EMG control of a 3D printed myo electric prosthetic hand

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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 Trans-radial 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. The computer aided 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 practical effectiveness of the Myoelectric Hand was demonstrated by grasping household objects such battery charger, wallet and water bottle.

1. Introduction

During the previous decade, great efforts has been done to improve the human-machine interfaces (HMI) and generating them in a more intuitive way. In order to accomplish HMI, an accurate body signal interpretation is required. Currently, the myoelectric prosthesis is the most advanced commercially available powered trans-radial prosthetic device [1]. The surface electromyogram (EMG) signals of amputee’s residual muscles are used to provide the input signal and control the prosthetic device [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 reference to [8], the measurements acquired from the Inertial Measurement Unit (IMU) worn at the wrist, and the Electromyogram (EMG) of muscles in the forearm were fused together in order to infer hand and finger movements. Furthermore, 12 gestures were defined as a set and Support Vector Machine (SVM) algorithm was implemented to classify and separate activity within the defined gesture classes.

Soon, 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 a smaller 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 Solid works® provides tools so that 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 trans-radial prosthetic device. Next section of the paper proposes the design and the mechanism of the trans-radial 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.

2. Computer Aided Design and Torque Calculations

2.1 Computer Aided Design
The proposed model of the prosthetic hand was designed using Solidworks®. In the proposed design, all fingers have revolute joints and work on the principle of Joint Coupling Mechanism. This mechanism helps to achieve synchronized motion of fingers through lesser number of actuators[7]. The proposed design is represented in Figure 1.

2.2 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;

\[ W = x \times g \]  \hspace{1cm} (1)

and;

\[ M = \frac{w}{\mu} \]  \hspace{1cm} (2)

Where, \( \mu = 0.87 \), \( g = 9.81 \frac{m}{s^2} \), \( \mu = \) Coefficient of rubber,
\( M = \) Required value of force for one finger.
For two points of contact,

\[ P = \frac{M}{2} \]

Figure 1. CAD Model of Myoelectric Hand
The calculated values for required force while lifting different weights are represented in Table 1 as

**Table 1: Calculated Force for Different Weights**

| Sr. No. | Mass in Kg | Required Force in N | Constant Point Force in N | Torque in 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       |

3. Signal Extraction and Processing

Electromyography is a technique used to evaluate and record the electrical activity produced by skeletal muscles upon activity. Thalamic Labs product MYO Arm Band has been used to acquire EMG signals. It is an application-based device which can receive 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 3.[5] Working steps of the proposed system is shown in figure 2.

According to [9], Myo provides two types of data for an application: spatial and gestural data. The special 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.

6 males and 4 females (age: 20 ±6) participated in experimentation for data collection. Able-bodied, right-handed, and reported to be 100% functional working hands subjects were chosen. The average wrist size of the 10 participants were found to be 16.3 ±1.1 cm with forearm size of 24.2 ±1.4 cm. The experimental model is shown in Table 2
| 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 |

### Table 2 Experimental Model

3.1. **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.

![Figure 4](image1)

*b*  

3.2. **Feature Selection**

Features measure characteristics from input data, and thus plays an important role when it comes to pattern recognition system design. In this study, feature extraction is carried out on the reference(input) EMG signals to reduce the data dimensionality such that the signal patterns which help to distinguish between the gesture classes were undisturbed. In order to portray an object to be recognized by measurements whose values are alike for objects in same category, and very different for objects in different categories, these characteristics are to be separated [13]. The feature set included MAV(Mean Absolute Value), VAR(Variance), WL(Waveform Length), Kurtosis and Peak. Results in Figure 5. showed that peaks & wave length feature showed the most accurate behavior.
3.3. Support Vector Machine (SVM)

Support Vector Machine (SVM) is an 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 a smaller 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.
4. Experimental Results

The functional effectiveness of the anticipated Myoelectric Hand was demonstrated by grasping a variety of household objects. The prosthetic device was able to grasp objects such as disposable glass, wallet, PEPSI can, smart phones & water bottles etc. These actions required slight 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.

![Prototype](image)

*Figure 6. Prototype of the hand during construction phase*

The accuracy achieved from SVM is 96.7%. 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.

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 7.

![Grasping Images](image)

*Figure 7. The prototype is grasping (a) Charger (b) Wallet (c) Hand Holding Water Bottle*

5. 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 must 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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