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A Prosthetic Arm Based on Electroencephalography by Signal Acquisition and Processing on MATLAB

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Abstract*: This paper presents the prosthetic arm based on electroencephalography by signal acquisition and processing. Around the world, there are 5-6 million people with partial hand amputation due to traumatic accidents, various health issues and wars. Recent advancements show prosthetic arms are purely mechanical and tedious. In order to solve this problem, Brain-Computer Interface (BCI)-based control strategies were introduced into robot control. The methods adopted should take into consideration the nature of the application, for example, Electroencephalography (EEG) signal is ideal for our application due to its convenient approach. Particularly, for EEG-based BCI systems, a set of sensors are needed to acquire the EEG signals from different brain areas. The Fast Fourier Transform algorithm is adopted for feature extraction of the EEG signals and python is used to save the data in .txt file. The .txt file is imported into MATLAB and data analysis is done by signal processing and analysis tool. Next, Signal classification is done and then the signal is carried to end-effector. Our findings indicate that the rise of 3D printing industry, advanced printers and materials will allow students to develop more 'commercial-like prosthetic devices – robust and durable systems that could benefit a wide range of people with a missing limb. With ongoing research, more technological advancements in EEG would definitely result in improvements which will hopefully lead to a system that is more durable and offers improved dexterity and control.

***Keywords*: Electroencephalography, Brain-Computer Interface (BCI), Steady-state visual evoked potential (SSVEP), Fast Fourier Transform (FFT).**

1. Introduction

The advancement of technologies in this era has great impact on human life. Now, people are able to travel faster and communicate in a more convenient way than in the past. Assistive computers and machines provide conventional input devices such as a keyboard, a mouse, or a joystick to be operated by the users. These devices are, however, difficult to be used by elderly or disabled individuals. For this reason, special interfaces such as sip-and-puff systems, single switches, and eye-tracking systems have been proposed [1]. Nevertheless, these special interfaces do not work for people suffering from severe neuromuscular diseases who cannot convey their intentions or operations to computers or machines with these interfaces. Consequently, even autonomous electric wheelchairs are unable to transport disabled people to their desired locations. Hence, there exists a growing demand and necessity for developing an alternative interface that can be used by the severely disabled population for communication with autonomous systems.

Brain-computer interface (BCI) system has been developed to address this challenge. BCIs are systems that can bypass conventional channels of communication [2]. A brain-computer interface (BCI) is a software and hardware system for establishing direct communication between human and computer, which enables people to send commands to the external world through brain activities, without depending on brain's normal output pathway of peripheral nerves and muscles activities [3]. BCI system is also useful to improve precision of control for vehicles and robots in hostile environments such as space, to let people live in intelligent e-homes, to integrate new electronics body enhancements, and to play and communicate in novel ways [4]. There are a vast group of control signals available for BCI systems. These signals can be generated at will by people, thus enabling BCI systems to interpret their intentions for command-and-control purposes. Particularly, in EEG-based BCI systems, the commonly used control signals are such as slow cortical potentials (SCP), event-related synchronization and desynchronization (ERS/ERD), event-related potentials (ERP), and visual evoked potentials (VEPs) [5]. The focus of this thesis is on steady-state visual evoked potential (SSVEP). In fact, when stimulated by a repetitive flicker of frequency 6 Hz and above, some sinusoidal oscillatory waveforms with the frequency same as the stimulus or its harmonics would be observed from the scalp of a person [6]-[8].

In this paper, an SSVEP-based BCI system for Robot Arm control is proposed. The system consists of a 16-channel EEG recording system for EEG measurement. Visual stimuli are developed on a laptop LCD screen for eliciting SSVEPs. Meanwhile, MATLAB is used as the main tool for signal processing of EEG signals and command recognition. The Fast Fourier Transform algorithm is adopted for feature extraction of the EEG signals. Signals are acquired by using a Bluetooth device Emotiv EPOC + which is a 16-channels electrode,

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placed on the scalp and python is used to save the data in .txt file. The .txt file is imported into MATLAB and data analysis is done by signal processing and analysis tool. Frequency domain algorithm tool for generating the frequency response of the data and plotting Magnitude and phase diagram. Prior to controlling the movement of Robot Arm. Finally, the subjects are instructed to move the Robot Arm in specific directions and the performance of the system in real-time is observed and analyzed.

2. Brain-Computer Interface (BCI)

Generally, a typical BCI system comprises five main consecutive stages, namely signal acquisition, signal pre-processing or signal enhancement, feature extraction, classification, and the control interface. The signal acquisition stage captures the brain signals and may also perform noise reduction and artefact processing. The aim of the pre-processing block is to bring the signals into a suitable form for further processing purposes. The discriminative information in the recorded brain signals is identified and extracted during the stage of feature extraction. Once measured, the signal is mapped onto a vector containing effective and discriminant features from the observed signals, upon which classification can be done. Feature extraction has always been a challenging task in the BCI system because brain signals are mixed with other signals originating from a finite set of brain activities that overlap in both time and space. The classification block classifies the signals based on the constructed feature vectors. Hence, the choice of good discriminative features is essential to achieve effective pattern recognition so as to correctly decipher the user's intentions. Finally, the control interface translates the classified signals into meaningful commands for any device connected, such as a wheelchair, Robot arm or computer.

A. Electroencephalography (EEG)

EEG is the recording of underlying human brain activity produced by the summation of electrical potentials generated by a large population of neurons that propagated through the skull. EEG is, as compared to MEG or fMRI, widely available, compact, inexpensive, usable at the bedside, and offers a reasonable trade-off between temporal and spatial resolution [24]. The major drawback of EEG, however, is the low SNR due to the poor-quality signals that have to cross the scalp, skull, and many other layers before reaching the recording electrodes. In addition, EEG is greatly distorted by background noise generated either inside the brain or externally over the scalp. EEG often appears as an alternating type of electrical activity comprise of various frequencies with typical amplitude ranging from 2 to 100 µV. The early studies are more towards the investigation of EEG for the diagnosis of neurological disorders and cognitive neuroscience studies. As the EEG normally appears as a random wave with various rhythms, quantitative measurement of EEG signal frequencies produces a convenient way to classify the signals. According to the frequency ranges that they occupy, EEG is categorized into several groups. As discussed in the above paragraphs, EEG is recorded by using electrodes. The placement of electrodes over the scalp is commonly based on the International 10-20 system which has been standardized by the American Electroencephalographic Society [6]. The system is based upon measurements of four standard points on the scalp, which is nasion, inion, left and right preauricular point the transverse and median planes divide the skull from these points. The electrode locations are determined by marking these planes at the intervals of 10% and 20% as shown in Figure.2. By following the standard procedure of the 10-20 system, the electrode locations are reproducible on different subjects.

The EEG signal is measured as the potential difference over time between signal or active electrode and reference electrode, where the reference electrode will be the same for all channels.

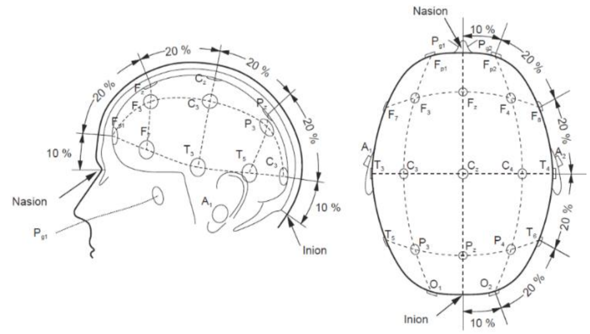


Fig. 1. The International 10-20 electrode placement system

There is no standard position for common reference electrodes but normally an inactive position that provides a fairly constant electrical potential will be chosen. Midline positions such as Cz and Fpz are sometimes used because they do not amplify the signal in any particular hemisphere. Multi-channel configurations can comprise up to 128 or 256 active electrodes. These electrodes are made up of silver chloride (AgCl). A good electrode application should create an electrical contact with an ideal impedance of below 5 kΩ to record an accurate signal.

B. The SSVEP-Based Controlling System

SSVEP are usually elicited through cathode-ray tube (CRT) monitors, light-emitting diodes (LEDs), or liquid crystal display (LCD). Experimental results proved that the spectrum of LED flicker was very simple which includes only the fundamental frequency and its harmonics. It was found that there were many high-frequency components related to the fresh frequency in the CRT spectrum low-frequency components in the LCD flickers except for the fundamental frequency and its harmonics.

There are several factors that contribute to the quality of the elicited SSVEP. One experiment which investigates the influence of stimuli colour on SSVEP-based BCI wheelchair control had been conducted by Singla *et al.* Four different stimuli colours were compared and experimental results showed that SSVEP response with violet stimuli are better than that with green, red, and blue stimuli besides, the patterns of the stimuli also affect the quality of the recorded signal. The commonly used patterns are such as letters, rectangles, checkerboards, or arrows which alternate between two colours or patterns at specific intervals.

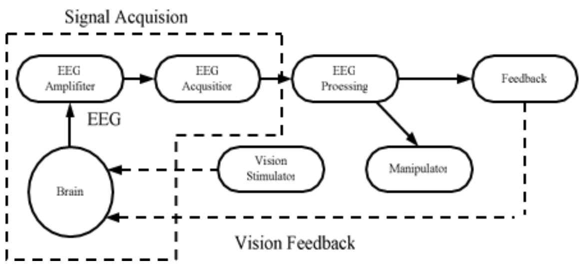


Fig. 2. SSVEP based controlling system

3. Implementation Methods

A. Hardware Implementation

The hardware system was composed is 14 channel (2 reference channels) Emotiv EPOC+ signal acquisition device, Prosthetic arm, Arduino UNO/MEGA, Power Supply and Voltage Regulators.

EMOTIV EPOC+ is the device used to acquire brain waves. Electrodes are placed on the scalp. It is a wireless device, raw signals are saved in a .txt file wirelessly using a Bluetooth device and software, Emotiv Research Edition SDK v2.0.0.20 Installer which came along with the hardware package.

PROSTHETIC ARM, create an operative low-cost 3D printed prosthetic arm there are copious designs and making challenges. We aim to develop an apparent mechanical model of the arm and electrical system drives which determines the functionality resemblance of the device impersonating the human arm. The goal is to develop a prosthesis that has the ability to benefit people with missing hands. We aim to build an affordable prosthetic which is marginally available for amputees.

The modularity of the arm: Amputation can happen anywhere along the arm and is different in every case. We aim to design an ideal design that supports a connection to a stump positioned anywhere along the arm. Scalability and Mathematical Model: The model should be so designed in order to have control over the degrees of freedom of the arm. The electrical motors should facilitate the free functioning of the arm. The arm should be strong enough to withhold the weights and any external stress and help in providing balance to the amputee.


Fig. 3. Fingers are controlled by tendons actuated through servo motors placed in the forearm

Arduino Uno is a microcontroller board based on the ATmega328P It has 14 digital input/output pins (of which 6 can be used as PWM outputs), 6 analogue inputs, a 16 MHz quartz crystal, a USB connection, a power jack, an ICSP header and a reset button. It contains everything needed to support the microcontroller; simply connect it to a computer with a USB cable or power it with an AC-to-DC adapter or battery to get started. The Arduino Uno can be programmed with the IDE (Arduino Software (IDE)).

B. Software Implementation

The software used for collecting the raw data from Emotiv PRO software and Emotiv Research Edition SDK v2.0.0.20 Installer for the process of signal pre-processing is MATLAB.

Fig. 4. EMOTIVPRO software

Data Pre-Processing:

In Bandpass Filtering of raw EEG Signals, frequencies that do not fall within the alpha and beta bands are eliminated because they do not reflect visual processing in the occipital region. This is achieved by constructing a 4th order Butterworth Infinite-Impulse Response (IIR) bandpass filter with a passband of 6 Hz to 30 Hz using the Signal Processing Toolbox in MATLAB. The main reason for selecting an IIR filter over Finite-Impulse Response (FIR) filters is due to the advantages of IIR filters which provide sharp cut-off with a much lower filter order and thus, low computational requirements as compared to FIR filters. Each electrode is connected to one input of a differential amplifier (one amplifier per pair of electrodes); a common system reference electrode is connected to the other input of each differential amplifier. Most EEG systems these days, however, are digital, and the amplified signal is digitized via an analogue-to-digital converter, after being passed through an anti-aliasing filter. Analogue-to-digital sampling typically occurs at 256–512 Hz in clinical scalp EEG; sampling rates of up to 20 kHz are used in some research applications. During the recording, a series of activation procedures may be used. The digital EEG signal is stored electronically and can be filtered for display. Typical settings for the high-pass filter and a low-pass filter are 0.5–1 Hz and 35–70 Hz respectively. The high-pass filter typically filters out slow artefacts, such as electro galvanic signals and movement artefacts, whereas the low-pass filter filters out high-frequency artefacts, such as electromyography signals. An additional notch filter is typically used to remove artefacts caused by electrical power lines (60 Hz in the United States and 50 Hz in many other countries).

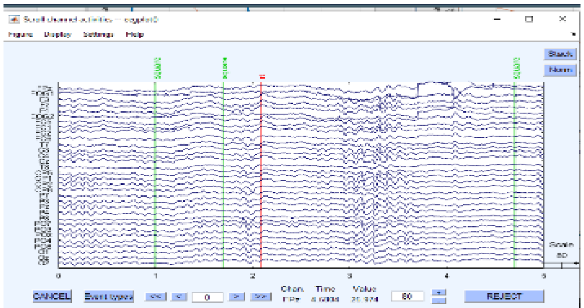


Fig. 5. Raw EEG signal on Time vs. Amplitude curve

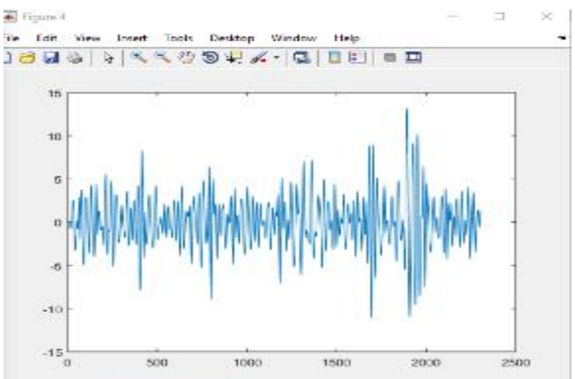


Fig. 6. Filtered EEG signal on Time vs. Amplitude curve

Feature Extraction:

For the SSVEP-based BCI system, a method to extract the valid frequency in a relatively short time is the core problem. As discussed previously, the SSVEP response has the same fundamental frequency as the stimulus. Therefore, methods to determine the power spectrum in the frequency domain can be employed to extract the meaningful EEG signal features. The power spectrum methods analyze the recorded EEG signals with the fast Fourier transform (FFT) algorithm of which the power for each frequency used in the BCI system is computed. In fact, Fourier transform is the most common method for examining the activity at different frequencies due to its low computational efforts, despite other feature extraction techniques such as wavelet transform (WT) being able to provide better time-frequency representation for the non-linear EEG signals. Zhang et al. had developed a CWT-based SSVEP classification method for the BCI system. Although the experiment results showed that the implementation of wavelet transform provided precise measurements of how the frequency content of an EEG waveform changes over time, the method is not often used as it required higher computational effort but is least necessary.

Signal Classification:

Threshold frequency:

In this work, the data classification is done by using threshold frequency, which is a relatively old classification technique developed by Vapnik and has shown to perform efficiently in several real-world problems, including BCI. Basically, SVM is a binary classifier that can separate two classes by using an optimal hyperplane which maximizes the separating margin between the two classes.

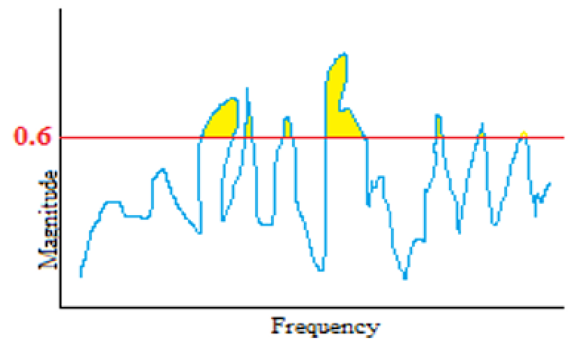


Fig. 7. Classification by setting the Threshold Frequency

In this context, after signal pre-processing and feature extraction of the raw EEG data obtained, we are using machine learning for signal classification and training of the model. There are different classifiers like Multilayer Perceptron (MLPNN), Support Vector Machines (SVM), K-Nearest Neighbors (KNN) etc., which can be used for signal classification.

Multi-layered Perceptron Neural Network (MLPNN):

Here we are implementing Multilayer Perceptron Neural Network (MLPNN) classifier. The architecture of MLPNN may contain two or more layers. A simple two-layer ANN consists only of an input layer containing the input variables to the problem and an output layer containing the solution of the problem. This type of network is a satisfactory approximator for linear problems. However, for approximating nonlinear systems, additional intermediate (hidden) processing layers are employed to handle the problem’s nonlinearity and complexity. Although it depends on the complexity of the function of the process being modelled, one hidden layer may be sufficient to map an arbitrary function to any degree of accuracy.

The determination of an appropriate number of hidden layers is one of the most critical tasks in neural network design. The most popular approach to finding the optimal number of hidden layers is by trial and error. In the present study, MLPNN consisted of one input layer, one hidden layer with 21 nodes and one output layer. Training algorithms are an integral part of ANN model development. A good training algorithm will shorten the training time while achieving better accuracy. Therefore, the training process is an important characteristic of the ANNs, whereby representative examples of the knowledge are iteratively presented to the network so that it can integrate this knowledge within its structure. There are a number of training algorithms used to train an MLPNN and a frequently used one is called the backpropagation training algorithm which is based on searching an error surface using gradient descent for points with minimum error, is relatively easy to implement.

In this method, we use lifting-based discrete wavelet transform (LBDWT) coefficients of EEG signals as an input to the classification system and obtain required discrete outputs. We provide faster wavelet decomposition in multi-channel EEG without any special hardware, by using LBDWT in a multi-channel EEG.

We can divide four-channel EEG recordings into sub-bands frequencies by using LBDWT. Since four-frequency band, which are alpha (D4), beta (D3), theta (D5) and delta (A5) is sufficient for the EEG signal processing, these wavelet sub-band frequencies (delta (1—4 Hz), theta (4—8 Hz), alpha (8—13 Hz), beta (13—30 Hz)) are applied to MLPNN input. Then we take the average of the four channels and give these wavelet coefficients (D3—D5 and A5) of EEG signals as an input to ANN. The MLPNN was designed with LBDWT coefficients (D3—D5 and A5) of EEG signal in the input layer; and the output layer consisted of one node representing whether the movement of the prosthetic arm was detected or not. A value of "0" is assigned when the experimental investigation indicates no hand movement and "1" for a movement in hand.

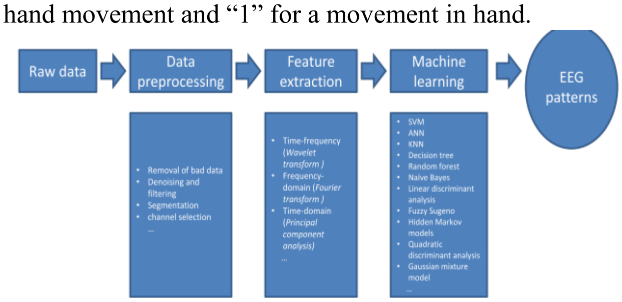


Fig. 8. Flow chart EEG pattern

4. Discussions

1. Signals are elicited and trained by Emotiv- EPOC device with greater accuracy.
2. Visual stimuli that give the best SSVEP response from MATLAB is developed.
3. The obtained raw data is pre-processed and Implementation of feature extraction and classification for real-time EEG signals is done.
4. Hardware interface between the host laptop and prosthetic arm is developed.
5. A prosthetic arm is developed by using EEG and real-time evaluation on the constructed system is performed.

Funding:

The overall cost excluding the EEG device is approximately 300 USD. This includes the prosthetic arm's 3D printing, components like battery, Arduino, Sensors and Servo motors. The Emotiv EPOC+ i.e., EEG device costs 1000 USD was provided for our research by our university. The cost of other EEG devices varies according to their specifications.

Overall System Performance: The final system provides relatively good performance and characteristics for a prototype 3D printed model. The device is fast and responsive to electroencephalography user input but offers limited strength. Over the course of testing the system has proven to be reliable and has required minimal maintenance since being assembled. The biggest downfall of this design is its lack of toughness. Certain regions such as the wrist are at a high risk of breaking if the device is subject to moderate forces. In the real world, a practical prosthetic arm must be able to absorb sudden shocks and support heavy loads without failing. The presented device provides a platform for future research by final year engineering students to develop and test advanced prosthetic designs such as sophisticated EEG control algorithms, integrated pressure feedback and other advanced bio-mechatronic concepts and designs.

5. Results

We aim to develop a real-time SSVEP-based BCI system for the command and control of prosthetic hands. For effective SSVEP response, which is dependent on colour and size of flickers and distance (form observer to the subject), the dominating one is colour. 3 different colours red, violet and black are used to check out the optimal colour which gave approximate frequency to the frequency of flickers.

Our objectives in this part work include:

- Development of visual stimuli that give the best SSVEP response by using high timing precision software such as Psychophysics Toolbox from MATLAB.
- Development and implementation of feature extraction and classification algorithms for real-time EEG signals processing and command recognition

Test conducted:

- Offline test- signals are taken, converted to .csv file then analyzed in MATLAB and transmitted to Arduino.

Analysis of Different Brain Signals:

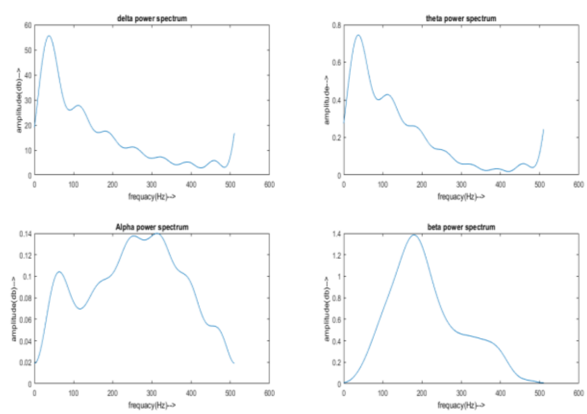


Fig. 9. Brain signals

Analysis of Different Alpha, Beta, Theta, Delta Signals in both Time and Frequency Domains

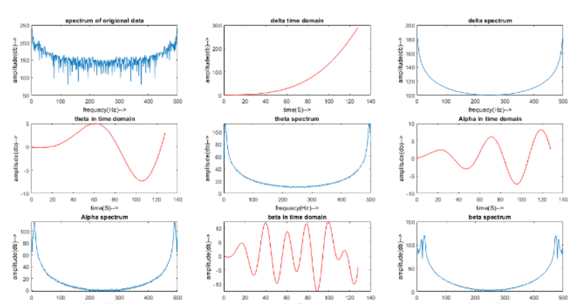


Fig. 10. Alpha, Beta, Theta, Delta Signals

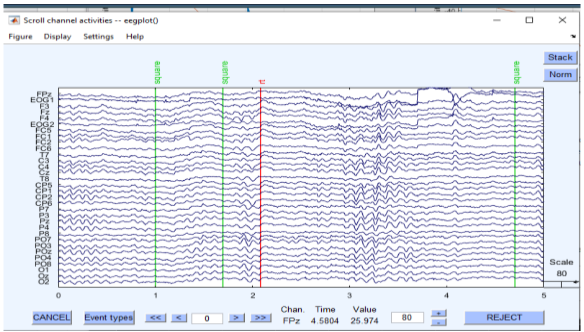


Fig. 11. Raw EEG Signals with 32 Channel in EEGLAB

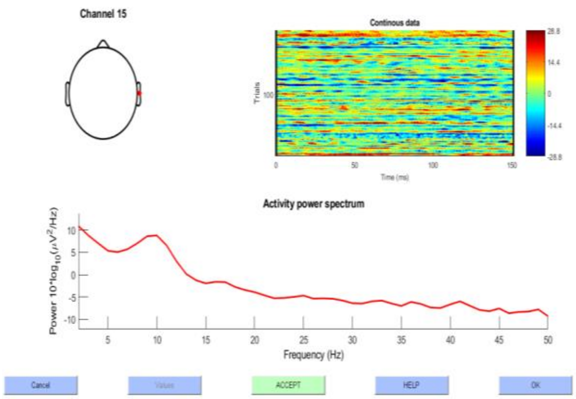
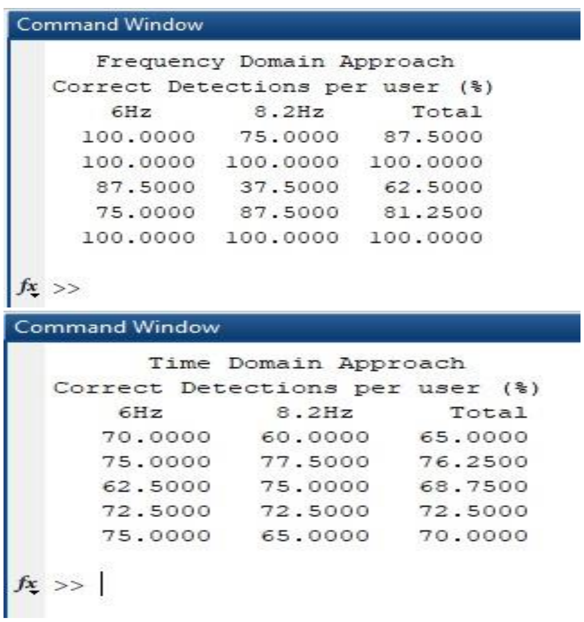


Fig. 12. Individual channel response


Command Window

Frequency Domain Approach

Correct Detections per user (%)

6Hz	8.2Hz	Total
100.0000	75.0000	87.5000
100.0000	100.0000	100.0000
87.5000	37.5000	62.5000
75.0000	87.5000	81.2500
100.0000	100.0000	100.0000

fx >>

Command Window

Time Domain Approach

Correct Detections per user (%)

6Hz	8.2Hz	Total
70.0000	60.0000	65.0000
75.0000	77.5000	76.2500
62.5000	75.0000	68.7500
72.5000	72.5000	72.5000
75.0000	65.0000	70.0000

fx >>

Fig. 13. MATLAB command window for time and frequency domain

6. Conclusion

The initial aim was to develop a low-cost 3D printed prosthetic arm. The goals and expectations for this paper have been achieved and it is hoped that the presented body of work allows for several new thesis topics to be researched in the future.

Benefits to an Amputee: At this stage, the presented prosthetic arm is not at a state where it can be used by an amputee – it is more so a low-cost bionic arm. With the design of a proper socket connection, the possibility exists for the University to arrange a collaboration with a medical institute to allow the device to be tested and used by amputees. Such testing would be invaluable in analyzing and improving the device's performance.

The paper discussed the development and tested advanced prosthetic designs such as sophisticated EEG control algorithms, integrated pressure feedback and other advanced bio-mechatronic concepts and designs. With the future growth of the 3D printing industry advanced printers and materials will allow students to develop more 'commercial-like prosthetic devices – robust and durable systems that could benefit a wide range of people with a missing limb. With ongoing research, improvements will hopefully lead to a system that is more durable and offers improved dexterity and control. Perhaps a future design will someday benefit amputees and improve the quality of people's lives.

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