Application of Brain-Computer Interface for Prosthesis

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***Abstract*—Neuro-prosthetics is a trending study for rehabilitation, substitution of limbs, mobility, cognition, hearing, vision and many other applications. My aim of this research is to create a BCI (Brain-Computer Interface) technology to enable sever motor impairment patients controlling prosthetics. The objective of this paper is to express the novelty of implementing a simple BCI system for prosthetic arm. This study uses SSVEP (Steady State Visually Evoked Potential) Method to read EEG (Electro-Encephalography) data, MATLAB and Openvibe softwares for signal processing and control of Open bionics Brunel hand. This paper also states the methods, challenges and further applications of BCI.**

***Index Terms*—SSVEP, BCI, nodes, flickering channels, frequency, CCA.**

I. Introduction

A BCI (Brain-Computer Interface) system is a communication system that reads brain activity converts it into commands for a computer or other devices. The major aim of this technology is for muscular or motor-neuron disabled users.

There are different ways for acquiring brain signals, these are classified into invasive and non-invasive techniques. While the invasive techniques are cortical (implanting electrodes near surface of the brain) and intracortical (implanting electrodes deep inside the brain) provides much better brain signals than non-invasive [1], they are also very dangerous as anything related to brain surgery is risky even in this era and the electrodes implanted may get rusted. The non-invasive techniques like Magnetoencephalography (MEG) and Functional magnetic resonance imaging (fMRI) may have merits like gaining better brain signals, but they also have demerits like equipment cost and non-portable devices. Among the non-invasive techniques, the EEG (Electro-Encephalography) is the current trending method for ease of use, low equipment cost and portable availability to acquire brain waves.

There are different signals in body that can be utilized for controlling external devices. These techniques other than EEG, which is based on neural activity detected on scalp EMG-Electromyogram based on muscle movements and EOG-Electrooculogram based on eye movement as input signals. The EEG based BCI are used with following methods: (i) the P300 response (ii) slow cortical potential (iii) motor imagery (iv) steady-state visual evoked potentials (SSVEP). In general, from physiological point of view the methods using BCI technology can be classified as endogenous and exogenous. The former being the use of endogenous devices are independent on user's response to external stimuli i.e. user autonomously recognises and detects brain signals pattern. Example, motor imaginary. The later being the use of exogenous devices by analysing the user's response to devices by providing some kind of stimuli to user. Example, P300 or visual evoked potential [2].

This paper uses SSVEP-based BCIs uses flashing regions on screen called stimuli also called as flickering regions. Each of these flickering regions are flashed with different frequency constantly as shown in Fig.(1). When one of these flickering regions are gazed on screen that specific frequency component of the source, will increase in the EEG being measured and gives better SNR (Signal to Noise Ratio) over the occipital lobe. Hence, while gazing at different flashing regions where each of them represents a predefined command, after the signal processing and statistical analysis the command to actuate the prosthetic hand is given by gazing onto the screen. The analysis can either be done by CCA (Canonical Correlation Analysis) or by using FFT (Fast Fourier Transformation), preferably including also the harmonics.

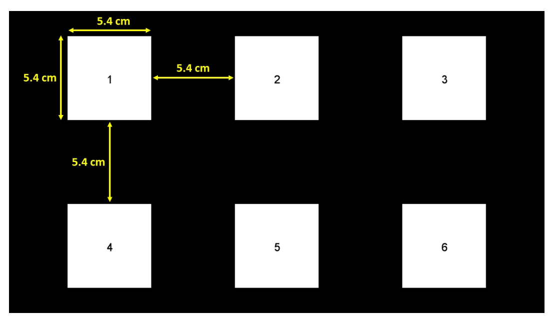

Fig. 1: Flickering regions

II. Literature Review

Why SSVEP? Because of its advantages such as ease of use, little user training and high ITR (Information Transfer Rate); Stable and Reliable System Performance; Low-Cost Hardware based on the experiment analysis[3].

The stimuli of SSVEP can be modulated for getting discreate flashing patterns, leading to decrease noise in the acquired signal. In a study, it described the three stimulus modulation approaches used in current VEP (Visually Evoked Potential) based BCIs: frequency modulation (f-VEP), time modulation (t-VEP) and pseudorandom code modulation (c-VEP). In t-VEP, the Flickering Regions are independent of each other.

They won't be in same phase and the time at which region flickers is different. In f-VEP the channels or regions are in different frequencies and they might be in same phase. In c-VEP each region has its own pseudo pattern, they flash at different patterns. Through the experiment conducted on four subjects in this article, it has been concluded that f-VEP and c-VEP are better used for online based system. For my research I am using f-VEP stimulus as it also has high ITR[4].

In another study the SSVEP based BCI experiment is carried on 6 different subjects for dry, wet and gel electrodes. Based on experiment, classification accuracy and average information transfer rate is higher for gel followed by water and then dry based electrodes. For this paper the electrodes used are dry electrodes as it is easy to use[5].

Another paper evaluated SSVEP based BCI experiment in offline mode using Openvibe as software. It also describes different steps on configuration, training acquisition, CSP (Common Spatial Pattern filters) training, classifier training used in Openvibe which are further used as reference for my experiment [6].

III. BCI USE ON PROSTHETIC HAND

The BCI has contributed to various fields of research, which include: medical, neuromarketing and advertisement, neuroergonomics and smart environment, games and entertainment, educational and self-regulation, and Security and authentication fields[7]. The medical field applications include: detection, prevention, rehabilitation, diagnosis and restoration.

The aim of this research is to build a BCI system that has potential to improve the daily lives of people with prosthetic Limbs, neuromotor disorder, severe motor impairment, lock in syndrome, etc. through simple hardware and ease of use system like SSVEP.

The prosthetic hand which is being used for this study is Open bionics Brunel hand 2.0. A 3D printed hand with four motors available to actuate the five fingers, where a motor is used for actuating both little and ring finger simultaneously and remaining motors actuates its corresponding fingers respectively. The hand uses chestnut PCB which is Arduino based hardware.

IV. MATERIALS AND METHODOLOGY

The aim of this research is to implement EEG-based BCI system using SSVEP for working of prosthetic hand. The research has been done using following materials and their images are displayed below:

- Stimulus or flickering regions
- Openvibe
- g.tec Sahara Box (Fig.2a)
- g.tec Mobilab+ (Fig.2b)
- g.tec GAMMcap (Fig.2c)
- LSL (Lab Streaming Layer)
- MATLAB
- Psychtoolbox
- Openbionics Brunel hand 2.0 (Fig.2d)

(a) g.tec Sahara Box

(b) g.tec MobiLab+

(c) g.tec GAMMcap

(d) Openbionics Brunel hand 2.0

In order to achieve the targets of this research, the following tasks have been broken down:

1) Acquisition and recording of EEG signals
2) Streaming EEG signals to filter
3) Filtering of EEG signals
4) Processing the filtered signals using CCA.
5) Sending the output to hand using Serial Communication.

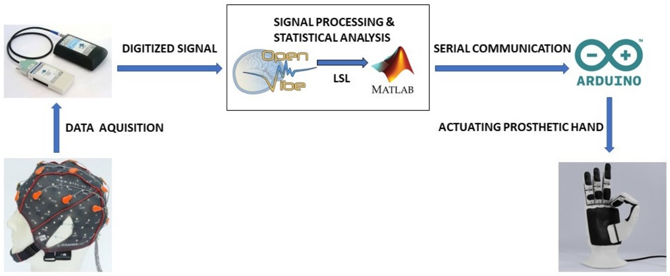

Fig. 2: Methodology flow chart

6) Actuating the hand based on gazed target frequency.

The EEG signals are acquired from a screen using stimuli by SSVEP method through use of a software platform called Openvibe at sampling rate of 256Hz. These signals are sent to MATLAB using LSL. The data acquired in MATLAB is in form of Matrix which is further filtered using butterworth band-pass filter which helps to remove unwanted noise as peripheral frequency obtained from flickering channel. For signal processing this study uses first high pass filter of filter order 6 from 4Hz and then low pass filter up to 34Hz of filter order 24. Later these filtered signals undergo Canonical Correlation Analysis (CCA), which provides the required output. The output obtained in MATLAB is sent to Arduino of the prosthetic hand using serial communication. The brunel hand is programmed to respond based on corresponding gazed frequency as output. This makes the programmed prosthetic hand to respond to commands obtained from MATLAB and actuate the hand as given in the flow chart Fig.4.

A. Properties of Stimulus:

The target frequencies used in this study are 6 f-VEP stimuli each flickering at rate of 8Hz, 9Hz,10Hz, 11Hz, 12Hz and 13Hz respectively as shown in fig and given table. The stimulus used are zero phased sinusoidal waves for visual flickers to occur on the screen. The flashing of the stimulus s(f,i) of corresponding frequency is generated in psychtoolbox by modulating the luminance on computer screen using the equation as stated below (1), where f is the frequency, i is the index of stimuli, R is refresh rate of screen[8].

$$S(f,i) = 1/2(sin[2 * \pi * f(i/R)] + 1) \tag{1}$$

In an article 10 subjects are experimented with BCI SSVEP system to determine magnitude of evoked signal as the function of frequency, as a result it was found that the frequency response around 10 Hz [9]. Similarly, in another article, its experiment resulted the identification of local maxima in response amplitude of SSVEP on input frequency within bands 7-10Hz, 15-20Hz and 40-50Hz at occipital electrodes, showing multiple response maxima for different subjects within these frequency bands[10].

In a study, it has been resulted that the interstimulus distances and size of stimulus play role in classification accuracy, where the spatial proximity and size of stimuli are measured using visual angle [11]. It also revealed optimum distance between stimuli and size of stimulus for better accuracy, which are greater than 5° and atleast 2° for spatial distances between stimuli and size of stimulus respectively.

The visual angle is quantified eq.(2) as given below in the equation [12]. This paper uses the spatial distances both vertical and horizontal between each stimulus as 5.4 cm and the size of stimuli is 300 pixels with side 5.4 cm as shown in Fig.1.

$$V = tan^{-1}(S/D) \tag{2}$$

In the above equation, V is visual angle, S is area of stimulus, D is distance between eye and the screen. On calculation of visual angle, the spatial distance and size of stimulus are 5.1° which is greater than 5°.

The stimuli are designed to flash in white colour, conducted experiments on 20 subjects in order to determine Event Related Spectral Perturbation (ERSP), the quantity that measures relative decrease or increase of EEG power on colours yellow, white, red, green and blue, which resulted white and yellow colours demonstrating highest ERSP near alpha band (14HZ) and also other frequency bands. There was not much significant difference between white and yellow colour's evoked amplitude of SSVEP response, where white being higher[13].

The gaze shifting duration is provided for 1 sec and the stimulus flashing duration is 4 sec. The visual angle of stimuli is 5.1°. Followed by, this study uses LCD screen.

B. EEG Headset and Connection

The g.GAMMAcap is connected with electrodes at parietal and occipital regions which encloses visual cortex and these regions produce maximum SNR (Signal to Noise ratio) i.e. good response for SSVEP [14]. The electrodes positions used are: Fpz, Cz, PO3, O1, POz, O2, PO4, Oz as shown in Fig 4.6. The ground and reference electrode positions are Fpz and Cz respectively. These electrodes are connected to g.Sahara Box which is connected to amplifier g.Mobilab+. The g.Mobilab+ is connected to Openvibe via Bluetooth and acquired signals are sent to Openvibe.

The Sahara box solves the noise problem in the ground circuit by using differential amplifiers. The differential amplifier records the potential difference between reference electrode (R) and the ground electrode (G) (which equals R-G) and the potential difference between an active electrode (A) and ground electrode (G) (which equals A-G). The amplifier's output will be difference between these two voltages ([A-G]-[R-G]), which results to the equation (A-R) that is implemented in physical electronic circuitry of Sahara box. This cancels out noise in 'G' as electrical noise from amplifier circuit will be same for R-G and A-G[15].

C. Acquiring EEG signals:

After the headset is connected and data is being streamed into Openvibe designer from g.Mobilab+ which is connected to Sahara Box via Bluetooth through a server called openvibe

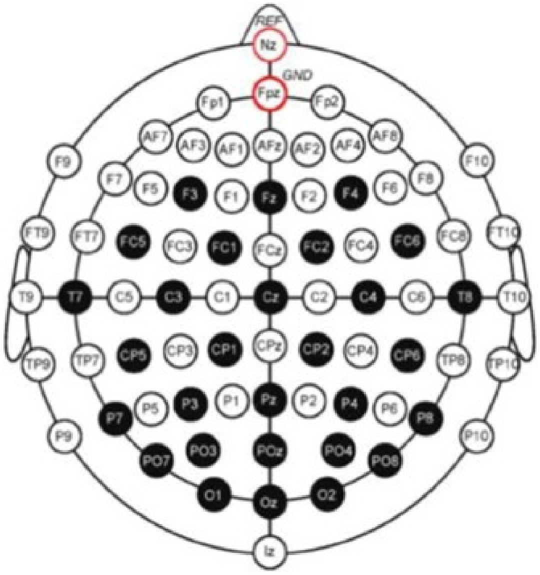

Fig. 3: Electrode positions on EEG cap

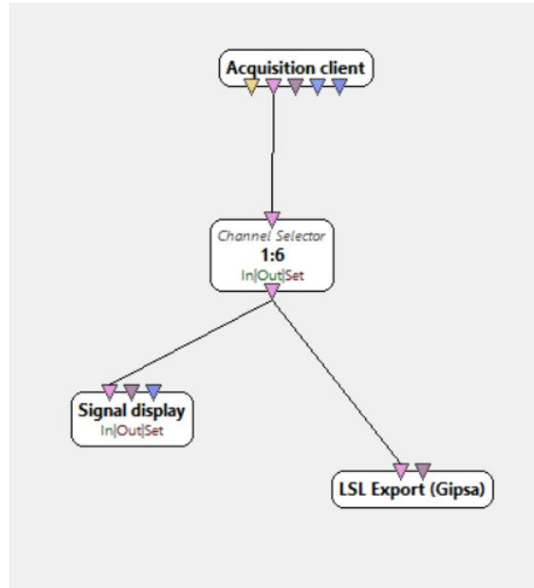

Fig. 5: Openvibe designer

acquisition client as shown in Fig.4 The Openvibe designer will select the channels for receiving data through use of channel selector box as shown in Fig.5. Later, the data is sent into LSL box.

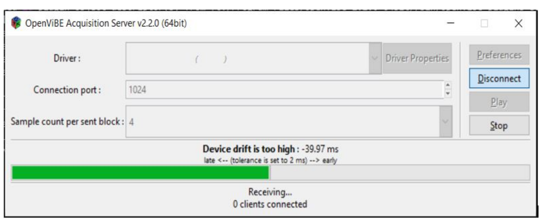

Fig. 4: Openvibe acquisition client

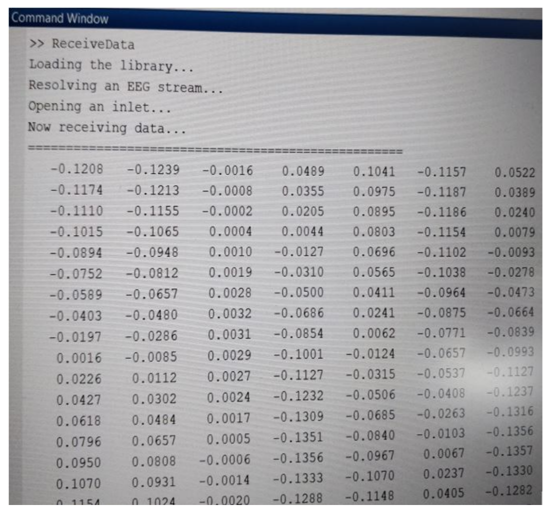

Fig. 6: Recorded EEG data into MATLAB

D. Streaming and Filtering EEG data:

The EEG data that is streamed into MATLAB is recorded as form of matrix where each column of the matrix represents each electrode data set as shown in Fig.6 The acquired EEG data is applied filter in order to reduce noise. The filter used is butterworth band-pass filter. For signal processing this study uses first high pass filter of filter order 6 from 4Hz and then low pass filter up to 34Hz of filter order 24. After removal of noise, the process undergoes CCA.

E. Canonical Correlation Analysis (CCA):

The CCA is a statistical analysis used to determine correlation between two sets of data. It is a multivariable statistical method, where first it finds canonical variables through a pair of linear combinations until the correlation between two sets of variables (each set consist of each electrode data) or canonical variables is maximized. Later, it finds correlation between uncorrelated set and first pair of canonical variables with next highest correlation. This process for construction of canonical variables extends until no. of variables in smaller set equals no. of pairs of canonical variables.

In CCA we can use more than two EEG channels for analysis of data. Let X indicate a matrix of multi-channel EEG data, where N comprises no. of samples recorded by EEG headset as shown in the eq.(3) and Y be matrix of reference signals eq.(4).

$$X = \begin{pmatrix} O1[1] & Oz[1] & O2[1] & PO3[1] & POz[1] & PO4[1] \\ O1[2] & Oz[2] & O2[2] & PO3[2] & POz[2] & PO4[2] \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ O1[N] & Oz[N] & O2[N] & PO3[N] & POz[N] & PO4[N] \end{pmatrix}_{N\times 6} \quad [3]$$

$$Y = \begin{bmatrix} \sin(2\pi hft) & \cos(2\pi hft) \end{bmatrix}_{N\times 2N_h} \quad [4]$$

Here is the no. of harmonics, h is the harmonic index where h= 1,2,3,…. N_h, f is stimulation frequency, N is data length, t is time i.e. n/f_s , f_s is sampling frequency, n= 1,2 3,……N.

In order to identify the SSVEPs frequency, CCA evaluates correlation between reference signals of its stimulation frequency and multi-channel SSVEPs. The frequency of SSVEPs is considered as maximum correlation of reference signals.

In the process, CCA finds two weight vectors W_X and W_Y such that their linear combinations $U = XW_X$ and $V = YW_Y$ is maximized. The correlation between U and V (r_{UV}) is illustrated by the following eq.(5):

$$r_{UV} = \frac{\sum_{i=1}^{N}(u_n-\overline{u})(v_n-\overline{v})}{(N-1)S_uS_v} \quad [5]$$

Where u_n and v_n are variables in U and V respectively, ¯u and ¯v are means of U and V, and S_u and S_v standard deviation of u and v respectively. This study uses MATLAB's 'canoncorr' function to calculate CCA.

As the background EEG activity is decreased the harmonics showed slower decrease in SNR. In order to get better results, we need to: 1) Increase no. of harmonics 2) increase the data length. In this study, data is acquired for upto 2 harmonics and data-length of 8sec for better results. In an article, it experimented with 5 subjects for SSVEP based BCI system, where three SSVEP harmonics resulted better classification accuracy than was the case for two or one harmonics[16]. The classification with increase in harmonics resulted with greater improvement in accuracy. It also increases the speed as (1/2f less than 1/f i.e. it needs less data length for detecting the harmonics). When noise content is more its better to take EEG data of longer length so that harmonics can be identified for better results. For detection of more frequency stimuli on screen requires more data length, according to condition of orthogonality[17].

V. RESULTS

This study uses an online-system, where it collects, processes and analyse the real-time data to compute the gazed target frequency on the screen as output. After CCA in MATLAB the system outputs the CCA values and max of this CCA values is resulted with its corresponding index of targeted flickering region as shown in Fig.7. Further, for a specific index number of target frequency resulted, a particular numerical digit is assigned which is sent as binary data from MATLAB to Arduino software through serial communication. The Brunel hand is programmed to respond to the sent binary data into Arduino Serial Monitor. As the Brunel hand is able to read the binary data with 'Serial.read()' command, conditional statements are applied in Arduino to create and an action in hand of that particular read binary data. The below Table.I shows the stimulus index and target frequency assigned to each action of Brunel hand. Correspondingly, the below Fig.8 illustrates the resulted actions of Brunel hand according to the allocated target frequency. As the little and ring fingers are connected to same motor, they move simultaneously.

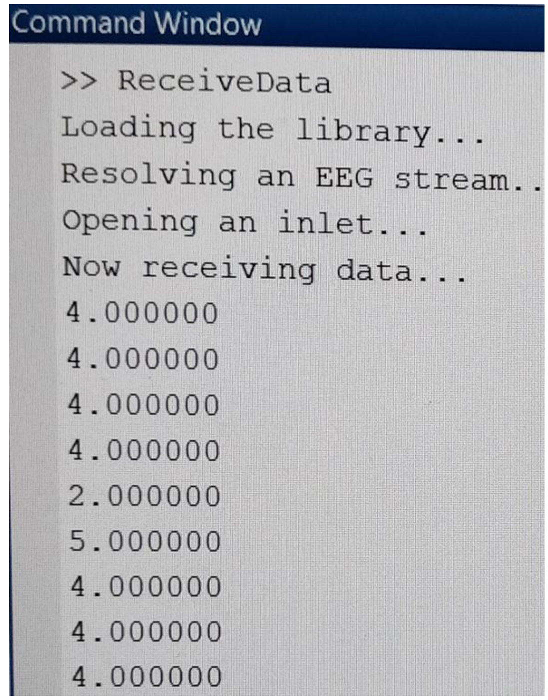

Fig. 7: The output of CCA: Stimulus number

Stimulus.No.	Frequency	Open Bionic hand action
1	8	Thumb closes
2	9	Index finger closes
3	10	Middle finger closes
4	11	Both little and ring finger closes
5	12	Little, ring and middle finger closes
6	13	Thumb, little and ring finger closes

TABLE I: Open bionic hand actions assigned for each target frequency

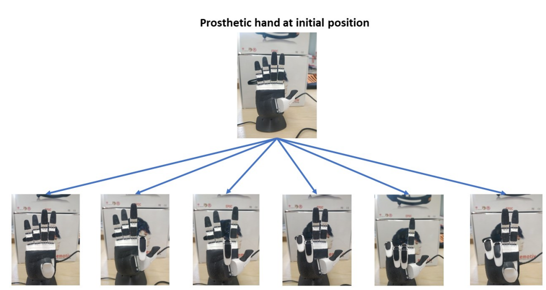

Fig. 8: Brunel hand actions based on output CCA values

VI. SUMMARY

A. Challenges:

Furthermore, the results obtained in the experiment also depends upon the subject's concentration on Flickering Region, surrounding noise problems around subject, light falling on screen, signal processing method, etc. Hence, these parameters are required to be followed strictly in order to gain better results. One of the challenges is the no. of flickering regions on the screen. If we increase more flickering regions on screen it will increase different options for operating prosthetic hand, but this will also decrease the space between each flickering regions, as a result there will be a possibility of increase in noise from other flickering region while computing CCA. While gazing at one flickering region the noise from nearby flickering region with different frequency will also be recorded, leading the EEG data collected having the noise.

B. Future Works:

1) Building feedback system:

Increasing more stimuli on screen increases different options for prosthetics hand to work, but this will also increase noise as stated above in the challenges. So, on implementing feedback system that is able to flash the flickering region at the relax time for identifying the gazed flashing region, and also by building a system such that while gazing at a flashing region it shifts to a new screen of different stimuli. We can able to increase no. of options for operating the prosthetic hand without increasing the noise.

2) EEG headset:

EEG data recorded also depends on user's concentration which requires his/her comfort for wearing the headset. The design of the EEG headset such that it is more comfortable to wear and gain better data would be very useful than the headset which is currently being used that acquires better signal by squeezing the electrodes on the scalp.

3) Optimising signal processing:

The adoption Joint Frequency Phase Modulation (JFPM) technique that creates unique flashing stimulus flashing at different frequency and phase making it easy to identify leading to reducing noise. And, improving signal processing filters can also increase the SNR and BCI communication rates.

4) Using Machine learning:

The SSVEP is not required much user training. But if training is done the results will be much better than non-training. By use of Machine learning the data acquired can be trained to get better result. Machine learning can also be used for getting optimal stimulus size, user specific time window and training to acquire better data to reduce different subjects variation while gazing at screen in performance.

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