Design of a sEMG controlled robotic hand prosthesis

Osman Onur AKIRMAK[1], Çağdaş TATAR[1], Ziya G. ALTUN[1] and
Yuriy MISHCHENKO[2]

[1]Department of Electrical & Electronics Engineering, Faculty of Engineering, Toros University, Mersin, Turkey
[2]Department of Biomedical Engineering, Faculty of Engineering, Izmir University of Economics
*Correspondence: yuriy.mishchenko@gmail.com

Abstract: *The problem of development of more advanced bionic prostheses for individuals who have undergone a wrist or extremity amputation is one of the fastest developing subjects in modern robotics and biomedical engineering. Very significant advances have been made in the past decade with respect to the so-called myoelectric hand and arm prosthetics controlled by electromyographic (EMG) signal. Despite that, such technology today remains firmly out of reach of the majority of the patients needing it, especially in the countries of developing world. This project aims to develop a simple and low cost surface EMG controlled hand prosthetic that can be built with moderate level of electrical-electronics engineering skills and well under 1000 USD. A special EMG sensor based on standard ECG electrodes is used together with a conventional mechanical hand prosthesis modified by adding servo motors and Arduino Uno clone-based signal processing and control circuit. This report covers the issues related to the design of such prosthetic starting from the principles of EMG signal generation in muscles, detection of EMG signals using surface EMG, design of the robotic hand mechanism, amplification and digitization electronic circuit, as well as the embedded software for digital signal processing and control.*

Key words: electromyography, EMG, sEMG, robotic prosthesis, robotic hand, bionic hand, neural prosthesis, ECG electrode, electronic circuit, signal filtering

1. Introduction

In recent years, the development of myoelectric (EMG) prosthetic devices has attracted significant attention in laboratories around the world as well as in private sector. A significant work has been performed in the literature on myoelectric prosthetics [24-30] as well as several advanced myoelectric prostheses are now available commercially on the market including the i-limb (Touch Bionics, UK), the DEKA arm (Deka Integrated Solutions Corporation, USA), the Michelangelo hand (Otto Bock Healthcare Product GmbH, Austria), and the Bebionic prosthesis (Steeper Group, UK). Unfortunately, the vast majority of such research and development has been confined so far to the advanced biomedical and robotics laboratories in the countries of developed world, whereas such existing designs uniformly feature high degree of complexity and reliance on advanced parts, both contributing to their cost and requiring high-expertise labor to assemble and maintain. Ready-made or commercially sold myoelectric prostheses come at the prices of tens of thousands of dollars. For example, the Bebionic hand prosthetic comes with a $35,000 price tag [12] and requires advanced components and expertise to maintain. Despite a significant need existing in such technologies in the countries of developing world, the above factors make it all but impossible to acquire such prostheses in developing countries, whereas neither the necessary parts nor the expertise may be available for such designs' local assembly, while the price tag of a typical commercially sold bionic prosthesis is well above the annual income of the patients that may need it. Thus, the EMG prosthetics are currently firmly out of reach of the vast majority of the patients needing them in developing world.

In this paper, we discuss the technologies and methods aimed at designing a surface electromyography-controlled motorized hand prosthesis. This design is intended to become a basis for a higher-functionality electromyographic signal acquisition system and battery powered robotic hand prosthesis in the future. The presented design is both simple and does not rely on advanced parts or technical expertise. The design employs off-the-shelf components including an EMG detector built by using standard Ag/AgCl ECG stick-on electrodes, an instrumentation amplifier signal amplification circuit, standard servo motors, an Arduino Uno board clone, and a conventional mechanical hand prosthetic modified by adding servo motors and electro-mechanical actuation and control mechanism. The simplicity, accessibility, and lack of reliance on advanced parts makes it possible to implement that design under the conditions existing in most countries of developing world, placing minimal technological and expertise requirements on such an implementation. All the necessary parts for the design can be acquired quite readily from small local electronics and medical distribution stores under an estimated of 1000 USD, with the main costs coming from the mechanical hand prosthetic itself. The design can be realized by a specialized small-scale operation or even an individual with the expertise of a senior student in electrical and electronics engineering. The design can be realized by modifying existing mechanical prostheses already in possession of individuals, or by adapting an off-the-shelf mechanical prosthesis available from local medical suppliers. These features of the presented design can provide a practical alternative for the hand and arm amputees living in the countries of developing world for acquiring motorized myoelectric prostheses that can significantly improve the quality of their life, as well as help draw attention to the needs of such amputees.

Electromyography (EMG) is a technique for sensing activity in peripheral nervous system by means of monitoring the skeleton muscles during their voluntarily contraction by an individual. EMG signals are particularly advantageous for the implementation of the so called neural prosthetics because of their direct relationship to individuals' motor actions. With respect to other neural interfacing modalities such as brain-computer interfaces, EMG has the key advantages of large signal magnitude, high temporal resolution, high specificity to individual's intentions, and the ease of detection including by noninvasive means from the surface of the skin. EMG interfaces are also easy for individuals to learn to control, as human individuals naturally can learn motor behaviors with great efficiency.

In the surface EMG, the sEMG interface senses the action potentials developing in activated skeleton muscles from the surface of the skin adjacent to such muscles. Skeleton muscle cells are surrounded by sarcolemma - a semi-permeable lipid membrane such that there is a voltage difference of approximately -90mV with respect to the exterior across the membrane under resting conditions. When muscle is activated, the muscle fibers depolarize and reverse polarity to about +10 mV. The activity of all muscle fibers summed during a muscle activation produces what is called a MUAP (Motor Unit Action Potential) signal [1,4-8], Figure 1. This signal can be detected from the surface of the skin proximal to the excited muscle by using electrical sensors, and then used to control external devices such as prosthetics. MUAP signals detected via sEMG can be further coupled with advanced muscle movement recognition software to allow for a reach repertoire of behaviors implementable by a powered neurally controlled limb prosthesis.

One of the key focus points of the presented project is to investigate the possibility of constructing such simple and low-cost while also feature-rich robotic hand prosthetics controlled by surface electromyographic signals. The present report covers the details of one initial such design starting with the principles of EMG signal generation, EMG detection by using skin based electrodes, signal amplification, digitization, and digital processing, as well as the design of a motorized hand actuator based on a conventional mechanical prosthesis and the necessary electro-mechanical actuation and digital control systems.

2. Materials and Methods

In this section we describe our implementation of the sEMG-controlled robotic hand prosthetics. All human subjects participating in the project did so voluntarily and with explicit informed consent. The works in this project had been approved by the Ethics committee of Toros University (Mersin, Turkey) in agreement with the principles of the WMA Declaration of Helsinki.

2.1 sEMG sensors

sEMG sensing systems rely on collections of electrodes placed over the skin immediately surrounding the respective muscles, which serve as the sensors for the electrical activity present in the muscle, and which work as a transducer of ionic current flowing in live tissue and the electronic currents present in electrical devices. The quality of sEMG electrodes depends on their shape, size, material, etc. Non-invasive sEMG electrodes also always produce noise: the transformation of the ionic currents flowing through live tissues into the electronic currents in metal electrodes always results in introduction of additional noise.

sEMG electrodes rely on chemical reactions to transform the ionic current into the electronic current. Thus, they are composed of an electrode and an electrolyte, whereas the current passes from the electrolyte a non-polarized electrode by oxidizing the electrode's atoms. The cations and electrons produced in the oxidization reaction move in the opposite directions: the electrons flow via the metal interface and into the cables, and the cations flow into the electrolyte. As the result of this reaction, a difference in electric potential known as the "half-cell potential" is formed between the negative electrode and the positive electrolyte.

In this work, we use standard Ag/AgCl 3M Red Dot ECG electrodes with foam tape and sticky gel 2560 [17] for sensing sEMG signal from the surface of the skin of subject's lower arm. We evaluate the circuit model of such Ag/AgCl electrodes in Figure 2. In Figure 1, Ehc is the half-cell potential, Rd and Cd are the impedances associated with the electrode-electrolyte interface and the polarization effects, Rs is the series resistance associated with the electrode-electrolyte interface as well as the electrolyte's resistance.

2.2 sEMG signal model

The input sEMG signal entering the first-stage electronic amplifier and then digitizer can be modeled as the combination of three parts: the differential sEMG signal (signal of interest), the common mode interferences, and the electrodes offset (differential), as shown schematically in Figure 3 [5-6]. The sEMG differential signal presents a maximum peak whose estimated value varies according to different muscle activities from $2mV$, peak to peak, to $6mV$, peak to peak. The second important component of the sEMG raw signal is the interference picked up by the human body from the power lines, fluorescent lights, and similar electromagnetic sources. This interference is common to all electrodes of the sEMG sensor system and thus can be totally rejected if the Common Mode Rejection Ratio (CMRR) of the front-end amplifier is large. The third component present in the sEMG raw signal is a DC offset between different electrodes of the sEMG sensor system due to the factors such as different skin impedance and the differences in the chemical reactions occurring between the skin and the electrode gel at the locations of different electrodes of the sEMG sensor system. This constant offset can be removed during the digital signal processing stage in the EMG prosthetic's software. The typical relative magnitudes of these sEMG signal components are shown in Figure 2.

2.3 sEMG sensor assembly

In sEMG sensing systems, the position of the electrodes is important for successful identification of needed muscle activations. For sEMG neural interfaces to be able to discriminate among many different activation patterns of subject's muscles, necessary to implement multiple patterns of finger movements in a sEMG robotic hand prosthesis, for example, a possible choice is to place the electrodes over the subject's lower arm. Figure 4 presents a possible choice of one such placement of the electrodes, whereas small adjustments from subject to subject may need to be made. The placement shown in Figure 4 attempts to map the sensor positions to specific muscles. In particular, the position of the Electrode 1 is over the flexor pollicis longus, which can be used to detect the flexion of the thumb. The position of the Electrode 2 is 1.5 cm away from the Electrode 1. Together, these electrodes can classify independent motions of thumb and index fingers of subject's hand, based on the flexor digitorum superficialis. In that scenario, the flexing of the index finger produces the highest sEMG signal. The position of the Electrode 3 is over the flexor carpi ulnaris, which allows one to detect the flexion of the pinkie finger. The positions of the Electrodes 4 through 7 are over the flexor carpi radialis and the palmaris longus muscles, which can be used to detect the flexion of the hand's middle finger. The position of the Electrode 8 is over extensor pollicis longus muscle, which can be used to detect the extension of the thumb finger. The position of the Electrode 9 is over extensor indicis muscle, which can detect the extension of the thumb, and the position of the Electrode 10 is on extensor carpi ulnaris muscle, to detect the extension of middle, ring and pinkie fingers. The muscles for finger adduction are located on the inner side of the hand, thus they are not detectable from the upper electrode assembly directly, in the context of a hand-prosthetic design. However, their response can be measured by changes in the activity of the upper side muscles of the lower arm, so that the adduction of different fingers can still be distinguished with the combination of the above sEMG signals [14]. In this work we use the placement indicated by Electrode 6 in Figure 1, with the purpose of detecting the muscle activity produced by the flexor carpi radialis and the palmaris longus muscles. A second electrode is placed at the end point of these muscles 1.5 cm away from the first electrode and towards the wrist-point of the arm, to measure the potential difference generated between the middle and the end points of that muscles during their activation. A third electrode is placed near the bone of the same hand to establish the ground level for the electronic amplifier and decoder circuit, to be described below. The assembly detects the adduction of the middle finger in an individual's wrist.

2.4 The electronic amplifier and decoder assembly

The first input stage of the hardware amplifier and decoder assembly applies hardware low pass and high pass filters to clean the raw sEMG signal coming from the skin sensing interface, using the precision instrumentation amplifier INA106. The INA106 is a differential amplifier that will measure and amplify with gain factor of at least G=110 the very small voltage differences between the sEMG electrodes placed over subjects' muscles. The frequency of the hardware filtering band here in the first stage is 16-800Hz. The INA106 has a very good CMRR of more than 115dB and the maximum common voltage applicable between two inputs of 80V, which allows the amplifier and decoder assembly to be potentially used also for electro-tactile feedback. In the second phase of the amplifier and decoder assembly, we're taking these very small signals measured in the signal acquisition phase and further amplify them. Two stages of amplification are present in this phase: the first is an inverting amplifier with a gain of at least -15 using the TL072 chip [19], one 150 kOhm resistor, and one 10 kOhm resistor. (In this case the Gain=-R2/R1=-150 kOhm / 10 kOhm=-15.). In the second stage, an active high pass filter is added to remove any DC offsets and low frequency noise components from the differential sEMG signals. To do this, we used two 150 kOhm resistors and a 0.01uF capacitor. Then, we rectify the signal with active full-wave rectifier, which takes the negative portion of the previously amplified and filtered sEMG signal and transforms it into positive, so that the entire signal becomes in the positive voltage region. The rectifier is used to turn our AC sEMG signal in into DC signal to be passed to a microcontroller.

An important specification to determine for the sEMG amplifier and decoder assembly is the minimum acceptable resolution of the signal. We observed the baseline level of noise at ±5 μV. Therefor, it is deemed necessary to digitize the signal with sufficient number of bits to allow even the faintest sEMG activity to be appreciably quantified. A 16-bit analog to digital system set at ±5 V provides the resolution of 0.153 μV (r.t.i.), for system with the gain of 1000. This means that the recorded noise will be resolved after digitization at least at 5 bits (that is, 32 quantization steps). This leaves ample resolution for resolving any sEMG activity, which will be decidedly larger than the baseline noise levels. Thus, we select 16-bit digitization system with gain of 1000, which is deemed to be sufficient given the dynamic range and the smallest resolution requirements [11].

The block schema of the sEMG signal processing system and the electronic schema of the sEMG amplifier and decoder circuit used in our sEMG hand prosthesis design are shown in Figure 5 and 6.

2.5 Digital filtering of the sEMG signal

After electronic amplification and digitalization, the digital analysis of the sEMG signal was performed using a digital filter and a simple neural network muscle activation classifier implemented as a C program loaded into the memory of an Arduino Uno board clone [16].

The digital filter for sEMG signals and the neural network classifier for muscle activations detection were first prepared using Matlab. First, we analyzed the spectra of the sEMG signal to try and determine the signal frequencies important for muscle activation detection. A band-pass digital filter with the high-pass corner frequency of 20 Hz and the low-pass corner frequency of 500 Hz, with the total gain in the pass band of about 2900 and the roll-off rate of -12 db/octave was thus selected for the sEMG signal digitized at the sampling rate of 1000 Hz. Only slight improvement has been observed in terms of the suppression of low frequency noise in the range of 0-15 Hz when the high-pass roll-off rate was doubled from -12db/octave to -24db/octave. A second-order high-pass filter was designed, whereas it was found that fourth-order filter performed nearly equally with our sample data. An example of the sEMG signal before and after the filtering with the selected digital filter is shown in Figure 7.

In order to detect the segments of the sEMG signal associated with the activations of target muscles, we chosen a single hidden-layer artificial neuronal network classifier. After the digital filtering stage, the muscle activations appear in the sEMG signal as distinct bursts waveforms. Therefore, we trained a 1-layer artificial neural network in Matlab to detect the occurrences of such waveforms. The architecture of the artificial neural network trained is shown in Figure 8. The neural network consisted of a single hidden-layer with 5 units with logit transfer-function and one output unit, also with logit transfer-function. Each unit in the hidden layer received inputs from 40 control-points spread uniformly over the most recent sEMG signal's wave-form at 20 msec intervals. These were summed inside the hidden units and then transformed by the logit nonlinearity and into the output. The outputs of the hidden inputs then drove the single output classifier unit, where they were likewise summed up and transformed by the logit function to produce a [0,1]-range output representing the confidence of the detection of the target muscles' activation. The neural network was trained using the Matlab Neural Network toolbox and a 2 minutes sample of sEMG data where a subject continuously contracted hand's middle finger at a rate of approximately one contraction per 2 seconds. A threshold of 0.999 was selected, whereas the neural network classifier's outputs above 0.999 were treated as valid muscle activation events and the outputs below 0.999 were ignored, and found to minimize the rate of false detection while retaining practically all correct detections. The performance of the neural network was evaluated on a separate segment of sEMG data and found to provide the accuracy of muscle activation detections of 94%. An example of the neural network classifier's output is shown in Figure 9.

2.6 Robotic hand prosthesis mechanism

We implemented two designs for the motorized hand actuator. The first design is shown in Figure 10 and featured a multiple-finger gripper with plastic fingers and palm structural elements. Each of the five fingers in that design was made of elastic plastic parts with two rubber joints. For each joint, it was possible to create a roughly equal torque across the joints by applying a force at the tip of the finger, tangential to the fingertip, by means of a string. The force at each fingertip was applied by a separate servo motor. The design could produce palm open and close motion, however, did not feature sufficient structural strength for practical applicability.

The second design was produced by adapting a commercial mechanical prosthetic hand. The said commercial prosthetic was a conventional movable hand prosthesis manufactured by Otto Bock (Otto Bock Healthcare Product GmbH, Austria), which could be activated normally by means of a mechanical string. By this, the prosthetic was equipped to perform a single grabbing and holding motion activated mechanically by pulling the string. The drawing of the mechanical part of this prosthetic is shown in Figure 11**.** We modified this prosthetic by removing internal closing springs and mounting a servo motor at the centre of the finger joints, and then covering thus motorized assembly with the plastic cosmetic glove, Figure 12. The electronic schema of the control system used for activation of the motorized prosthetic hand mechanisms is shown in Figure 13. The servo motor was controlled by the sEMG electronic circuit and enabled the actuator to perform a grubbing and holding action as activated by an individual's voluntary contraction of the flexor carpi radialis and the palmaris longus muscles in the lower arm.

3. Results and conclusions

In this article we present a design of a simple and low-cost electromyographically controlled hand prosthetics. The design consists of 4 main parts: (1) the sEMG sensing assembly, (2) the electronic amplificatier and decoder circuit, (3) the embedded-software digital filter and neural network classifier for muscle activation detection, and (4) the servo motor actuation and mechanical prosthetic hand systems.

The sEMG sensing system is based on standard Ag/AgCl stick-on electrodes used in ECG. Two of such electrodes are placed over the skin of lower arm at the mid- and end-points of the flexor carpi radialis and palmaris longus muscles, and provide the measurements of the voltage differences existing between these two points along that muscles. A third electrode is placed close to a bone in a remote location of the same arm, to provide the ground level for the first-stage electronic amplificatier and decoder circuit.

In the electronic amplificatier and decoder circuit, the sEMG signals is filtered, amplified, and transformed into digital form. The amplificatier and decoder circuit is based on a standard precision instrumentation amplifier INA106 and provides amplification and digitization of the sEMG signal at 0.153 μV, 16 bit, 1000 Hz.

The digital filter and neural network classifier for muscle activation detection are implemented on the base of an Arduino Uno board clone, as embedded-software of the prosthetic, and perform the digital filtering of the sEMG signal to the frequency band most closely associated with the muscle activation signals and the detection of muscle activations by means of a single-layer artificial neural network classifier. The examination of the sEMG signal has allowed us to identify the range of frequencies the most significant for observing the muscle activations in sEMG signal. Digital filter then is constructed to retain those frequencies and suppress the irrelevant fluctuations in the sEMG signal, especially at 0-15 Hz low-frequency range. After filtering, the muscle activations appear as distinct burst-like waveforms in the sEMG signal. A single-layer neural network then has been trained to detect those waveforms in the digitally filtered sEMG signal.

The servo motor and the mechanical hand prosthetic comprise the mechanical elements of the prosthetic. The mechanical hand prosthetic is Otto Bock conventional mechanical prosthetic hand modified by replacing hard springs and activation string with a servo motor. The original mechanical mechanism of the prosthetic allows for a single action of grabbing and holding. Correspondingly, the robotic EMG prosthetic that we built can produce that one motion of grabbing and holding, now controlled by a user voluntary contracting his or her flexor carpi radialis and palmaris longus muscles. Thus constructed EMG prosthetic hand performed well in our trials, performing by executing the grabbing and holding task, Figure 14 and Figure 15. The EMG prosthetic hand could recognize and respond to the sEMG muscle activation patterns with well over %90 accuracy.

Some limitations are present in our design. We designed the digital filter and the neural network detector for muscle activations on a PC by using Matlab software. The step of selecting the digital filter and the neural network muscle activation detector can be also automated as a component of the embedded software programmed into the Arduino Uno board-clone, controlling the prosthetic. In that case, the selection of the digital filter and the neural network classifier can be performed by the prosthetic automatically, upon a user initiating a calibration session, with little complexity added to the original design.

The original mechanical prosthetic hand mechanism that we used was capable of performing a single action of grabbing and holding. For that reason, our final design was also restricted in that sense to execute one EMG action. It is possible to produce a larger number of motions with a myoelectric prosthesis; however, that adds quickly to the complexity and the osts of the resulting design, with the great majority of the cost and complexity associated with a significantly more complex mechanical prosthetic mechanism needed to reproduce a greater range of hand motions. For example, the costs of multiple-motion mechanical prosthetics available on the market are far above the simple Otto Bock mechanical prosthetic that we used in this work.

Our sEMG sensing assembly detects the activations of the flexor carpi radialis and palmaris longus muscles related to the user's middle finger adduction. The activation of a greater number of muscles can be incorporated into the design by using a larger number of sEMG electrodes. However, that also negatively affects the cost and the complexity of the design. In the end, the benefit of sensing a larger number of muscle activations is directly related to the capabilities of the mechanical prosthetic actuator mechanism, which in our case was capable of implementing a single movement, and causing a dramatic rise in cost and complexity with just a moderate increase in such capabilities of the hand actuator.

Finally, the Ag/AgCl disposable electrodes that we used in the sEMG sensing assembly pose a problem with respect to their longevity and long-term prosthetic use. As an alternative, stainless steel [20] or conductive rubber dry [21] electrodes can be used at the cost of slightly higher design price. An elastic band wrapped around the forearm can be used to offer a greater stability and durability of the contacts of such electrodes with the arm's skin [22].

The design of a sEMG prosthetic hand presented in this work is guided by the trade-offs of simplicity and cost, and the technological performance. The design provides modest EMG functionality as compared to existing advanced bionic prosthetics. However, it also comes with minimal requirements for the use of advanced components and the expertise needed for its implementation. The cost of the electronic and mechanical parts of the present design, with the exception of the prosthetic hand mechanism itself, is estimated to be under USD50, with the electronic parts costing approximately USD20 and the mechanical parts costing USD30 (USD25 for the servo motor and the remainder for the aluminum parts used in the hand gripper). The main cost of the prosthesis is the mechanical hand prosthetic itself. We modified a mechanical Otto Bock prosthetic hand in this project. A user may already be in possession of such a prosthesis or the prosthesis can be acquired from a local medical distributor. If acquired new, the cost of such prosthesis may vary greatly due to circumstances. In Turkey, the country of residence of the authors, such commercial non-motorized mechanical prosthesis could be acquired at the time of the writing for USD150 to USD250, or 450 and 650 TL [23].

In summary, in this work we describe the design of an electromyographically controlled hand prosthesis with the focus on simplicity and costs of the design and its implementation, in order to facilitate implementations by small-scale operations typical in the conditions of most developing countries, and aimed to offer an opportunity for improving the quality of life of the patients living in such countries. Existing myoelectric prosthetics are costly and require advanced parts, making them all but inaccessible in the countries of developing world. This leaves a great number of people that could benefit immensely from such prosthetics without needed help. Our work offers a contribution towards solving this problem and improving the qualities of life of such people.

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Figures

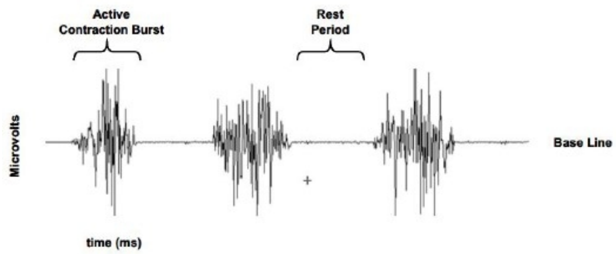

Figure 1. An example of the raw EMG MUAP signal.

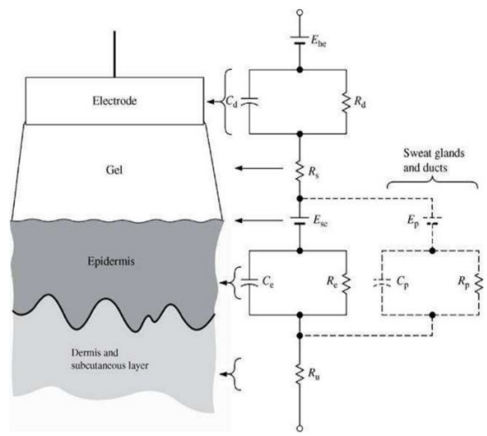

Figure 2. The circuit model of the Ag/AgCl electrode used in this work for sensing the sEMG signal from skin surface.

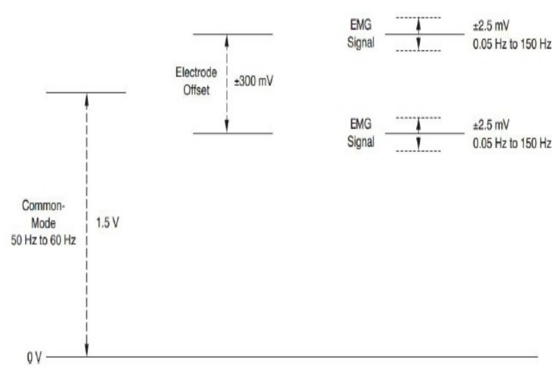

Figure 3. The schematic representation of the sEMG raw signal composition.

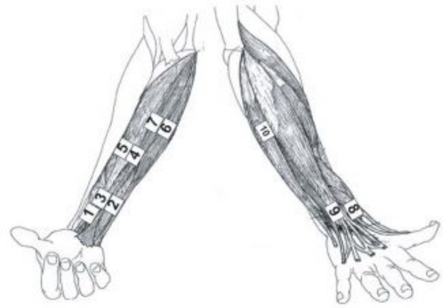

Figure 4. Possible positions of the sEMG sensing electrodes for detecting finger movements on lower arm.

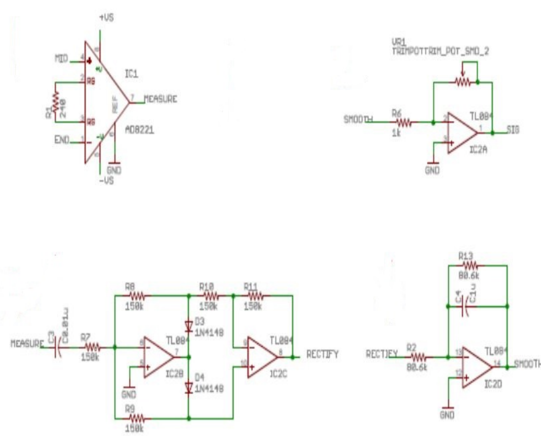

Figure 5. The electronic schema for our sEMG amplifier and decoder circuit based on the schematics from Advancer Technologies EMG amplifier and decoder in [15].

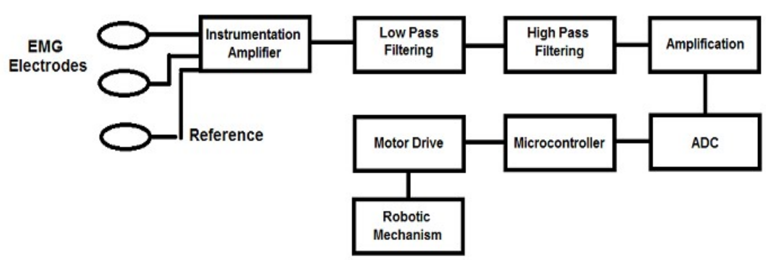

Figure 6. The block schema of the sEMG signal processing system used for driving the robotic hand mechanism in our sEMG hand prosthesis design.

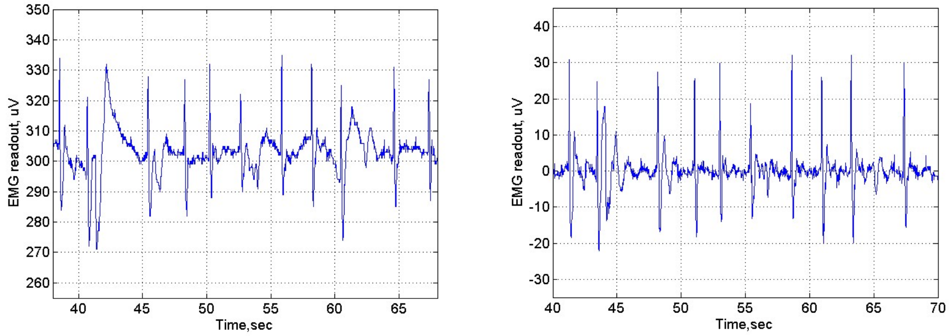

Figure 7. An example of the EMG signal before (left) and after (right) digital filtering. The raw EMG signal was acquired from the electronic signal amplifier and decoder circuit, digitized at 1000 Hz, and then filtered using a digital band-pass filter defined by the high-pass corner frequency of 20 Hz, low-pass corner frequency of 500 Hz, gain of 2900, and roll-off rate of -12 db/octave.

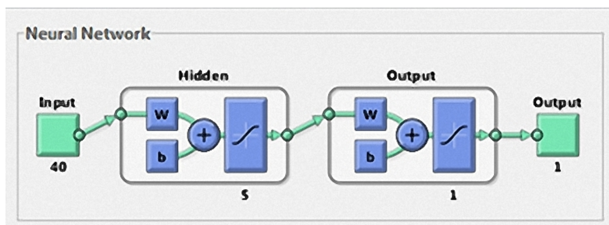

Figure 8. The artificial neural network implemented for detection of flexor carpi radialis and the palmaris longus muscle activations in the digitally filtered sEMG signal.

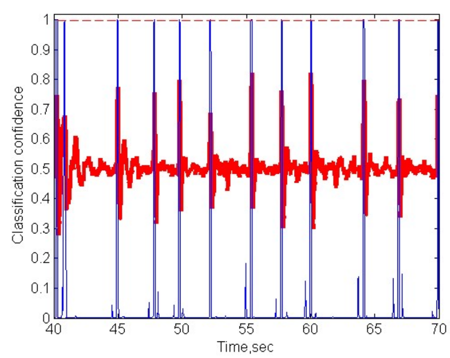

Figure 9. An example the detections of the flexor carpi radialis and palmaris longus muscle activations by using the neural network in Figure 7, trained with the Matlab's Neural Networks Toolbox**.** The red line is the filtered EMG signal input and the blue line is the Neural Network's detection confidence output. The accuracy of the detections of the target muscle activation events is calculated at 94% with the detection threshold set at 0.999, shown by the dashed red line at the top.

Figure 10. Design of a multi-finger hand actuator for a robotic sEMG hand prosthesis using flexible rubber and plastic parts.

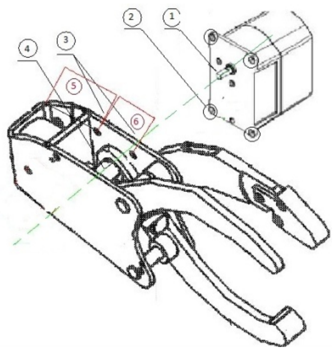

Figure 11. The mechanical drawing of the second hand actuator for a robotic sEMG hand prosthesis adopted from a movable non-motorized Otto Bock mechanical hand prosthesis. Numbers indicate: 1. The rod of the servo motor; 2-3. The fitting screws 4. The rod place bracket 5. The forearm prosthetic connection area 6. The fitting screw mounting holes.

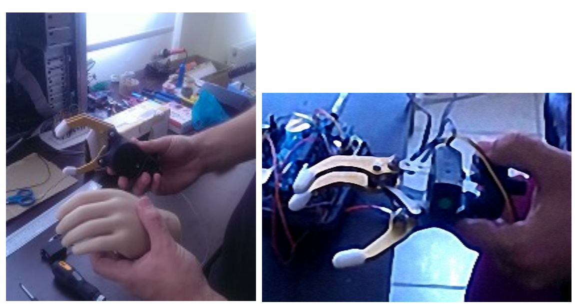

Figure 12. The photographs of the second design of the actuator part of the robotic sEMG hand prosthesis used in this work, adopted from movable non-motorized commercial hand prosthesis.

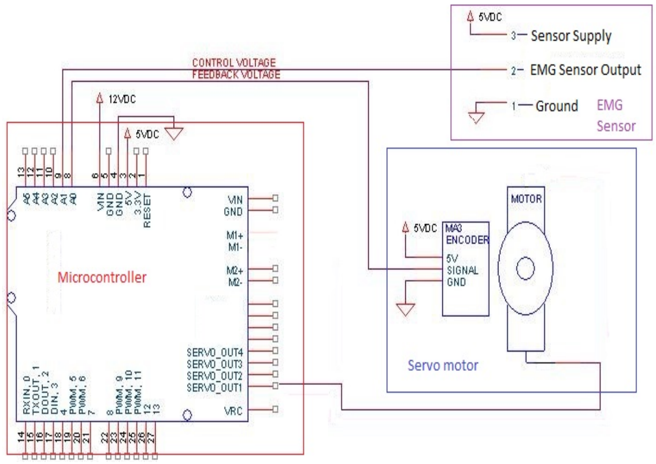

Figure 13. The electronic control system design for the motorized prosthetic hand mechanism.

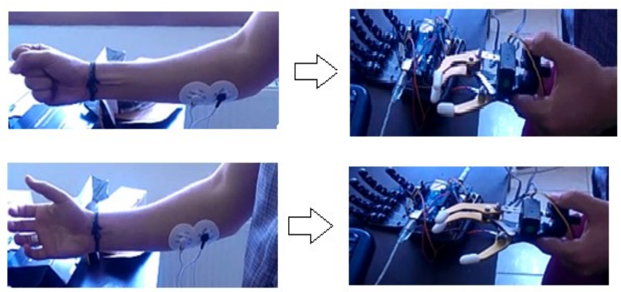

Figure 14. Activation of grabbing motion in our sEMG hand prosthetic design using the contraction of the flexor carpi radialis and the palmaris longus muscles.

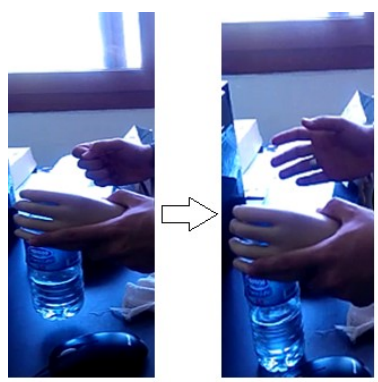

Figure 15. Performing grabbing and holding task using our sEMG robotic hand prosthetic design.