Biomimetic Robot Hand Control By Using Surface Electromyography

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Abstract: Undesirable events may happen to people at unexpected times. About 15% of the world's population lives with some form of disability. Most prosthetic devices have limited number of gestures and cannot fully replicate movements of the body. The system utilizes non-invasive surface electromyography (sEMG) for extracting signals from the forearm and uses neural network for pattern recognition. The EMG signals were recorded and calibrated for one participant only. The datasets were sampled to create the input matrix, which are loaded to MATLAB for training, validation, and testing. As shown after successive trials, fatigue or muscle weakness is a significant factor in creating neural networks for pattern recognition. It was verified that the system could successfully extract, classify and output 10 individual finger gestures and 4 manual grasps with a classification accuracy of 93.6%. Statistical analysis was used to assess the classification accuracy based on the results and the original training data with 99% level of confidence.

Keywords—**Electromyography, Neural Network, Pattern Recognition**

1. Introduction

Undesirable events may happen to people at unexpected times. Many disabled people lose part/s of their body from accidents like vehicular accidents, touching sharp or hot objects, or from diseases like cancer and diabetes that requires amputation. Some disabled people have even lost part/s of their body due to abnormalities during birth, such as the birth defect Amelia. According to the World Health Organization, about 15% of the world's population lives with some form of disability, of whom 2-4% experience significant difficulties in functioning [1]. Most of these people need prosthetic devices to face the challenges in their daily life. Most prosthetic devices have limited number of gestures and cannot fully replicate movements of the body [2]. Otto Bock, Touch Bionics, and RSL Steeper are some examples of prosthetic companies responsible for several innovations in the field of prosthetics. Examples of advanced prosthetic devices are the Michelangelo [3], i-Limb Ultra [4] and Bebionic 3 [5].

During muscle activation, an electrical signal, better known as the myoelectric signal, is generated by the exchange of ions through the muscle membranes. The movement of the human body is achievable with the perfect integration of the brain, nervous system, and muscles. The brain sends excitation signals through the Central Nervous System to excite certain muscles needed for an activity. The muscles are classified and innervated into groups or junction points where the motor neurons and muscle fibers meet, termed Motor Units. As long as the muscle is needed to generate force, the Central Nervous System continuously repeats the activation of the motor unit, which produces Motor Unit Action Potential (MUAP) trains. These trains superimpose to produce the resulting electromyography, abbreviated as EMG, signal. By using noninvasive electrodes, these electrical activities produced by the muscles of the human body can be detected, evaluated, and recorded. This supports electromyography or EMG as a valuable technology to provide a natural way of sensing, detecting, and classifying the different movements of the human body. According to previous studies, even if a person were to lose his hand, the electromyography activity is still evident and strong as long as the amputees nerve endings are still intact and had not suffered any nerve damage [6].

In general, the research aims to design a bionic hand system capable of receiving electromyography (EMG) signals from the muscles on the forearm and emulating human hand movements with a wide range of motion including but not limited to finger gestures (i.e. Thumb Extension, Thumb Flexion, Index Extension, Index Flexion, Middle Extension, Middle Flexion, Ring Extension, Ring Flexion, Little Extension, and Little Flexion) and manual grasps (i.e. spherical, cylindrical, tip, and lateral) [7][8]. The design applies the principles of surface electromyography, amplifiers, and filters to extract Motor Unit Action Potentials of the forearm [6].

An Arduino-based microcontroller is used to classify hand movements from the pre-programmed database and will perform the pre-programmed sequence to control an artificial bionic hand.

2. Proposed Biomimetic Robot Hand

2.1 System Architecture

Fig. 1 shows the system design and process flow. The entire system is composed of four main parts: the Sensor Circuit, MATLAB, the Arduino Microcontroller, and the Robot Hand. The sensor circuit is comprised of the noninvasive surface EMG electrodes, the amplifier and filter circuit and is responsible for collecting and extracting the data from the muscles of the forearm. The data is then sent by the Arduino microcontroller to MATLAB, which classifies the data based from its neural network and cross-references its neural signature. Once the data has been classified, MATLAB sends a command to the microcontroller that executes a predetermined sequence from a preprogrammed database that controls the Robot Hand. Predetermined movements were classified and stored in the database. These classified movements are then preprogrammed to mimic actual hand movements. Calibration and classification of neural signatures was done through a series of testing. Simulated movements with known actual movements were tested for the participant to check the precision and accuracy of the device. The device must be able to classify and identify the specific movement and run the pre-programmed sequence to mimic the actual hand movement. The test included running different sets of simulated movements and checking the output of the system.

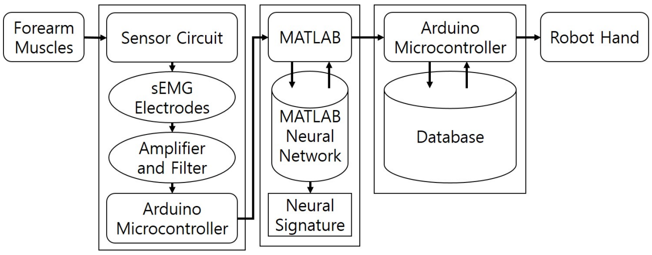

Figure 1. System design and process flow.

2.2 Circuit Design

Fig. 2 shows the block diagram and signal process flow for the sensor circuit. First, the EMG signal is acquired through the Ag-AgCl electrodes, labeled as Electrode 1, Electrode 2, and Electrode REF for each channel. Because the signal amplitude is merely a few microvolts and is easily susceptible to noise, the signal needs to be amplified through a cascade of amplifiers and filters before it can be captured. The EMG signal is acquired by the electrodes (Electrode 1 and Electrode 2) and passes through the high voltage protection and HF rejection circuit, which serve two purposes, to protect the circuit from electrostatic discharge and to protect the forearm (user) from electric shock from failing circuitry. The signal then goes to through a high quality instrumentation amplifier, which amplifies the EMG signal and lowers the impedance, which makes it less sensitive to noise. It measures the voltage difference between the two locations on the muscle (electrode). Before the signal is amplified again, it passes through a high pass filter to remove the DC-voltage offsets, as large DC-voltages tend to build up by accumulating electric charges on the surface of the electrodes. The high pass filter has a cutoff frequency of about 0.16 Hz.

The signal is once again amplified through a standard, non inverting amplifier with a controlled gain regulator followed by an identical second high pass filter before passing through a third order low pass Besselworth filter, which minimizes the distortion caused by aliasing which occurs when the signal is converted to a digital signal. The third order Besselworth filter (not a standard term) is a combination of a Butterworth and a Bessel filter. The resulting filter has a knee on the boundary between the pass band and transition band that is more rounded than that of a Butterworth filter, but sharper than that of a Bessel filter.

To power the sensor circuit, it is possible to utilize the built-in 3V or 5V supply of the Arduino microcontroller. Following the supply from the Arduino microcontroller is the switching noise filter, which is made up of an inductor and three capacitors. Because real-world capacitors only work well within a limited frequency band, more than one capacitor must be used. One capacitor would handle the higher frequency components, while the other the lower frequency components. This filter is used to reduce the switching noise. The amplifiers required a dual power supply that supplies both the positive and negative power rail, but the built-in power supply of the Arduino microcontroller provides only a single voltage. To remedy this, the AREF signal is fed to an operational amplifier to drive a virtual ground, VGND. In turn, to avoid confusion, we renamed the GND of the microcontroller to AGND and are now used as the negative power rail to power the amplifiers, while the VGND now acts as the virtual ground point for the amplifiers.

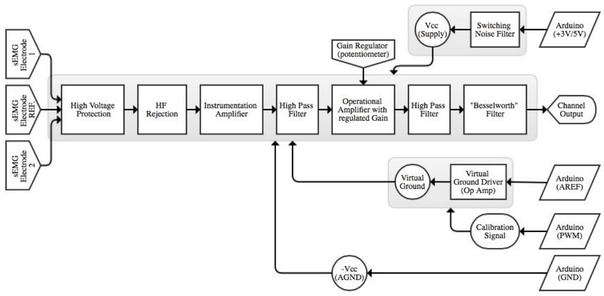

Figure 2. Block Diagram and Signal Process Flow.

2.3 Design of the Neural Network

To build the neural network model, the training data must first be generated. The process involves data collection, network configuration, network training, and network validation. There are 50 samples for each finger movements, and manual grasps. These samples as well as an addition of 250 samples for a control to act as the reference state into an input matrix.

To train, validate, and test the neural network, the samples were randomly divided 70% for training, 15% for validation, and 15% for testing. The training samples were presented to the network, and its error would adjust the network. The validation samples were used to measure network generalization, and to halt training when generalization stops improving. The testing samples have no effect on training and would only provide an independent measure of network performance during and after training. The neural network that was used for pattern recognition is a two-layer feed-forward network, with sigmoid transfer functions in the hidden layer. Scaled Conjugate Gradient back propagation algorithm was used to train the neural network.

2.4 Design of the Robot Hand

The robot hand was made by carving stacks of layered acrylic sheet bonded with super glue and then painted over. Two servomotors will control the movements of the thumb. A servomotor will serve as the Carpometacarpal (CMC) joint that connects to the Trapezium (carpal bone of the wrist), while the other will serve as the Metacarpophalangeal (MCP) joint and controls the Interphalageal joint of the thumb with steel wire [9].

Four sets of servomotors will also control the remaining four fingers (index, middle, ring and little finger). Similar to the thumb, a servomotor will serve as the MCP joint that connects to the metacarpal bones for the remaining four fingers. The servomotor will control the Proximal Interphalageal joint of the four fingers with steel wire. The Distal Interphalageal joints of the remaining four fingers are fixed. An Arduino Microcontroller controls the servomotors.

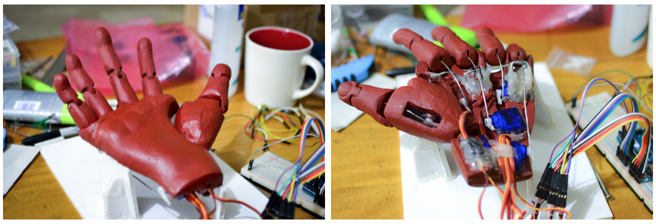

Figure 3. Implementation of proposed robot hand.

3. Results and Discussion

3.1 Data Gathering and Testing

According to [8], given a small set of gestures, the performance of intact-limb and amputee subjects is statistically indistinguishable so an intact-limbed subject was selected to participate on this test. The intact-limbed participant performed actual finger movement with his arm position fixed resting on a pillow. The participant was also asked to execute the finger movements with a moderate, constant force, and non-fatiguing contraction to the best of his ability for five trials. Each trial had a minimum of 30 minutes interval to allow the subject time to rest.

The classification accuracy was done with movement classes done at regular time intervals of 10 seconds to allow the participant to rest, but the different movement classes was done at random; this means that any movement would not be done in succession, but at random order. In a confusion matrix, the results in the diagonal are the correct classification rates while the results outside the diagonal line are the errors. The sum of the off-diagonal cells in each row of the confusion matrix indicates the classification error for that particular movement class. Classification error means that the actual movement class was classified into a different predicted movement class.

Output movement

Target Movement / Action	CTRL	TE	TF	IE	IF	ME	MF	RE	RF	LE	LF	SG	CG	TG	LG	Total Cl.	Total CE
CTRL	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0
TE	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0
TF	0	1	9	0	0	0	0	0	0	0	0	0	0	0	0	9	1
IE	0	0	0	9	0	0	0	1	0	0	0	0	0	0	0	9	1
IF	0	0	0	0	9	0	0	1	0	0	0	0	0	0	0	9	1
ME	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	10	0
MF	0	0	0	0	0	0	9	0	0	0	1	0	0	0	0	9	1
RE	0	0	0	0	0	0	1	9	0	0	0	0	0	0	0	9	1
RF	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	10	0
LE	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	10	0
LF	0	1	1	0	0	0	0	0	0	0	8	0	0	0	0	8	2
SG	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	10	0
CG	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	10	0
TG	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	10	0
LG	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	10	0

*Legend: Classification Error (CE), Control (CTRL), Thumb Extension (TE), Thumb Flexion (TF), Index Extension (IE), Index Flexion (IF), Middle Extension (ME), Middle Flexion (MF), Ring Extension (RE), Ring Flexion (RF), Little Extension (LE), Little Flexion (LF), Spherical Grip (SG), Cylindrical Grip (CG), Tip Grasp (TG), and Lateral Grasp (LG).

Figure 4. Confusion matrix of trial 1.

Class	Trial 1			Trial 2			Trial 3			Trial 4			Trial 5		
	CC	TC	CA	CC	TC	CA	CC	TC	CA	CC	TC	CA	CC	TC	CA
CTRL	10	10	100	10	10	100	10	10	100	10	10	100	10	10	100
TE	10	10	100	10	10	100	10	10	100	10	10	100	10	10	100
TF	9	10	90	10	10	100	9	10	90	9	10	90	9	10	90
IE	9	10	90	9	10	90	10	10	100	9	10	90	8	10	80
IF	9	10	90	8	10	80	8	10	80	9	10	90	8	10	80
ME	10	10	100	10	10	100	10	10	100	9	10	90	10	10	100
MF	9	10	90	10	10	100	9	10	90	10	10	90	7	10	70
RE	9	10	90	8	10	80	8	10	80	8	10	80	10	10	100
RF	10	10	100	8	10	80	9	10	90	9	10	90	8	10	80
LE	10	10	100	10	10	100	10	10	100	10	10	100	10	10	100
LF	8	10	80	8	10	80	10	10	100	9	10	90	9	10	90
SG	10	10	100	10	10	100	10	10	100	10	10	100	8	10	80
CG	10	10	100	10	10	100	9	10	90	9	10	90	10	10	100
TG	10	10	100	10	10	100	10	10	100	9	10	90	10	10	100
LG	10	10	100	10	10	100	10	10	100	10	10	100	9	10	90
Total	141	150	95.3	141	150	94	142	150	94.7	140	150	93.3	138	150	90.7

*Legend: Number of Correct Classification (CC), Total Classification (TC), Classification Accuracy (CA), Control (CTRL), Thumb Extension (TE), Thumb Flexion (TF), Index Extension (IE), Index Flexion (IF), Middle Extension (ME), Middle Flexion (MF), Ring Extension (RE), Ring Flexion (RF), Little Extension (LE), Little Flexion (LF), Spherical Grip (SG), Cylindrical Grip (CG), Tip Grasp (TG), and Lateral Grasp (LG).

Figure 5. Summary and overall classification accuracy of each movement class and trial.

Fig. 5 shows the summary and overall average classification accuracy with their respective standard deviation for all finger and grip movement classes investigated of all trials.

Although intervals between trials were done to reduce the effect of fatigue on the subject, Fig. 5 shows that because of the strain on the muscles for some movements, over time the effect of fatigue becomes more evident. This entails that fatigue is a significant factor that must be considered when implementing this technology for everyday use.

3.2 Statistical Analysis

The hypotheses to be validated are: 'The classification accuracy of the actual hand movements for the first trial, where the muscles are said to be physiologically normal, can accurately approximate the 95.7% classification accuracy of the neural network with the original training data' and 'The effect of fatigue or strain on the muscles lowers or degrades the classification accuracy of the actual hand movements to approximate the 95.7% classification accuracy of the neural network with the original training data.'

Z-test was used to determine whether the true value of proportion (percentage or probability) of the first trial in Fig. 5 is equal to or greater than the 95.7% classification accuracy of the original training data with 99% level of confidence. Table 1 shows the statistical data for the first hypothesis.

Because the Z-value is greater than -2.33, we accept the null hypothesis that the classification accuracy of the actual hand movements from the first trial where the muscles are said to be physiologically normal can accurately approximate

Table 1. Statistical Data for Hypothesis 1

Null Hypothesis	$H_0 : P = 0.957$
Alternative Hypothesis	$H_1 : P < 0.957$
Correct Classification	141
Number of samples	150
Level of Confidence	99%
Level of Significance	$\alpha = 0.01$
Reject Condition	Reject H_0 if $Z \leq -2.33$
Z-value	$Z = -1.02637$

Table 2. Statistical Data for Hypothesis 2

Null Hypothesis	$H_0 : P < 0.957$
Alternative Hypothesis	$H_1 : P \geq 0.957$
Correct Classification	702
Number of samples	750
Level of Confidence	99%
Level of Significance	$\alpha = 0.01$
Reject Condition	Reject H_0 if $Z \geq -2.33$
Z-value	$Z = -2.83504$

the 95.7% classification accuracy of the neural network with the original training data with 99% level of confidence. However, to show the effect of fatigue or strain on the muscles, statistical analysis on all five trials were also done.

Z-test was also used to determine whether the true value of proportion (percentage or probability) of the combination of all the five trials in Fig. 5 is less than the 95.7% classification accuracy of the original training data with 99% level of confidence. Table 2 shows the statistical data for the second hypothesis.

Because the z-value is less than -2.33, we accept the null hypothesis that fatigue or strain on the muscles lowers or degrades the classification accuracy of the actual hand movements to approximate the 95.7% classification accuracy of the neural network with the original training data.

4. Conclusion

This research presented a system that is capable of extracting EMG signals from the muscles on the forearm to control a robotic hand. The custom-built sEMG sensor circuit is capable of amplifying and filtering the raw EMG signals before being processed by the neural network. It utilizes the use of an artificial neural network to recognize patterns generated by muscles on the forearm through non-invasive surface electromyography. The datasets of sEMG signals were sampled to create the input matrix to generate the artificial neural network. The feedforward neural network was used because of its simplicity and suitability for pattern recognition to classify the neural signatures. The robot hand was able to emulate a wide range of motion by performing preprogrammed sequences from the microcontroller. It was verified that the system could successfully extract, classify and output 10 individual finger gestures and 4 manual grasps (combination of finger) with a classification accuracy of 93.6%. Through Z-test, it was verified that the classification accuracy of the actual hand movements with muscles that are physiologically normal could accurately approximate the classification accuracy of the neural network with the original training data with 99% level of confidence. However, fatigue or strain on the muscles degrades the classification accuracy of the system.

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