EMG Control of a 3D Printed Myo Electric Prosthetic Hand

Umer Farooq
Department of Mechatronics Engineering
Air University
Islamabad, Pakistan
maill2Umer@gmail.com

Usman Ghani
Department of Mechatronics Engineering
Air University
Islamabad, Pakistan
mugbaks@gmail.com

Syed Ali Usama
Department of Mechatronics Engineering
Air University
Islamabad, Pakistan
140609@students.au.edu.pk

Neelum Yousaf Sattar
Department of Mechatronics Engineering
Air University
Islamabad, Pakistan
line 5: neelumyousafsattar@gmail.com

Abstract— **Recent technological advances have enabled the prosthetic developers to derive an ideal replacement for the human arm in near future. This research presents design of a 3D Printed Myo Electric Prosthetic Hand that grasp symmetrical objects through Electromyographic signals and is intended for people suffering from Transradial Amputation. In the current study, a set of data about three motions that include hand open, close and rest position was been acquired from forearm muscles of a human arm. CAD model of the prosthetic hand was developed in SolidWorks® which was later 3D printed using Poly Lactic Acid (PLA).The proposed design was based closely on tendon actuation, related to human hand functionality. Signal acquisition and processing has been done using Myo Armband. Different features were selected such that they can be passed through classification process in order to control the hand motions. Using the Bluetooth transmitter, the filtered data was sent and saved in Arduino Uno® controller. Later, the Support Vector Machine (SVM) was been evaluated as a classifier. The classification accuracy obtained from SVM was 96.7%. The results were found significant (p<0.01) for twelve able bodied subjects. EMG based grasp control was implemented with successful testing of designed prosthetic hand for three different motions. The functional utility of the Myoelectric Hand was demonstrated by grasping household objects such battery charger, wallet and water bottle.**

Keywords—Transradial Amputation, 3D printed, Myo Electric, EMG, MYO Arm Band, LDA, SVM

I. Introduction

During the previous decade, great efforts has been done to improve the human machine interfaces (HMI) and make them more intuitive. In order to accomplish a HMI, an accurate body signal interpretation is required. Nowadays, the most advanced commercial externally powered transradial prosthesis is the myoelectric prosthesis [1]. The skin surface electromyogram (EMG) signals of amputee's stump or residual muscles are to be used as the input signal to control the myoelectric prosthesis [1-3]. Numerous researches have revealed that electromyographic signals (EMG) are one the most feasible option for this application, as it provides very accurate information regarding limb motions [4][1]. The use of electromyographic signals has been spread out by the medicine field, implementing it on prosthetic devices for amputee[5], for patients who have suffered from limb paralysis[6], . In [8] the signals of an Inertial Measurement Unit (IMU) worn at the wrist, and the Electromyogram (EMG) of muscles in the forearm were fused to infer hand and finger movements. A set of 12 gestures were defined,Hidden Markov Models (HMMs) were used as classifiers to discriminate between the defined gesture classes. They achieved a recognition rate of 97.8% in session-independent, and of 74.3% in person-independent recognition

In the near future, machines are supposed to be making decisions in any arbitrary environment. They will be able to think and act like humans, which is out of practice in today's human. Development in research sector has been evolved and new trails are emerging. One of them is Machine-learning technique. Under such a topic comes a bunch of ideas that can be implemented on a machine so that it can learn and behave better than it was in the past[9].

In order to distinguish the data from any daily life problem, classifiers are used. Classifiers cannot work standing alone. There is a need to feed right data into right classifier. Typically, a classifier with several parameters is flexible, but there are also exceptions. Feature selection followed by extraction plays a vital role in performance of any classification technique. For less number of classes, Support Vector Machine (SVM) is preferred in general practice. A classifier that minimizes the sum of training error and a term that is a function of the flexibility of the classifier is thought to be a good classifier. SVM offers relatively easy training. Unlike neural networks, there is no local optimal present. Dimension scaling is carried out significantly; such that it gives better results, .One can easily control classifier complexity.

Raw data like can be used as input to SVM, instead of feature vectors.

Virtual environments, as Solidworks® provides tools so that a there is no need to manufacture a physical device rather than the feasibility of any design can be tested and implemented, virtually off course.[10] The computer-aided models are been designed in such environment to check how a device would work in reality.

Therefore, this paper proposes design and EMG based grasp control of transradial prosthetic device. Next section of the paper proposes the design and the mechanism of the transradial prosthetic arm. In section II, EMG Signal Acquisition and processing is presented. In section III, classification results and hardware results are discussed. The final section presents the conclusion

I COMPUTER AIDED DESIGN AND TORQUE CALCULATIONS

A. *Computer Aided Design*

The proposed model of the prosthetic hand was designed using Solidworks. In the proposed design, all fingers have revolute joints and works on the principle of Joint Coupling Mechanism. This mechanism helps to achieve synchronized motion of fingers through lesser number of actuator/ . The proposed design is represented in Figure 1.

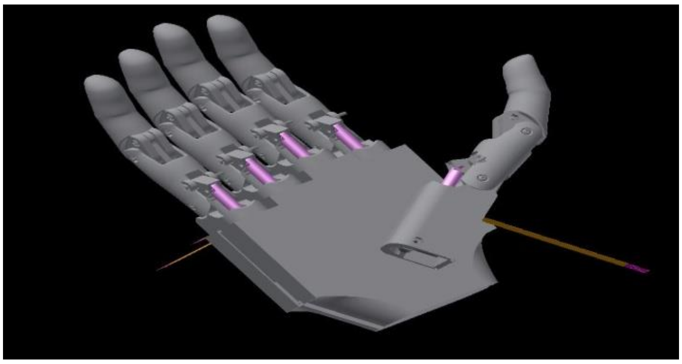


Fig. 1. CAD Model of Myoelectric Hand

B. *Design Calculations*

The proposed calculations in this section are valid for symmetric objects frequently used in daily life . To find the mathematical relations, it has been supposed that

If 'x' is the mass of the object then;

$$\text{weight} = x \times g \quad (1)$$

Where,

$$\mu = 0.87, \quad g = 9.81\frac{m}{s^2}$$

$$Y = \frac{weight}{\mu} \quad (2)$$

Where,

μ= Coefficient of rubber.

Y= Force required for one finger.

For two points of contact,

$$Z = \frac{Y}{2}$$

Sr. No.	Mass 'm' (Kg)	Required Force 'F' (N)	Force at contact point 'Y' (N)	Torque 'τ' (Nm)
1	0.7	7.8	1.57	0.2041
2	0.5	5.63	1.12	0.1456
3	0.3	3.38	0.67	0.0871
4	0.2	2.25	0.45	0.0585

TABLE I

Force Required For Different Weights

II. SIGNAL ACQUISTION AND PROCESSING

Electromyography is a technique to evaluate and record the electrical activity produced by skeletal muscles. Thalamic Labs product MYO Arm Band has been used to acquire EMG signals. It is an application based device which is capable of receiving surface EMG data at about 200Hz.[11] It consists of 9 axes inertial IMU which contains a gyroscope, accelerometer and magnetometer which are of three axes each respectively as illustrated in figure 2.[5]

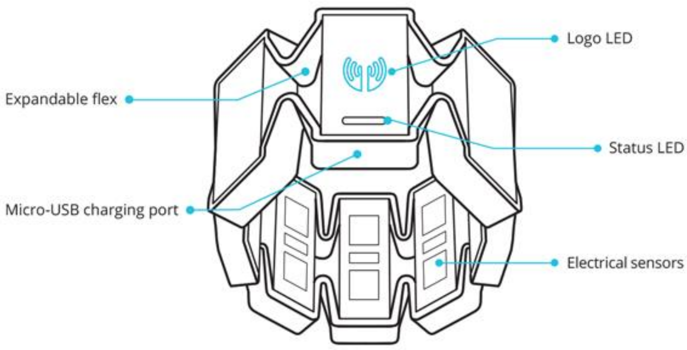


Fig. 2. Myo Armband

Flow diagram of the proposed system is shown in Fig.3

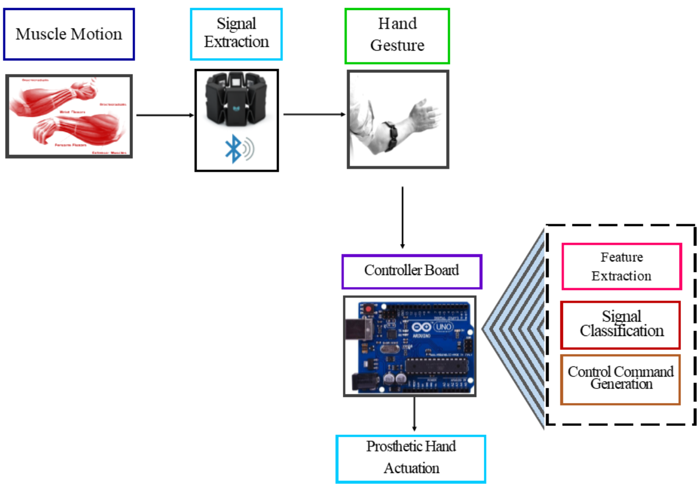


Fig.1. Flow Diagram

According to [9], Myo provides two types of data for an application: spatial and gestural data. The spacial data notifies about the orientation and movement of subject's arm. [12]Whereas, the gestural data represents the subject hand motion. The EMG signals were acquired through MYO Capture and then were used to extract features from the signals.

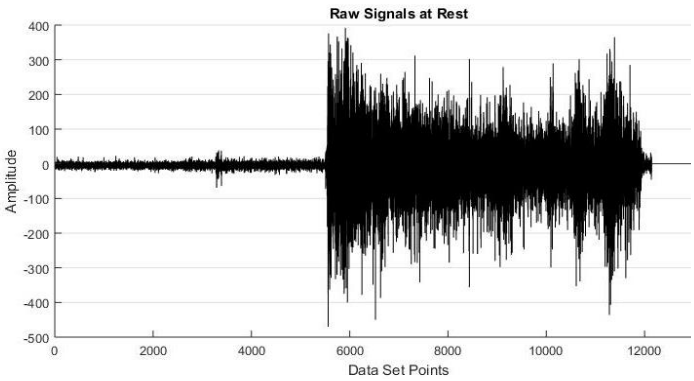
Ten participants, 6 males and 4 females (age: 20 ±6) were recruited for the data collection. All the participants were able- bodied, right-handed, and reported to be 100% functional with their working hands. The average wrist and forearm sizes of the 12 participants were 16.3 ±1.1 cm and 24.2 ±1.4 cm respectively. The experimental model is shown in Table 2

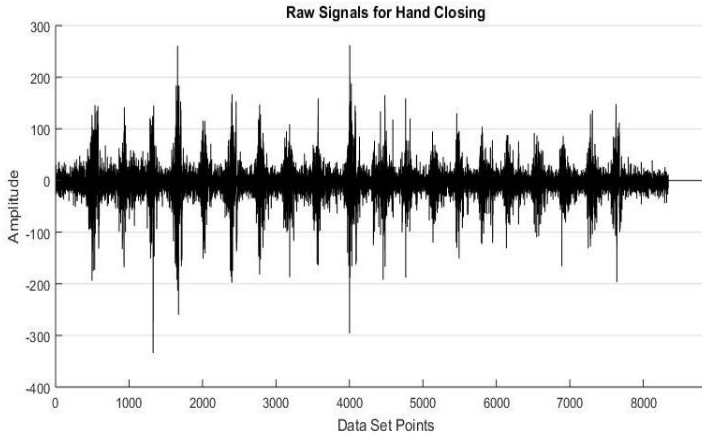
Table 2Experimental Model

Total Subjects (9 males & 3 females)	**12**
Initial Rest Time	**30 sec**
No. of trials (per subject)	**5**
Resting Time	**3 min.**
Time for signal extraction	**35 sec**

A. *Signal Investigation*

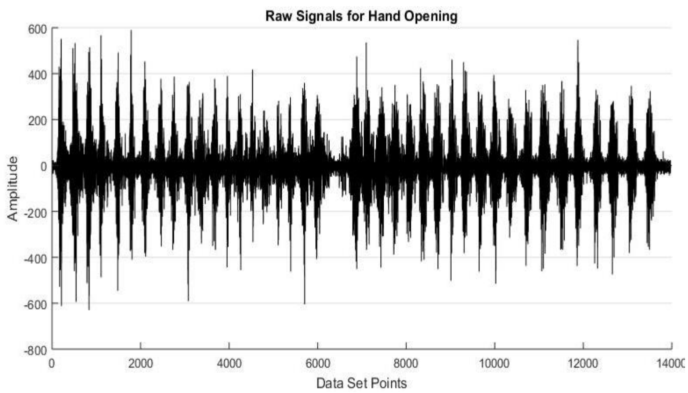
The extracted signals were analyzed for further processing in MATLAB®. Figure 4 symbolizes raw EMG signals extracted from able bodied individuals. It also represents electrodes activity upon forearm muscle action.





(a)

(b)

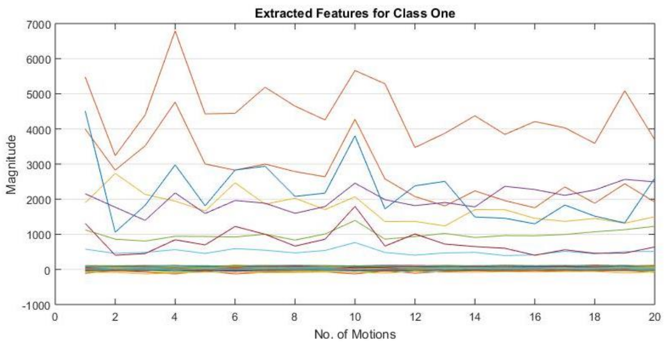


(c)

Fig. 4. Raw Electromyographic signals of an able bodied individual for a) Hand close b) Hand open and c) rest position

B. *Feature Selection*

Feature extraction measure feature or properties from input data, and thus is essential in pattern recognition system design. Feature extraction is carried out on the EMG signals to reduce the data dimensionality while preserving the signal patterns which help to differentiate between the gesture classes. Goal of feature extraction is to characterize an object to be recognized by measurements whose values are very similar for objects in same category, and very different for objects in different categories.[13]The extracted features included Mean, Absolute Value, Variance, Waveform Length, Kurtosis and Peak among which only peaks & mean length showed the best behavior. Figure 5 is representing features extracted for three different classes and no of peaks detected for each motion. The obtained peaks and mean were used for classification process.



(a)
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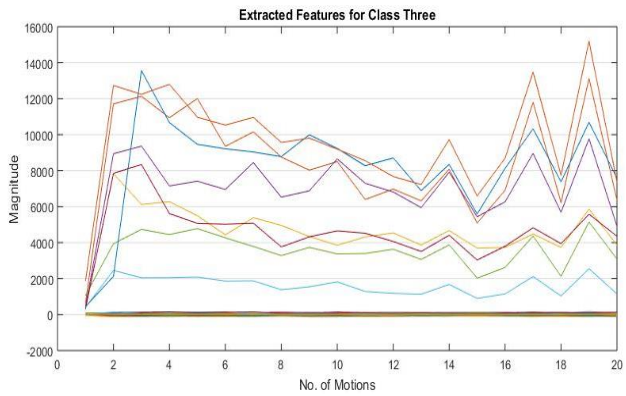
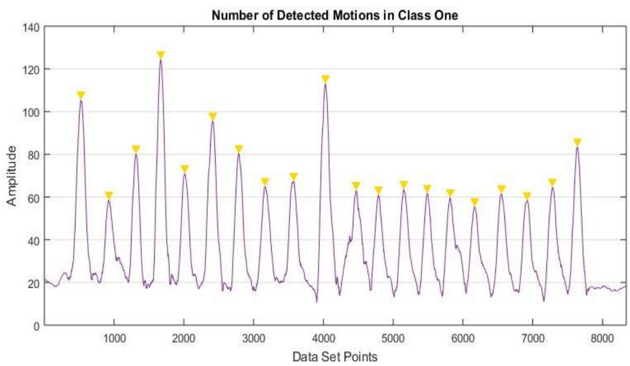
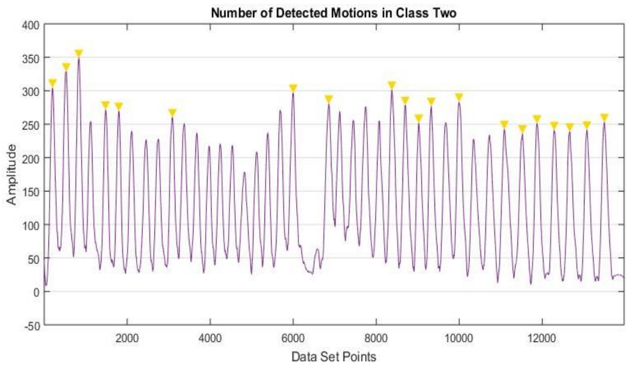


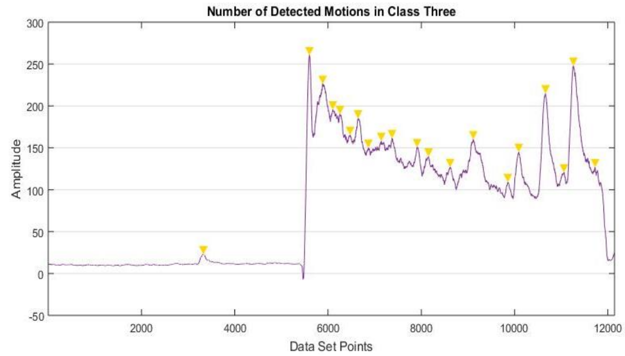
(c)



(d)



(e)



(f)

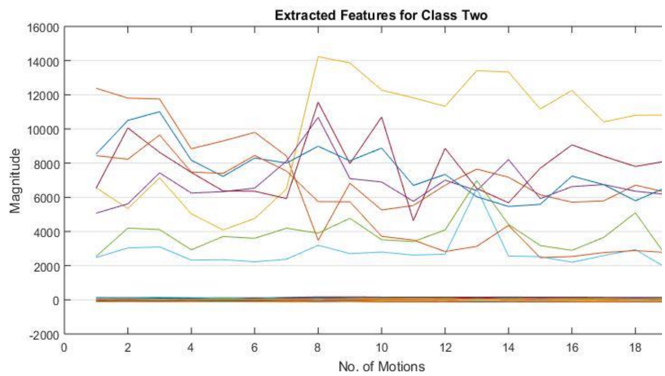
Fig. 5 Extracted features for a) one class b) two classes c) three classes d) Turning Points or Detected Peaks Showing the Frequency as the Motion is Performed for class one e) two classes f) three classes

C. *Support Vector Machine (SVM)*

Support Vector Machine (SVM) is a easy understanding classifier. A classifier offers linear algorithms in the output or the feature capacity that they are equivalent to a non-linear algorithm as compared to the input. Standard linear algorithms, generally characterized to their non-linear form by analyzing its feature space. SVM is a useful alternative to neural networks. The concept of this classifier is that support vectors are the samples closest to the separating the raw data or featured data. They are the most difficult patterns to classify.[14]

For less number of classes, Support Vector Machine (SVM) is preferred in general practice. A classifier that minimizes the sum of training error and a term that is a function of the flexibility of the classifier is thought to be a good classifier. SVM offers relatively easy training. Unlike neural networks, there is no local optimal present. Dimension scaling is carried out significantly; such that it gives better results, .One can easily control classifier complexity. Raw data like can be used as input to SVM, instead of feature vectors.

Current algorithms for defining the SVM classifier include subgrade gradient and coordinated decline. Both practices have established to offer major advantages over the old-fashioned tactic when dealing with large, uncommon data sets. Subgrade approaches are particularly efficient when there are several training examples and coordinate descent plays well in the ground when the feature possibility dimension is high.



III. Experimental Results

The functional utility of the proposed Myoelectric Hand, was demonstrated by grasping a variety of household objects. The prosthetic device was easily able to grasp objects such as disposable glass, wallet, PEPSI can, smart phones & water bottles etc. These actions required little or no assistance at all.

Figure 6 represents the 3D printed prototype of the device that was used to check the feasibility of the proposed CAD design.

Fig. 6. Prototype of the hand during construction phase

The accuracy achieved from SVM is 96.7% and the confusion matrix can be seen in Fig. 7. It depicts that the classifier is not doing any mistake as for differentiating the signals coming from human muscle hence resulting in reduced error or no error at all. The real time procedures are feasible with this much accuracy and the system can be implemented on any patient.

Fig. 7. Confusion Matrix Representing the Accuracies

The primary task was to move the fingers according to the EMG sensed data that was been achieved successfully. However, there were some problems present in the finger movement due to wrong classification of EMG signals. The Myo-electric hand gripped the following objects without damaging them,

a. Disposable glass
b. Pepsi bottle
c. Wallet
d. Pepsi Can
e. Air-Conditioner remote
f. Smartphone

All these objects were gripped using prismatic power grip. In prismatic power grip, force was been applied between the fingers and palm that in contrast with circular pinch grip is better.

The results for holding real life objects are shown in Figure 8

(a)

(b)

(c)

Fig. 8. The prototype is grasping (a) Charger (b) Wallet (c) Hand Holding Water Bottle

Conclusion

The results obtained from this research work shows that the day is not far when we will have a complete functional artificial hand. The user has to bring the Myoelectric Hand near the object and with the control commands generated based on the EMG signal the hand will start opening or closing based on the intentions coming from the muscle. The controller is responsible for classification of real time signals to actuate the motors. As the accuracy is more than 95%, imparting that it is a rare chance for the hand to behave abnormally. The hand will remain in the desired position as organized from the controller.

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