109

MYO Armband Controlled Robotic Arm

Jheric Byrd and Zackary Minshew
Department of Electrical and Computer Engineering

Faculty Mentor: Dr. Fernando Rios-Gutierrez

Introduction.

In today's society it is apparent that the role and use of robotics and process automation is becoming increasingly more prominent in various fields and applications, from self-driving automobiles to various types of manufacturing. The expansion of these fields is driven by the persistent insatiable consumer market, not just in the United States, but in the world. This desire of advancement is typically looking for a means to reduce work or cost. Such as the advancement of robotics in manufacturing that leads to reduced labor and the liability of that labor. A byproduct of reducing the amount of human labor is usually higher profits and lower liability (insurance and safety). Another desire for these advancements is to reduce error, which could be done by a more advanced autonomously driving vehicle; or to be able to provide someone who has lost a limb with a fully functional prosthetic that emulates a human limb very well.

Implementation.

This project explores the use of the eight surface electromyographic sensors (sEMG) on the Myo® Armband (*Thalmic Labs*) that provide the data to train a feed-forward pattern recognition artificial neural network. The LattePanda Delta ultimate mini-board (*DFRobot*) is used to execute the classified output from the neural network as a physical output to control a 3D printed robotic hand. This project demonstrates cost alternative options to that of advanced medical prosthetics while saving a significant amount of money.

Background.

An electromyographic signal is a signal that is transmitted from the motor neurons, which send electrical signals to the respective muscle(s) causing it/them to contract or relax. EMG signals provide diagnostics of the command signals for muscles. This information is instrumental in helping doctors to diagnose and help patients. There are two different types of electromyographic signal. One type is placed on the surface of the skin, hence surface electromyographic sensor. The other, more invasive type is to puncture the skin with needles and to stick the needles into muscle tissue to record muscle activity [1].

For this project the Myo armband was used to acquire the sEMG signals. The armband allowed for advanced data collection with a simple means of obtaining that data. The Myo has eight surface electromyographic sensors that are evenly displaced. The signals from these sensors can be obtained from a computer via BLE dongle (*Bluetooth low-energy communication protocol*).

Artificial Neural Networks are computerized systems that model the neural network structure of animalia brains. Neural networks can be used for the recognition of patterns, prediction of future events based off past trends, and for the classification of data and information by learning from historical data [2]. For this project the Deep-Learning Toolbox in MATLAB is used to design, train, and classify the selected hand gestures.

Methods.

A. Experimental Design Process

Up until the recent isolation due to the coronavirus the experiment has been conducted using only two test subjects. One person being a 6'5", 268 pounds, 23-year-old male and the other person being a 6'2", 205 pounds, 23-year-old male. However, it is now only using the latter of the two aforementioned individuals. The armband shall be placed on the right forearm, with the Myo logo positioned on top of the brachioradialis and the subject should stand vertically with the right hand parallel with body pointing towards the ceiling/sky.

B. Signal Conditioning and Data Processing

The artificial neural network required a buffer to be implemented for the data collection process because the startup time was inconsistent which led to variations of signal values in the database. This was implemented by a simple preprocessing task that would run two timed trials of the data collection process upon start up, and then deleting that gathered data because it is not desired.

C. Artificial Neural Network Architecture

An artificial neural network was designed and trained to classify the *x* amount of selected (*5*) hand gestures. The artificial neural network was a pattern recognition network with eight inputs and x amount of outputs (depending on the number of desired gestures selected by the user (*5*)). For the testing, two hidden layers comprised of 125 neurons each were used; along with the epochs being set at 400 (Fig. 1). There were 71,640 total signals (*8955*8*) used for the input. For training the artificial neural network, 70% of these signals were used for training while the other 30% was used evenly for validation (*15%*) and training (*15%*) of the neural network. Each input had a target value of one, this is crucial for the gesture classification. The possible outputs of the artificial neural network were the *x* amount of different hand gestures.

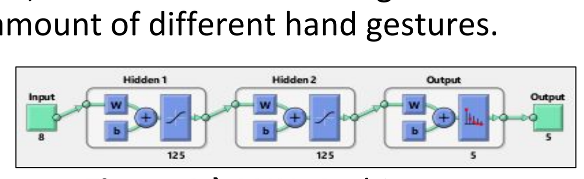

Figure 1.) ANN Architecture

D. Application Development and Implementation

An application was created in MATLAB to provide easier interfacing to the armband and artificial neural network. As of now there are three main functions of the app: a data collection process, building/training the artificial neural network function, and a classified gesture output section that also trends the live data from the surface electromyographic sensors on the Myo armband (Fig. 2).

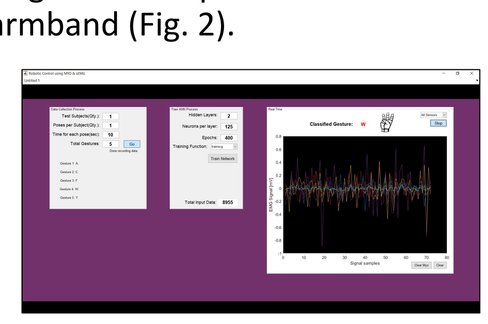

Figure 2.) App created for this project

Once the artificial neural network was built, trained, and tested; a function to stream live data from the sensors of the armband to the artificial neural network was created. The data from the armband was sampled every 350 milliseconds. The classified gesture output (text in red) that is displayed is what will also be the output from the neural network that determines what command to send to the servo motors that control the hand.

Results.

The data provided to the neural network for training and testing was the result of recording five gestures for ten seconds each. The five gestures for this specific experiment where the letters A, C, F, W, & Y of the American Sign Language. The results of the accuracies from the trained neural network are significantly lower compared to previous tests that involved gestures that required a significant amount more of muscle flexion in the forearm.

The neural network used the "dividerand" algorithm for data division, "scaled conjugate gradient" algorithm for training the network, and "crossentropy" algorithm for the network's performance. For this test, the network was able to reach the maximum epochs (400 iterations) without reaching the maximum validation checks that was set at fifty (Fig. 3).

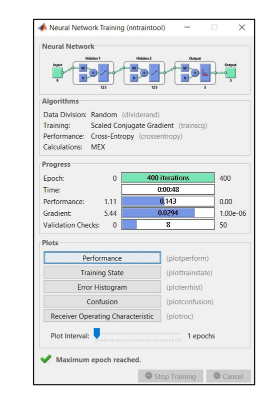

Figure 3.) NN Tool displaying data from trained ANN

From the confusion matrix (Fig. 4) it may be observed that the overall accuracy of the trained neural network was 68.8%. Class one (gesture A) had the highest accuracy rate at 73.5%. Class two (gesture C) had an accuracy rate of 69.8%. Class three (gesture F) had an accuracy rate of 67.4%. Class four (gesture W) had an accuracy rate of 73.1%. Class five (gesture Y) had the worst accuracy rate at 60.6%.

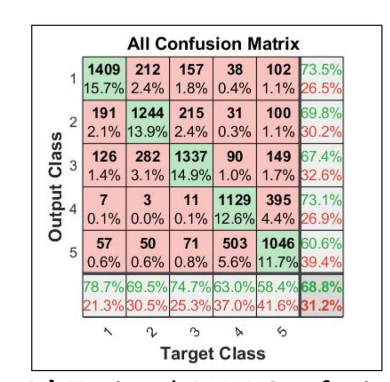

Figure 4.) Trained ANN Confusion matrix

Looking at the confusion matrix again, one can see that the neural network had significant difficulty distinguishing the difference between classes four and five. This may also be observed in the stem plot (Fig. 5) where the red represents incorrectly targeted outputs and the green shows the outputs that were correctly targeted.

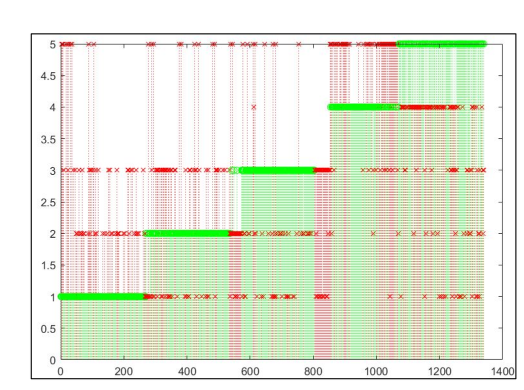

Figure 5.) Stem plot showing the classified outputs

Future Work.

The hopes of this project are to continue to explore the cost alternative options for human prosthetic control via live human body signals (EMG in this case). Upon the completion of adding more gestures a goal would be to incorporate the use of the inertial measurement unit that has accelerometers and a gyroscope for the sensing components.

Discussion.

- One of the top findings was the significant difference in accuracy between gestures requiring more forearm muscle flexion such as waving the hand in or making a fist versus gestures for alphabetic letters of the American Sign Language, which do not necessarily require much muscular force from the forearm.
- This is significant because it exposes a weak point if this was to be used for something such as sign language. If this was used in real life, there would be more error using it to perform sign language versus using it to grab an object or to hold something that requires a distinct force of the forearm muscle.
- This work is important because it is using open source technology and cheaper resources to show a possible alternative of low to middle end prosthetics that still cost anywhere from $5000-$25,000. This project's cost was approximately $500, which is significantly cheaper than any medical prosthetic currently on the market today.

We would like to thank Dr. Rios and the entire Electrical and Computer Engineering Department faculty for all the knowledge, guidance, and support in which they provided us throughout our time here at Georgia Southern University.

References

[1] William Morrison, "Electromyography (EMG)". Internet: https://www.healthline.com/health/electromyography. 2018 [Accessed Mar. 23, 2020].

[2] "What Is a Neural Network?". Internet: https://www.mathworks.com/discovery/neural-network.html, 2019 [Accessed Mar. 23, 2020].

2020 Student Research Symposium
Statesboro, Georgia
April 24, 2020

GEORGIA SOUTHERN UNIVERSITY
ALLEN E. PAULSON COLLEGE OF ENGINEERING AND COMPUTING

GEORGIA SOUTHERN UNIVERSITY