

Real Time Control of Hand Prosthesis Using EMG

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Project Demonstration: <https://www.youtube.com/watch?v=ORtPjpPia-U>

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Abstract: Current solutions for below the elbow amputees include affordable prosthesis allowing only a single movement or highly expensive prosthesis allowing several gestures. In this project, our goal was to design a system that provides an inexpensive, multi-functional solution for the hand prosthesis problem. We construct a real-time, portable system based on the Myo armband and a 3D printed prosthesis and show that this framework can provide a good and inexpensive solution for below the elbow amputees of all ages.

Keywords: Prosthetic Hand, Real-time Gesture Classification, Myo Armband.

1. Introduction

In the USA alone, there are 500,000 below the elbow amputees. The causes vary from trauma, disease, or congenital conditions [1]. Since this condition has a significant impact on daily functionality, the use of a hand prosthesis can assist in regaining the lost functionality. The current solutions are far from perfect, due to both price and functionality range. Current hand prostheses range from mechanical prostheses, allowing only a single movement and costing several thousand dollars [2], to myoelectric prostheses, a prosthetic hand powered by Electromyography (EMG) signals which allows several movement types but with a price range of 20,000\$ and up [2]. These high costs mean that many people around the world, especially in the developing world, cannot afford such solutions. This is especially problematic for children amputees since new prostheses are needed as the child grows, which can accumulate to very high costs. Current solutions for the problem are mostly provided by non-profit organizations such as e-NABLE [3], which offers free online blueprints for printing single action prostheses in 3D printers, costing only 50\$. However, these prostheses are limited in their functionality and are capable of performing only a single movement (closing of the hand).

Previous work involving myoelectric prostheses addressed different aspects of the problem, but did not provide a complete solution. For example, a work from 2005 [4] presented a real-time system with classification success rates of 93-98%. However, the system requires 7 EMG electrodes in inconvenient locations and the control of the system is unintuitive. In addition, the data processing is pc-based, allowing no portability, and the total price is not considered.

Another work from 2015 [5] uses the Myo Gesture Control Armband Sensor [6], to activate a 3D printed prosthesis. However, the system is based on the software provided with the Myo armband, which allows only a small set of identifiable motions with no resemblance to intuitive daily movements. In addition, the success rates of the suggested system are not presented.

In this project, our goal was to design a system that provides an inexpensive, multi-functional solution for the hand prosthesis problem. For this purpose, we revise available

blueprints of a single movement prosthesis and construct an affordable, intuitive and real-time prosthesis that is multi-functional and can be assembled without any special skills. In addition, we examine several signal-processing algorithms in order to allow the correct detection and classification of the desired movement.

The following requirements were addressed in the design of the system:

1. Real-time response. The response time, from command to execution of a movement, should be shorter than the user's reaction time (less than 250ms) [7].
2. Reliability. The classification rate should be higher than 90%, the “gold standard” of previous work [7].
3. Portability. A fully portable and stand-alone system is required, without dependence on network availability.
4. A large variety of gestures. Allows the users to gain higher functionality. We aim for a range of 6 gestures.
5. Intuitive interface. The activation of the prosthetic hand, based on EMG, should be similar to the natural activation of the hand in order to simplify the learning stage.
6. Short setup time. The calibration time, after each attachment of the prosthesis, should be less than 1 minute.

We show that our constructed system satisfies all these requirements and provides a good, inexpensive solution for below the elbow amputees of all ages.

This project involved an interdisciplinary team from Biomedical Engineering and Electrical Engineering Departments, along with advisors from Mechanical Engineering at the Technion and Physical Therapy Department at Haifa University.

2. System overview

The constructed system is composed of 3 main elements: EMG sensors (Myo armband [6]), Intel Edison board and a printed prosthetic hand (Figure 1). This framework allows the user to operate the prosthesis by contracting the forearm muscles in an intuitive way. We focused on 6 gestures, based on the common movement types used in high-end commercial myoelectric prostheses. Figure 2 presents the implemented gestures which include (from left to right) neutral position, extending the thumb, closing the hand, extending the index finger, pinch and “Frisbee” catch.



Figure 1: System overview.

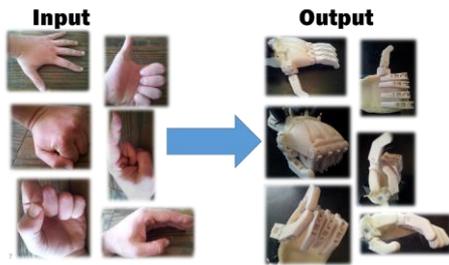


Figure 2: The six implemented hand gestures.

- a. **EMG sensor:** The Myo Gesture Control Armband Sensor [6] is used for recording the EMG activity. The sensor is located on the user's forearm and records the EMG signal using a circular array of 8 sensors. The EMG signal is sampled at 200Hz and sent via Bluetooth to the embedded system.

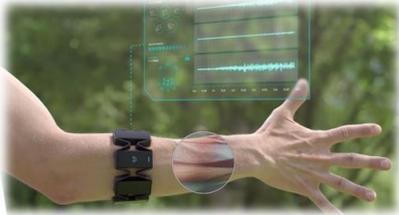


Figure 3: Myo armband EMG sensor [6]

- b. **Embedded system:** Implemented on an Intel Edison board, located on the prosthesis. The embedded system collects the data from the Myo armband and applies a classification algorithm to the EMG signals in order to identify the current hand gesture. Based on the gesture classification, a command is sent to the motor units in order to perform the desired gesture.
- c. **The prosthesis:** The prosthesis was printed using a 3D printer, Objet 24 [8]. The 3D design of the hand prosthesis is based on modifications of blueprints from the e-NABLE group [3], "Raptor Reloaded" (RR). The hand described by the RR blueprints is open by default and closes using a mechanical lever. Modifications of the blueprints included replacement of the lever with 3 motor units (servos s960) to allow 3 degrees of freedom and, in addition, the thumb of the hand was replaced. The motor units are operated by commands received from the Edison board in a form of Pulse-width modulation (PWM). The resulting prosthesis complex is presented in Figure 4.

The system development included 3 stages. First, the classification algorithm was devised in an offline environment. The algorithm was then implemented in a real-time environment and finally, the prosthesis, including the mechanical parts, motor units and Edison board, was assembled.



Figure 4: The constructed prosthetic hand.

3. Classification Algorithm in an Offline Environment

The main goal here is to determine the performed hand gesture, based on the received EMG data from the forearm, while maintaining real-time response. For this purpose, we examined several existing methods for simple feature extraction and several classification algorithms. The considered algorithms included only those simple enough to be implemented in real-time with low computational costs.

In the offline setting, EMG signals were collected using the Myo armband, sent via Bluetooth and then analyzed using MATLAB. The data is composed of 8 vectors, one per sensor, sampled at 200Hz [6]. We note that the frequency content of the EMG signal can range up to 400Hz [7]. This presented significant challenges, limiting the possible choices of feature extraction methods to simple, time-domain methods.

We applied the following algorithm to the recorded data:

1. Segmentation of the data into time-frames of $N=40$ samples.
2. Feature extraction from each time segment (containing data from the 8 EMG channels).
3. Classification of each time segment to one of the 6 gesture classes using K-Nearest Neighbors (K-NN).

For the feature extraction stage we examined several features commonly used in the literature [7, 9-11]. The mean absolute value (MAV) outperformed all other features due to its simplicity and due to the restriction imposed by the low sampling rate. Figure 5 presents a visualization of the first 3 principal components of the MAV feature, applied to recorded EMG data of the 6 different gestures. A clear separation between the different gesture classes can be seen in the 3D space.

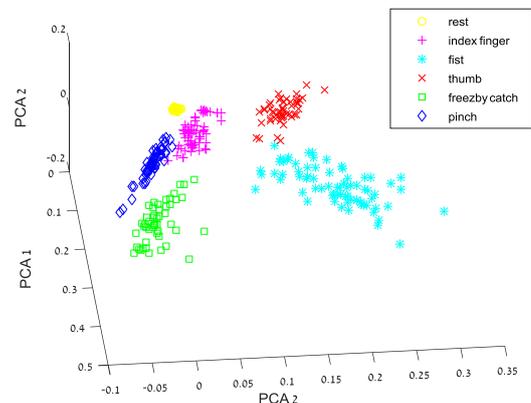


Figure 5: Data after MAV feature extraction.

4. Real time algorithm

Several adjustments were required for the real-time system. First, due to differences between people and differences in the placement of the Myo armband, a calibration stage was added. The calibration stage is required each time the armband is placed and therefore was restricted to 1 minute. It includes recording a short execution of all 6 implemented gestures. Second, in the offline simulation environment, the available Myo armband drivers handled the Bluetooth communications. However, in the embedded platform (Edison board), new drivers were written for sample acquisition from the Myo armband and conversion of the raw data to a readable format. In addition, due to voltage requirements of the 3 motor units controlling the prosthesis movement, a voltage adapter was needed. The adapter includes user interface buttons for the calibration stage.

Finally, the MATLAB code was converted to Python and implemented in the Edison board. A flow chart of the online algorithm appears in Figure 6.

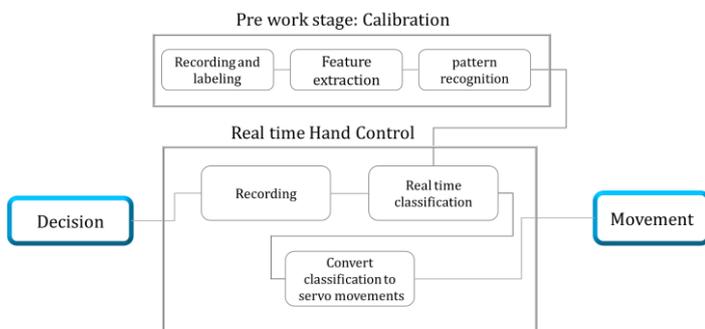


Figure 6: Real-time algorithm workflow.

5. Results and Discussion

5.1 Offline Algorithm Success Rate

EMG data from 5 healthy subjects were recorded using the Myo armband. For each of the 6 gestures a 10 second recording was obtained from each subject. For each subject separately, we performed 30 iterations of cross-validation and randomly partitioned the data into a train-set containing 75% of the data and a test-set containing 75% of the data. The algorithm described in Section 3 was then applied to the acquired data. Table 1 presents the classification results for each subject.

Test Subject	1	2	3	4	5	6
Mean (%)	99.6	99.9	99.8	99	99	99
Variance (%)	2.3×10^{-3}	8.4×10^{-4}	9.1×10^{-4}	2.1×10^{-3}	2.3×10^{-3}	1.2×10^{-4}

Table 1: Offline algorithm success rate.

We note that when combining data from different subjects, the classification results are insufficient and domain adaptation is required. We addressed this issue differently, as part of the calibration stage, as described in Section 4.

5.2 Affordability of system

The costs of the components of the constructed system appear in Table 2.

Part	Price
3D printed hand [3]	50\$
Motor unit (MG996R Servo) X3	15\$
Microcontroller Intel Edison	80\$
Sensor MYO armband [6]	200\$
Total Cost	345\$

Table 2: System costs

6. Conclusions

In this project, our goal was to design an inexpensive solution for the hand prosthesis problem. We presented an affordable real-time hand prosthesis framework and proved the feasibility of our suggested solution. Finally, we showed that the set objectives and system requirements can be fully accomplished.

In the future, we plan to address several weaknesses of our solution. First, we plan to examine different measurement modalities in order to obtain higher sampling rates which will allow more flexibility in the choices of window size and feature extraction algorithms. In addition, this could lead to further reduction of the system's price due to the high cost of the Myo armband. Second, we plan to address the high variability between different people and implement a domain adaptation algorithm in order to shorten the classification stage and increase the size of the train-set.

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