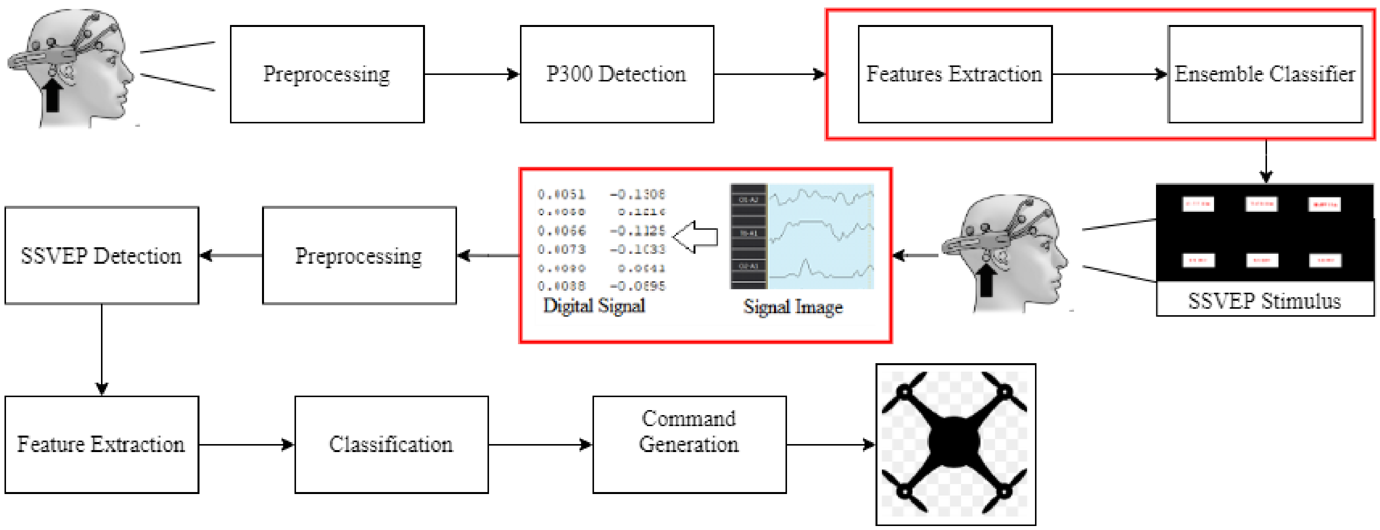

Figure 19 : Proposed Methodology of sequential hybrid P300/SSVEP

3.4.1 *Ensemble classification for P300*

Average of trials is needed for the appropriate P300 signal detection. As P300 is difficult to detect in single trial, so strong classifier is needed for classification. We are using ensemble SVM for classification of P300. A good surface decision can be made by using ensemble SVM, if the input features are well organized. We have 3240 samples of the single subject. After shuffling and normalization, data is divided into training and test data in the ratio of 4:1. Training data is further split into three equal division by the method of Bootstrap Aggregation commonly called bagging. In this method samples from observation is selected randomly with replacement.

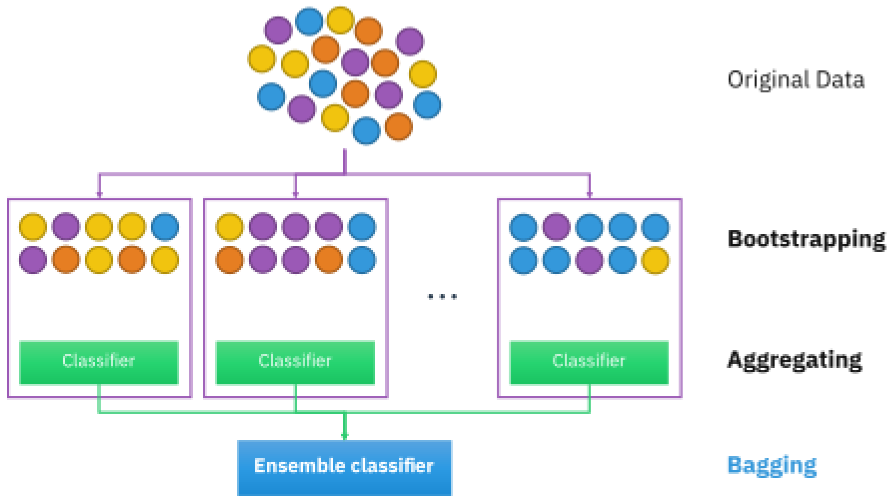

Figure 20 : Bootstrap Aggregation

https://en.wikipedia.org/wiki/Bootstrap_aggregating

After the splitting of training data into three subset, SVM model is developed from the each concatenated features dataset. SVM model with polynomial kernel of order two is used for training.

$$G(x_j,x_k)=(1+x_j'x_k)^q \tag{4}$$

The output from all the standalone models of same types is gathered. The final prediction is based on the aggregation of prediction of each base models. For testing and validation, the test data is passed through each three trained models of SVM and predicted. By voting method, final prediction can be made.

$$Y = \max(\text{prediction}(M_1,M_2,M_3),x) \tag{5}$$

Where M_1,M_2,M_3 are the trained models of SVM and x is the test sample.

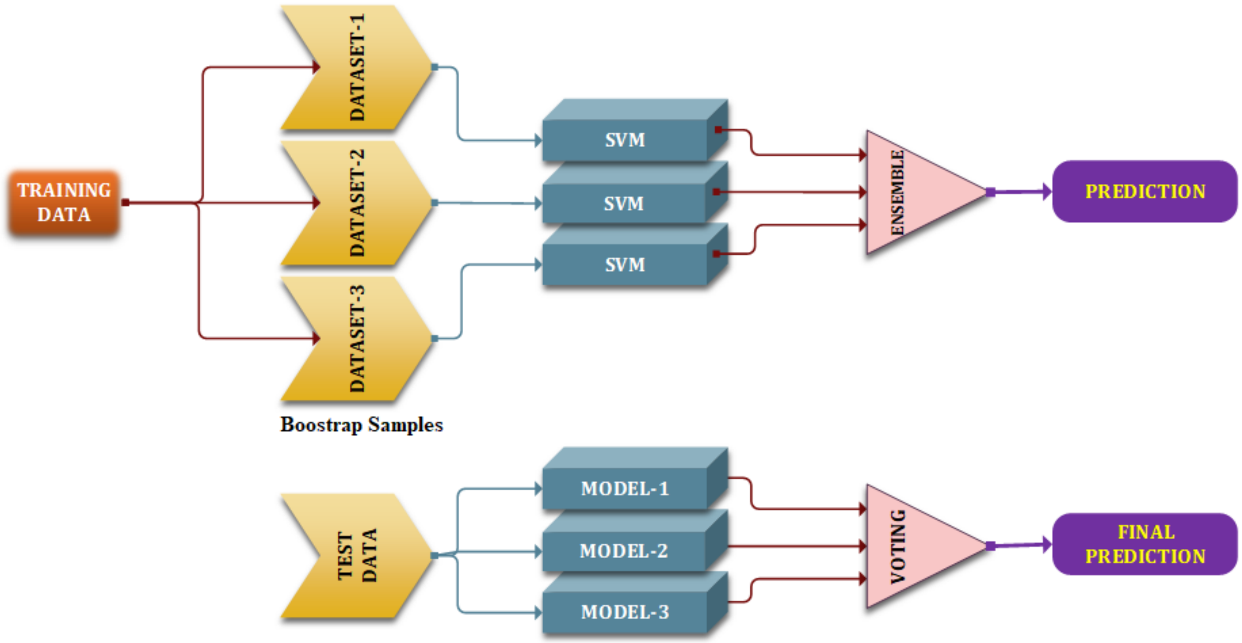

Figure 21: Ensemble SVM Model

3.4.2 *SSVEP Classification*

SSVEP Classification is done by Linear SVM. It is easy to detect, so with little training of data can give remarkable results. In AVI SSVEP dataset, we have 100 samples, 80 random samples are separate out for training.

Figure 22: SSVEP Classification

3.4.3 SSVEP/P300 Combine Algorithm

P300 dataset is composed of six images stimulus. If target P300 is detected by ensemble classifier e.g. an oddball signal is generated in response to stimulus 1 then on SSVEP paradigm, stimulus listed on the position one starts to be flickered with its mentioned frequency. SSVEP signal is further classified by the SVM model and command is generated. The final output is fed to quadcopter in visual environment.

CHAPTER 4: APPLICATION

Brain Computer interface (BCI) provides a way of communication using robotics. Flight control of quadcopter is one of the application of BCI. The classified command decoded from sequential hybrid BCI system is transmitted with a fixed time interval to the quadcopter [45]. In MATLAB Stimulation 3D virtual environment is created with quadcopter. When P300 is detected, it trigger the SSVEP stimulus. After SSVEP classification final command is generated which is given to quadcopter for flight [46] [47]. Graphical User Interface (GUI) is developed. Which display the flight of quadcopter and other control parameters such as start, trajectory and stop buttons. As we are using six commands to drive the applications, display panel on the GUI show the respective commands for all the six outputs generated from the hybrid model.

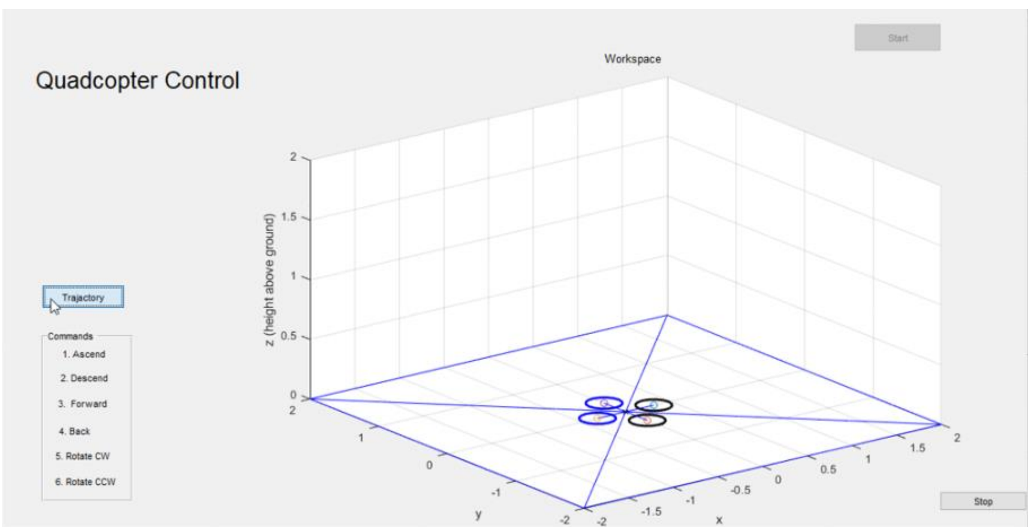

Figure 23 : Graphical User Interface for quadcopter

CHAPTER 5: IMAGE TO SIGNAL CONVERSION

5.1 Background

Signal Acquisition form EEG devices required some special tools such as file format converter. Mostly signal devices import their files in csv. or mat. Format. Which are easy to process in computational software's such as MATLAB, PyCharm etc. Most standard EEG-processing toolboxes can deal with a wide range of EEG data formats. Number of EEG devices which are mostly utilized for clinical or monitoring purposes are only display the signal on computer screen and unable to give file in some process-able format. One solution is to purchase the license of these devises but they are little bit expensive. For academic purpose such devices are useless if they don't import data into readable file.

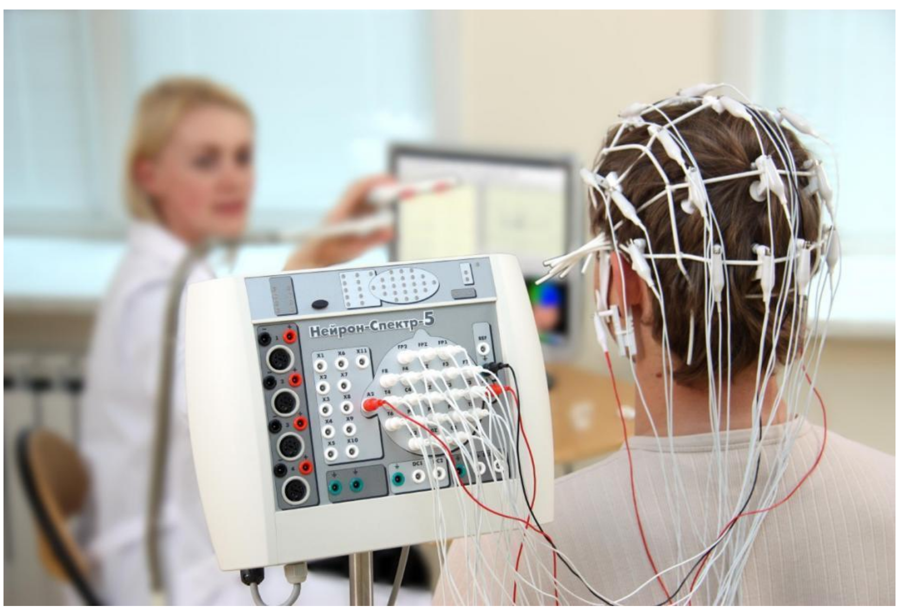

Figure 24: Clinical monitoring EEG device

https://www.medicalnewstoday.com/articles/325191#uses

5.2EEG Device

ARC Essentia is an EEG device manufactured by Cadwall company. It gives good quality performance in cerebral monitoring of patients. It is 32 channel EEG device with offers 250 and 500 Hz storage rates and streaming data. The integrated EEG device package includes a remote input headphone with secure cable connectors that ensures easy setup and integrity recording. The unique design of Arc Essentia hardware ensures high quality EEG signals, or in noisy environments. Its rough and water-resistant design will withstand the use and abuse of real-life practice. With following pros, it has one disadvantage. It don’t decode the file in mat. or csv. file format.

Figure 25: ARC Essentia EEG device

https://www.medicalexpo.com/prod/cadwell-industries/product-110929-874403.html

5.3 Proposed Solution

To solve the data importing problem, we have presented the **Image to Signal Conversion** algorithm. Images of the display screen is captured and converted into signal vector my using image processing technique. Flow chart of the algorithm is given below.

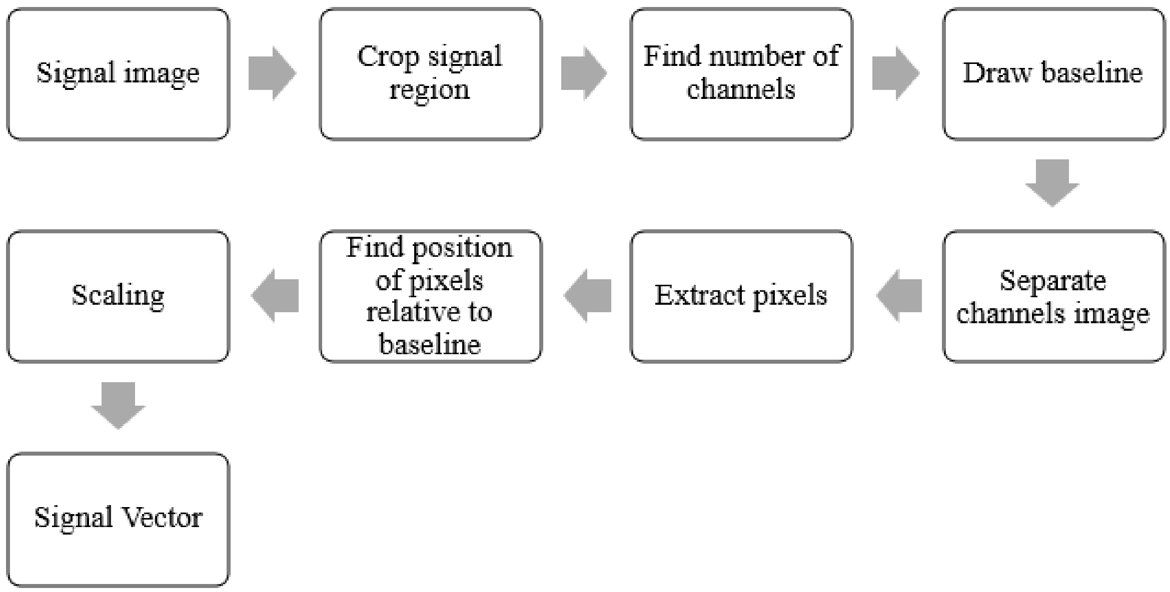

Figure 26: flow chart of Image to Signal Conversion

5.4 Implementation

When EEG device display the signal on the computer screen, it is recorded in the form of video. As recorded video is basically consist of multiple frames. When we split video in frames, we have obtained images of the EEG display which is processed by image processing techniques. In proposed solution, input consists of input video or image, scaling parameters and number of channels. The algorithm is made on MATLAB with the help of image processing toolbox.

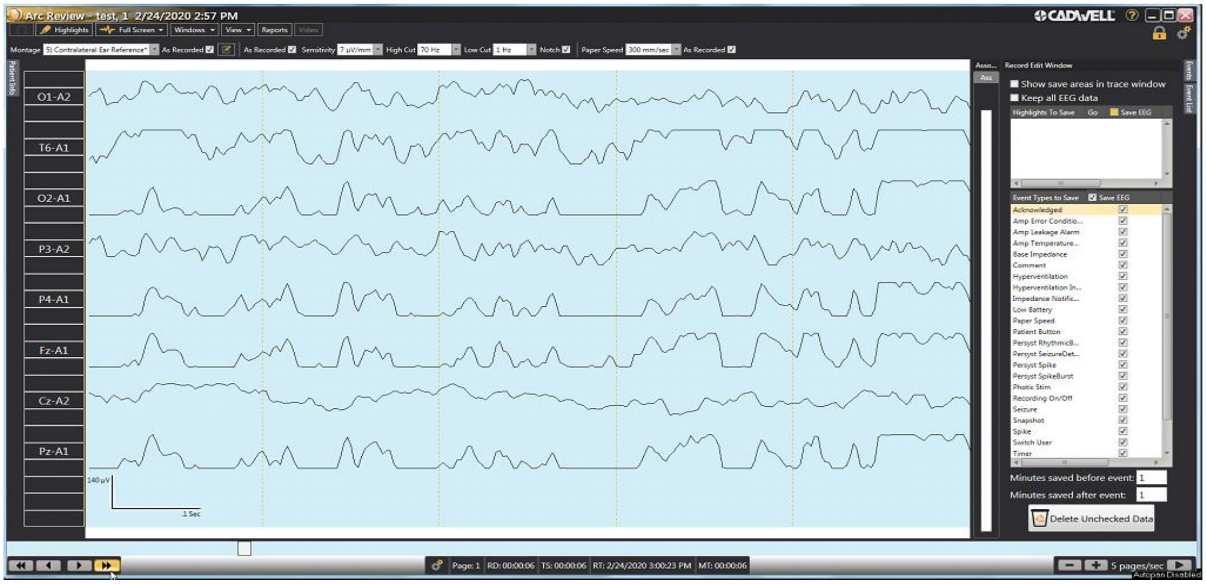

Figure 27: Display of ARC Essnetia EEG device

Implementation steps are explained below:

1. Firstly we have to extract area, where only signal waves are displayed. By using crop command in MATLAB, unwanted area is separated from the image. As show in Figure.

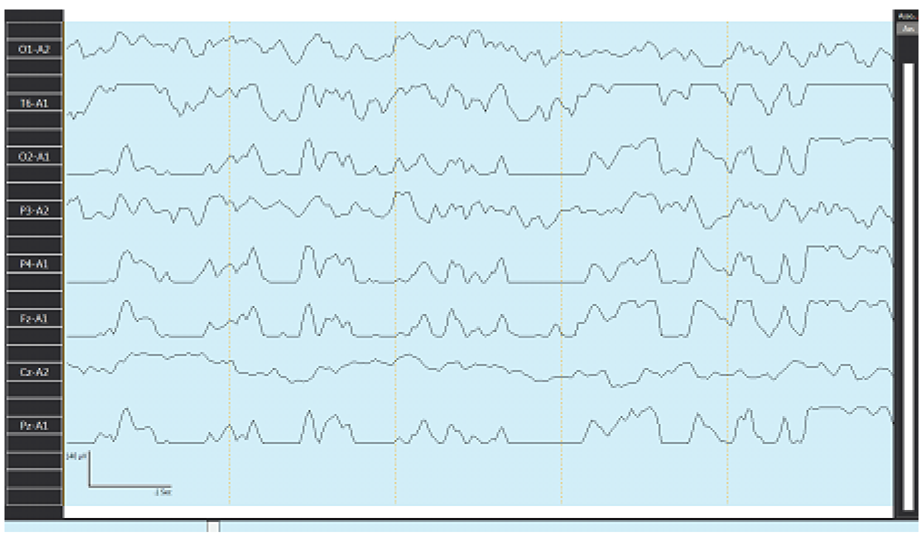

Figure 28 : Cropped EEG signal area

2. When signal area is chopped off from the display image, channels are estimated by analyzing the left hand column using gradient change approach.

3. For estimated channels, draw a baseline or a reference line from the center of each signal wave. This baseline act as a x-axis or the signals.

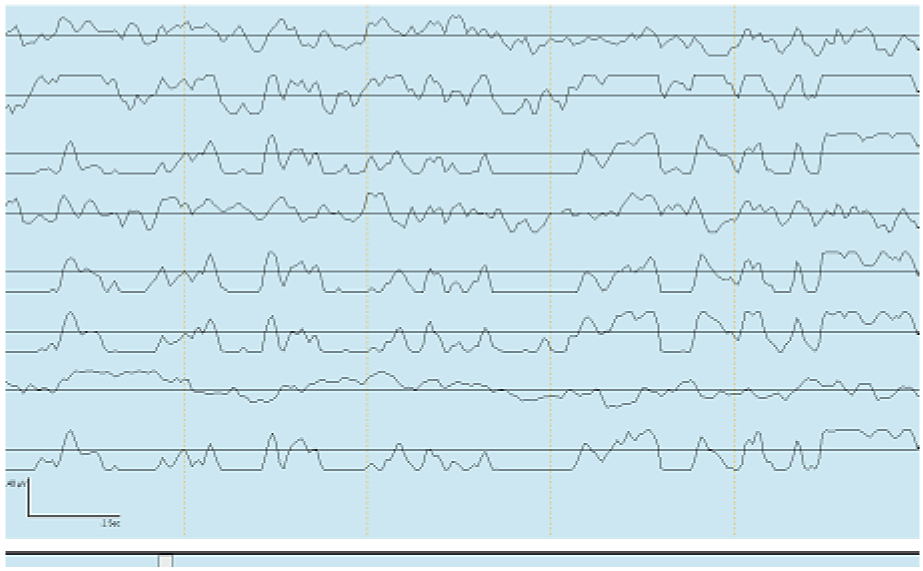

Figure 29 : Baseline implementation

4. Next step is to separate the channels into multiple images.

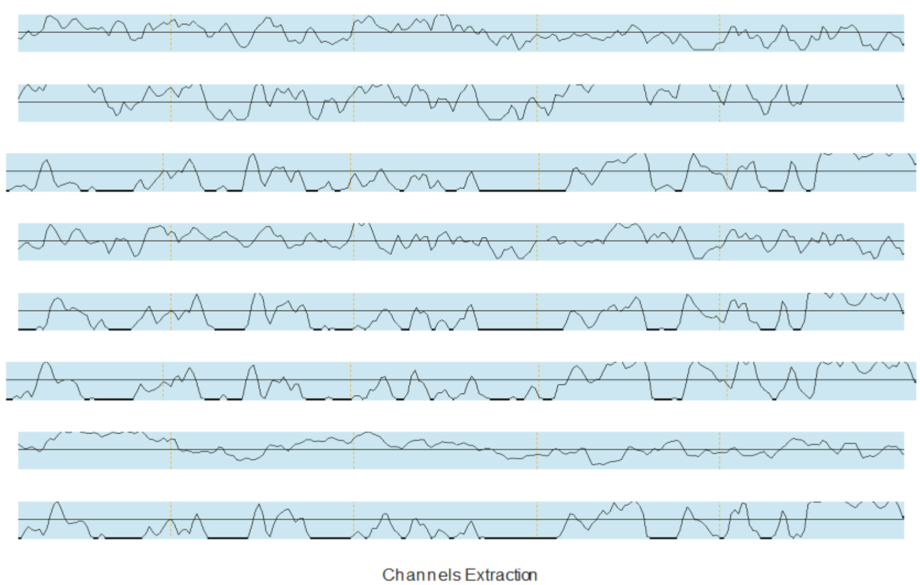

Figure 30 : Channels separation

5. Separated channel images are then undergo a pixels extraction process. Image is converted to binary image by setting threshold level such that only signal lines appear in black and background remains in white. Locate the black signal pixels position in reference to the baseline. Each pixel act as a signal point in signal vector.

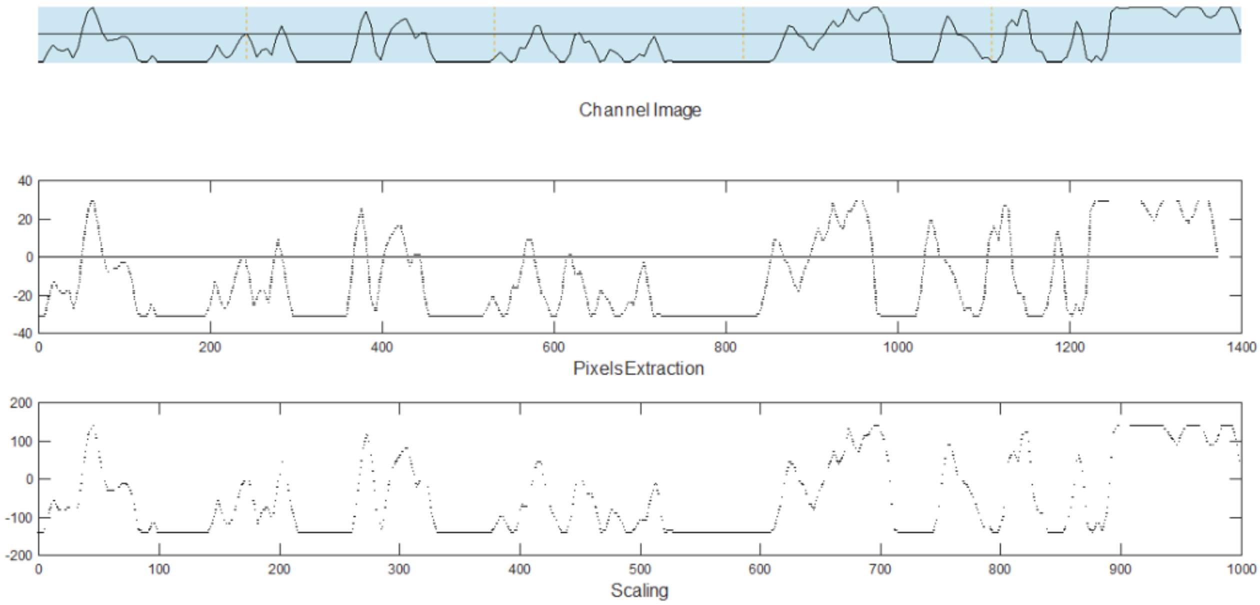

Figure 31 : Pixels to point extraction

6. As extracted points are scaled according to the cropped image dimensions, so they are rescaled according to the device scale.

5.5 Validation

5.5.1 EEG Data Images

Previous EEG data of eight subjects for P300 detection is used for validation of algorithm. For each subjects trial samples are extracted with the channels of Cz, Pz, Oz. By using subplot in MATLAB, following channels are plotted. Images of the plots are saved. Image to signal conversion approach is applied on these saved images

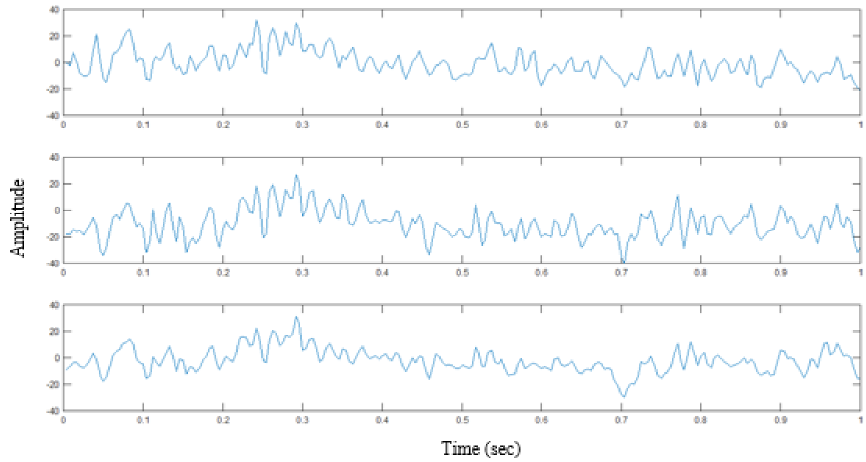

Figure 32 : Input signal image

For validation, testing procedure such as filtration and power spectrum are applied on the extracted results.

5.5.2 *Detection of SSVEP signal from images*

Due to covid, we are unable to record as much data for the validation. We have required EEG data using emotive epoch head set for a single person. SSVEP signal is extracted for two stimulus frequencies i.e. 7Hz and 8 Hz. Four channels data is recorded that are Fz, Cz, Pz,Oz. In addition to display the signal, Emotive head set also import the data in csv file. We record the signal video during activity and also import its csv file for comparison.

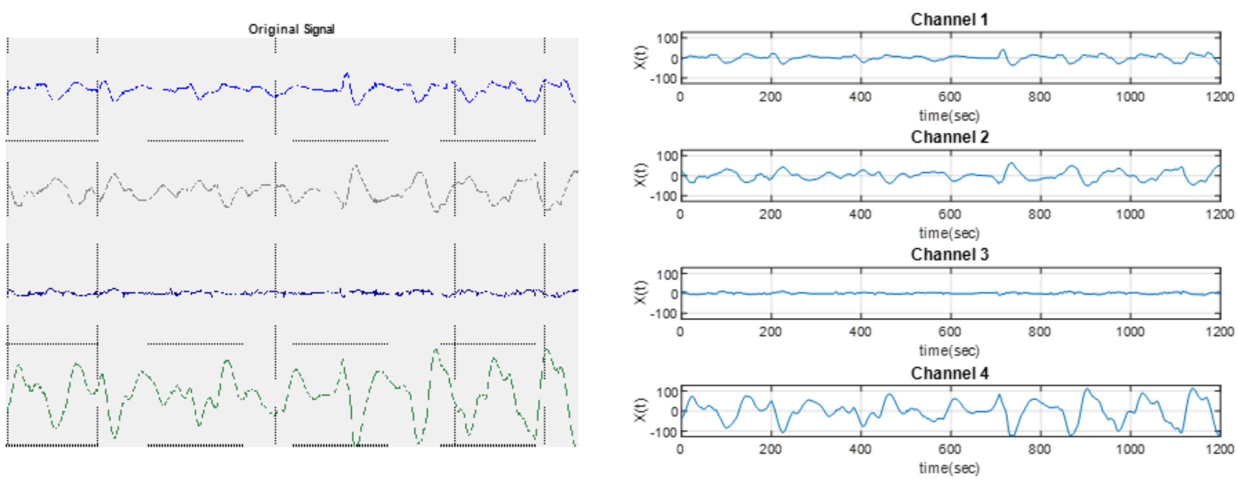

Figure 33 : Epoch headset Image to signal conversion

For SSVEP detection, reconstructed signal is preprocessed by using bandpass filter of 6-9 Hz. Then signal is converted into frequency domain by taking FFT. When power spectrum of a signal is taken, prominent peak is obtained at the desired frequency.

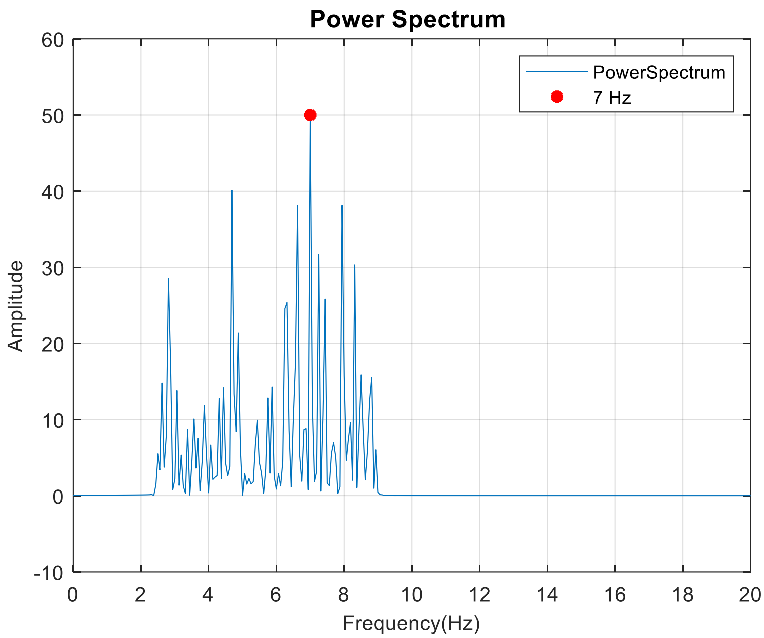

Figure 34: 7Hz SSVEP signal

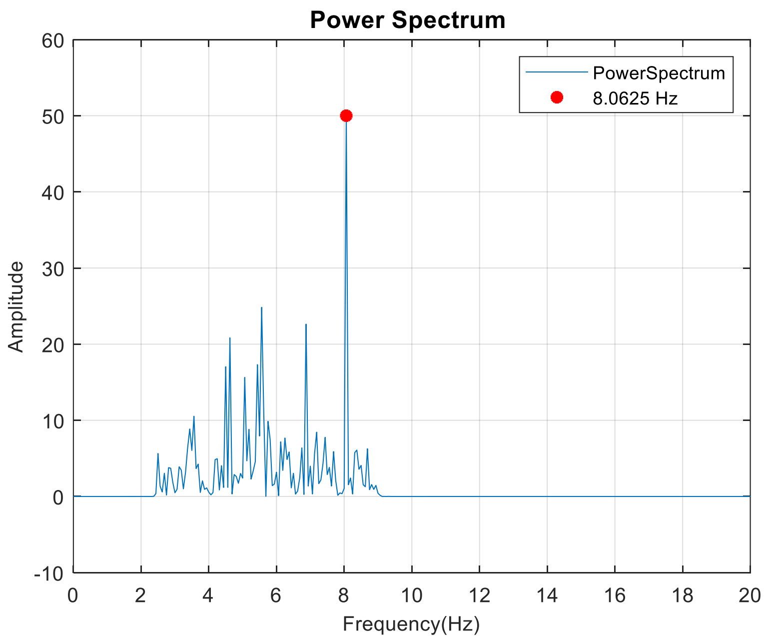

Figure 35: 8Hz SSVEP signal

CHAPTER 5: RESULTS

5.1 P300 Signal Processing

P300 is a week signal. It required the average of several trials for target detection. In proposed method preprocessing step includes channel selection, windsorizing, normalization and LMS filter. The filtered output for eight subjects with target and non-target P300 results are shown below.

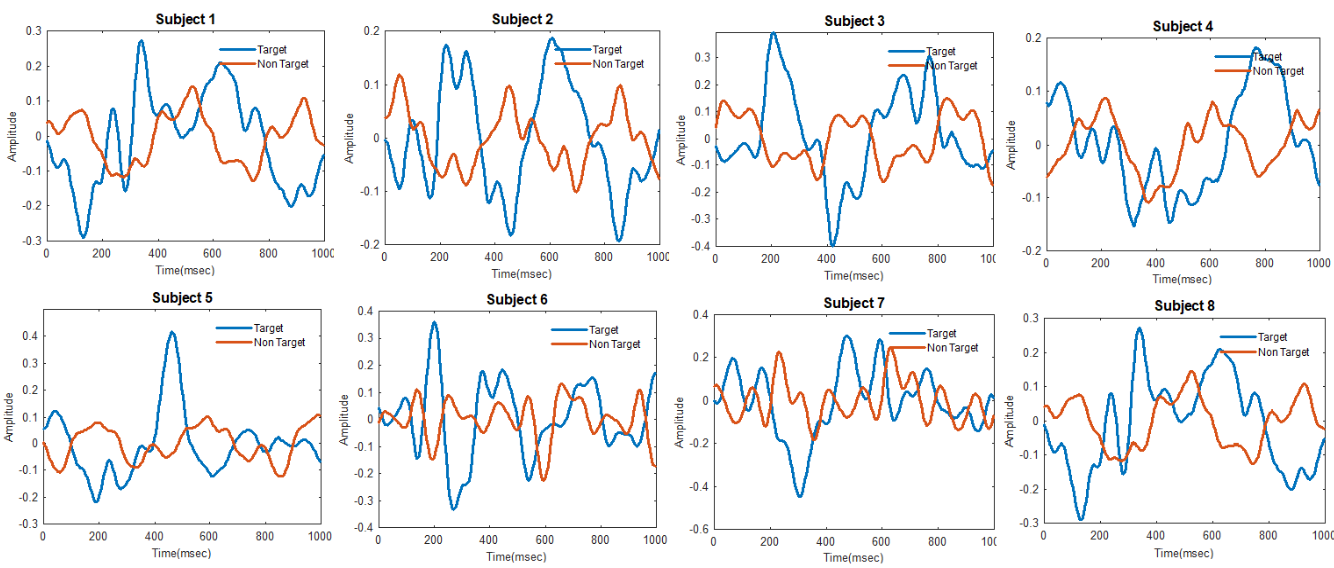

Figure 36 : P300 Preprocessing results

In results, target signal is shown in blue whereas non-target signal is in red. The positive deflection of P300 signal of target stimulus is observed in results.

5.2Ensemble Classifier

The ensemble SVM classifier is used for classification purpose. We have implemented the three models of SVM and final prediction is made by the aggregation of the prediction form each model. Receiver operating characteristic (ROC) curve plots are used to analyze the threshold value for classifier. It illustrates the performance of classification model at all classification threshold.

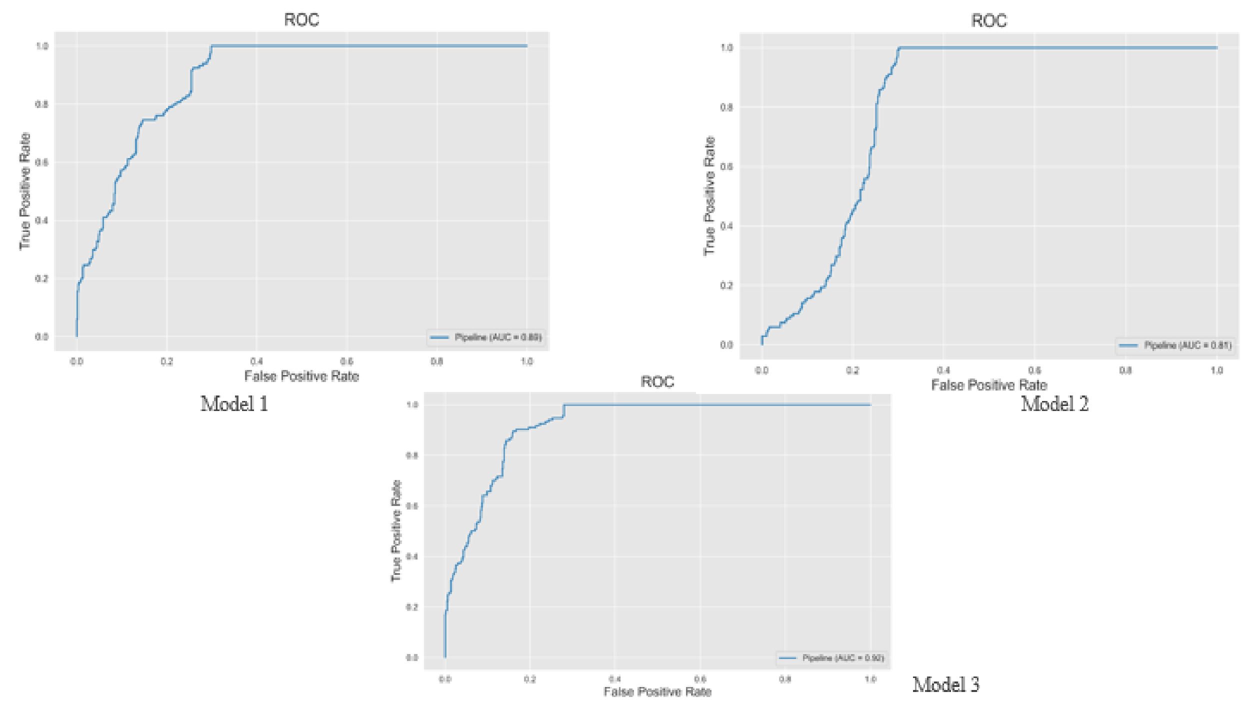

Figure 37 : ROC plots for SVM models

The accuracy for eight subjects using eSVM model is relative higher than 90%. Subject 5 achieved minimum accuracy of 94% and subject 7 achieved highest accuracy among all subject with the percentage of 97.84. The comparison of all subjects with eLDA model and eSVM model are represented in a graph.

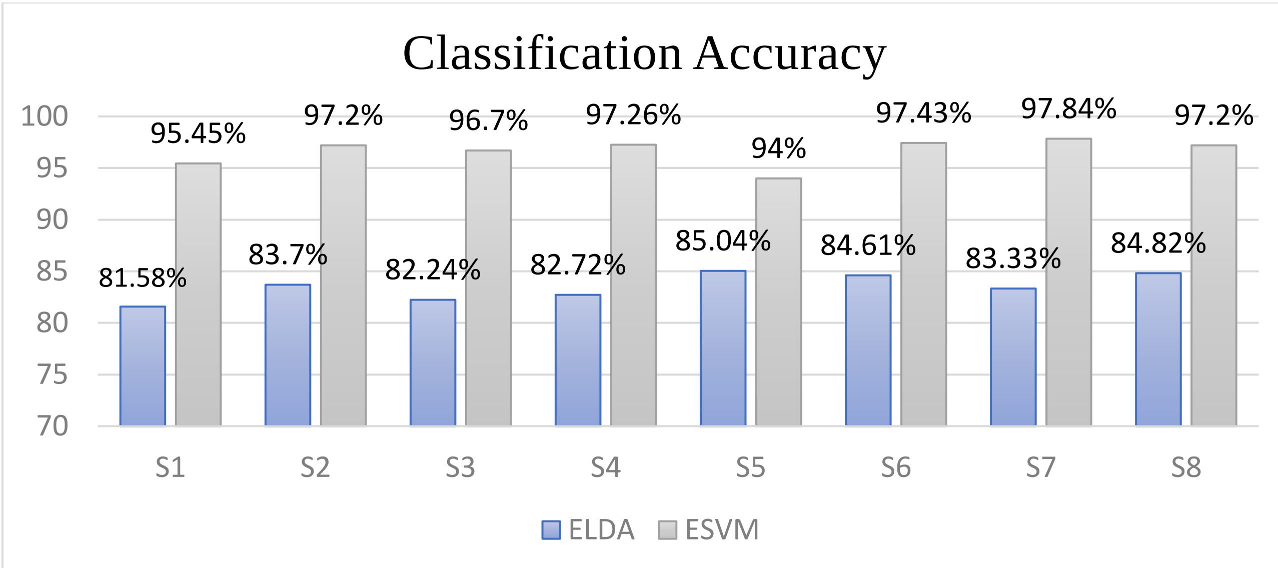

Figure 38: eSVM Accuracy plot

5.3 SSVEP signal Processing

SSVEP data consist of six stimulus frequencies. The raw data is of single channel Oz. Its preprocessing is done by bandpass filtering. The figure shows the result of bandpass filtering, power spectrum followed by the FFT for all six frequencies.

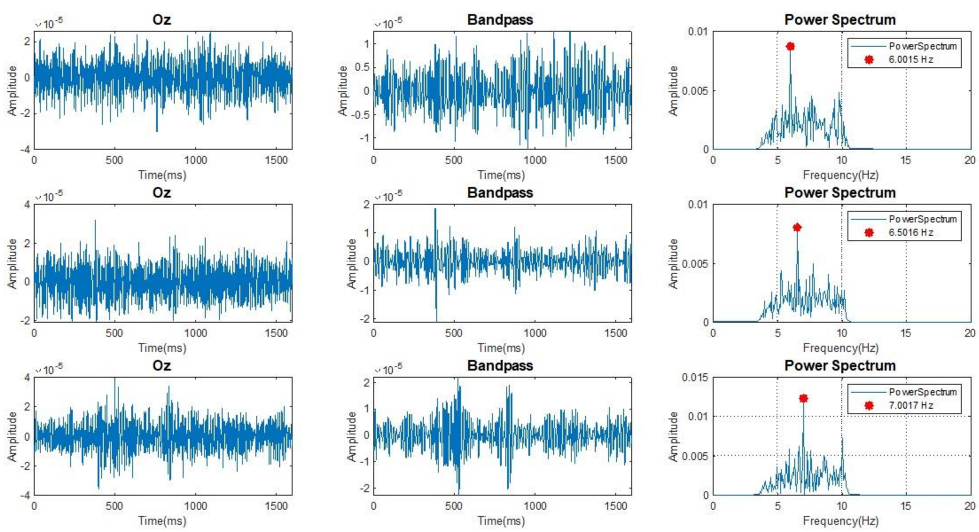

Figure 39 : SSVEP Preprocessing at 6Hz, 6.5Hz, 7 Hz

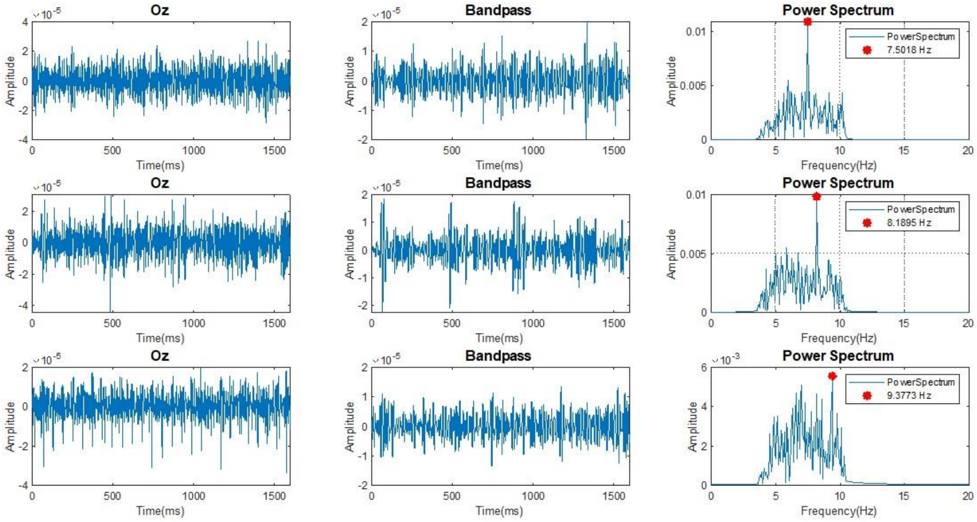

Figure 40: SSVEP Preprocessing at 7.5Hz, 8.2Hz, 9.3 Hz

The red marked point represent the maximum power of the frequency in the signal. It is used as a feature for classification

5.4 Classification Accuracy

Classification of SSVEP is simply done by linear SVM. Total training example for a subject is 80 and 20 are test. The average accuracy for all subjects is reported on test set as 94.6% . Confusion matrix are shown below.

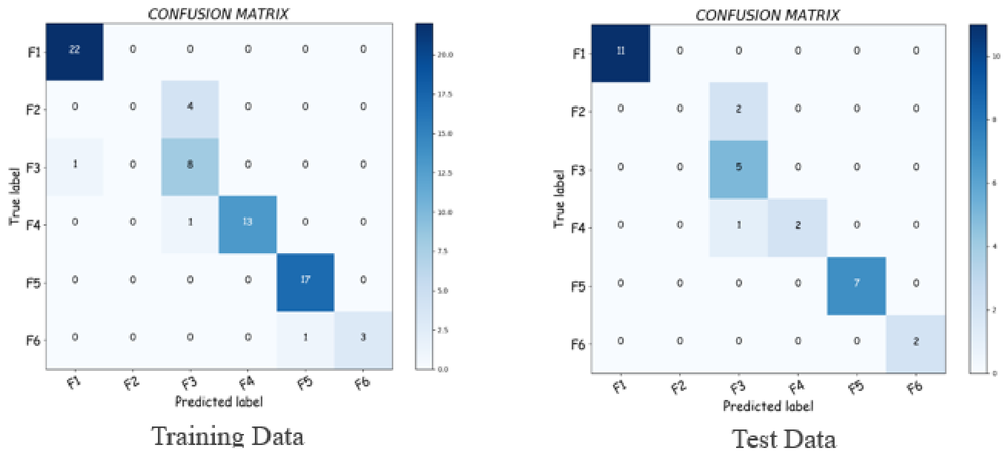

Figure 41 : Confusion matrices

5.5 Image to Signal Conversion Results

The output image form EEG device is reconstructed by image to signal conversion method. The final result in comparison to output display is shown in figure.

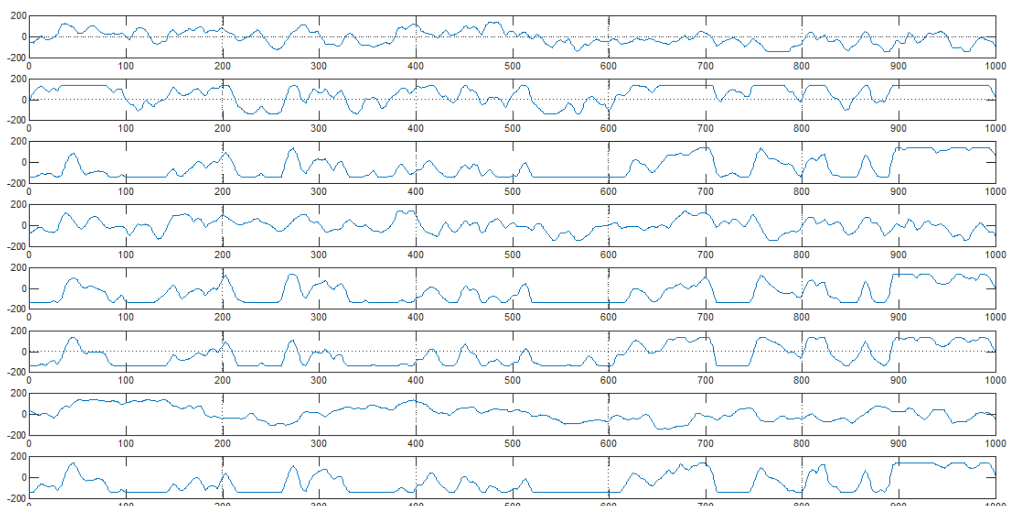

Figure 42 : EEG device reconstructed signal

We have also check algorithm on the ECG signal its resultant image is shown below.

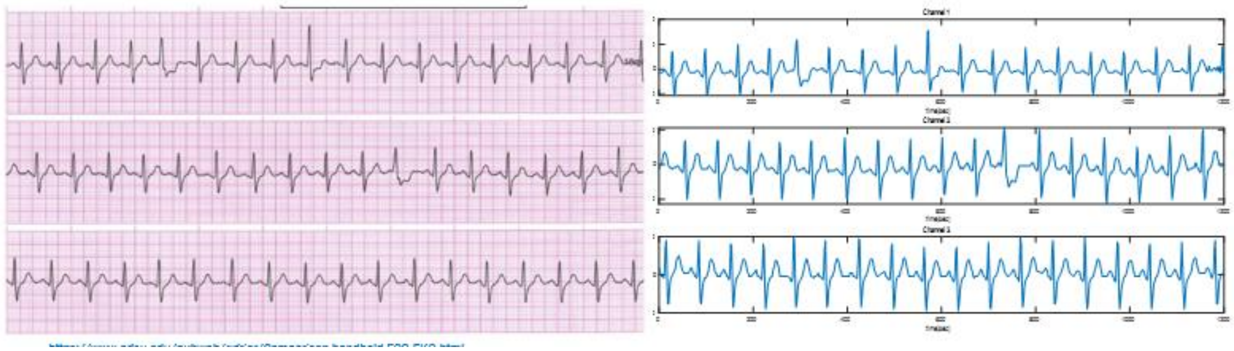

Figure 43 : ECG image signal conversion

The validation results for EEG dataset along with their testing is shown below. Blue lines represents the original signal plot and red line represents the reconstructed signal.

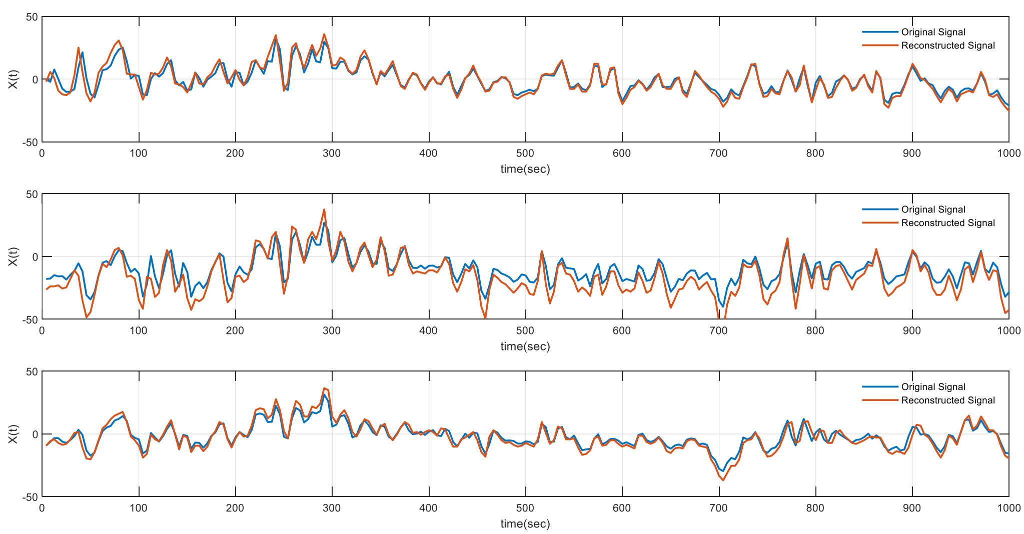

Figure 44: EEG signal conversion results

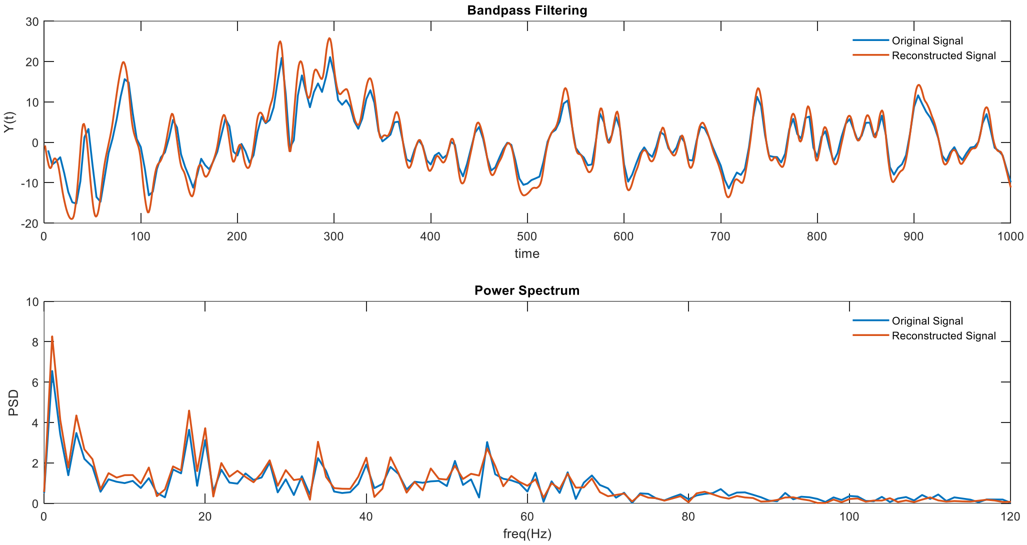

Figure 45: Filtering of reconstructed signal

Statistical analysis of data proves the validation of algorithm. The *t*-test average score is 196.36, Mean square error for all subjects is reported as 1.049%. The p-value is less than 0.05 which represent that there is minimum significance difference between the original signal and reconstructed signal. Other accuracies graphs are given below.

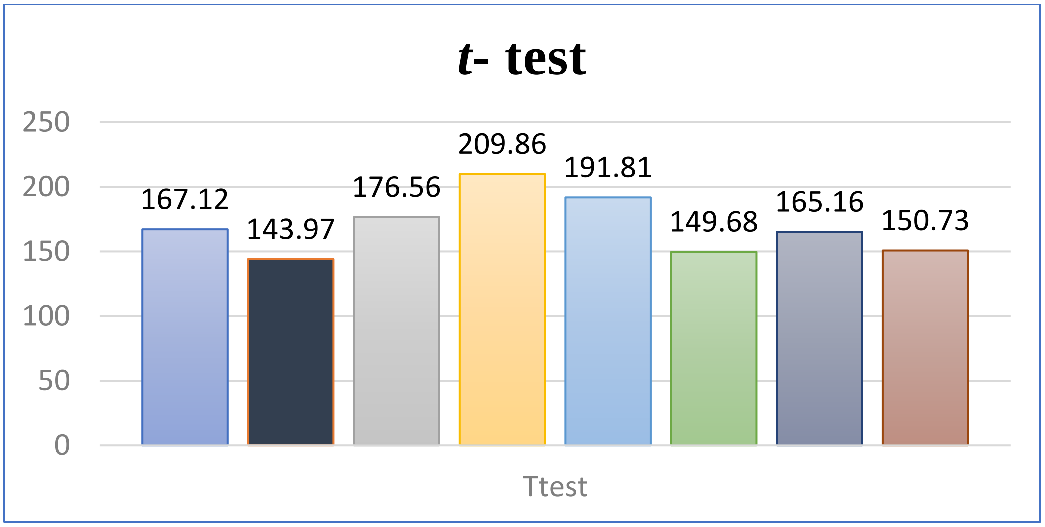

Figure 46 : t test results

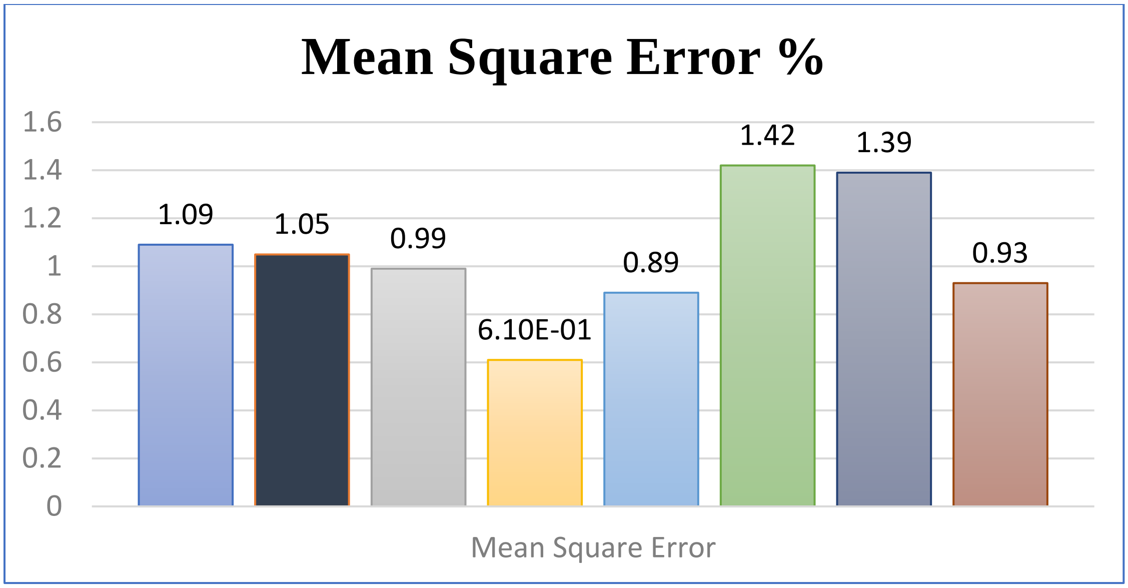

Figure 47: Mean Square Error results

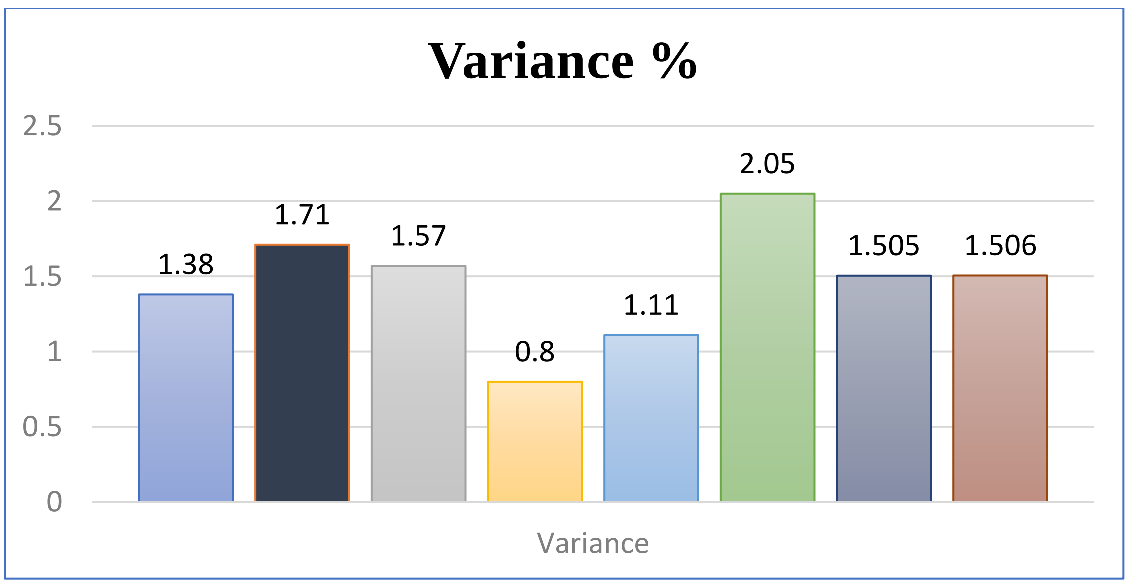

Figure 48: Variance results

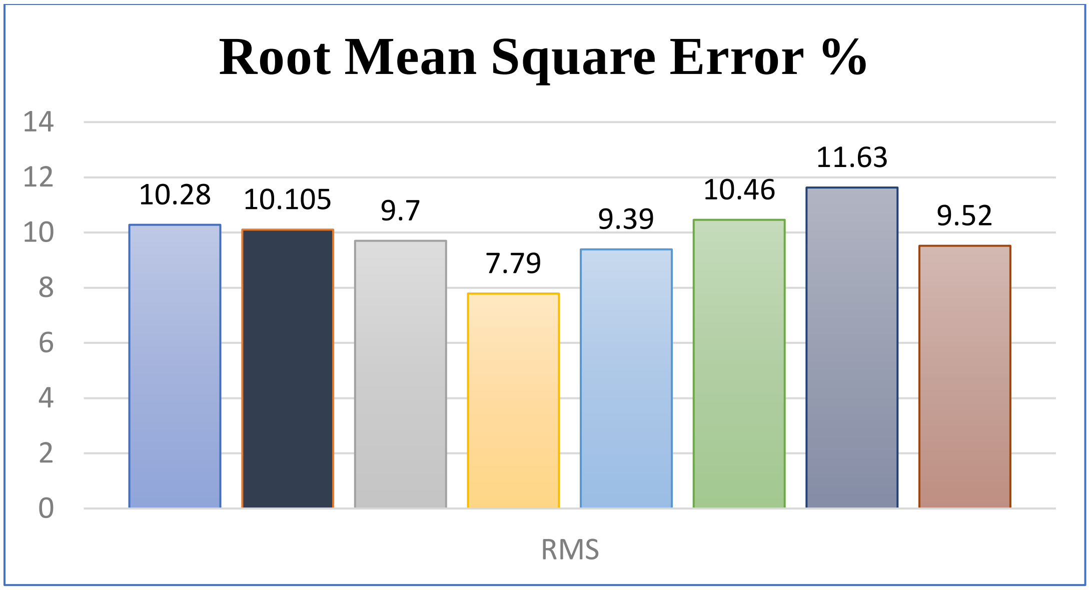

Figure 49: Root Mean Square Error results

Table 1

Image to Signal Conversion	Ttest	P-Value	Mean Square Error %	Variance %	Root Mean Square %
Subject 1	167.1188	5.35E-223	1.090625	1.388125	10.28063
Subject 2	143.9738	2.97E-217	1.054375	1.7125	10.105
Subject 3	176.5581	1.53E-160	0.999375	1.5775	9.706875
Subject 4	209.86	2.88E-241	0.61625	0.800625	7.7925
Subject 5	191.81	5.28E-248	0.896875	1.118125	9.39
Subject 6	149.6803	7.00E-165	1.415	2.05	10.46875
Subject 7	165.1675	1.30E-214	1.393125	1.505625	11.63063
Subject 8	150.7388	1.77E-222	0.933125	1.50625	9.52875

5.6 Quadcopter flight

Multiple trajectories are executed using virtual quadcopter.

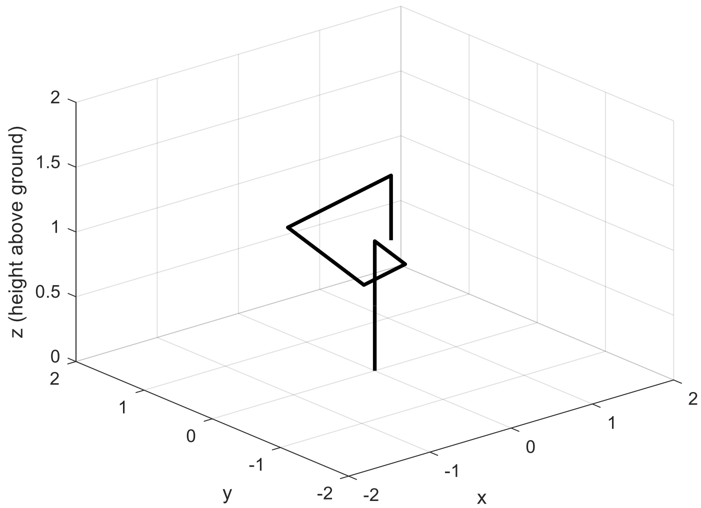

Figure 50 Quadcopter Trajectory 1

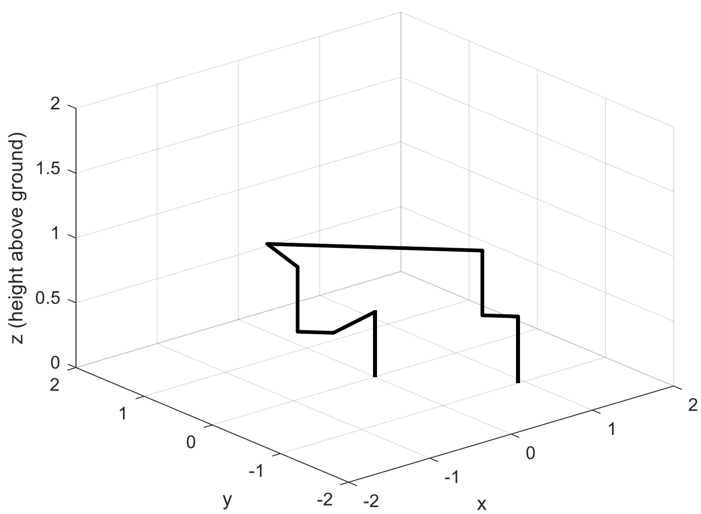

Figure 51: Quadcopter Trajectory 2

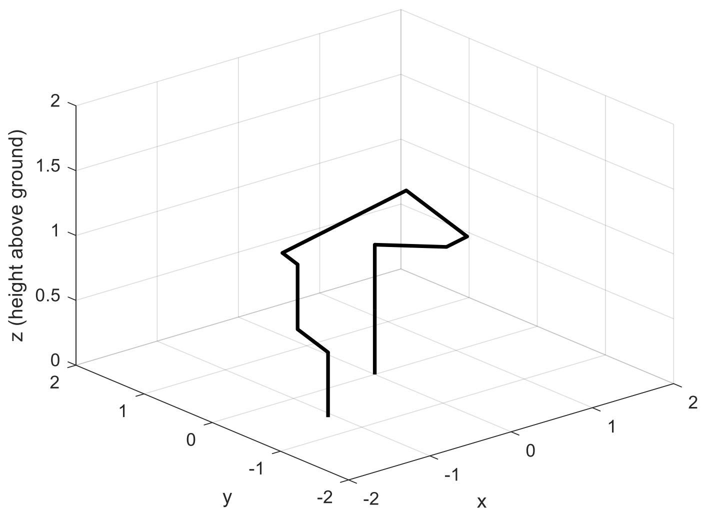

Figure 52: Quadcopter Trajectory 3

DISCUSSIONS

In the following research we have implemented sequential hybrid EEG for reactive BCI system, which have improved the accuracy for six command BCI system. Due to covid and unavailability of EEG device we have used previous recorded dataset of P300 and SSVEP. P300 dataset is composed of six images stimulus. If target P300 is detected by ensemble classifier e.g. an oddball signal is generated in response to stimulus 1 then on SSVEP paradigm, stimulus listed on the position one starts to be flickered with its mentioned frequency. SSVEP signal is further classified by the SVM model and command is generated. The final output is fed to quadcopter in visual environment. In the results P300 signal classification accuracy is enhanced by using ensemble learner. Moreover LMS filter helps to prominent the P300 wave. SSVEP required less training for its detection. If we combine these two modalities there is less chance of false detection.

Table 2

Average Accuracy Reported in Literature	
Kunda et al.[31]	95.5% (P300)
Katyal et al.[48]	92.30 % (P300/SSVEP)
Merino et al. [22]	85%(SSVEP)

The image to signal conversion algorithm shows remarkable results with the p-value of $1.92e^{-161}$. Previously, there is no research reported on this unique method of signal extraction. It provides a new way of signal acquisition for unlicensed devices.

CONCLUSION

We have implemented sequential hybrid P300/SSVEP system that generates six commands. Six images stimulus oddball paradigm is used to generate the P300 signal. After filtration followed by preprocessing, features are extracted and feed into ensemble SVM model. Classified output trigger the SSVEP paradigm and frequency respective to ensemble output starts to flicker. EEG signal for SSVEP detection is recorded. After signal acquisition and filtering, extracted features are classify by simple LDA algorithm. Generated output is used to control the virtual quadcopter on MATLAB simulation. The collective accuracy for Hybrid Model achieved using ensemble classifier was 96.98%, relatively improved than other conventional classifiers. Image to signal conversion approach gives encouraging results with the p-value of 1.92e-161.

FUTURE WORK

In the future research, the scope is widened to include modeling of neuronal activity in different region according to the acquired and extracted EEG-P300/SSVEP signals as an input and output, respectively. The objective is to improve efficiency of the BCI system using adaptive filtering to investigate the mechanisms that shape evoked EEG-P300 responses, and hybrid modalities. This generative model is a neural mass model of hierarchically arranged of two BCI system. Image to signal conversion approach gives a new direction in the research field of signal extraction.

References

[1] Y. Yu, Z. Zhou, Y. Liu, E. Yin, N. Zhang, and Z. Wang, "Self-Paced Operation of a Wheelchair based on a Hybrid Brain-Computer Interface Combining Motor Imagery and P300 potential," vol. 4320, no. c, pp. 1–10, 2017.

[2] J. Ma, Y. Zhang, A. Cichocki, and F. Matsuno, "A Novel EOG / EEG Hybrid Human – Machine Interface Adopting Eye Movements and ERPs : Application to Robot Control," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 3, pp. 876–889, 2015.

[3] Y. Zhang, Q. Zhao, J. Jing, and X. Wang, "human faces A novel BCI based on ERP components sensitive to configural processing of human faces," no. June 2014, 2012.

[4] M. R. Meshriky, S. Eldawlatly, and G. M. Aly, "An Intermixed Color Paradigm for P300 Spellers : A Comparison with Gray-scale Spellers," no. c, 2017.

[5] Z. Oralhan, "A New Paradigm for Region-Based P300 Speller in Brain Computer Interface," *IEEE Access*, vol. 7, pp. 106618–106627, 2019.

[6] X. Yin, B. Xu, C. Jiang, and Y. Fu, "Classification of Hemodynamic Responses Associated With Force and Speed Imagery for a Brain-Computer Interface," 2015.

[7] M. Xu, H. Qi, B. Wan, T. Yin, and Z. Liu, "A hybrid BCI speller paradigm combining P300 potential and the SSVEP," 2013.

[8] Y. Lee and H. Kim, "Biomedical Signal Processing and Control A data partitioning method for increasing ensemble diversity of an," *Biomed. Signal Process. Control*, vol. 39, pp. 53–63, 2018.

[9] T. Review, "Review of real brain-controlled wheelchairs," 2016.

[10] R. Sharma, "EEG Signal Based Movement Control for Mobile Robots Un ed d ve rs pu is d," no. March, 2019.

[11] Q. Liu *et al.*, "Kinematics Analysis and Motion Planning of a Redundant Robotic Manipulator for Surgical Intervention," pp. 5–10, 2017.

[12] A. Rakshit, A. Konar, S. Member, and A. K. Nagar, "A Hybrid Brain-Computer Interface for Closed- Loop Position Control of a Robot Arm," vol. 7, no. 5, pp. 1344–1360, 2020.

[13] Z. Wang, Y. Yu, M. Xu, Y. Liu, E. Yin, and Z. Zhou, "Towards a Hybrid BCI Gaming Paradigm Based on Motor Imagery and SSVEP Towards a Hybrid BCI Gaming Paradigm Based on Motor Imagery and SSVEP," *Int. J. Human–Computer Interact.*, vol. 00, no. 00, pp. 1–9, 2018.

[14] M. J. Khan and K. Hong, "Hybrid EEG–fNIRS-Based Eight-Command Decoding for BCI: Application to Quadcopter Control," vol. 11, no. February, 2017.

[15] J. Long, J. Wang, and T. Yu, "An Efficient Framework for EEG Analysis with Application to Hybrid Brain Computer Interfaces Based on Motor Imagery and P300," vol. 2017, 2017.

[16] H. Neuroscience, M. J. Khan, M. J. Hong, and K. Hong, "Decoding of four movement directions using hybrid NIRS-EEG brain-computer interface," vol. 8, no. April, pp. 1–10, 2014.

[17] F. Li, Y. Xia, F. Wang, D. Zhang, X. Li, and F. He, "applied sciences Transfer Learning Algorithm of P300-EEG Signal Based on XDAWN Spatial Filter and Riemannian Geometry Classifier," no. Mi.

[18] E. Yin, T. Zeyl, S. Member, R. Saab, T. Chau, and S. Member, "A Hybrid Brain – Computer Interface Based on the Fusion of P300 and SSVEP Scores," vol. 23, no. 4, pp. 693–701, 2015.

[19] G. Schalk and J. Mellinger, "Brain Sensors and Signals," pp. 9–36, 2010.

[20] J. Li *et al.*, "An Online P300 Brain – Computer Interface Based on Tactile Selective Attention of Somatosensory Electrical Stimulation," *J. Med. Biol. Eng.*, no. 0123456789, 2018.

[21] R. Fazel-rezai, "A Review of P300 , SSVEP , and Hybrid P300 / SSVEP Brain-Computer Interface Systems," 2013.

[22] L. Meriño *et al.*, "Asynchronous control of unmanned aerial vehicles using a steady-state visual evoked potential-based brain computer interface," *Brain-Computer Interfaces*, vol. 2621, no. March, pp. 1–14, 2017.

[23] U. Hoffmann, G. Garcia, J. Vesin, K. Diserens, and T. Ebrahimi, "A Boosting Approach to P300 Detection with Application to Brain-Computer Interfaces."

[24] A. Nourmohammadi, M. Jafari, and T. O. Zander, "A Survey on Unmanned Aerial Vehicle Remote Control Using Brain – Computer Interface," pp. 1–12, 2018.

[25] M. Wasim, M. Sajjad, F. Ramzan, U. G. Khan, and W. Mahmood, "A Review and Classification of Widely used Offline Brain Datasets," vol. 9, no. 2, pp. 399–408, 2018.

[26] A. M. Norcia, L. G. Appelbaum, J. M. Ales, B. R. Cottereau, and B. Rossion, "The steady-state visual evoked potential in vision research : A review," vol. 15, pp. 1–46, 2015.

[27] Y. Zhang, Q. Zhao, J. Jin, and X. Wang, "A novel BCI based on ERP components sensitive to configural processing of human faces," 2012.

[28] U. Hoffmann, J. Vesin, T. Ebrahimi, and K. Diserens, "An efficient P300-based brain – computer interface for disabled subjects," vol. 167, pp. 115–125, 2008.

[29] R. Spies and R. Gassert, "A penalized time-frequency band feature selection and classification procedure for improved motor intention decoding in multichannel EEG," *J. Neural Eng.*, p. aaf046, 2019.

[30] A. Turnip, K. Hong, and M. Jeong, "Real-time feature extraction of P300 component using adaptive nonlinear principal component analysis," pp. 1–20, 2011.

[31] S. Kundu and S. Ari, "ScienceDirect P300 based character recognition using sparse autoencoder with ensemble of SVMs," *Integr. Med. Res.*, vol. 39, no. 4, pp. 956–966, 2019.

[32] M. Xu, J. Han, Y. Wang, and T. Jung, "Implementing over 100 command codes for a high - speed hybrid brain - computer interface using concurrent P300 and SSVEP features," *IEEE Trans. Biomed. Eng.*, vol. PP, p. 1, 2020.

[33] Z. T. Al-qaysi, B. B. Zaidan, A. A. Zaidan, and M. S. Suzani, "Computer Methods and Programs in Biomedicine A review of disability EEG based wheelchair control system : Coherent taxonomy , open challenges and recommendations," *Comput. Methods Programs Biomed.*, vol. 164, pp. 221–237, 2018.

[34] F. Lotte *et al.*, "A review of classification algorithms for EEG-based brain – computer interfaces To cite this version : HAL Id : inria-00134950 A Review of Classification Algorithms for EEG-based Brain-Computer Interfaces," 2007.

[35] N. V Manyakov, N. Chumerin, A. Combaz, and M. M. Van Hulle, "Comparison of Classification

Methods for P300 Brain-Computer Interface on Disabled Subjects," vol. 2011, 2011.

[36] J. Zhao, W. Li, and M. Li, "Comparative Study of SSVEP- and P300- Based Models for the Telepresence Control of Humanoid Robots," pp. 1–18, 2015.

[37] A. Turnip, S. S. Hutagalung, J. Pardede, and D. Soetraprawata, "P300 Detection Using a Multilayer Neural Network Classifier Based on Adaptive Feature Extraction," vol. 2, no. 5, pp. 63–75, 2013.

[38] S. Kundu and S. Ari, "Biomedical Signal Processing and Control P300 based character recognition using convolutional neural network and support vector machine," *Biomed. Signal Process. Control,* vol. 55, p. 101645, 2020.

[39] F. E. M. Labib and I. A. Fouad, "MULTIPLE CLASSIFICATION TECHNIQUES P300 BCI SYSTEM," vol. 32, no. 2, pp. 1–12, 2020.

[40] H. Wang, Y. Li, and J. Long, "An asynchronous wheelchair control by hybrid EEG – EOG brain – computer interface," 2014.

[41] M. Aljalal, R. Djemal, and S. Ibrahim, "Robot Navigation Using a Brain Computer Interface Based on Motor Imagery," *J. Med. Biol. Eng.*, no. 0123456789, 2018.

[42] A. Vilic and L. Revision, "The AVI SSVEP Dataset," pp. 1–6, 2013.

[43] X. Jiang and G. Bian, "Removal of Artifacts from EEG Signals : A Review," pp. 1–18, 2019.

[44] P. S. Kumar, R. Arumuganathan, K. Sivakumar, and C. Vimal, "Removal of Artifacts from EEG Signals using Adaptive Filter through Wavelet Transform," pp. 2138–2141, 2008.

[45] B. H. Kim, M. Kim, and S. Joevaluated, "Quadcopter fl ight control using a low-cost hybrid interface with EEG-based classi fi cation and eye tracking," *Comput. Biol. Med.*, pp. 1–11, 2014.

[46] X. Duan, S. Xie, X. Xie, Y. Meng, and Z. Xu, "Quadcopter Flight Control Using a Non-invasive Multi-Modal Brain Computer Interface," vol. 13, no. May, pp. 1–11, 2019.

[47] K. Lafleur, K. Cassady, A. Doud, K. Shades, E. Rogin, and B. He, "Quadcopter control in three-dimensional space using a noninvasive motor imagery-based brain – computer interface," vol. 046003.

[48] A. Katyal and R. Singla, "Biomedical Signal Processing and Control A novel hybrid paradigm based on steady state visually evoked potential & P300 to enhance information transfer rate," *Biomed. Signal Process. Control*, vol. 59, p. 101884, 2020.