Fabrication of Cost-Effective Prosthetic Arm Using Electroencephalography Signal

Shihab Ahmed, Animesh Mitra, Sumon Saha and Md. Afsar Ali
Department of Mechanical Engineering
Bangladesh University of Engineering and Technology (BUET)
Dhaka, Bangladesh
arup2196@gmail.com, mitranimesh13@gmail.com, sumonsaha@me.buet.ac.bd,
mdafsarali@me.buet.ac.bd

Arnab Bhattacharjee
Department of Electrical and Electronics Engineering
Bangladesh University of Engineering and Technology (BUET)
Dhaka, Bangladesh
arnabeee10@eee.buet.ac.bd

Abstract

This paper entirely focuses on actuating prosthetic arm using EEG (Electroencephalogram) signal. EEG records the electrical activity of brain in micro-volts. Analyzing these electrical activities, it is possible to predict the generic movement of limbs. Brain-computer interface (BCI), which is a collaboration between a brain and a device, enables signals from the brain to direct some external activity through the actuation of a prosthetic arm in this research. Moreover, the current study attempts modeling a cheaper prosthetic arm and analyzing the accuracy of the arm's movement.

Keywords
Bionic arm, Prosthetic arm, Brain-Computer-Interface, EEG controlled arm and Electroencephalography.

1. Introduction
It has not been long that design of prosthetic limbs has rapidly grown. Earlier prosthetic limbs were simple passive prosthetic devices made of wood or such materials. With the advancement of time, different mechanical systems such as pulleys, metal hooks, etc., have started to incorporate with the prosthetic limbs. These passive prosthetic limbs have no control systems. Now, researchers have started to focus on incorporating control and feedback systems with prosthetic limbs. Recent technological advancement confirms that electronic signals and activities of the brain, one of the most complex and fascinating elements of this world, can be read and understood.

The work of this paper is based on the usage of the electronic activity of the brain to actuate a 3D printed prosthetic arm. EEG is an electrophysiological monitoring method to record electrical activity of the brain. It is typically non-invasive with the electrodes placed along the scalp, although invasive electrodes are sometimes used such as in electrocorticography. EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain (Farnsworth 2017).

There are also other techniques such as Magnetic Resonance Imaging (MRI), Magnetencephalography (MEG), Positron Emission Tomography (PET), etc. The present work is to support people, who are an amputee. In such context, one has to carry a brain imaging device. Therefore, the device must be a small, portable, light-weighted device that must have a high time resolution. Only EEG meets all these requirements.

After acquiring EEG data from the sensor, different features can be extracted for the supervised machine learning. Feature extraction is a significant method to extract useful information from the EEG signal and to remove any unwanted part and interferences. In machine learning and pattern recognition, a feature is an individual measurable property or characteristics of a phenomenon being observed (Bishop 2006). The selection of features and performance of the classifier is completely dependent on the purpose of BCI system and different noises that might have attributed to EEG signal (Lotte et al. 2018).

A great variety of features have been attempted to design BCI such as amplitude values of EEG signals, band powers (BP), power spectral density (PSD) values, autoregressive (AR) and adaptive autoregressive (AAR) parameters, time frequency features and inverse model-based features (Lotte et al. 2017). To be successful in classification (a type of supervised machine learning), three main cascaded modules should be carefully considered that consist of data pre-processing, feature extraction and classification methods, particularly selection of an optimal feature vector (Boostani and Mooradi 2003) .
In this research, the features that were extracted from EEG signal are: mean, mode, median, skewness, entropy, logarithm of variance, logarithm of range, kurtosis and modified absolute mean. After extracting different features, quadratic support vector machine (SVM), cubic SVM, bagged ensemble and subspace k-nearest neighbors (kNN) ensemble classifiers are used to prepare the trained model and to test their accuracies with the same features for new EEG signals.

Using the model and prosthetic arm, a brain computer interface is developed. A brain–computer interface is a communication system that does not require any peripheral muscular activity (Sabra and Wahed 2011). Indeed, BCI systems enable a subject to send commands to an electronic device only by means of brain activity. Such interfaces can be considered as being the only way of communication for people affected by a number of motor disabilities (Lotte et al. 2007).

1.1 Objectives

The specific objectives of the present research work are as follows:

(i) To design and develop a 3D printed prosthetic arm.
(ii) To use EEG signal for controlling the movement of the prosthetic arm.
(iii) To analysis the accuracies of the movement of the prosthetic arm for different classifier algorithms.

2. Literature Review

Day by day, civilization is approaching an advanced trans-human integration between computer, machine and body. Several researchers have paved ways to understand EEG signals and to utilize that signal to control machines. Some of those research are mentioned below:

- In 2007, a group of neurologists surveyed classification algorithms to design effective BCI systems. The results obtained were compared in BCI context and the team concluded that Support Vector Machines (SVM), a relatively simpler classifier, was best suit to BCI. They also concluded that the selection of features and the performance of the classifier were completely dependent on the purpose of BCI system and different noises that might have attributed to EEG signal (Lotte et al. 2007).
- Two monkeys were implanted with intracortical and microelectrode arrays in their primary motor cortices by a research team of the University of Pittsburgh, Pennsylvania (Velliste et al. 2008). Each monkey used signals to control a robotic arm to feed themselves. The monkeys could grab and feed themselves with about 61% and 78% success rate respectively.
- McFarland and Wolpaw (2011) studied accuracy of BCI on different patients and found that the accuracy increased with every session.
- Esfahani and Sundararajan (2012) explored the potential of BCIs as user interfaces to distinguish between primitive shapes that were imagined by a user, where users weared an electroencephalogram (EEG) headset and imagined the shape of a cube, sphere, cylinder, pyramid or a cone and result showed with an average accuracy of 44.6%.
- Meng et al. (2016) studied on 13 healthy humans for non-invasive EEG based control of robotic arm to grasp objects and demonstrated that subjects were able to control a robotic arm to reach and grasp and move objects located in a constrained 3D space. The time scale of completing these intricate tasks was 20-60 seconds with the exact duration depending on the complexity of the task and the performance of the subject.
- As investigated by McGimpsey et al. (2017) from the Bioengineering Institute Center for Neuroprosthetics at the Worcester Polytechnic Institute, the cost of a prosthetic arm varied by the type of arm and the level of

amputation. For example, a cosmetic arm and hand might cost $3,000-$5,000. A functional prosthetic arm with a "split hook" at the end might cost $10,000. A myoelectric prosthetic arm with a realistic-looking, functioning hand might cost $20,000- $30,000 or more.

- Gao et al. (2017) suggested a hybrid BCI system combining Electromyograph signal for controlling a robotic arm for writing task and achieved an accuracy of about 73%.
- Xu et al. (2018) studied shared control of a robotic arm using non-invasive brain–computer interface and computer vision guidance on five healthy people and achieved a success of 70% even with no specific user training.
- Hassan et al. (2020) focused on using Electromyograph signals to actuate prosthetic arm. In their research, they tested on six subjects and used linear SVM method of classification to obtain an accuracy of about 89.82%.
- Fatima et al. (2020) studied on 15 patients and concluded that the mean response time to execute 3-D reach and grasp task by the robotic-assisted limb was relatively longer (46.8 +/−101.5 s) compared to the neuro-muscular stimulated orthotics (15.8 +/−15.2 s).

3. Overview of Experimental Setup

In this experiment, EEG data are collected using OpenBCI Ganglion board. OpenBCI ganglion is a high quality, affordable, bio sensing device. The data are sampled at 200 Hz. It sends data to computer using bluetooth technology. The device uses a Simblee as on-board micro-controller. The micro-controller has a 24 bit ADC. The board can be powered with 3.3 to 12 V DC battery and draws 14 mA current when idle and 15 mA current when it streams data.

The prosthetic arm is designed using SolidWorks software. The arm is manufactured using 3D printing technology. The material used is ABS plastic. The arm has six degree of freedom. The fingers can be moved independently and the wrist can be rotated. Each of these actuations is done using servo motors. The arm is designed in a manner to house all the servo motors in the forearm. Each finger is connected to servo motor via nylon wire. This nylon wire acts as tendon and helps to bend or relax the fingers on rotation of servo motor. To attach the nylon wires to the servo motors, customized horns are designed. The servo motors used in this arm has a torque of 14 kg_f-cm, when operated at 5V. Different components of the experimental setup are shown in figure 1.

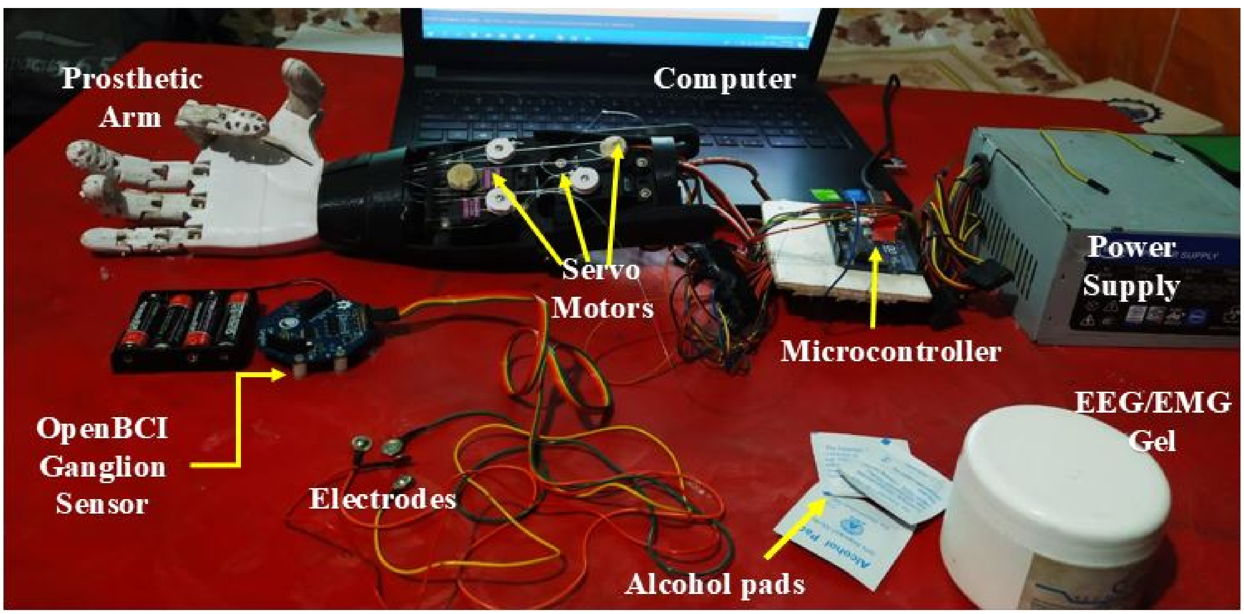


Figure 1. Photograph of different components of the prosthetic arm.

The OpenBCI sensor takes input from the user and sends it to the GUI. Outputs from the GUI are raw EEG data which are processed using the MATLAB software. Then the microcontroller generates a command signal utilizing these processed data. Finally, the prosthetic arm moves according to the command. The functional block diagram of the entire experimental setup is given in figure 2.

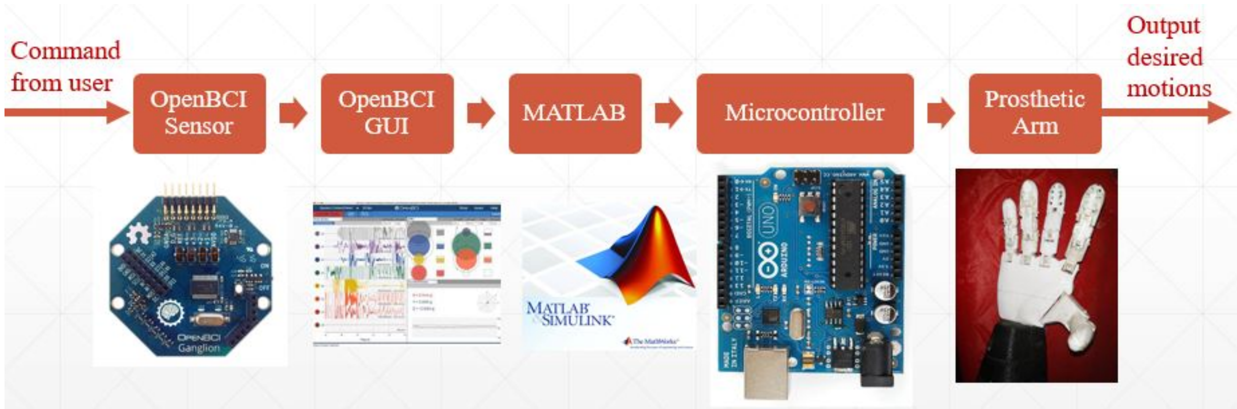


Figure 2. Functional block diagram for the operation of the prosthetic arm.

Servo motors are connected to the output pins of Arduino microcontroller. The circuit diagram shown in figure 3 illustrates the connection between the servo motors and the Arduino.

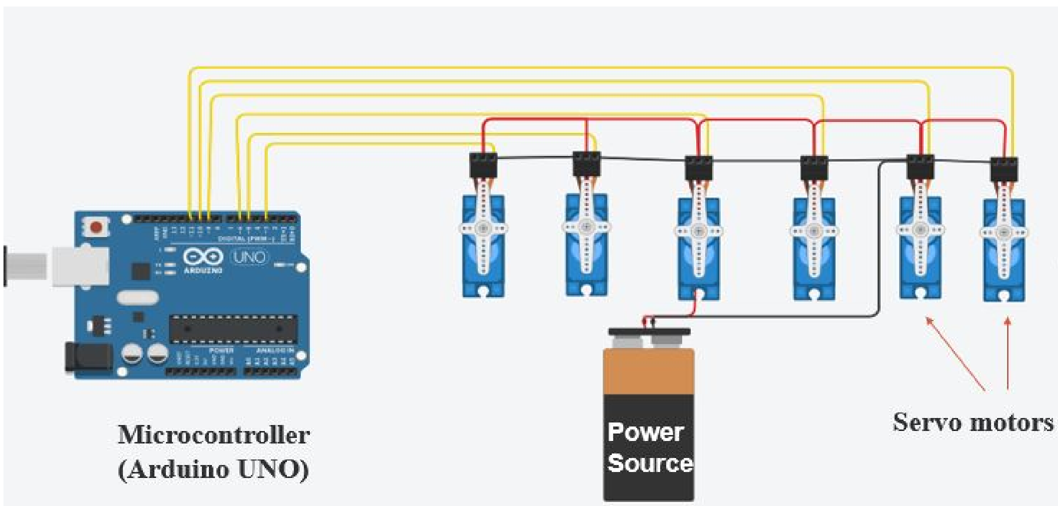


Figure 3. Circuit diagram for controlling the servo motors of the prosthetic arm.

Six gold cup electrodes are connected to the pins +1, +2, +3, +4, REF and D_G (Driven Ground). Pins +1, +2, +3 and +4 are input pins. These pins are connected to all those electrodes that will bring EEG signal to the ganglion board. The pin D_G allows ganglion to share 0V or ground with the body. Electrodes attached to this pin are used on one of the ears. The REF pin creates a reference and all the signals will be measured against this REF electrode. The REF electrode is used on the other ear.

To collect EEG data, the input electrodes are placed following the 10-20 system of placing electrodes. The electrodes are placed on Fp1(channel 1), Fp2 (channel2), C3 (channel 3) and C4 (channel 4). After placing all the electrodes, some bandages are used to hold them tightly. During the first experiment, some marks are created on the location where the electrodes are placed, so that during every future observation, electrodes are placed on the exact same location. Figure 4 shows the electrode placement on the head.

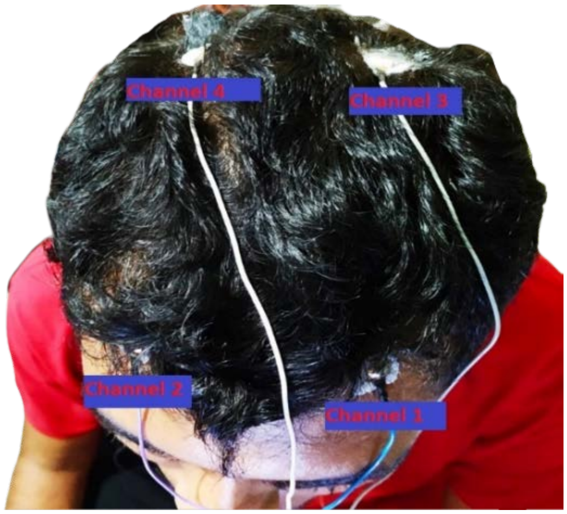


Figure 4. Electrode placement on the subject's heard for EEG.

In this experiment, data is acquired and processed through OpenBCI GUI. It is a default application software that stores data from any OpenBCI hardware. The data processing, feature extraction and classification are done using MATLAB software. “Classification learner”, a built-in MATLAB app is used to prepare the trained models for various classifiers used during this experiment.

4. Data Collection and Processing

While taking data the user is commanded to fist grip, pen grip and to relax the arm. The user has to perform these commands for 10 seconds at a stress. In this way at first, 50 data each of 10 seconds are taken for the three classes namely - fist grip, pen grip and arm relax, and initial machine learning is done using these data. Later, to increase the accuracy of the trained model, another 50 data of 10 seconds are taken for all these three classes. After acquiring the EEG raw data from OpenBCI ganglion board, it is normalized to achieve usable time domain data in the manner shown in figure 5

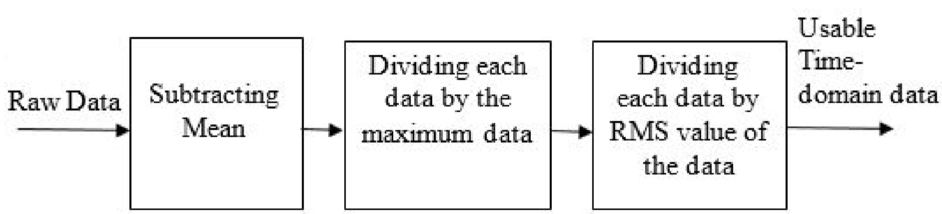


Figure 5. Normalization of the signal

Subtracting mean eliminates the dc data. Dividing by the maximum data gives amplitude normalization of the signals and dividing by the RMS value gives energy normalization. After acquiring time-domain data they are decomposed into frequency domain using fast Fourier transformation (FFT). The data is then divided into five bands namely, alpha, beta, delta, theta and sigma according to their respective frequency ranges. After the data is pre-processed, features described previously are extracted and the signal is made ready for classifiers. In this experiment, different types of SVM and ensemble classifications are used to prepare the trained model. During the preparation of the model, five folds data are used for cross validation.

5. Results and Discussion

5.1 Accuracies of different trained model

The accuracy for the models using these classifiers for EEG data is listed in table 1.

Table1**.** Accuracies of different trained model for EEG data.

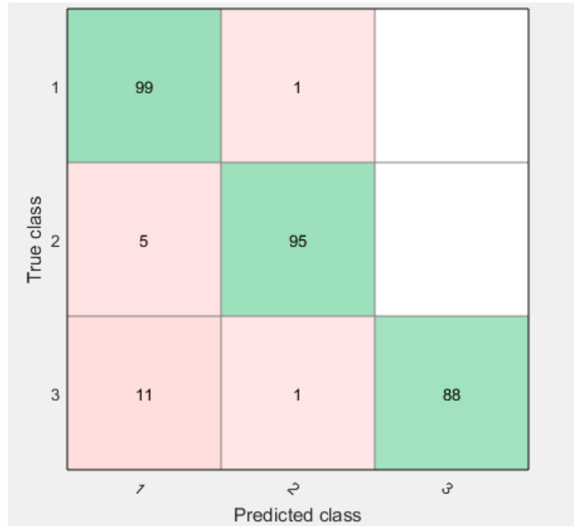
Name of the Classifier	**Sub division of the classifier**	**Accuracy (%)**
SVM	Linear SVM	87.3
	Quadratic SVM	94.0
	Cubic SVM	93.7
	Fine Gaussian SVM	63.5
	Medium Gaussian SVM	92.0
	Coarse Gaussian SVM	82.4
Ensemble	Boosted Tree	92.0
	Bagged Tree	96.0
	Subspace Discriminant	94.0
	Subspace KNN	89.7
	RUSBoosted Trees	91.0

Accuracies of these four classifiers can be shown in confusion matrices. Confusion matrix allows one to understand how many mistakes a certain classifier did in predicting the datasets. It is a n×n matrix, where n is the number of classes that are predicted. Confusion matrices for bagged ensemble, subspace KNN ensemble, cubic SVM and quadratic SVM are given in figures 6(a)-(d), respectively.

(a)

(b)

(c)



(d)

Figure 6. Confusion Matrix for (a) Bagged Ensemble, (b) Subspace KNN Ensemble, (c) Cubic SVM, (d) Quadratic SVM.

Once the trained models are prepared, new EEG signals are used to test the accuracy of the trained model.

5.2 Performance Analysis of the Prosthetic Arm

Test data are taken from a user by means of EEG sensor. Figure 7 illustrates the results for predicting different movements of the arm i.e. grip and arm relaxation of the user by using different models (quadratic and cubic SVM, bagged and subspace kNN ensemble) that are made previously.

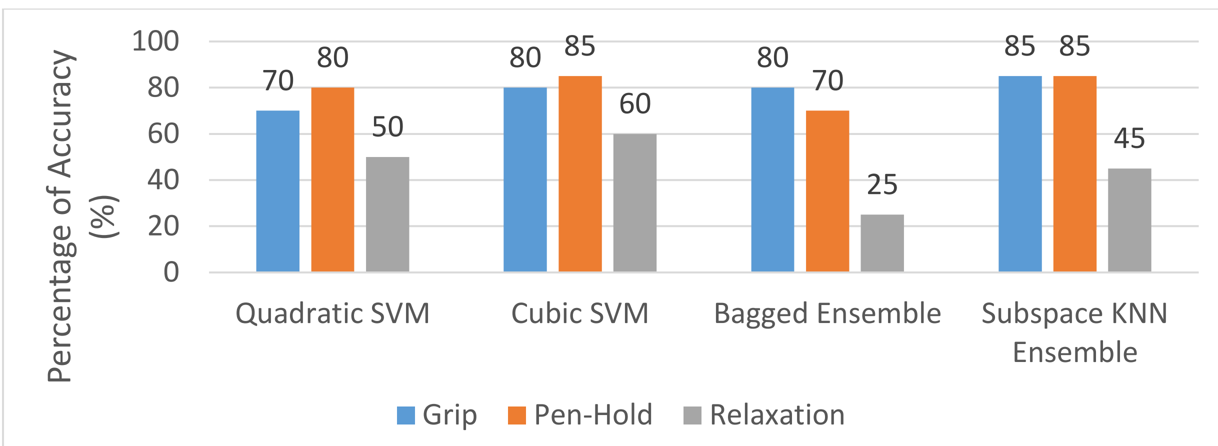


Figure 7. Accuracy for predicting the motion of arm using EEG data

The prosthetic arm developed here is cheap and light as it is 3D printed with ABS plastic. The battery used in this prototype is a 3 cell Li-Po battery of 1200 mAh. It is seen that the arm runs for about 1.5 hours to 2 hours.

5.3 Cost Analysis

The prosthetic arm presented in this work costs a total of around BDT **57,700** (approximately US$700) and the breakup cost analysis is shown in table 2.

Table 2. Cost of different components used in this prosthetic arm.

Components	Price (BDT)
3D printing of prosthetic arm	6,000.00
6 x Servo Motors	12,000.00
OpenBCI Ganglion board with electrodes and conductive gel	32,700.00
Electronics (Arduino, Battery, Buck Module, Wires, PCB, etc.)	6000.00
Miscellaneous (Nylon wire, bolts, etc.)	1000.00
Total Cost	**57,700.00 (approx. US$700)**

5.4 Discussion

Noises, which can be identified in FFT (Fast Fourier Transformation) plot, may affect the result significantly. There are several noises, among them electric line noise affects the FFT plot most significantly and conspicuously. Devices connected to the AC outlet (frequency 50 Hz) near the EEG sensor produce a conspicuous peak in FFT plot. It is shown in figure 8.

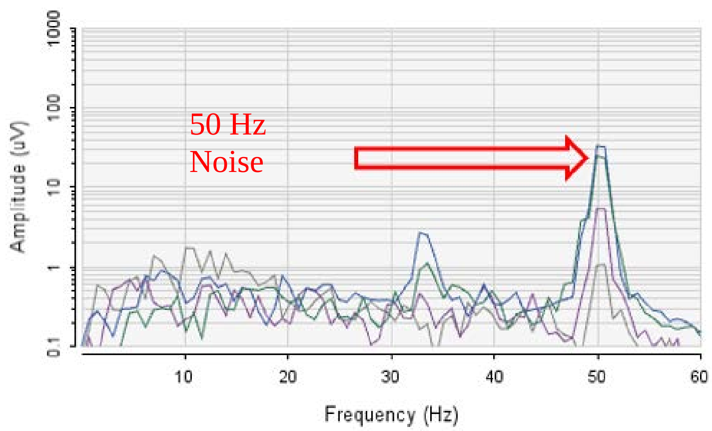


Figure 8. FFT graph showing noise for 50 Hz electrical line during data acquisition.

Also, while taking reading, if the user blinked eye or moved his eyes, data variations are seen. Thus, to prepare the trained model, while taking reading, user is asked to blink or move eyes as little as possible. Noise due to eye blink is shown in figure 9.

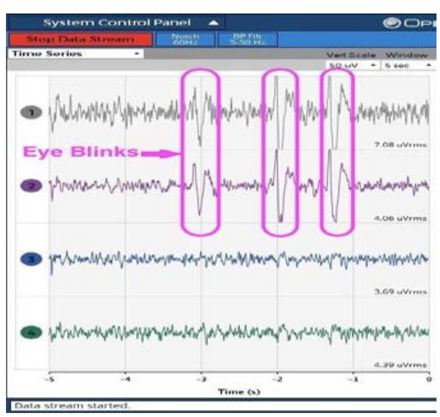


Figure 9. Noise for eye blinks

6. Conclusion

In this study, four types of different classifier algorithms have been used to train a model. This trained model is used to predict the new test data set whether it is for fist grip, pen-hold grip or arm relaxation. This prediction is finally used for controlling the prosthetic arm. However, this research has some limitations. In data acquisition, only four electrodes are used. To acquire better accuracy, more electrodes are required which the Ganglion board does not offer. The system is not fully portable yet. Single board computer like Raspberry Pi can be used to provide portability.

The arm designed gave the privilege to actuate the fingers and rotate the wrist independently. In future, one can plan to control the spacing in between the fingers, which would allow better grip control. Also, to have a better control of the prosthetic arm, it is necessary to combine the EMG and EEG signal, which may eradicate a lot of signal noises. The prosthetic arm prototype is not of high enough quality. The arm is not rigid enough and thus structure and rigidity are to be increased with improved designing and better use of materials. In this experiment, ABS plastic is used for 3D printing. Nylon can be used for 3D printing as well and offers significantly more strength than ABS. Reviews from 3D printing specialists show clear advantages in strength for Nylon over ABS (Taulman, 2019). However, the nylon filament costs about four times more than ABS filament.

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Biographies

Shihab Ahmed received his B.Sc. in Mechanical Engineering from Bangladesh University of Engineering and Technology (BUET) on 2018. His research interest involves micro-electro-mechanical system (MEMS), biomedical engineering and Mechatronics. He has already published one research paper on this topic in an international conference proceedings.

Animesh Mitra received his B.Sc. in Mechanical Engineering from Bangladesh University of Engineering and Technology (BUET) on 2018. His research interest involves micro-electro-mechanical system (MEMS), biomedical engineering and Mechatronics. He has already published one research paper on this topic in an international conference proceedings.

Dr. Sumon Saha received his PhD in Engineering from the University of Melbourne, Victoria, Australia in 2014. He completed his B.Sc. and M.Sc. in Mechanical Engineering from Bangladesh University of Engineering and Technology (BUET), Dhaka, Bangladesh on 2004 and 2007, respectively. His major field of study is numerical analysis on problems of thermo-fluid. He is now working as an Associate Professor in the Department of Mechanical Engineering of Bangladesh University of Engineering and Technology (BUET). He already published more than 130 research papers in International Journals and Conference Proceedings and coauthor of two books in engineering field. His fields of interests are turbulent flows, computational fluid mechanics, computational heat transfer and thermal postbuckling analysis. Dr. Saha is the editor of one international journal and reviewers of several international conference proceedings and international journals. He is currently senior member of International Association of Computer Science and Information Technology (IACSIT), Singapore. Moreover, he is a life member of Bangladesh Solar Energy Society. He has received many professional awards like International Postgraduate Research Scholarship by the Australian federal government; Melbourne International Research Scholarship by the University of Melbourne; RHD Studentship by University of Melbourne, and so on.

Dr. Md. Afsar Ali received his M. Sc. in Mechanical Engineering and Ph.D. in Engineering from Tohoku University, Japan in 1997 and 2000, respectively. He completed his B.Sc. in Mechanical Engineering from Bangladesh University of Engineering and Technology (BUET), Dhaka, Bangladesh in 1992. His major research interests are numerical simulation, fracture mechanics, composite materials, and functionally graded materials. He is now working as a full-time Professor in the Department of Mechanical Engineering of Bangladesh University of Engineering and Technology. He so far published more than 100 research papers in International Journals and International and Domestic Conference Proceedings. Dr. Afsar was awarded the Japanese Monbusho scholarship for his postgraduate studies, Post-Doctoral Fellowship by the Brain Korea 21 (BK 21) Project Corps at Changwon National University for the period of 1 March 2008 to 28 February 2010, Korean Research Fund (KRF) for a short-term collaborative research, and Commonwealth scholarship for Post-Doctoral research.

Arnab Bhattacharjee is currently working as an Assistant Professor at the Department of Electrical and Electronic Engineering (EEE), Bangladesh University of Engineering and Technology (BUET). He obtained his M.Sc and B.Sc in EEE from the same institution in September, 2018 and March, 2016, respectively. His research interest lies in Biomedical Signal Processing, Image Processing and Deep learning. He received Best Paper Award in IEEE WIECON 2017.