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Six Prosthetic Arm Movements Using Electromyogram Signals: A Prototype

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Abstract - **Electromyogram signal is a biomedical signal that measures electrical activity produced in a muscle during its contraction. This work presents a prototype system for moving a prosthetic lower arm, without prior operation intervention, using electrodes that measure electromyogram (EMG) signals placed on two muscles only. The signals are then read by sensors connected to Arduino microcontroller, processed and passed to MATLAB via Bluetooth where features are extracted and input to a neural network to classify one out of six movements. A servo motor receives a driving signal to move the simulated arm to the required position. The system enables the arm to do six movements without any external help. The system results are compared to other systems' results and it was able to achieve 99.7% classification rate which is considered, among other systems, the highest for classifying six movements.**

Keywords - EMG signals; upper limb amputation; prosthetic lower arm; movement classification.

I. INTRODUCTION

All Current commercial devices help people who have limb amputation to restore the appearance of a limb, and to improve the quality of life. The prosthetic devices should enable the patient to perform normal limb movements to a great extent. Those devices should also be light weight and affordable. Considering upper limb amputation, there are three broad categories of upper limb prosthesis: passive (cosmetic), body-powered and externally powered. Body-powered components are light, durable and have limited sensory feedback. They exploit the body's own strength to provide the power to drive this form of prosthesis. The externally powered prosthesis use components that are driven by an external power source, such as electricity or some other source of power external to the body. There are five types of arm amputation [1]: 1- Finger or digit amputation, where the thumb or one or more of the fingers are amputated. 2- Wrist disarticulation, where the amputation occurs through the wrist joint, removing the hand. 3- Elbow disarticulation – where the amputation occurs through the elbow joint, removing the hand, wrist and forearm. 3- Transradial amputation, where the hand and a section of the arm are amputated below the elbow. 4- Transhumeral amputation, where the hand and a section of the arm are amputated above the elbow. The system proposed is concerned with the last type which is Transhumeral amputation. The electromyogram (EMG) is an electrical signal that is generated as a result of normal muscle contraction. The amplitude of the signal is proportional to the level of contraction of the muscle. Myoelectric components are chosen because they don't put any effort on the shoulders as they don't utilize the shoulder power. Above all, they provide output force independent of physical ability [2]. Hybrid systems, which are combination of body-powered and myoelectric components, are commonly used to handle amputation at or above the elbow. They allow two joints to be controlled at once – one with body power and one with myoelectric control. They are generally less heavy and less expensive than a completely externally powered system. Controlling the movement of a prosthetic arm based on EMG is the objective of this work. In [3], a three degrees freedom system was proposed with classification rate of 90%. In [4], another system was proposed which could detect the amputee's intended motion among six kinds of motions using the multi channel EMG signals with 97.6% classification. Another system was presented in [5] where the intended action of the arm is understood from the EMG signal parameters. The pulses are generated by using microcontroller and the respective motor is driven for movements of the hands and wrist. A project prototype in [6] proposed a controlled arm that uses EMG electrical signals from the forearm Flexo-Extensors muscles that control the hand movements. In 2013, another research [7] was done where the designed prosthetic arm had one degree of freedom. It was able to do one action (grabbing action) by capturing the EMG signals from the muscles which are responsible of opening and closing of a hand. In [8], a classifier for four movements was proposed using EMG signals based on an autoregressive (AR) model representation and a neural network, and two myoelectric control strategies based on Finite State Machine. A rate of classification ranging from 91% to 98% was achieved by combining a low-order AR model with a feed-forward neural network. In 2014, a research was done [9] to classify four arm movements using ANN and EMG. There are a number of researches done on prosthetic hand motion recognition. Few are listed hereafter. Work in [10] designed

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a prosthetic hand controller for 10 movements with 91.5% discrimination rate. Another work for prosthetic hand wrist motion identification was done in [11] where six specific hand and wrist motions are identified from the EMG signals obtained from ten different able-bodied wrist. Accuracy was 91%±1.9. Another work for hand and wrist is presented in [12] where five movements for the wrist-hand mobility were identified using EMG and neural network. The work in [13] focused on minimizing the misclassifications and increasing the robustness of hand prosthesis controllability. Upper limb human control was also presented in [14]. A prosthesis or rehabilitation device control must be quite simple and at the same time give the user a degree of freedom to select a motion from several movements. Having a system with light weight components that don't harness the shoulders is not quite enough. It is important that the system is affordable too. In this paper, a prototype system is presented that satisfies these requirements for controlling the movement of a prosthetic lower arm using EMG signals.

II. MATERIALS

The amplitude of EMG signal is typically between 0-10 mV (+5 to -5) mV. The majority of signal information lies between the frequencies of 15 and 400 Hz. An amplifier is necessary for EMG signal. The amplitude of the EMG contains a great deal of the signal information. Based on [16], EMG densities fell in between the theoretic Gaussian and Laplacian densities. Of these two densities, the Gaussian density best described the data which can be modeled as a Gaussian random process. The time-varying standard deviation (SD) value is only one of different estimators of muscular activity. The most used is the Root Mean Square (RMS) value, but the Absolute Mean and the Difference Absolute Mean values are often used in microcontroller based system because of their low computational cost. The time windows length also plays an important role

Fig. 1 shows the system hardware. It consists of EMG bipolar electrodes, sensors, microcontroller (Arduino Uno), servo motor and power supply.

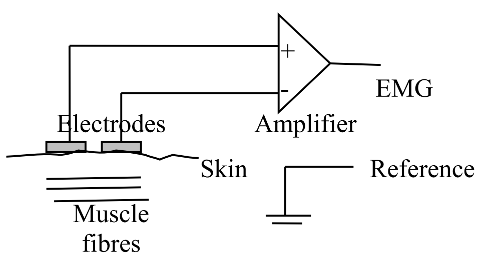

Figure 1. System hardware

The software used is MATLAB. The bipolar configuration acquires the EMG signal using two EMG detecting surfaces (electrodes) and a reference electrode which acts as a reference point for the 2 electrodes. The two detecting electrodes are placed 1-2 cm from each other. The signals from the two EMG surfaces are connected to a differential amplifier which amplifies the signal between the two electrodes differentially with respect to the reference electrode. Electrical noise is gained by the EMG signal while moving through the tissues. The configuration eliminates the common noise between the two electrodes and hence a better signal-to-noise ratio. After reading the signals, features are extracted and fed into Artificial Neural Network (ANN) to classify the movement required to be done by the prosthetic limb. The output from the ANN is connected to microcontroller, Arduino Uno, whose output drives a servo motor, placed in the arm joint, to move with a specific degree causing a motion on the prosthetic limb. Fig. 2 shows the system assembly.

The Muscle Sensor Toolkit used is a very small kit in the size of a coin. It is connected to the muscle via bipolar electrodes and to the Arduino board as shown in fig. 3.

It is very sensitive that it can produce electrical signals when a small contraction of the muscle occurs. It is designed to be used directly with a microcontroller. The sensors do not output a raw EMG signal but rather an amplified, rectified, and smoothed signal that will work well with a microcontroller's analog to digital converter (ADC). Besides its availability in the local market and its lower price relative to other sensor kits, the toolkit has the following features: 1- Small Form Factor (1x1inch). 2- Adjustable Gain – Improved Ruggedness. 3- New On-board 3.5mm Cable Port. 4- Pins fit easily on Standard Breadboards. Table I shows the toolkit power specifications.

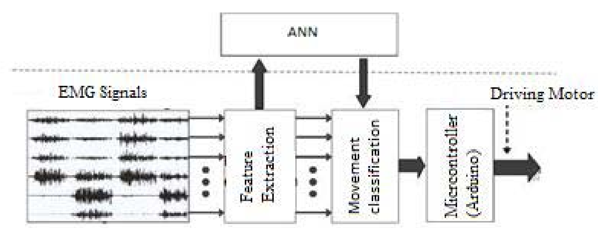

Figure 2. System assembly

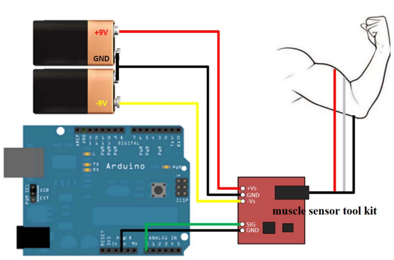

Figure 3. Muscle sensor tool kit connection

TABLE I. SENSOR TOOLKIT POWER SPECS

Parameter	Min	Typ	Max
Gain Setting, Gain = 207*(X /1 kΩ)	0.01 Ω (0.002x)	50 kΩ (10,350x)	100 kΩ (20,700x)
Power Supply Voltage (Vs)	±3V	±5V	±30V
Output Signal Voltage (Rectified & Smoothed)	0V	--	+Vs
Differential input voltage	0 mV	2-5mV	+Vs/Gain

The Arduino Uno is a microcontroller board based on ATmega328. It weighs 25g. It has 14 digital input/output pins (of which 6 can be used as PWM outputs), 6 analog inputs, 16 MHz ceramic resonator, a USB connection, a power jack, an ICSP header, and a reset button. To get it started, simply connect it to a computer with a USB cable or power it with an AC-to-DC adapter or battery. The Arduino Uno can be programmed with the Arduino software. MATLAB-2013 was used for signal pre-processing, dataset creation, feature extraction, training ANN, generating prototype algorithms, and sending motor commands. ARDUINO-MATLAB library enabled us to read data from Arduino and send data to Arduino via MATLAB commands. This library contains a class called Arduino.m that enabled the communication with Arduino. It also contains .Uno file which works on Arduino Uno board.

The servo motor is powered by two external batteries, each 2600 mAh. The Arduino software comes with a servo library. The specifications of the servo motor are:
Dimension: 40.8 x 20.1x 38 mm , Voltage: 4.2-6v,
Speed: 0.18 sec/60degree (4.8v), 0.16 sec/60degree (6v),
Torque: 6 kg.cm (4.8v), 7.5 kg.cm (6v), Stall torque, Weight: 36g. Fig. 4 shows the connection of the servo motor to the Arduino board.

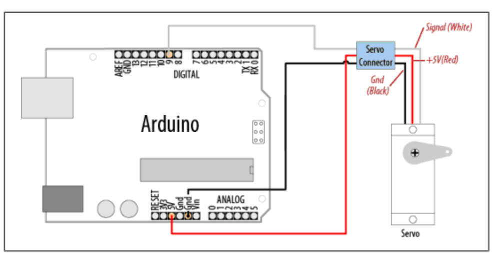

Figure 4. Arduino – servo motor connectivity

The control signal sent from the microcontroller to the motor is in the form of a pulse. The width of the pulse corresponds to the angle that the motor will turn to.

III. METHODOLOGY

A. Dataset

The scope of motion of the proposed system is six arm movements: 90° - full extension, 90°- full flexion, Full extension to 90°, full flexion to 90°, full extension to full flexion and full flexion to full extension. The scope of the amputees is those who did not have Targeted Muscle Reinnervation. To the best of our knowledge, there was no dataset available to be used in training/testing of the ANN. Based on [17], there isn't significant difference between the strength of the muscles of a healthy subject and amputated person as long as the nerve is not dead. Accordingly, we generated the dataset. Human elbow is mainly actuated by two muscles: biceps and triceps, although it consists of more muscles. The contraction of the biceps flexes the elbow while the contraction of the triceps extends the elbow. By measuring the amount of force generated by these two muscles, the elbow angle can be controlled. Ten healthy subjects volunteered to participate in creating the dataset. The subjects were five males and five females within age group of 15-24 years. From each, 15 samples for each movement of the above mentioned six movements were collected. Each reading session consists of 15 readings for every subject. The reading takes 1 second to record 500 samples for triceps and 500 samples for biceps. The readings are further used to train different classifiers.

B. Setup

The EMG signals were recorded as follows:

- The first electrode is placed in the middle of the target muscle body, after cleaning the skin thoroughly, and is connected to the cable's snap connector.

- The second electrode is placed at one end of the target muscle body and connected to the other cable's snap connector.

- The third electrode is placed on a bony non-muscular part near the target muscle and is connected to the cable's snap connector.

- The Arduino is then connected to the sensors and connected to a Laptop by a cable or by Bluetooth.

MatLab 2013 was used for EMG signal preprocessing, creating datasets, feature extraction, training artificial neural network (ANN), and sending motor commands.

The signal recording is based on a rectangular window with amplitude 1 and width 500 (which means 1 second window) that passes through the signal. The window and the original signal are multiplied. Wavelet transform is then applied to the resultant signal and features are extracted. The features vector is considered as an input to the neural network. If the network recognizes the input as one of the six movements, MATLAB sends servo write command to the Arduino which moves the servo motor with the proper angle that corresponds to the movement detected by the neural network. The window is then shifted by 500 to begin recording a new movement. If the movement is not recognized, nothing is sent to the motor and hence no motion occurs, however, the window is shifted by 50 to search for another movement in the signal.

C. *Feature Extraction*

Arduino should read 500 analog samples in only one second. To achieve this, a modification was done in the timer class and analogRead function of MatLab.

For training and testing the ANN, features were extracted from two types of signals; raw signals and processed signals.

1- Raw Data: where the EMG signals are sampled directly and fed into the ANN. This methodology is very simple and easy to implement however; it is very slow.

2- Wavelet Transform: since almost all biological signals like ECG, EEG and EMG are non-stationary, wavelet transform is more suitable to be applied on EMG than Fourier transform [15].

The EMG signals can be easily affected by various noises while passing through different fibers. Typical band pass filter was applied to the signal to reduce noise from electrodes, motion artifacts and electric power lines. A notch filter of 3dB gain and 49-51 Hz has been used to remove the 50 Hz power line noise since this frequency is not within the dominant frequency (70-300 Hz) range of recorded EMG signals. Wavelet transform method has been further applied. Daubechies (db2) mother wavelet function has been selected and applied on detail wavelet co-efficient for noise reduction. The wavelet transform techniques can successfully localize time and frequency components and can provide good frequency resolution at high frequencies. It helps in identifying and eliminating the noise components in the signal by preserving important high-frequency transients. For de-noising the EMG signals, a wavelet transform of six level decompositions has been applied giving 8 samples for the EMG signal. Fig 5 shows the original signal while Fig. 6 shows the rebuild from level 6 decomposition coefficients. Coefficients of further decompositions could not rebuild the original signal. Fig. 7 shows the deteriorated rebuild of the signal from further decomposition coefficients. It is worth noted here that the level at which the decomposition stops is subject to trial of several levels and getting the best results.

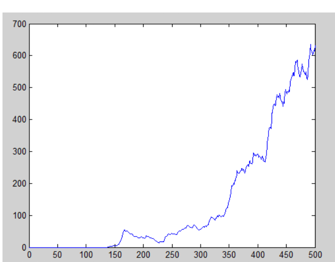

Figure 5. Original signal

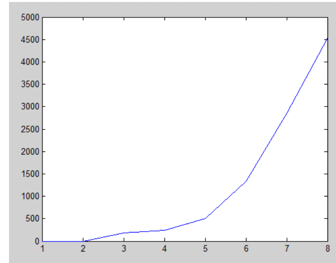

Figure 6. Signal generated from level 6 decomposition

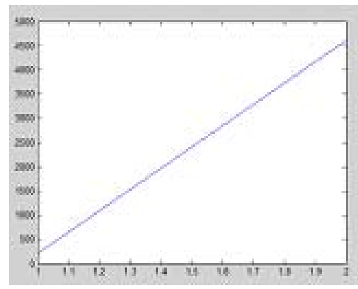

Figure 7. Deteriorated rebuild of the signal

D. *Classification*

Two categories of networks were tested; supervised and unsupervised. For the supervised category, configurations used are as follows:

1- A feed-forward backpropagation network with sigmoid functions in hidden neurons and linear functions in output neurons, (CONFIG A).

2- A feed-forward backpropagation network, with sigmoid function in both hidden and output neurons layers, (CONFIG B).

3- A feed-forward network whose ith level neurons forward their outputs to all of the successive level neurons, (CONFIG C).

For the unsupervised category Self Organizing Map (SOM) was tested as an unsupervised model.

IV. RESULTS AND ANALYSIS

A. *Supervised networks*

Each of the networks tested was trained with 55% of data, 15% validation and 30% testing after applying wavelet transform to the EMG signal.

The best performance results were the following configurations:

1- 99.7487% for CONFIG A network with 10, 30, 10 neurons in the corresponding layer. Elapsed time was 0.093s. Fig. 8 shows the performance of the network with various configurations.

2- 99.2063% for CONFIG B network with 30, 10 neurons in the corresponding layer. Elapsed time was 0.084s. Fig. 9 shows the performance of the network with various configurations.

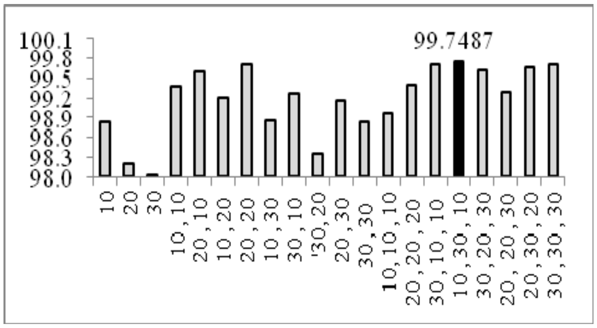

Figure 8. Performance of CONFIG A

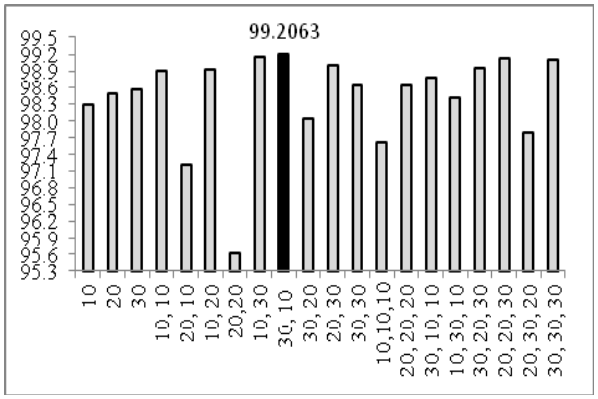

Figure 9. Performance of CONFIG B

3- 99.3915% for CONFIG C network with 10, 30, 10 neurons in the corresponding layer. Elapsed time was 0.233s. Fig. 10 shows the performance of the network with various configurations.

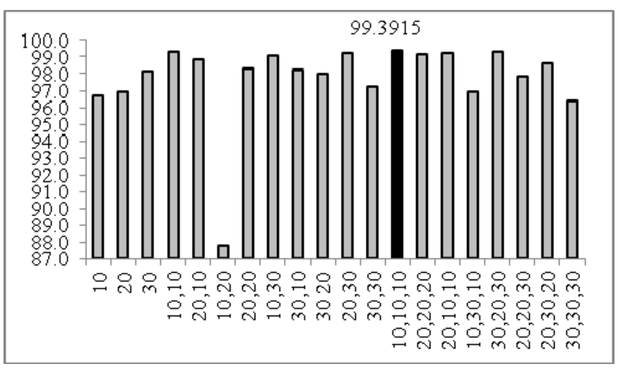

Figure 10. Performance of CONFIG C

B. *Unsupervised networks*

Several unsupervised networks were tested but the results were not promising. SOM network results are presented in fig. 11 which shows 6 clusters that indicate the 6 arm movements in consideration. Ideally, each cluster of the 6 clusters should contain 195 (1170 / 6) samples. However, the figure shows that one cluster contains quite a small number of samples (106) and another cluster contains relatively a huge number of samples (437). The SOM network was not capable of classifying the movements.

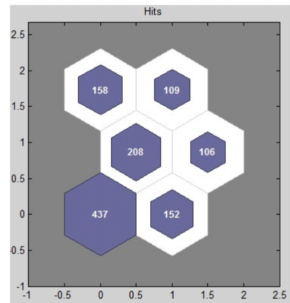

Figure 11. SOM Results

The FFBP networks were the most successful. All hit rates were above 99%. The best was the FFBP that achieved 99.74% classification. This is the highest rate achieved for 6 movements' classification.

A new feature was introduced to the system which was using Bluetooth module on the Arduino shield to communicate with the Matlab program on PC. The response time of the Bluetooth version was the same as in the wired version. The Bluetooth version makes the system more user friendly as it enables the patient to go anywhere without any wires connected from the Arduino to the PC. To enable the Bluetooth, a modification is done in the pde file (Arduino code) and the Matlab file running on the PC where the baud rate between the PC and the Arduino must be 9600 not 115200 to enable sending and receiving data without any failures.

Table II shows a comparison between the proposed system and other systems. The first [7] deals with six arm movements. Amputees in [7] and the proposed one did not undergo Targeted Muscle Reinnervation (TMR) operation which transfers residual arm nerves to alternative muscle sites. The second compared system [18] deals with 11 arm movements' classification on amputees who had undergone TMR. In ref [19], 11 movements classification system is compared.

TABLE II. COMPARISON BETWEEN THE PROPOSED SYSTEM AND OTHER SYSTEMS

System reference number	Movements performed	Network	Amputee preparation	Bluetooth	Accuracy	Response time
[7]	6 movements: Elbow flexion, Elbow extension, Wrist supination, Wrist pronation, Grasp, Rest.	Multilayer Perceptron network using time series model parameters for 5000 iterations	No	No	97.6%	Not available
Proposed system	6+1 movements: 90 to full flexion, 90 to full extension, Full extension to 90, Full flexion to 90, Full extension to full flexion, Full flexion to full extension, Rest.	Feedforward backpropagation network with three hidden layers (10 , 30 , 10)	No	Yes	99.74%	0.0.093 s
[18]	11 movements: Elbow flexion and extension, Wrist flexion and extension, Wrist pronation and supination, Hand opening, 3 hand grasps, No- movement	Linear discriminant analysis (LDA)	TMR, which transfers residual arm nerves to alternative muscle sites	No	90-100% depending on the motion	Not available
[19]	6 movements: Grip control open and close, wrist extension and flexion, left and right rotation of the robotic arm .	Eucleadian distance between DFS coefficients of unknown movement and stored coefficients	No		81.6%	Not available

V. CONCLUSION

A prototype system was proposed to simulate the movement of a prosthetic arm. The system was able to achieve 99.7% real time classification rate which is considered among other systems, the highest for classifying 6 motions. The system is also affordable regarfing price and the on-body mass. The price of the hardware used was EGP 1840 which was equivalent to about 300U$ while the weight of the equipment 25 g for the board, 36g for the motor totaling, 100g for the prosthetic lower arm model, and 500g for the two batteries adding to a total of 2.61kg. Some codes in MatLab modules had to be modified to adjust to the devices used. A dataset was also created for 6 lower arm movements. The future work will focus on 2 things: embedding the system in one unit and including hand movement beside the arm movements.

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