



# BRADLEY University

## **EMG Based Human Machine Interface Final Report**

By Aditya Patel and Jim Ramsay  
Advised by Dr. Yufeng Lu and Dr. In Soo Ahn  
Published May 3, 2018

## **Abstract**

Surface Electromyography (EMG) is a non-invasive technique which records the electrical activity of muscles using electrodes placed directly on the skin. The use of EMG signals has been gaining prevalence in prosthetic control and gesture-control applications. This project aims to develop an EMG-based human machine interface system. A Myo Armband with eight electrode pairs is worn by a user to acquire and wirelessly transmit EMG data to a central controller. A pattern recognition algorithm is implemented on a central controller to recognize three different hand gesture commands. As a demonstration, we built a camera system equipped with servo motors. The recognized commands can remotely pan each camera and select one of multiple video feeds to display. Our study demonstrates that the EMG-based pattern recognition could be a viable human machine interface option for a broad range of applications in industrial, medical, and consumer markets.

## **Acknowledgements**

We would like to thank our advisors, Drs. Yufeng Lu and In Soo Ahn. The time and effort they contributed in advising us was integral in the success of this project. We were the benefactors of their willingness to share their extensive knowledge in signal processing and neural network design. In addition to our advisors, we would also like to extend our gratitude to Bradley University and the ECE department faculty and staff for their dedication to providing the highest quality of learning experiences. Finally, we would be remiss to not express gratitude to our friends and family for all of their support. The support provided by our friends and family has enabled us to complete this project as well as our entire undergraduate degrees.

# Table of Contents

<b>1. Introduction</b> .....	6
A. EMG Applications	
B. Pattern Recognition Algorithms	
<b>2. Project Goals</b> .....	9
<b>3. System Design</b> .....	10
A. Functions and Gestures	
B. System Diagram	
C. Myo Gesture Control Armband	
D. Raspberry Pi	
E. Servo Motors	
F. Monitor	
G. Software Packages	
<b>4. Technical Specifications</b> .....	14
A. Myo Gesture Control Armband	
B. Raspberry Pi 3B	
C. Raspberry Pi Camera Module v2	
<b>5. Results</b> .....	17
A. Raw Data Collection and Preliminary Results	
B. Filtering	
C. Implemented Classification Method	
<b>6. Future Work</b> .....	25
<b>7. Summary</b> .....	26
<b>8. References</b> .....	28
<b>Code Appendix</b> .....	29

## List of Tables and Figures

**Table 1:** Functions and their associated gestures

**Table 2:** Sensor groupings

**Table 3:** Confidence values given for different pairings of top sensor groupings

**Table 4:** Example of confidence points awarded

**Figure 1:** Raw EMG data (normalized) from 8 sensors on one user, making one gesture

**Figure 2:** System flowchart

**Figure 3:** System Diagram

**Figure 4:** Raw EMG Data with Palm Facing In, Wrist Action Out

**Figure 5:** Raw EMG Data with Palm Facing In, Wrist Action In

**Figure 6:** – EMG sensor data (for all 8 sensors) when passed through each filter option

**Figure 7:** Three stages of preprocessing raw EMG data, for three different gestures.

**Figure 8:** Sensor group sum data with the group average lines

**Figure 9:** Line plots representing the group averages of different motions

**Figure 10:** Confusion matrix using the raw EMG data as the PNN inputs

**Figure 11:** Confusion matrix using the preprocessed EMG data as the PNN inputs

# 1. Introduction

Electromyography (EMG) is a technique for monitoring electrical signals associated with movement of muscles. EMG signals can be obtained via an intramuscular needle, or by an electrode placed directly on the skin. Intramuscular EMG (iEMG) is more accurate than surface EMG (sEMG) but sEMG allows electrical signals to be measured without the need for intrusive or bulky measurement tools. Acquiring sEMG signals only requires electrodes to be placed directly above the target muscle. When placed on the forearm, sEMG electrodes detect muscle activity associated with the movement of a user's hand. Since this project is focused on the analysis of sEMG signals, when the term "EMG signal(s)" is used throughout this report, the reader should assume these signals were collected by using the sEMG method.

EMG signals can range from 0V to 10V, peak-to-peak. The difficult part of collecting and analyzing the raw EMG data is the wide range of frequencies it can produce. EMG signals can be anywhere between 10Hz to 500Hz, depending on the person and how active their muscles are. As shown in Figure 1, even when the same person holds the same gesture for a period of time, the amplitude and frequency of the EMG signal can still vary quite a bit.

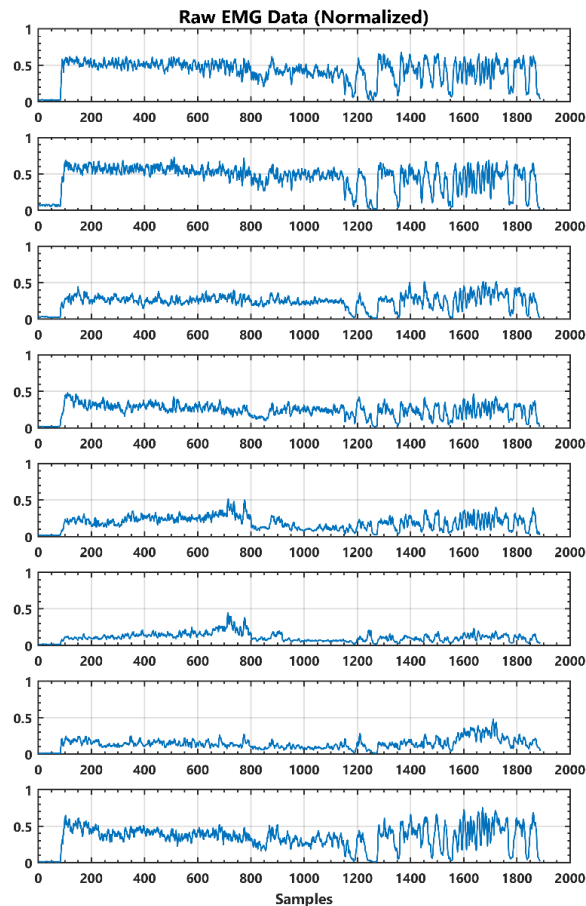


Figure 1 – Raw EMG data (normalized) from 8 sensors on one user, making one gesture

## **A. EMG Applications**

### Medical Diagnosis and Rehabilitation

Detection of EMG signals is becoming commonplace in the biomedical field. It is being used in medical research for diagnosis and rehabilitation [1]. In the most common case, an EMG test can be conducted to test for a variety of muscle and nerve related conditions and injuries [2]. Conditions that EMG testing helps diagnose include carpal tunnel syndrome, a pinched nerve, neuropathies, muscle diseases, muscular dystrophy, and Lou Gehrig's disease [3].

### Prosthetic Control

In research, EMG signals are used to help recovering amputees control prosthetic limbs. Even if an amputee is missing a limb, their mind can still try to move the limb that is not there. In doing so, electrical impulses are sent to that region of the body as if the limb was still there. For example, an individual missing their forearm can have a prosthetic arm controlled by the EMG signals detected in their shoulder/upper arm [4].

There are great strides being made in EMG based prosthetics. For example, researchers at Japan's Hokkaido University developed an EMG prosthetic hand controller that uses real-time learning to detect up to ten forearm motions with 91.5% accuracy [5]. Additionally, research done at Abu Dhabi University aimed to develop a virtual reality simulation of an arm using EMG signals. They achieved an 84% success rate in simulating the correct movements made by amputees [6]

## **B. Pattern Recognition Algorithms**

Pattern recognition is a subset of machine learning that can be broken into two main categories: supervised and unsupervised. In supervised learning, the algorithm is "trained" by giving the algorithm data that is already classified. This allows the program to have a baseline understanding of the pattern so that it knows what to look for in the future. In unsupervised learning, the algorithm is not given any classification information, and must draw inferences from data on its own [7]. "The most common unsupervised learning method is cluster analysis, which is used for exploratory data analysis to find hidden patterns or grouping in data. The clusters are modeled using a measure of similarity which is defined upon metrics such as Euclidean or probabilistic distance" [8].

A critical part of machine learning is an artificial neural network (ANN). ANN's are designed to mimic the human brain, where neurons and axons are represented by nodes and wires. Neural networks can be designed in countless different configurations. One form of neural network that is of interest to this project is a pattern recognition neural

network (PNN). These algorithms are used to classify input data. The network is trained by associating training input data with known classifications. After the network is trained, new input data is entered and the output of the neural network is a classification for the input, based on the training stage results. The inputs for the network play a key role in the accuracy of the network. The network will get increasingly more accurate with more inputs, so long as there is a correlation to the classification. Some common inputs types are raw data, filtered data, averaged data, RMS data and other forms of data manipulation that help to relate each series of inputs to one classification.



## 2. Project Goals

The current market for gesture-based control of systems rely solely on the use of cameras to detect user movements. These systems require heavy processing and restrict the user to gesture only in the field of view of the cameras. To address these issues, this project created an EMG-based controlled system with the following goals.

### A. Acquire EMG data from a user

The EMG data must be collected wirelessly so as to not restrict the user. The wireless communication needs to be reliable and quick to connect. Additionally, the data must be sampled at a rate high enough for real-time operation.

### B. Detect different user hand gestures in real time

This system uses three different hand gestures to control it: a fist, wave inward, and wave outward. It has only been tested on the right hand, though it should be possible to use any hand. The system needs a calibration mode to allow for anybody to use it. The calibration should be quick and allow for fast and accurate gesture recognition. Users must receive feedback about the state of the system through the console.

### C. Implement gesture detection to control a system

The system is comprised of two cameras, each attached to its own servo motor. The hand gestures allow the user to adjust the position of the motors, as well as the camera feed that is displayed on an external monitor. The motors rotate 180°, 90° in each direction from the initial position. The cameras operate at 30 frames per second and 720p resolution.

### 3. System Design

In this project, gestures are captured by a Myo Gesture Control Armband made by Thalmic Labs Inc. The armband houses eight electrodes for capturing EMG signals as well as an inertial measurement unit (IMU). Since this project is focused on creating a system interface with the use of EMG signals, the IMU data is ignored while collecting data from the armband. The gestures are used to control a camera system.

#### A. Functions and Gestures

Table 1: Functions and their associated gestures

Function	Gesture
Toggle armband sleep / standby	Fist
System Control Activate	Palm in, wave out
Camera Control Activate	Palm in, wave in
Switch to Camera 1	Palm in, wave out
Switch to Camera 2	Palm in, wave in
Pan left	Palm in, wave in
Pan right	Palm in, wave out

The full flow of logic for our system is shown below.

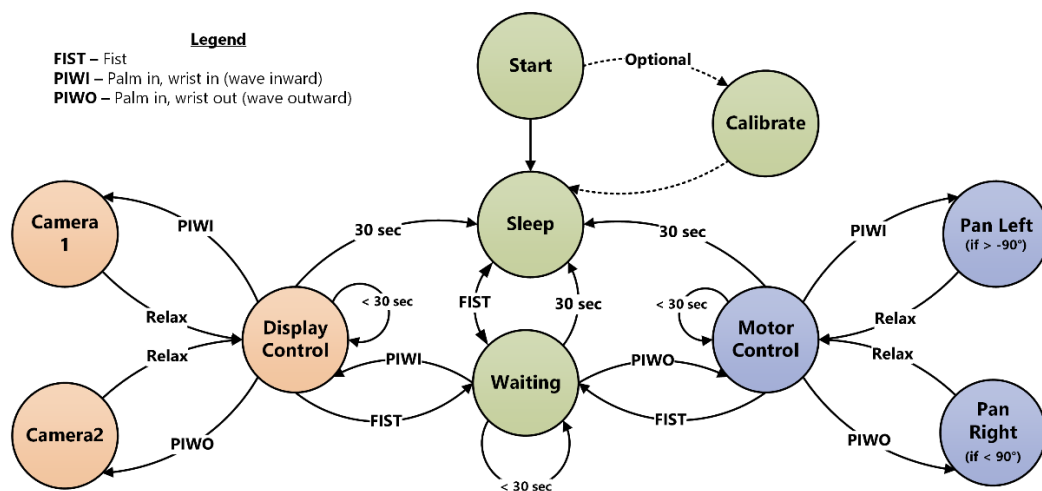


Figure 2: System flowchart

## B. System Diagram

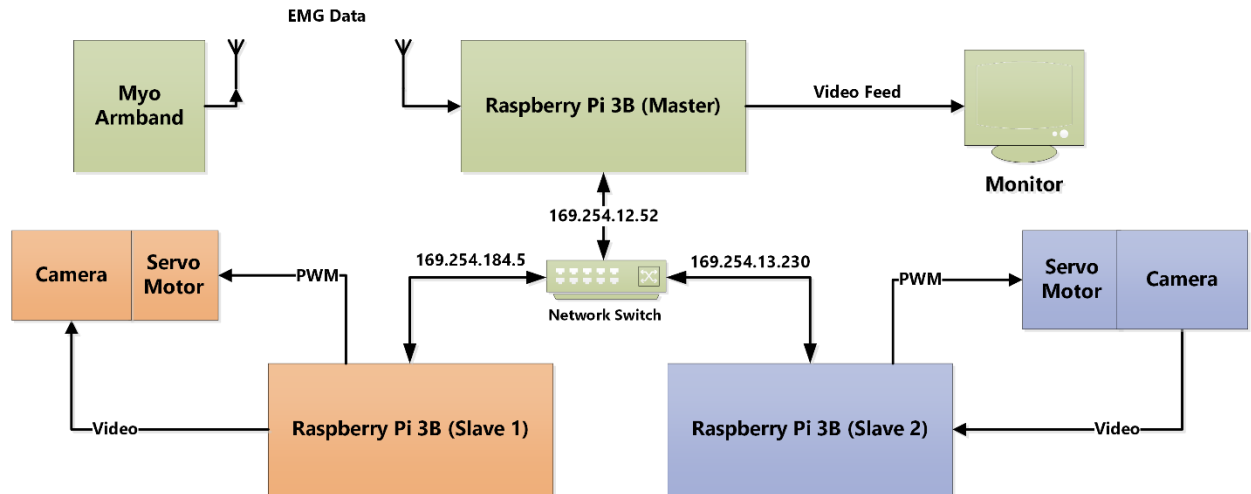


Figure 3: System Diagram

There are three Raspberry Pi 3B computers used in this project, one master and two slaves. The Myo armband sends EMG data via Bluetooth to the master Raspberry Pi. The master receives, processes and then communicates desired actions to one of the two slave Pi's. When the slave Pi gets a command, it executes a function to move the attached servo motor in a specific direction. The camera feeds stream on a webpage and, if the gesture calls for it, the master will switch the display to show the desired video stream. All master/slave communication is done on a local area network.

## C. Myo Gesture Control Armband

The HMI device used for this project is an EMG armband, designed by Thalmic Labs. It is comprised of eight EMG sensors as well as a nine-axis IMU. Once connected to the armband via Bluetooth, the data is transmitted in real-time. The data is transmitted from the armband at 200 Hz and is in the form of an 8-bit unsigned integer. The raw EMG data is not the actual voltage that is sensed by the electrodes. Rather, it is a representation of muscle activation. The exact activation-to-voltage relationship is not made public by the developer of the armband.

## D. Raspberry Pi

### Master

The master Pi board is the heart of the EMG Security Monitoring System. It receives the armband signal via a Bluetooth USB dongle. This signal is then processed by algorithms that identify gestures made by the user. The master Pi also sends commands to the slaves when a gesture is made to move the motors. The master is responsible for keeping track of and making adjustments to the duty cycle of the control signal sent to

the motors. The master also selects one of two different camera feeds to display on an external monitor.

### Slave(s)

There are two Raspberry Pi 3B computers that act as slaves to the master Pi board. Each slave is equipped with an attached camera and servo motor. They process the video signals from their respective cameras and stream the video to a webpage. The Pi cameras connect directly to the Raspberry Pi 3b and have the ability to stream live video in 1080P. These Pi boards also run the scripts (when directed by the master Pi board) to generate a change in the servo motor's PWM duty cycle. This, in turn, controls the angle at which the camera is pointed.

## **E. Servo Motors**

The system includes two servo motors (one per camera) that are used to pan the camera views from side to side. The motors are attached to a case which houses the Raspberry Pi and camera. The motors are powered by +5V, from the Pi GPIO pins. The Pi's also are equipped with a GPIO pin (12) that is designed to support PWM signal outputs—this is the pin used to transmit the PWM signal to the motor in this system. The camera angles are adjusted by increasing/decreasing the respective motors PWM duty cycle. The desired adjustment (per recognized gesture) is approximately 30 degrees. The master Pi board keeps track of the duty cycle and has built-in limitations of  $\pm 90^\circ$ .

## **F. Monitor**

The monitor setup is initialized when the system is turned on. In this system, the display switches between camera feeds based on the gestures recognized by the master Raspberry Pi board. The display is in full screen and is changed by a Python script that toggles between browser tabs that each video feed is streaming to.

## **G. Software**

### Bluetooth Communication

Because the Myo armband does not come with first-party compatibility for Linux-based operating systems, we had to seek out open source software packages. The one that we found that worked best is called PyoConnect\_v2.0, developed by *dzhu* and Fernando Cosentino [9][10]. This software package was designed to function in Linux just like the original software functions in Windows. The only part of this code that we used was the armband communication protocol. In this package is a file called "myo\_raw.py" that executes the Bluetooth communication between the USB dongle and the armband. It is this file that we edited to function as our main code for gesture detection.

## Video Feed

After exploring numerous different packages for the Raspberry Pi Camera module, we found one that perfectly aligned with our needs. Not only did it do everything we needed, it was much easier to install and configure than anything else that we had tried. The software is called the RPi-Cam-Web-Interface [11]. It allowed us to adjust the picture resolution, aspect ratio, framerate, overlaid text, and countless other items.

This software captures the video from the attached camera and streams the video feed to the Pi's IP address, so that the URL looks like: 169.254.13.230/html/index.php. It works for local area networks as well as when connected to the internet. Because it is browser based, all that was needed to switch between video feeds was to have both open in their own tab, and to send the "ctrl+Tab" command to the Raspberry Pi.

## Programming Language

The programming language for this project was essentially chosen for us. The vast majority of documentation on programming the Raspberry Pi and the Myo Armband used Python, so this was the natural choice for this project. For us, python was a brand new language, with a steep learning curve. Once we got a grasp on the jargon and syntax, it became very easy to write our own code from scratch and not have to rely on finding reference code online.

The primary benefit of using Python (2.7.14) is that anything is possible with the language. The drawback of this though, is that the code can be very slow to execute, especially when combined with the slow clock speed and limited processing power of the Raspberry Pi 3B. Nonetheless, we were able to execute our entire gesture detection and control loop in less than five milliseconds. If the execution time got much longer than that, we found that the Bluetooth communication would hang up and the code would stall.

## 4. Technical Specifications

### A. Myo Gesture Control Armband

- **Physical**
  - Weight: 93g
  - Flexibility: Fits arms ranging between 7.5" and 13"
  - Thickness: 0.45"
- **Sensors**
  - Surface EMG electrode pairs (8 pairs)
  - 9-Axis IMU
    - 3-Axis gyroscope
    - 3-Axis accelerometer
    - 3-Axis magnetometer
  - Made of medical grade stainless steel
- **Computer / Communication**
  - ARM Cortex M4 processor
  - Wireless Bluetooth 4.0 LE communication
  - Battery
    - Built-in Lithium Ion battery
    - Micro USB charge
    - 1 full day of usage
  - EMG Data
    - Sampling rate: 200 Hz
    - Unitless – muscle activation is represented as an 8-bit signed value
    - Time stamp is in milliseconds since epoch (01/01/1970)
  - Compatible Operating Systems (for the SDK)
    - Windows 7, 8, and 10
    - OSx 10.8 and up
    - Android 4.3 and up
  - Haptic feedback with short, medium and long vibration options

## B. Raspberry Pi 3B

- **Processor**
  - Broadcom BCM2387
  - 1.2 GHz Quad-Core ARM Cortex-A53
  - 802.11 b/g/n Wireless LAN
  - Bluetooth 4.1 (Classic and LE)
- **GPU**
  - Dual Core VideoCore IV Multimedia Co-Processor
  - OpenVG and 1080p30 H.264 high-profile decoder
- **Memory**
  - 1 GB LPDDR2
- **Operating System**
  - Boots from Micro SD card
  - Runs Linux OS or Windows 10 IoT
- **Dimensions**
  - 85 mm x 56 mm x 17 mm
- **Power**
  - Micro USB socket 5v1, 2.5A
- **Peripherals**
  - Ethernet
    - 10/100 BaseT socket
  - Video Out
    - HDMI (rev 1.3 & 1.4)
    - Composite RCA (PAL and NTSC)
  - GPIO
    - 40-Pin 2.54 mm expansion header 2x20 strip
    - 27-Pin GPIO
    - +3.3V, +5V and GND supply lines
  - Camera
    - 15-Pin MIPI Camera Serial Interface (CSI-2)

- Display
  - Display Serial Interface 15-way flat flex cable connector with two data lanes and a clock lane

## **C. Raspberry Pi Camera Module v2**

- **Camera**
  - Sony IMX219 8-megapixel sensor
- **Video**
  - 1080p30
  - 720p60
  - VGA90
- **Photo**
  - 8 MP
- **Compatibility**
  - Raspberry Pi 1, 2, 3 (all models)
  - Numerous open-source software libraries



## 5. Results

### A. Raw Data Collection and Preliminary Results

While collecting preliminary data, our goal was to test the raw armband data to verify that we can see differences in the data when different motions are made. The armband was always placed onto the thickest part of the right forearm, with sensor 4 on top, and sensors 1 and 8 on the bottom. Two different motions were captured: palm in, wrist action out (wave out) and palm in, wrist action in (wave in).

The first thing we noticed, which can be seen in both Figure 4 and Figure 5, was that there is a distinct difference in the EMG data when the arm muscles are activated. To prove this, we took samples in 10-second intervals and performed the actions in sets of 1, 3 and 5 actions. We observed clear differences between when the user's arm was at rest and when the user was making a gesture.

The second important detail we noted was a noticeable difference between the EMG sensor data when we performed different actions. Figure 4 shows the EMG data when the wrist is moved outward and we can see that the most muscle activation is on sensors 3, 4, and 5. Some action is observed in 2 and 6, while a relatively low amount of action is seen in sensors 1, 7 and 8. Figure 5 shows the EMG data for when the wrist is moved inward. In this case, we see that the most activation occurs on sensors 1, 7, and 8. There is also some activation on sensors 2, 3 and 6, while almost no activation was observed on sensors 4 and 5.

From this point, we shifted our focus to filter and analyze the data and then implement pattern recognition algorithms. To validate the pattern recognition algorithms, we collected and tested data from multiple users, performing multiple actions/gestures.

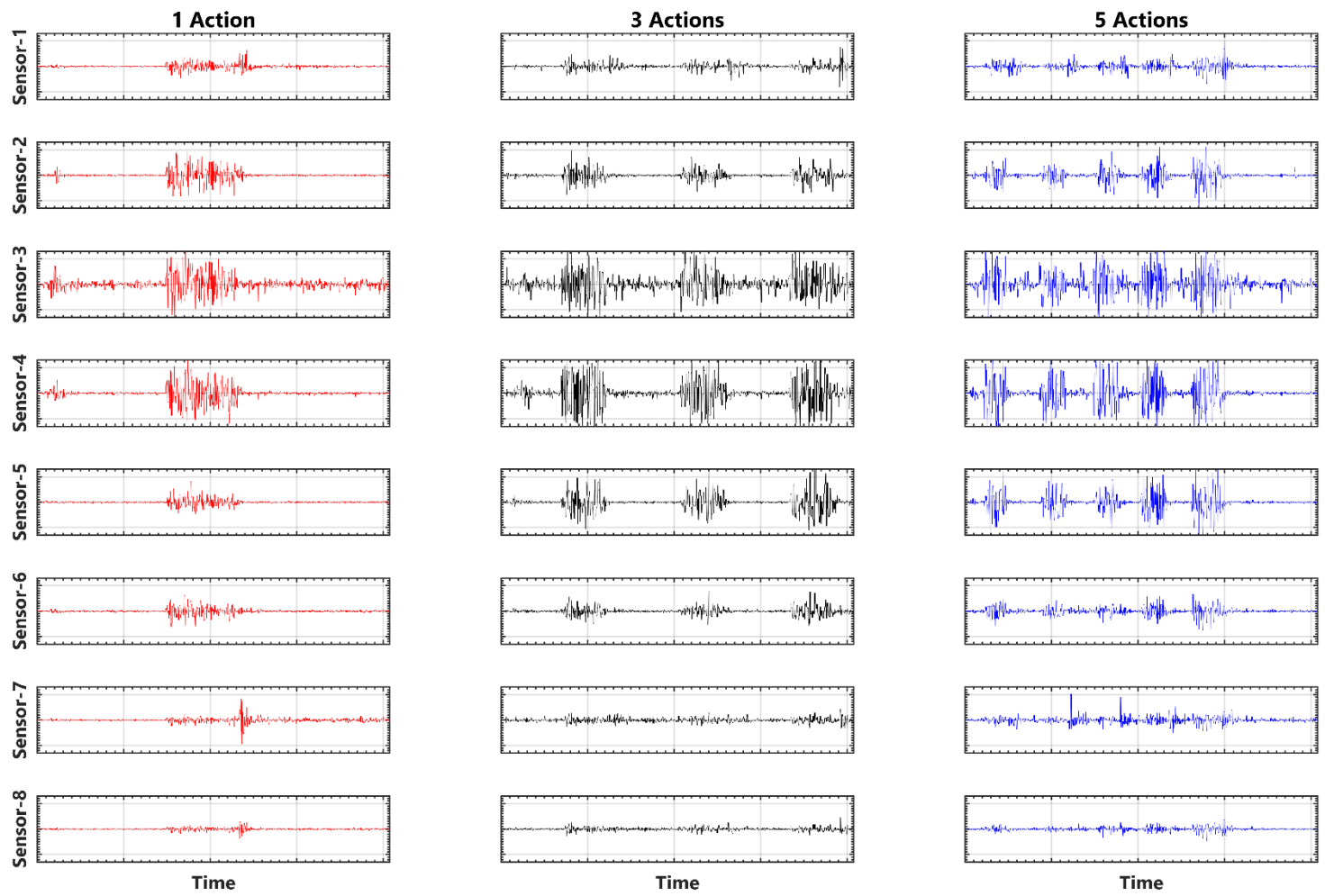


Figure 4: Raw EMG Data with Palm Facing In, Wrist Action Out

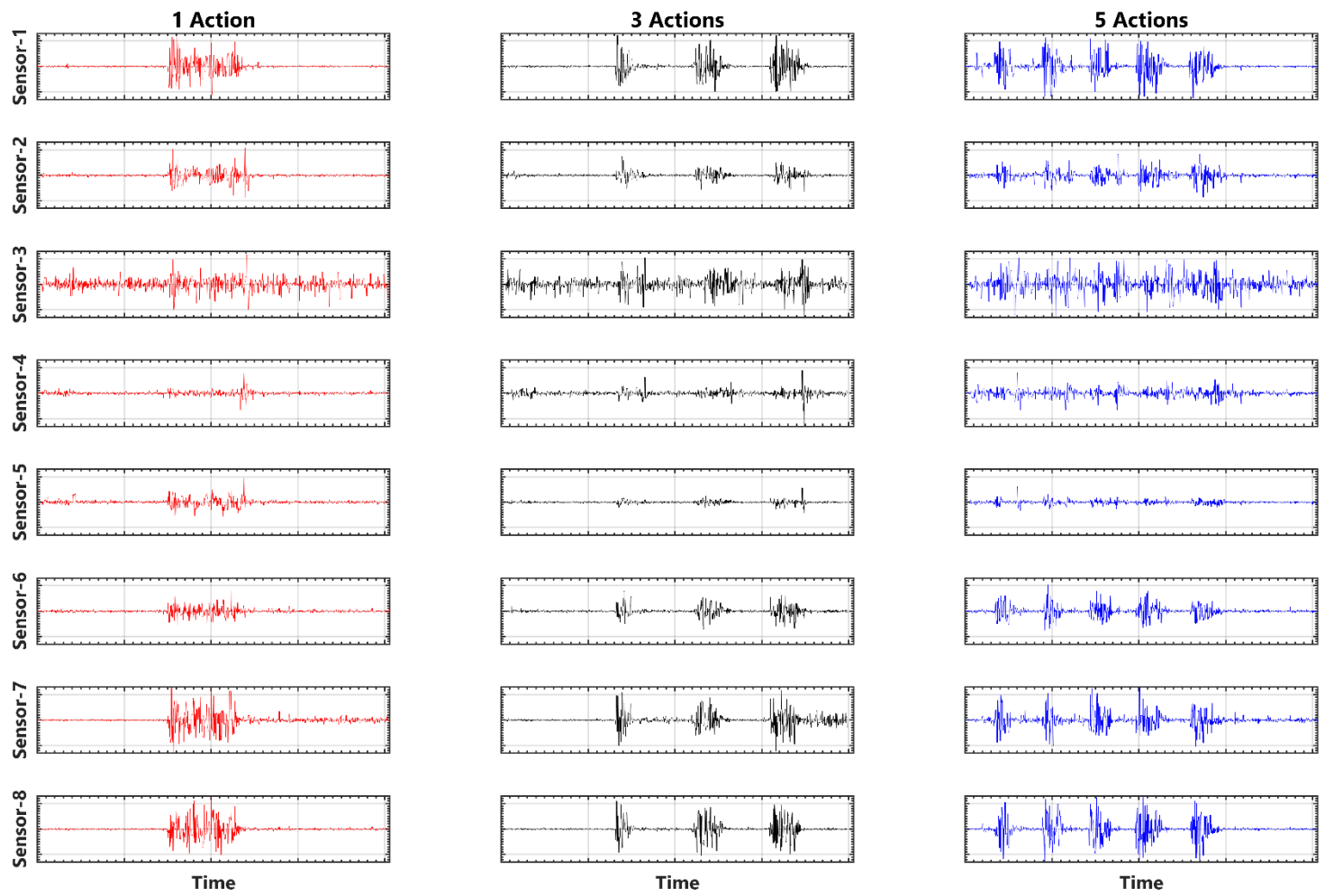


Figure 5: Raw EMG Data with Palm Facing In, Wrist Action In

## B. Filtering

The first stage in preprocessing the data was applying a Kaiser filter. Multiple filter options were considered and built using MATLAB's filter design tool. The two best filters turned out to be a 50<sup>th</sup> order Hamming filter and a 248<sup>th</sup> order Kaiser filter, both pictured in Figure 6. After some experimenting, we decided that the Kaiser filter was our best option and that is what we went with.

Although the filtered data was better than just the raw signal, the data still needed to be processed further to make any sense of it. After the filter was applied, a 100-sample moving average was calculated to remove any residual noise and smooth out the data. This gave us the ability to clearly identify when the user was gesturing and which gesture was being performed.

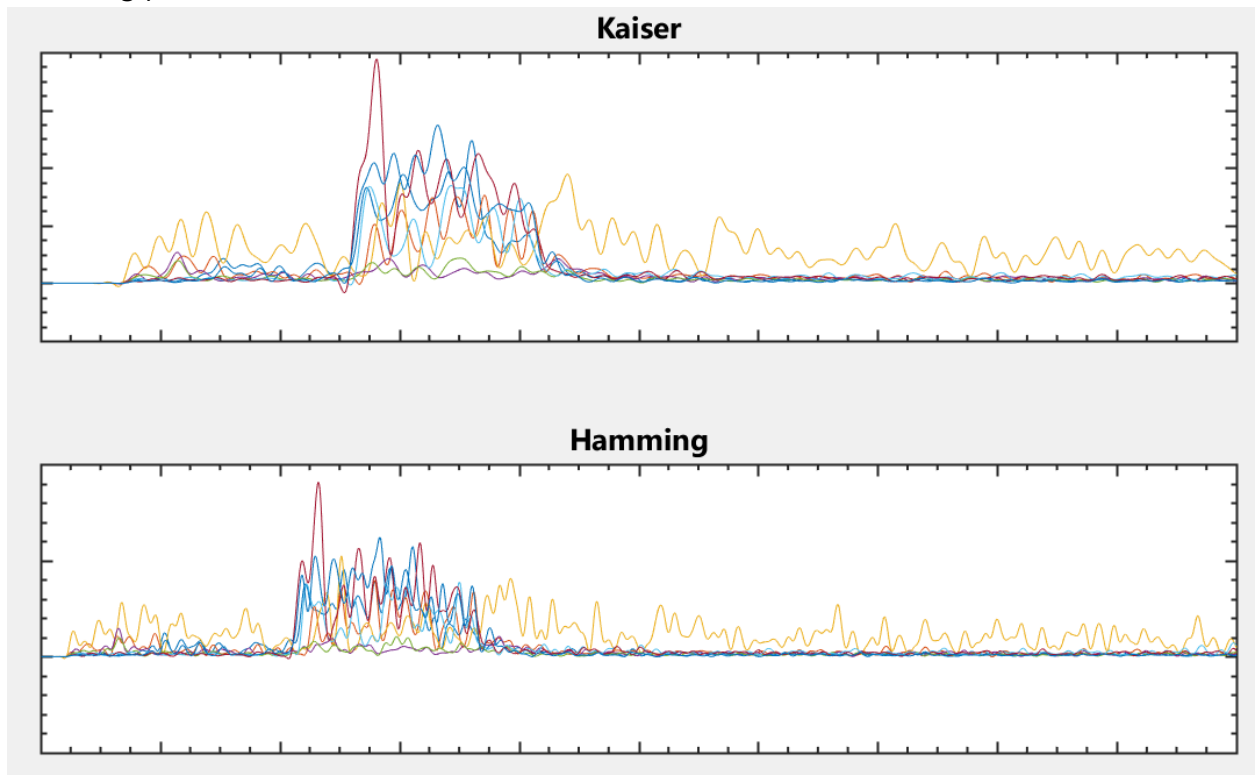


Figure 6: EMG sensor data (for all 8 sensors) when passed through each filter option

As shown in Figure 7, after each stage of preprocessing the data, the distinction between which sensors are active becomes clearer.

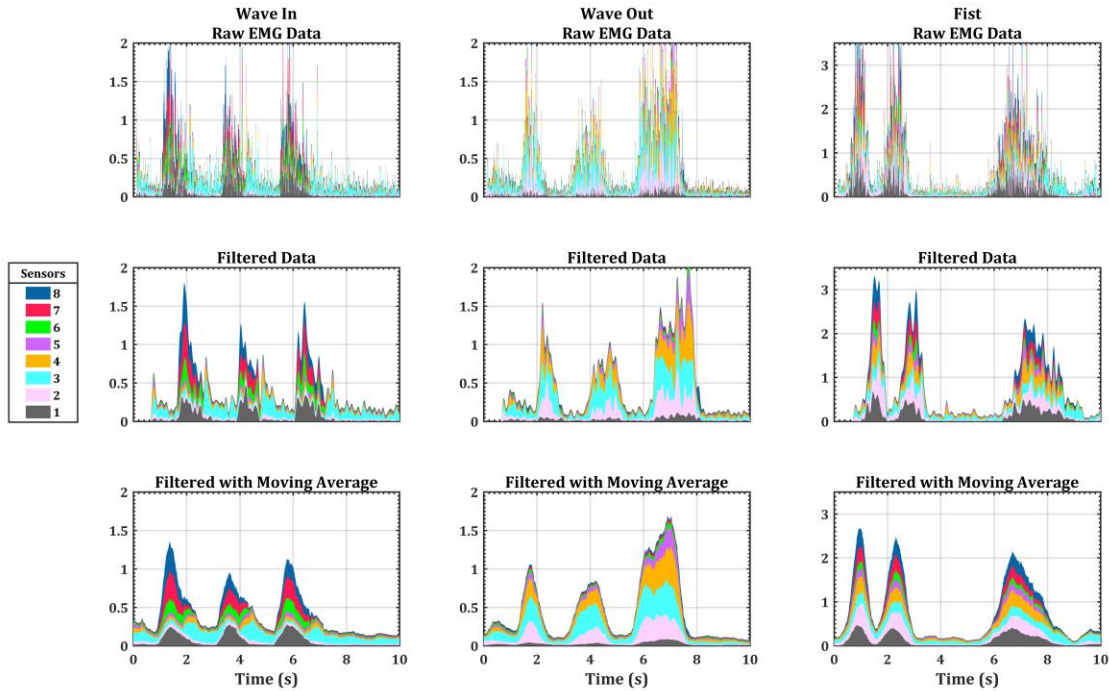


Figure 7: Three stages of preprocessing raw EMG data, for three different gestures

### C. Gesture Detection Algorithm

During the process of setting up the Raspberry Pi boards, the motors and the cameras, we developed a somewhat simplistic, yet reliable method for gesture detection.

The first step in this process is get the averages of multiple groups of sensors. By grouping the sensors, we lower the chances of the algorithm being affected by inaccuracies or fluctuations in just one of the sensors. The sensor groups are shown in Table 2.

Table 2: Sensor groupings

Group	Sensor Combination
1	1, 2, 3
2	2, 3, 4
3	3, 4, 5
4	4, 5, 6
5	5, 6, 7
6	6, 7, 8
7	7, 8, 1
8	8, 1, 2

The next step was to get some useful data from the groups. In both calibration and real-time data processing, the individual sensor values in each group are summed and divided by 3 to get a group average. The three groups with the highest averages are then selected to represent a gesture.

Calibration data is collected and the three highest group averages, for each gesture, are stored as a variable. When a user gestures with their arm, the confidence algorithm (described below) compares the groups of the real-time data to the groups of each calibrated gesture. Then, based on the relationship of matching groups, each calibrated gesture is assigned a confidence level. A threshold was implemented for the highest confidence level, which needed to be met to confirm that a perceived gesture was intentionally performed by the user. If the minimum threshold (10) is satisfied by at least one of the gesture comparisons, the algorithm has confirmation that the gesture with the highest confidence value is indeed the gesture that was made by the user.

To compare the real-time gesture data to the calibration data, each “match” of the top three groups are assigned a weight. For example, if the highest group average in one of the gestures calibration data matches the highest group of the real-time data, then the confidence in that action rises by 10. Then, if the second highest groups match, the confidence level for that action is increased, again, by 6. Finally, if the third groups also match, an additional 4 points are added to that gesture’s total. In this case, the total points for that gesture would be 20 (10 + 6 + 4), which is the highest level of confidence possible. Lower confidence points are awarded for partial matches, which would be when the groups match but in a different order. See Table 3 for the confidence points assignments. See Table 4 for an example of how the totaling of points works.

Table 3: Confidence values given for different pairings of top sensor groupings

		Calibration		
		1st	2nd	3rd
Real Time Data	1st	10	7	3
	2nd	4	6	2
	3rd	2	3	4

Table 4: Example of confidence points awarded

Real Time Max Groups	5	6	2	Total Points
				20
PIWI Calibration	1	5	2	$0+4+4=8$
PIWO Calibration	5	6	2	$10+6+4=20$
FIST Calibration	1	4	8	$0+0+0=0$

In the example shown in Table 4, the confidence algorithm would have returned PIWO as the gesture detected because it had the highest confidence level (20), and the confidence level exceeded the threshold for gesture confirmation (9). The first, second and third highest values all matched, in the correct order, to the PIWO calibration data.

The values assigned for the confidence points were obtained experimentally through trial and error. We started out by using a plot (see Figure 8) to make a visual comparison between the highest group averages. As you can see, we started with the data on the plot but that format made it difficult to recognize patterns in the data. We then decided to remove the data and only keep the group average lines (see Figure 9), which significantly helped in identifying patterns in the top three group averages. We then started to assign values by simply using values of one, two and three but quickly realized that was not going to work. We then realized that the correct order of the max averaged groups should increase the confidence, since it is another quality of the relationship between the real-time and calibrated data. We also lowered the point awarded for the matches that were out of order but did not want to completely disregard this relationship because the max group order does vary from time to time. We set it up so that if the max sensor groups matched, it was enough points to confirm a gesture. If not, then if the second and third highest matched, that would also tally enough confidence points that the gesture would also be confirmed. The final points we settled on were shown in Table 4.

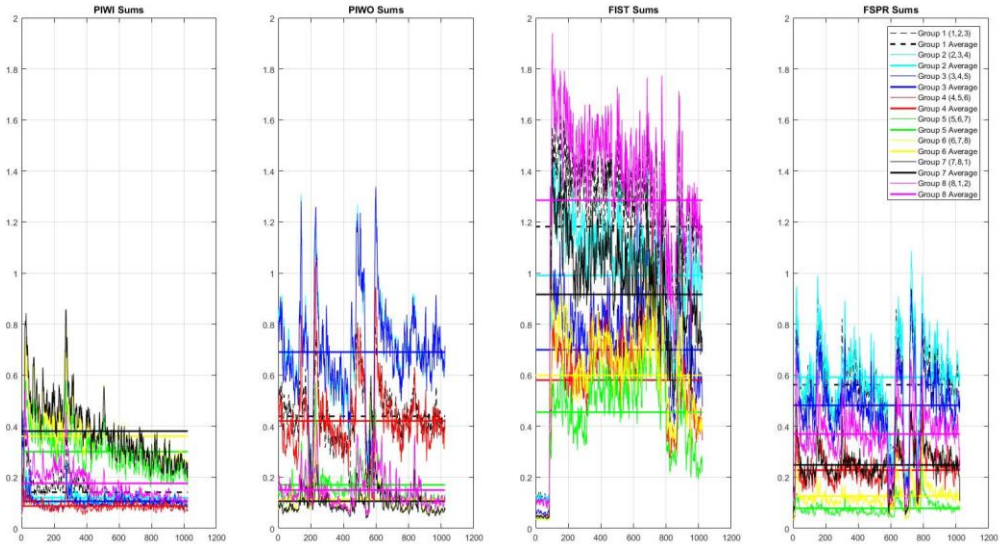


Figure 8: Sensor group sum data with the group average lines

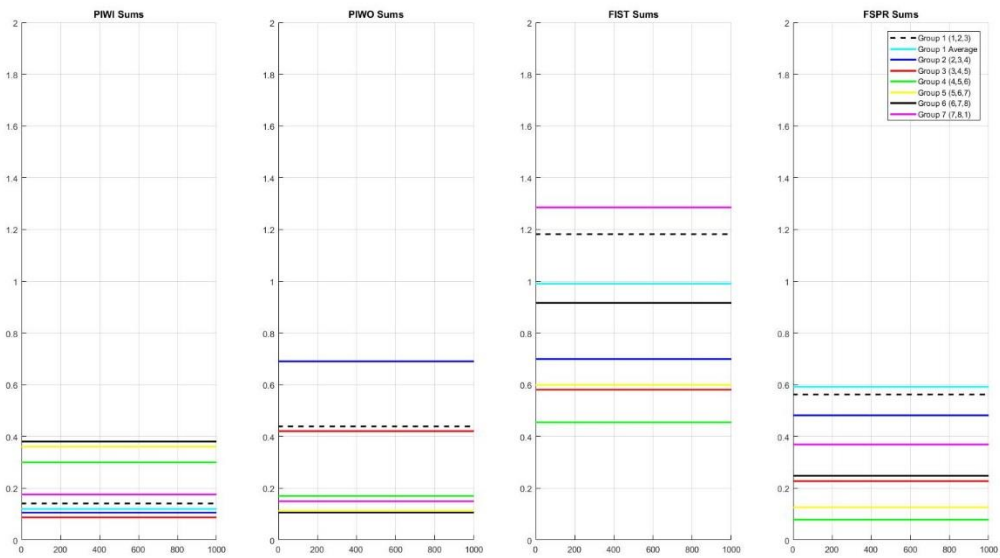


Figure 9: Line plots representing the group averages of different motions



## 6. Future Work

We highly suggest that research into using EMG data from the Myo armband be continued. For future projects, if our pattern recognition algorithms are not suitable, we would suggest implementing a neural network for gesture detection.

In this project, our efforts were not concentrated on implementing a neural network. We did, however, begin a small amount of research into the using a neural network. MATLAB has a built in neural network toolbox that we utilized. According to the MATLAB documentation on the *newpnn* function, a probabilistic neural network (PNN) is “a kind of radial basis network suitable for classification problems [12].”

To start out with, we used raw data and used the sensor values and their sum (for each sample) as the training input and used a numerical representation of the gesture (1 through 5) for the target vector. We trained the neural network with one set of data and used data from a second person to validate the accuracy.

Using just the nine original inputs (eight raw sensor values and their sum) the PNN could only achieve an accuracy of 77.8%, which is shown in Figure 10. Since this accuracy would not be sufficient for use, we then used the preprocessed data (filtered and with the moving average), the average of the eight samples and their sum as the inputs. With more inputs to the training network, we were able to get a much higher accuracy of 86.0%. The confusion chart shown in Figure 11 represents the accuracy using these inputs.

It became clear that with more inputs, or at least more meaningful inputs, to the PNN, the accuracy would continue to increase. We did not, however, intend on the use of the PNN for this project due to the limitations of our system. Our research into the PNN was meant as a starting point, should this project be continued in the future. If a neural network is considered for a future project, more powerful microprocessors or digital signal processors (DSP) would be needed to replace the Raspberry Pi computers we used to process the data.

**Confusion Matrix**

Output Class	1	77517 64.3%	415 0.3%	87 0.1%	119 0.1%	212 0.2%	98.9% 1.1%
	2	332 0.3%	4252 3.5%	3495 2.9%	6569 5.5%	1866 1.5%	25.7% 74.3%
	3	30 0.0%	519 0.4%	5024 4.2%	667 0.6%	5162 4.3%	44.1% 55.9%
	4	144 0.1%	1779 1.5%	371 0.3%	4949 4.1%	979 0.8%	60.2% 39.8%
	5	250 0.2%	1801 1.5%	130 0.1%	1811 1.5%	2020 1.7%	33.6% 66.4%
			99.0% 1.0%	48.5% 51.5%	55.2% 44.8%	35.1% 64.9%	19.7% 80.3%
		1	2	3	4	5	
		Target Class					

Figure 10: Confusion matrix using the raw EMG data as the PNN inputs

**Confusion Matrix**

Output Class	1	78040 64.8%	205 0.2%	27 0.0%	108 0.1%	90 0.1%	99.5% 0.5%
	2	115 0.1%	4868 4.0%	91 0.1%	91 0.1%	0 0.0%	94.2% 5.8%
	3	111 0.1%	940 0.8%	8871 7.4%	3154 2.6%	8500 7.1%	41.1% 58.9%
	4	3 0.0%	2753 2.3%	109 0.1%	10523 8.7%	284 0.2%	77.0% 23.0%
	5	4 0.0%	0 0.0%	9 0.0%	239 0.2%	1365 1.1%	84.4% 15.6%
			99.7% 0.3%	55.5% 44.5%	97.4% 2.6%	74.6% 25.4%	13.3% 86.7%
		1	2	3	4	5	
		Target Class					

Figure 11: Confusion matrix using the preprocessed EMG data as the PNN inputs

## 7. Summary

Historically, the ability to control a system with hand gestures has been limited. Gesture control often required bulky equipment or relied on image processing to track user motion within the viewing range of a camera. This project addressed this limitation by developing a lightweight system that is controlled only by hand gestures detected via electromyography. Hand gestures are detected by analyzing the EMG signals produced by muscle activity in a user's arm. The EMG signals from the arm are captured by the Myo Gesture Control Armband. We developed an algorithm to process the EMG data to quickly and accurately recognize three unique hand gestures. It is these hand gestures that are used to control the camera system.

In addition to getting this system running, we explored advanced methods of pattern recognition, including neural networks and support vector machines. We achieved fairly high accuracy using a pattern recognition neural network, and are confident that given more time and effort, this method can be a viable form of gesture detection.

From the start of this project, our goal was to collect and analyze raw EMG data with the intention of putting it to use in a control system. Our goal has been accomplished by implementing an algorithm to detect gestures and control a camera system. Additionally, we have laid the groundwork for future projects in the EMG based HMI field by starting the research into more accurate methods of gesture detection.

## 8. References

- [1] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin, "Techniques of EMG signal analysis: detection, processing, classification and applications," *Biological Procedures Online*, vol. 8, no. 1, pp. 163–163, Oct. 2006.
- [2] "Electromyography," *Medline Plus*, 06-Nov-2017. [Online]. Available: <https://medlineplus.gov/ency/article/003929.htm>. [Accessed: 10-Nov-2017].
- [3] J. H. Feinberg, "EMG Testing: A Patients Guide," *Hospital for Special Surgery*, 21-Oct-2009. [Online]. Available: [https://www.hss.edu/conditions\\_emg-testing-a-patient-guide.asp](https://www.hss.edu/conditions_emg-testing-a-patient-guide.asp). [Accessed: 05-Nov-2017].
- [4] S. Sudarsan and E. C. Sekaran, "Design and Development of EMG Controlled Prosthetics Limb," *Procedia Engineering*, vol. 38, pp. 3547–3551, Sep. 2012.
- [5] D. Nishikawa, Wenwei Yu, H. Yokoi and Y. Kakazu, "EMG prosthetic hand controller using real-time learning method," *Systems, Man, and Cybernetics, 1999. IEEE SMC '99 Conference Proceedings. 1999 IEEE International Conference on*, Tokyo, 1999, pp. 153-158 vol.1.
- [6] L. Fraiwan, M. Awwad, M. Mahdawi, and S. Jamous, "Real time virtual prosthetic hand controlled using EMG signals," in *Biomedical Engineering (MECBME), 2011 1st Middle East Conference on*, 2011, pp. 225-227.
- [7] C. Donalek, "Supervised and Unsupervised Learning," *Caltech Astronomy*, Apr-2011. [Online]. Available: [http://www.astro.caltech.edu/~george/aybi199/Donalek\\_Classif.pdf](http://www.astro.caltech.edu/~george/aybi199/Donalek_Classif.pdf) . [Accessed: 01-Nov-2017].
- [8] "Unsupervised Learning," *MATLAB & Simulink*. [Online]. Available: <https://www.mathworks.com/discovery/unsupervised-learning.html>. [Accessed: 2018].
- [9] D. Zhu, "myo-raw," Dec-2014. [Online]. Available: <https://github.com/dzhu/myo-raw>. [Accessed: May-2018].
- [10] F. Cosentino, "PyoConnect\_v2.0," [Online]. Available: <http://www.fernandocosentino.net/pyoconnect/> [Accessed: May-2018]
- [11] "RPI-Cam-Web-Interface," *elinux.org*. March 18, 2018. [Online]. Available: <https://elinux.org/RPi-Cam-Web-Interface>. [Accessed: May-2018].
- [12] Mathworks. (2017). *Neural Network Toolbox: User's Guide* (r2017a). [Online]. Available: [https://www.mathworks.com/help/nnet/ref/newpnn.html?searchHighlight=newpnn&s\\_tid=doc\\_srchtile](https://www.mathworks.com/help/nnet/ref/newpnn.html?searchHighlight=newpnn&s_tid=doc_srchtile)

## Code Appendix

Please disregard any formatting abnormalities you see in the below code. The original code with clean formatting can be found on our github repository: [https://github.com/abpatel2/2017-2018\\_EMG\\_senior\\_project](https://github.com/abpatel2/2017-2018_EMG_senior_project).

### A. main.py

```
1  ...
2  AUTHOR: Aditya Patel and Jim Ramsay
3  DATE CREATED: 2018-03-01
4  LAST MODIFIED: 2018-04-12
5  PLATFORM: Raspberry Pi 3B, Raspbian Stretch Released 2017-11-29
6  PROJECT: EMG Human Machine Interface
7  ORGANIZATION: Bradley University, School of Electrical and Computer Engineering
8  FILENAME: main.py
9  DESCRIPTION:
10     Main script that:
11         - initializes/executes bluetooth protocol (not written by Aditya/Jim -- see note below)
12         - starts reading emg data.
13         - detects gestures
14         - commands two slave raspberry pi's to rotate servo motors
15         - switches between displaying video feed from each of the slaves
16
17     Gestures (right hand only, have not tested on left hand):
18     rest -- do nothing, arm relaxed
19     fist -- tight fist
20     piwo -- palm in, wrist out (wave outward)
21     piwi -- palm in, wrist in (wave inward)
22
23     Master:
24     emgPi_3 -- pi@169.254.12.52 password is "ee00"
25
26     Slaves:
27     ssh commands recognize the defined names for the slaves using ssh_keys. Using the defined
28     names and saved keys bypasses password requirements.
29
30     emgPi_1 -- pi@169.254.184.5 password is "ee00"
31     emgPi_2 -- pi@169.254.13.230 password is "ee00"
32
33     NOTE:
34     Original by dzhu
35     https://github.com/dzhu/myo-raw
36
37     Edited by Fernando Cosentino
38     http://www.fernandocosentino.net/pyoconnect
39
40     Edited further by Aditya Patel and Jim Ramsay
41     There are a lot of global variables used to function like constants. This is likely not good practice
42     but had to be done to meet deadlines.
43
44     The majority of the code that we wrote is at the bottom of the script, after all of the Bluetooth and armband related code.
45     ...
46
47     from __future__ import print_function
48     import enum
49     import re
50     import struct
51     import sys
52     import threading
53     import time
54     import string
```

```

55 import serial
56 from serial.tools.list_ports import comports
57 from common import *
58
59 ''' Additional Imports '''
60 import os
61 import numpy as np
62 import csv
63 import datetime
64 from ringBuffer import ringBuffer
65 import displayControl as display
66 from calibrate import Calibrate
67 from guppy import hpy
68
69 ...
70     GLOBAL VARIABLES
71     note: a lot of these are meant to function like a "DEFINE" in C. They are never written to.
72 ...
73
74 ''' ARRAYS '''
75 global emg_data
76 emg_data = []
77
78 global duty
79 duty = [50, 50] # initial duty cycle for each motor
80
81 ''' INTEGERS '''
82 global GETTINGCALDATA; global CALIBRATING; global SLEEP; global WAITING; global DISPLAYCONTROL; global MOTORCONTROL
83 GETTINGCALDATA = 0
84 CALIBRATING = 1
85 SLEEP = 2
86 WAITING = 3
87 DISPLAYCONTROL = 4
88 MOTORCONTROL = 5
89
90 global REST; global FIST; global PIWI; global PIWO
91 REST = 0
92 FIST = 1
93 PIWI = 2
94 PIWO = 3
95
96 global calMode
97 calMode = REST
98
99 global EMGPI_1; global EMGPI_2
100 EMGPI_1 = 0
101 EMGPI_2 = 1
102
103
104 global fistCalData; global piwiCalData; global piwoCalData;
105 fistCalData = []
106 piwiCalData = []
107 piwoCalData = []
108
109 global curPi
110 curPi = 0
111
112 t0 = time.time()
113 global t_endWaiting
114
115 gestureString = ["fist", "piwi", "piwo", ""]

```

```

116 modeString = ["", "", "SLEEP", "WAITING", "DISPLAY CONTROL", "MOTOR CONTROL"]
117
118 def multichr(ords):
119     if sys.version_info[0] >= 3:
120         return bytes(ords)
121     else:
122         return ''.join(map(chr, ords))
123
124 def multiord(b):
125     if sys.version_info[0] >= 3:
126         return list(b)
127     else:
128         return map(ord, b)
129
130 class Arm(enum.Enum):
131     UNKNOWN = 0
132     RIGHT = 1
133     LEFT = 2
134
135 class XDirection(enum.Enum):
136     UNKNOWN = 0
137     X_TOWARD_WRIST = 1
138     X_TOWARD_ELBOW = 2
139
140 class Pose(enum.Enum):
141     RESTT = 0
142     FIST = 1
143     WAVE_IN = 2
144     WAVE_OUT = 3
145     FINGERS_SPREAD = 4
146     THUMB_TO_PINKY = 5
147     UNKNOWN = 255
148
149 class Packet(object):
150     def __init__(self, ords):
151         self.typ = ords[0]
152         self.cls = ords[2]
153         self.cmd = ords[3]
154         self.payload = multichr(ords[4:])
155
156     def __repr__(self):
157         return 'Packet(%02X, %02X, %02X, [%s])' % \
158             (self.typ, self.cls, self.cmd,
159              ''.join('%02X' % b for b in multiord(self.payload)))
160
161 class BT(object):
162     '''Implements the non-Myo-specific details of the Bluetooth protocol.'''
163     def __init__(self, tty):
164         self.ser = serial.Serial(port=tty, baudrate=9600, dsrdtr=1)
165         self.buf = []
166         self.lock = threading.Lock()
167         self.handlers = []
168
169     ## internal data-handling methods
170     def recv_packet(self, timeout=None):
171         t0 = time.time()
172         self.ser.timeout = None
173         while timeout is None or time.time() < t0 + timeout:
174             if timeout is not None: self.ser.timeout = t0 + timeout - time.time()
175             c = self.ser.read()
176             if not c: return None

```

```

177
178         ret = self.proc_byte(ord(c))
179         if ret:
180             if ret.typ == 0x80:
181                 self.handle_event(ret)
182                 return ret
183
184     def recv_packets(self, timeout=.5):
185         res = []
186         t0 = time.time()
187         while time.time() < t0 + timeout:
188             p = self.recv_packet(t0 + timeout - time.time())
189             if not p: return res
190             res.append(p)
191         return res
192
193     def proc_byte(self, c):
194         if not self.buf:
195             if c in [0x00, 0x80, 0x08, 0x88]:
196                 self.buf.append(c)
197                 return None
198             elif len(self.buf) == 1:
199                 self.buf.append(c)
200                 self.packet_len = 4 + (self.buf[0] & 0x07) + self.buf[1]
201                 return None
202             else:
203                 self.buf.append(c)
204
205             if self.packet_len and len(self.buf) == self.packet_len:
206                 p = Packet(self.buf)
207                 self.buf = []
208                 return p
209             return None
210
211     def handle_event(self, p):
212         for h in self.handlers:
213             h(p)
214
215     def add_handler(self, h):
216         self.handlers.append(h)
217
218     def remove_handler(self, h):
219         try: self.handlers.remove(h)
220         except ValueError: pass
221
222     def wait_event(self, cls, cmd):
223         res = [None]
224         def h(p):
225             if p.cls == cls and p.cmd == cmd:
226                 res[0] = p
227         self.add_handler(h)
228         while res[0] is None:
229             self.recv_packet()
230         self.remove_handler(h)
231         return res[0]
232
233     ## specific BLE commands
234     def connect(self, addr):
235         return self.send_command(6, 3, pack('6sBBBBH', multichr(addr), 0, 6, 6, 64, 0))
236
237     def get_connections(self):

```



```

238         return self.send_command(0, 6)
239
240     def discover(self):
241         return self.send_command(6, 2, b'\x01')
242
243     def end_scan(self):
244         return self.send_command(6, 4)
245
246     def disconnect(self, h):
247         return self.send_command(3, 0, pack('B', h))
248
249     def read_attr(self, con, attr):
250         self.send_command(4, 4, pack('BH', con, attr))
251         return self.wait_event(4, 5)
252
253     def write_attr(self, con, attr, val):
254         self.send_command(4, 5, pack('BHB', con, attr, len(val)) + val)
255         return self.wait_event(4, 1)
256
257     def send_command(self, cls, cmd, payload=b'', wait_resp=True):
258         s = pack('4B', 0, len(payload), cls, cmd) + payload
259         self.ser.write(s)
260
261         while True:
262             p = self.recv_packet()
263
264             ## no timeout, so p won't be None
265             if p.typ == 0: return p
266
267             ## not a response: must be an event
268             self.handle_event(p)
269
270 class MyoRaw(object):
271     '''Implements the Myo-specific communication protocol.'''
272
273     def __init__(self, tty=None):
274         if tty is None:
275             tty = self.detect_tty()
276         if tty is None:
277             raise ValueError('Myo dongle not found!')
278
279         self.bt = BT(tty)
280         self.conn = None
281         self.emg_handlers = []
282         self.imu_handlers = []
283         self.arm_handlers = []
284         self.pose_handlers = []
285
286     def detect_tty(self):
287         for p in comports():
288             if re.search(r'PID=2458:0*1', p[2]):
289                 print('using device:', p[0])
290                 return p[0]
291
292         return None
293
294     def run(self, timeout=None):
295         self.bt.recv_packet(timeout)
296
297     def connect(self):
298         ## stop everything from before

```

```

299 self.bt.end_scan()
300 self.bt.disconnect(0)
301 self.bt.disconnect(1)
302 self.bt.disconnect(2)
303
304
305 ## start scanning
306 print('scanning for bluetooth devices...')
307 self.bt.discover()
308 while True:
309     p = self.bt.recv_packet()
310     print('scan response:', p)
311
312     if p.payload.endswith(b'\x06\x42\x48\x12\x4A\x7F\x2C\x48\x47\xB9\xDE\x04\xA9\x01\x00\x06\xD5'):
313         addr = list(multiord(p.payload[2:8]))
314         break
315 self.bt.end_scan()
316
317 ## connect and wait for status event
318 conn_pkt = self.bt.connect(addr)
319 self.conn = multiord(conn_pkt.payload)[-1]
320 self.bt.wait_event(3, 0)
321
322 ## get firmware version
323 fw = self.read_attr(0x17)
324 v0, v1, v2, v3 = unpack('BHHBHHHH', fw.payload)
325 print('firmware version: %d.%d.%d.%d' % (v0, v1, v2, v3))
326
327 self.old = (v0 == 0)
328
329 if self.old: # if the firmware is 0.x.xxxx.x
330     ## don't know what these do; Myo Connect sends them, though we get data
331     ## fine without them
332     self.write_attr(0x19, b'\x01\x02\x00\x00')
333     self.write_attr(0x2f, b'\x01\x00')
334     self.write_attr(0x2c, b'\x01\x00')
335     self.write_attr(0x32, b'\x01\x00')
336     self.write_attr(0x35, b'\x01\x00')
337
338     ## enable EMG data
339     self.write_attr(0x28, b'\x01\x00')
340     ## enable IMU data
341     self.write_attr(0x1d, b'\x01\x00')
342
343     ## Sampling rate of the underlying EMG sensor, capped to 1000. If it's
344     ## less than 1000, emg_hz is correct. If it is greater, the actual
345     ## framerate starts dropping inversely. Also, if this is much less than
346     ## 1000, EMG data becomes slower to respond to changes. In conclusion,
347     ## 1000 is probably a good value.
348     C = 1000
349     emg_hz = 50
350     ## strength of low-pass filtering of EMG data
351     emg_smooth = 100
352
353     imu_hz = 50
354
355     ## send sensor parameters, or we don't get any data
356     self.write_attr(0x19, pack('BBBBHBBBB', 2, 9, 2, 1, C, emg_smooth, C // emg_hz, imu_hz, 0, 0))
357
358 else: #normal operation
359     name = self.read_attr(0x03)

```

```

360     print('device name: %s' % name.payload)
361
362     ## enable IMU data
363     self.write_attr(0x1d, b'\x01\x00')
364     ## enable vibrations
365     self.write_attr(0x24, b'\x02\x00')
366     # Failed attempt to disable vibrations:
367     # self.write_attr(0x24, b'\x00\x00')
368
369     # self.write_attr(0x19, b'\x01\x03\x00\x01\x01')
370     self.start_raw()
371
372     ## add data handlers
373     def handle_data(p):
374         if (p.cls, p.cmd) != (4, 5): return
375         c, attr, typ = unpack('BHB', p.payload[:4]) # unpack unsigned char, unsigned short, unsigned char
376         pay = p.payload[5:]
377         if attr == 0x27:
378             vals = unpack('8HB', pay) # unpack 8 unsigned shorts, and one unsigned char https://docs.python.org/2/library/struct.html
379                                     ## not entirely sure what the last byte is, but it's a bitmask that
380                                     ## seems to indicate which sensors think they're being moved around or
381                                     ## something
382             emg = vals[:8]
383             moving = vals[8]
384             self.on_emg(emg, moving)
385         elif attr == 0x1c:
386             vals = unpack('10h', pay)
387             quat = vals[:4]
388             acc = vals[4:7]
389             gyro = vals[7:10]
390             self.on_imu(quat, acc, gyro)
391         elif attr == 0x23:
392             typ, val, xdir, _, _ = unpack('6B', pay)
393
394             if typ == 1: # on arm
395                 self.on_arm(Arm(val), XDirection(xdir))
396                 print("on arm")
397             elif typ == 2: # removed from arm
398                 self.on_arm(Arm.UNKNOWN, XDirection.UNKNOWN)
399                 print("NOT on arm")
400             elif typ == 3: # pose
401                 self.on_pose(Pose(val))
402         else:
403             print('data with unknown attr: %02X %s' % (attr, p))
404
405     self.bt.add_handler(handle_data)
406
407     def write_attr(self, attr, val):
408         if self.conn is not None:
409             self.bt.write_attr(self.conn, attr, val)
410
411     def read_attr(self, attr):
412         if self.conn is not None:
413             return self.bt.read_attr(self.conn, attr)
414         return None
415
416     def disconnect(self):
417         if self.conn is not None:
418             self.bt.disconnect(self.conn)
419
420     def start_raw(self):

```

```

421     '''Sending this sequence for v1.0 firmware seems to enable both raw data and
422     pose notifications.
423     '''
424
425     self.write_attr(0x28, b'\x01\x00')
426     #self.write_attr(0x19, b'\x01\x03\x01\x01\x00')
427     self.write_attr(0x19, b'\x01\x03\x01\x01\x01')
428
429 def mc_start_collection(self):
430     '''Myo Connect sends this sequence (or a reordering) when starting data
431     collection for v1.0 firmware; this enables raw data but disables arm and
432     pose notifications.
433     '''
434
435     self.write_attr(0x28, b'\x01\x00')
436     self.write_attr(0x1d, b'\x01\x00')
437     self.write_attr(0x24, b'\x02\x00')
438     self.write_attr(0x19, b'\x01\x03\x01\x01\x01')
439     self.write_attr(0x28, b'\x01\x00')
440     self.write_attr(0x1d, b'\x01\x00')
441     self.write_attr(0x19, b'\x09\x01\x01\x00\x00')
442     self.write_attr(0x1d, b'\x01\x00')
443     self.write_attr(0x19, b'\x01\x03\x00\x01\x00')
444     self.write_attr(0x28, b'\x01\x00')
445     self.write_attr(0x1d, b'\x01\x00')
446     self.write_attr(0x19, b'\x01\x03\x01\x01\x00')
447
448 def mc_end_collection(self):
449     '''Myo Connect sends this sequence (or a reordering) when ending data collection
450     for v1.0 firmware; this reenables arm and pose notifications, but
451     doesn't disable raw data.
452     '''
453
454     self.write_attr(0x28, b'\x01\x00')
455     self.write_attr(0x1d, b'\x01\x00')
456     self.write_attr(0x24, b'\x02\x00')
457     self.write_attr(0x19, b'\x01\x03\x01\x01\x01')
458     self.write_attr(0x19, b'\x09\x01\x00\x00\x00')
459     self.write_attr(0x1d, b'\x01\x00')
460     self.write_attr(0x24, b'\x02\x00')
461     self.write_attr(0x19, b'\x01\x03\x00\x01\x01')
462     self.write_attr(0x28, b'\x01\x00')
463     self.write_attr(0x1d, b'\x01\x00')
464     self.write_attr(0x24, b'\x02\x00')
465     self.write_attr(0x19, b'\x01\x03\x01\x01\x01')
466
467 def vibrate(self, length):
468     if length in xrange(1, 4):
469         ## first byte tells it to vibrate; purpose of second byte is unknown
470         self.write_attr(0x19, pack('3B', 3, 1, length))
471
472
473 def add_emg_handler(self, h):
474     self.emg_handlers.append(h)
475
476 def add_imu_handler(self, h):
477     self.imu_handlers.append(h)
478
479 def add_pose_handler(self, h):
480     self.pose_handlers.append(h)
481

```

```

482     def add_arm_handler(self, h):
483         self.arm_handlers.append(h)
484
485
486     def on_emg(self, emg, moving):
487         for h in self.emg_handlers:
488             h(emg, moving)
489
490     def on_imu(self, quat, acc, gyro):
491         for h in self.imu_handlers:
492             h(quat, acc, gyro)
493
494     def on_pose(self, p):
495         for h in self.pose_handlers:
496             h(p)
497
498     def on_arm(self, arm, xdir):
499         for h in self.arm_handlers:
500             h(arm, xdir)
501
502
503 def controlLogic(mode, gesture, confidence):
504     global SLEEP; global WAITING; global DISPLAYCONTROL; global MOTORCONTROL;
505     global REST; global FIST; global PIWI; global PIWO
506     global duty; global curPi; global t_endWaiting; global t_30_SLEEP
507
508     if ( mode == SLEEP ):
509
510         if ( gesture == FIST ):
511             mode = WAITING
512             t_endWaiting = time.time() + 1
513             print("SWITCHING MODE: WAITING\t\t\tConfidence Level: ", confidence)
514             t_30_SLEEP = time.time() + 30
515
516     if ( mode == WAITING ):
517         if ( time.time() >= t_30_SLEEP ):
518
519             mode = SLEEP
520             print("SWITCHING MODE: SLEEP")
521
522         else:
523
524             # print("MODE = WAITING")
525             if ( time.time() > t_endWaiting ):
526                 if ( gesture == FIST ):
527
528                     mode = SLEEP
529                     print("SWITCHING MODE: SLEEP\t\t\tConfidence Level: ",confidence)
530
531                 elif ( gesture == PIWI ):
532
533                     mode = DISPLAYCONTROL
534                     print("SWITCHING MODE: DISPLAYCONTROL\t\t\tConfidence Level: ",confidence)
535                     t_endWaiting = time.time() + 1
536                     t_30_SLEEP = time.time() + 30
537
538                 elif ( gesture == PIWO ):
539
540                     mode = MOTORCONTROL
541                     print("SWITCHING MODE: MOTORCONTROL\t\t\tConfidence Level: ",confidence)
542                     t_endWaiting = time.time() + 1

```

```
# Reset the sleep timer once you leave SLEEP
```

```

543         t_30_SLEEP = time.time() + 30
544
545 if ( mode == DISPLAYCONTROL ):
546     if ( time.time() >= t_30_SLEEP ):
547
548         mode = SLEEP
549         print("SWITCHING MODE: SLEEP")
550
551     else:
552
553         if ( time.time() > t_endWaiting ):
554             if ( gesture == FIST ):
555
556                 mode = WAITING
557                 print("SWITCHING MODE: WAITING\t\t\t\tConfidence Level: ",confidence)
558                 t_endWaiting = time.time() + 1
559                 t_30_SLEEP = time.time() + 30
560
561             elif ( ( curPi == 0 ) and ( gesture == PIWI ) ):
562
563                 curPi = display.switchDisplay()
564                 print("Switching to Camera 2")
565                 t_endWaiting = time.time() + 1
566                 t_30_SLEEP = time.time() + 30
567
568             elif ( ( curPi == 1 ) and ( gesture == PIW0 ) ):
569
570                 curPi = display.switchDisplay()
571                 print("Switching to Camera 1")
572                 t_endWaiting = time.time() + 1
573                 t_30_SLEEP = time.time() + 30
574
575 if ( mode == MOTORCONTROL ):
576     if ( time.time() >= t_30_SLEEP ):
577
578         mode = SLEEP
579         print("SWITCHING MODE: SLEEP")
580
581     else:
582
583         if ( time.time() > t_endWaiting ):
584             ''' Select which slave to control '''
585             if ( curPi == 0 ):
586
587                 curPi_name = "emgPi_1"
588                 currentMotor = 0
589
590             elif ( curPi == 1 ):
591
592                 curPi_name = "emgPi_2"
593                 currentMotor = 1
594
595             ''' Check Gesture '''
596             if ( gesture == PIWI ):
597
598                 # Pan Clockwise
599
600                 if (duty[curPi] <= 70):
601
602                     duty[curPi] += 10
603

```

```

604         ssh_string = "ssh " + curPi_name + " 'python /home/pi/scripts/moveMotor.py " + str(duty[curPi]) + " 0 0' &"
605         os.system(ssh_string)
606
607     elif ( ( duty[curPi] > 70 ) and ( duty[curPi] < 80 ) ):
608         duty[curPi] = 80
609         ssh_string = "ssh " + curPi_name + " 'python /home/pi/scripts/moveMotor.py " + str(duty[curPi]) + " 0 0' &"
610         os.system(ssh_string)
611         print("Motor is at limit.")
612
613         t_endWaiting = time.time() + 1
614         t_30_SLEEP = time.time() + 30
615
616
617     elif ( gesture == PIWO ): # Pan Counter Clockwise
618
619         if ( duty[curPi] >= 30 ):
620
621             duty[curPi] -= 10
622             ssh_string = "ssh " + curPi_name + " 'python /home/pi/scripts/moveMotor.py " + str(duty[curPi]) + " 1 0' &"
623             os.system(ssh_string)
624
625             elif ( ( duty[curPi] < 30 ) and ( duty[curPi] > 20 ) ):
626
627                 duty[curPi] = 20
628                 ssh_string = "ssh " + curPi_name + " 'python /home/pi/scripts/moveMotor.py " + str(duty[curPi]) + " 1 0' &"
629                 os.system(ssh_string)
630                 print("Motor is at limit.")
631
632             else:
633                 print("Motor is out of range. Cannot rotate CCW")
634
635                 t_endWaiting = time.time() + 1
636                 t_30_SLEEP = time.time() + 30
637
638         elif ( gesture == FIST ):
639
640             mode = WAITING
641             print("SWITCHING MODE: WAITING\t\t\t\t\tConfidence Level: ", confidence)
642             t_endWaiting = time.time() + 1
643
644     return mode
645
646
647 def getConfidence(realTimeData, calData):
648
649     matchCounter = 0
650
651     ...
652         calibrated: 823
653         actual:      832
654         result:      10 + 2 + 3 = 15
655
656         calibrated: 781
657         actual:      832
658         result:      7
659
660         calibrated: 231
661         actual:      832
662         result:      1 + 6 + = 7
663     ...
664

```

```

665     if (realTimeData[0] == calData[0]):
666         matchCounter += 10
667     if (realTimeData[0] == calData[1]):
668         matchCounter += 7
669     if (realTimeData[0] == calData[2]):
670         matchCounter += 3
671
672     if (realTimeData[1] == calData[0]):
673         matchCounter += 4
674     if (realTimeData[1] == calData[1]):
675         matchCounter += 6
676     if (realTimeData[1] == calData[2]):
677         matchCounter += 2
678
679     if (realTimeData[2] == calData[0]):
680         matchCounter += 2
681     if (realTimeData[2] == calData[1]):
682         matchCounter += 3
683     if (realTimeData[2] == calData[2]):
684         matchCounter += 4
685
686     return matchCounter
687
688 ...
689
690     If the gesture is the same as the last one, increment the counter. If the gesture is different from the last gesture,
691     update the variable, lastGesture, and reset the counter. This allows us to wait for n counts of the same gesture before
692     considering a gesture valid.
693 ...
694 def confirmGesture(gesture):
695     global CONFIRM_COUNTER
696
697     if ( confirmGesture.lastGesture != gesture ):
698         confirmGesture.flag = False
699
700     if ( confirmGesture.counter < CONFIRM_COUNTER ):
701         confirmGesture.counter += 1
702         confirmGesture.flag = False
703     else:
704         confirmGesture.lastGesture = gesture
705         confirmGesture.counter = 0
706         confirmGesture.flag = True
707
708     return confirmGesture.flag
709
710 confirmGesture.flag = False # static variable initialization for the above function
711 confirmGesture.counter = 0
712 confirmGesture.lastGesture = REST
713
714 if __name__ == '__main__':
715
716     m = MyoRaw(sys.argv[1] if len(sys.argv) >= 2 else None) # this has to come first, and proc_emg() second (see below)
717
718     def proc_emg(emg, moving, times = []): # data is sent in packets of two samples at a time. I *think* we only save half of
719     these
720         global calMode; global emg_data
721         global fistCalData; global piwiCalData; global piwoCalData;
722
723         emg = list(emg) # convert tuple to list
724         emg_data = emg
725

```



```

726
727         if ( mode == GETTINGCALDATA ):
728
729             if (calMode == FIST):
730                 fistCalData.append(emg_data)
731             if (calMode == PIWI):
732                 piwiCalData.append(emg_data)
733             if (calMode == PIWO):
734                 piwoCalData.append(emg_data)
735
736     ...
737     INITIALIZATION
738     this code is only executed once
739     ...
740 m.add_emg_handler(proc_emg)
741 m.connect()
742 global GETTINGCALDATA; global CALIBRATING; global SLEEP; global WAITING; global DISPLAYCONTROL; global MOTORCONTROL;
743 global REST; global FIST; global PIWI; global PIWO; global calMode; global curPi; global CONFIRM_COUNTER;
744
745 os.system("python displayControl.py &")
746
747 confidenceArray = []
748
749 curPi = 0
750 gesture = REST
751 isResting = 0
752
753 BUFFER_SIZE = 100
754 emg_buffer = ringBuffer(BUFFER_SIZE)
755 counter = 0
756
757 CONFIDENCE_LEVEL = 10
758 CONFIRM_COUNTER = 150
759 SENSITIVITY = 75
760
761 NUM_CALS = 4
762
763 CALIBRATION_SIZE = 500
764 n = CALIBRATION_SIZE
765 CSVFILE = "./adityaCal.csv"
766 minValueFromCal = 9999
767 iWantToCal = 0
768 calibrateFlag = 1
769
770 if ( iWantToCal == 1 ):
771     mode = GETTINGCALDATA
772 else:
773     mode = SLEEP
774
775 os.system("ssh emgPi_1 'python /home/pi/scripts/initMotor.py 50' &")
776 os.system("ssh emgPi_2 'python /home/pi/scripts/initMotor.py 50' &")
777
778 print("MOTORS INITIALIZED")
779 os.system("clear")
780
781 while True:
782     m.run()
783
784     emg_buffer.append(emg_data)
785
786     if (counter >= BUFFER_SIZE * 2):

```

# write calibration data to a global array

# initializes the display on every run

# size of circular buffer

# counter

# allows for tuning. Max = 20. Min = 0. See getConfidence()  
# number of samples of same gesture required to confirm a gesture  
# upper and lower threshold = minValueFromCal +/- SENSITIVITY

# this is always 1 greater than the number of calibrations

# file to write/read calibration data from  
# initially an arbitrarily large value  
# set to '1' when switching users or when recalibration is needed

# skip GETTINGCALDATA and CALIBRATING states

# The ampersand is essential here. If this does not run in the background ...  
# the bluetooth protocol fails and the system is frozen.

# run the program indefinitely, or until user interruption

# there was an undiagnosed issue with 7 null data points causing havoc.

```

787
788
789
790
791
792
793
794
795
796
797
798
799
800
801
802
803
804
805
806
807
808
809
810
811
812
813
814
815
816
817
818
819
820
821
822
823
824
825
826
827
828
829
830
831
832
833
834
835
836
837
838
839
840
841
842
843
844
845
846
847

# this ensures that those are gone before proceeding
average = emg_buffer.getAvg() # average value of each sensor in the buffer. [ 1 x 8 ]
bufferAvg = np.mean(np.array(average)) # average value of the whole buffer. type: float, [1 x 1]

maxGrouping = emg_buffer.getMaxGrouping()

if ( mode >= SLEEP ): # where the main gesture detection and control happens
    if ( calibrateFlag == 1 ): # load saved cal data
        with open(CSVFILE, 'rb') as csvfile: # Example: [ 7, 6, 1]; [ 4, 2, 5]; [ 0, 2, 7]; [ 157.6, 157.6, 157.6]
            CalReader = csv.reader(csvfile, delimiter=',')
            i = 0
            for row in CalReader:
                savedCalData = np.genfromtxt(CSVFILE, delimiter=',')

            print("Calibration Data: \n", savedCalData)
            print("MODE = SLEEP")
            calibrateFlag = 0
            fistGrouping = savedCalData[0]
            piwiGrouping = savedCalData[1]
            piwoGrouping = savedCalData[2]
            minValueFromCal = savedCalData[3,1]

        fistConfidence = getConfidence(maxGrouping, fistGrouping)
        piwiConfidence = getConfidence(maxGrouping, piwiGrouping)
        piwoConfidence = getConfidence(maxGrouping, piwoGrouping)

        confidenceArray = [fistConfidence, piwiConfidence, piwoConfidence]

        maxMatch = np.argmax(confidenceArray) # index of the gesture that returned the most confidence
        maxConfidence = confidenceArray[maxMatch] # confidence level of the most confident gesture

    if ( ( bufferAvg >= ( minValueFromCal + SENSITIVITY ) ) ):
        if ( maxMatch == 0 ) and ( fistConfidence >= CONFIDENCE_LEVEL ) :
            if ( confirmGesture(FIST) ): # if we saw FIST for n times
                gesture = FIST
                print("\tFIST CONFIRMED\t\t\t\tConfidence Level: ", fistConfidence)
                isResting = 0

            elif ( maxMatch == 1 ) and ( piwiConfidence >= CONFIDENCE_LEVEL ):
                if ( confirmGesture(PIWI) ): # if we saw PIWI for n times
                    gesture = PIWI
                    print("\tPIWI CONFIRMED\t\t\t\tConfidence Level: ", piwiConfidence)
                    isResting = 0

            elif ( maxMatch == 2 ) and ( piwoConfidence >= CONFIDENCE_LEVEL ):
                if ( confirmGesture(PIWO) ): # if we saw PIWO for n times
                    gesture = PIWO
                    print("\tPIWO CONFIRMED\t\t\t\tConfidence Level: ", piwoConfidence)
                    isResting = 0

            else:
                if ( confirmGesture(REST) ): # if we saw REST for n times
                    gesture = REST

```

```

848         print("\n\n\tMOTION DETECTED BUT NO GESTURE MATCH: REST ASSUMED")
849         print("\n\n\tMinimum Accepted Confidence: ", CONFIDENCE_LEVEL)
850         print("\n\n\tFIST Confidence: ",fistConfidence, "\n\n\tPIWI Confidence: ",,piwiConfidence, "\n\n\tPIWO Confidence: ",,piwoConfidence)
851         print("\n\n\tStill in mode: ", modeString[mode])
852         print("\n\n")
853
854     elif ( (bufferAvg < (minValueFromCal - SENSITIVITY)) ): #isResting or
855
856         #print("REST CONFIRMED")
857         gesture = REST
858         isResting = 1
859
860     #else:
861
862         # print("UNKNOWN")
863         # print("Sensitivity: ", SENSITIVITY)
864         # print("minValueFromCal: ", minValueFromCal)
865         # print("Buffer average: ", bufferAvg)
866
867     mode = controlLogic(mode, gesture, maxConfidence) # get new mode
868
869     ...
870     CALIBRATION
871     note: this can probably be put into a function later. Maybe not all of it, but enough that it becomes a little easier to follow
872     ...
873     if ( ( mode == GETTINGCALDATA ) and ( calMode < NUM_CALS ) ):
874
875         if (n >= CALIBRATION_SIZE):
876
877             n = 0 # reset calibration timer
878             print("Cal Mode = " + gestureString[calMode])
879             print("Hold a " + gestureString[calMode] + " until told otherwise")
880             calMode += 1
881             # time.sleep(2) # WARNING: THIS BREAKS THE CODE! # sleep to give user time to switch to next gesture
882
883         n += 1
884         if (bufferAvg < minValueFromCal): # this gets the minimum 8-sensor average from the time that calibration was run
885             minValueFromCal = bufferAvg # it sets the threshold that separates gestures from resting.
886
887     else:
888
889         if ( calibrateFlag == 1 ):
890             mode = CALIBRATING
891
892             gesture = REST
893             mode = controlLogic(mode, gesture, 0)
894
895     if ( mode == CALIBRATING ) :
896
897         print("mode = CALIBRATING")
898         fistCal = Calibrate()
899         fistGrouping = fistCal.getMaxGrouping(fistCalData)
900
901         piwiCal = Calibrate()
902         piwiGrouping = piwiCal.getMaxGrouping(piwiCalData)
903
904         piwoCal = Calibrate()
905         piwoGrouping = piwoCal.getMaxGrouping(piwoCalData)
906
907         minValueFromCalArray = [minValueFromCal,minValueFromCal,minValueFromCal]
908

```

```

909
910         with open(CSVFILE, 'w') as csvfile:
911             writer = csv.writer(csvfile)
912             writer.writerow(fistGrouping)
913             writer.writerow(piwiGrouping)
914             writer.writerow(piwoGrouping)
915             writer.writerow(minValueFromCalArray)
916
917         calibrateFlag = 0
918         mode = SLEEP
919
920         print("Fist Group: ", fistGrouping)
921         # print(fistCalData)
922         print("Piwi Group: ", piwiGrouping)
923         # print(piwiCalData)
924         print("Piwo Group: ", piwoGrouping)
925
926
927     else:                                     # Runs until data is guaranteed to be good
928
929         counter += 1
930         # print(counter, "Data contains null values\n")
931
932

```

## B. calibrate.py

```

933 '''
934 AUTHOR: Aditya Patel
935 DATE CREATED: 2018-04-08
936 LAST MODIFIED: 2018-04-09
937 PLATFORM: Raspberry Pi 3B, Raspbian Stretch Released 2017-11-29
938 PROJECT: EMG Human Machine Interface
939 ORGANIZATION: Bradley University, School of Electrical and Computer Engineering
940 FILENAME: calibrate.py
941 DESCRIPTION:
942     Calibration class. Create a unique Calibrate() object in the parent function for each gesture.
943     Primary use of this class is to get the top three sensor groupings in the calibration data,
944     i.e., the three trios of consecutive sensors with the highest average EMG value.
945
946     Ex:
947         If the calibration data is:
948             [ 99    100    32    03    14    16    42    95 ]
949
950             index: 0      1      2      3      4      5      6      7
951
952             The top three sensor groups would be, in order,
953             [ 701, 670, 012 ]
954
955             Giving the return:
956             [ 7, 6, 0 ]
957 '''
958
959 import numpy as np
960
961 class Calibrate():
962
963     def __init__(self):

```

```

964
965     self.size()
966     self.data = []
967     self.sums = [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]
968     self.avg = []
969     # self.avg = np.array([0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]) # this has to be a numpy array to use the 'divide' function below
970     self.groupingAvg = []
971
972     """
973     Sets the class variable, data, equal to the calibration data.
974     """
975     def setData(self, calData):
976
977         self.data = calData
978
979     """
980     Computes an average down each column of data.
981     writes to self.avg, 1 x 8 array containing average value of each sensor
982     """
983     def getAvg(self):
984
985         self.sums = [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0] # reset sums to prevent it from accumulating forever. This is NOT elegant or efficient
986         self.avg = np.array([0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0])
987         for r in range(0, len(self.data)):
988             for c in range(0, 8):
989                 self.sums[c] = self.sums[c] + self.data[r][c]
990
991         np.divide(self.sums, float(len(self.data)), out = self.avg) # compute the average by dividing the sums by the size of the data array
992         #return self.avg
993
994     """
995     Function to compute the average value of each of the eight groupings of three sensors.
996     @return none, only writes to class variable, groupingAvg
997         [ 123   234   345   456   567   678   781   812]
998         where each of these is the average of the sensors
999     """
1000     def getGroupingAvg(self):
1001
1002         self.groupingAvg = [0, 0, 0, 0, 0, 0, 0, 0]
1003
1004         for startIndex in range(0, 8):
1005             sum = 0
1006
1007             for i in range(startIndex, startIndex + 3):
1008
1009                 if ( i > 7 ):
1010                     i %= 8 # if i exceeds the range of the data, do the modulus operator. This allows for groupings 781 and 812 to work.
1011                     sum += self.avg[i]
1012                     i += 1
1013
1014             self.groupingAvg[startIndex] = sum / 3.0
1015
1016     """
1017
1018     Function to compute the three highest sensor groups.
1019     @return maxGrouping, [1 x 3] integer list of the index of the top three sensor groups in the calibration data
1020     @example maxGrouping = myCalibrationObject.getMaxGrouping(gestureCalibrationData) --> maxGrouping: [ 6, 5, 0]

```

```

1021     '''
1022     def getMaxGrouping(self, calData):
1023
1024         maxGrouping = [0, 0, 0]
1025         self.setData(calData)
1026         self.getAvg()
1027         self.getGroupingAvg()
1028
1029         array = np.array(self.groupingAvg)
1030         temp = array.argsort()
1031         ranks = np.empty_like(temp)
1032         ranks[temp] = np.arange(len(array))
1033
1034         maxGrouping[0] = int( np.where(ranks == 7)[0] )
1035         maxGrouping[1] = int( np.where(ranks == 6)[0] )
1036         maxGrouping[2] = int( np.where(ranks == 5)[0] )
1037
1038         return maxGrouping
1039
1040     '''
1041     Used for Testing/Debugging Purposes
1042     '''
1043     if __name__ == '__main__':
1044
1045         t1 = []
1046         #t2 = [0, 1, 2, 3, 4, 5, 6, 7]
1047         t2 = [100.0, 100.0, 7.0, 7.0, 0.0, 0.0, 0.0, 100.0]
1048
1049         t1.append(t2)
1050         t1.append(t2)
1051         t1.append(t2)
1052         cal = Calibrate()
1053         maxGrouping = cal.getMaxGrouping(t1)
1054
1055
1056         print(maxGrouping)

```

### C. ringBuffer.py

```

1057     '''
1058     AUTHOR: Aditya Patel and Jim Ramsay
1059     DATE CREATED: 04/01/2018
1060     LAST MODIFIED: 2018-04-09
1061     PLATFORM: Raspberry Pi 3B, Raspbian Stretch Released 2017-11-29
1062     PROJECT: EMG Human Machine Interface
1063     ORGANIZATION: Bradley University, School of Electrical and Computer Engineering
1064     FILENAME: ringBuffer.py
1065     DESCRIPTION:
1066         Class that implements a ring/circular buffer to hold the emg data. It stores data until full, then
1067         overwrites the oldest element every time. It also has a method to take an average of the last n
1068         data points.
1069
1070     KNOWN FLAW:

```

```

1071     Instead of only ignoring the oldest element when computing the average, I flush the entire buffer.
1072     Then the full n-length sum is taken. This is grossly inefficient, but was not found to be a bottleneck
1073     in implementation. Thus, it was ignored.
1074
1075 EDIT HISTORY:
1076     20180409 -- Added functions to compute groupingAvg and maxGrouping. The groupings are as follows:
1077
1078             [ 123    234    345    456    567    678    781    812 ]
1079
1080             In main, this allowed us to calculate the three groupings with the highest average sensor value.
1081
1082 '''
1083 import numpy as np
1084
1085 class ringBuffer:
1086     def __init__(self, size_max):
1087         self.max = size_max
1088         self.data = []
1089         self.sums = [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]
1090         self.avg = np.array([0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0])
1091         self.full = False
1092         self.groupingAvg = []
1093
1094     class __Full:
1095         def append(self, x):
1096             self.data[self.cur] = x
1097             self.cur = (self.cur + 1) % self.max
1098
1099     def getAvg(self):
1100         self.sums = [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]
1101         for r in range(0, self.max):
1102             for c in range(0, 8):
1103                 self.sums[c] = self.sums[c] + self.data[r][c]
1104
1105         np.divide(self.sums, float(self.max), out = self.avg)
1106         return self.avg
1107
1108     def get(self):
1109         return self.data[self.cur:] + self.data[:self.cur]
1110
1111     '''
1112     Function to compute the average value of each of the eight groupings of three sensors.
1113     @return none, only writes to class variable, groupingAvg
1114         [ 123    234    345    456    567    678    781    812]
1115         where each of these is the average of the sensors
1116
1117     '''
1118     def getGroupingAvg(self):
1119         self.groupingAvg = [0, 0, 0, 0, 0, 0, 0, 0]
1120
1121         for startIndex in range(0, 8):
1122             sum = 0
1123
1124             for i in range(startIndex, startIndex + 3):
1125                 if ( i > 7 ):

```

```

1127         i %= 8 # if i exceeds the range of the data, do the
1128 modulus operator. This allows for groupings 781 and 812 to work.
1129         sum += self.avg[i]
1130         i += 1
1131
1132         self.groupingAvg[startIndex] = sum / 3.0
1133
1134     """
1135     Function to compute the three highest sensor groups.
1136     @return maxGrouping, [1 x 3] integer list of the index of the top three sensor groups in the ring buffer
1137     @example maxGrouping = myRingBuffer.getMaxGrouping() --> maxGrouping: [ 6, 5, 0]
1138     """
1139     def getMaxGrouping(self):
1140
1141         maxGrouping = [0, 0, 0]
1142
1143         self.getAvg()
1144         self.getGroupingAvg()
1145
1146         array = np.array(self.groupingAvg) # REFERENCE: https://stackoverflow.com/questions/5284646/rank-
1147 items-in-an-array-using-python-numpy
1148         temp = array.argsort()
1149         ranks = np.empty_like(temp)
1150         ranks[temp] = np.arange(len(array))
1151
1152         maxGrouping[0] = int( np.where(ranks == 7) [0] )
1153         maxGrouping[1] = int( np.where(ranks == 6) [0] )
1154         maxGrouping[2] = int( np.where(ranks == 5) [0] )
1155
1156         return maxGrouping
1157
1158     def append(self,x): # append an element to the end of the buffer until it
1159 is full
1160         self.data.append(x)
1161
1162         if len(self.data) == self.max:
1163             self.cur = 0
1164             self.full = True
1165             self.__class__ = self.__Full # Permanently change class from not full to full
1166
1167     def get(self): # return list of elements from oldest to newest
1168         return self.data
1169
1170
1171     """
1172     Used for Testing/Debugging Purposes
1173     """
1174
1175     if __name__ == '__main__':
1176         x = ringBuffer(3)
1177         print "average: ", x.avg
1178         print "sums: ", x.sums
1179         emg1 = [1,1,1,1,1,1,1,1]
1180         emg2 = [2,2,2,2,2,2,2,2]
1181         emg3 = [3,3,3,3,3,3,3,3]
1182         x.append(emg1); x.append(emg2); x.append(emg3);
1183         x.append(emg3); x.append(emg3);x.append(emg3);

```



```
1184     average = x.getAvg()
1185
1186     print "Average: ", average
1187
```

## 1188 **D. common.py**

```
1189 import struct
1190
1191 def pack(fmt, *args):
1192     return struct.pack('<' + fmt, *args)
1193
1194 def unpack(fmt, *args):
1195     return struct.unpack('<' + fmt, *args)
1196
1197 def text(scr, font, txt, pos, clr=(255,255,255)):
1198     scr.blit(font.render(txt, True, clr), pos)
1199
```

## 1200 **E. displayControl.py**

```
1201 '''
1202 AUTHOR: Aditya Patel and Jim Ramsay
1203 DATE CREATED: 2018-03-31
1204 LAST MODIFIED:
1205 PLATFORM: Raspberry Pi 3B, Raspbian Stretch Released 2017-11-29
1206 PROJECT: EMG Human Machine Interface
1207 ORGANIZATION: Bradley University, School of Electrical and Computer Engineering
1208 FILENAME: videoControl.py
1209 DESCRIPTION:
1210     Script to control the display of the two different camera feeds.
1211 NOTE:
1212     There is no logic needed in the switchDisplay() function, as this is a binary system. The main function will contain the logic.
1213 REFERENCES:
1214     [1] https://stackoverflow.com/questions/279561/what-is-the-python-equivalent-of-static-variables-inside-a-function
1215 '''
1216
1217 import os # used to execute shell commands
1218 from time import sleep
1219
1220 def init():
1221     os.environ['DISPLAY'] = ":0" # allows us to launch GUI applications and control the mouse. Limited to the scope of the call of
1222     this function.
1223     os.system("killall firefox-esr")
1224     os.system("nohup firefox http://169.254.184.5/html/ &") # 'nohup' -- ignore HANGUP signals generated by firefox (there are a ton)
1225     sleep(15)
1226     os.system("nohup firefox http://169.254.13.230/html/ &")
1227     sleep(2)
1228     os.system("xdotool key ctrl+Tab") # Cycle tab to the "Restore session" tab that always comes up
1229     os.system("xdotool key ctrl+w") # Close the tab
1230     sleep(3)
1231     os.system("xdotool key F11") # launch browser in full screen
1232     sleep(3)
1233     os.system("xdotool mousemove 600 200 &") # enlarge camera 1
1234
1235
```

```

1236     sleep(0.1)
1237     os.system("xdotool click 1")
1238     sleep(0.1)
1239     os.system("xdotool key ctrl+Tab")
1240     sleep(3)
1241     os.system("xdotool click 1")           # enlarge camera 2
1242     os.system("xdotool key ctrl+Tab")
1243     os.system("xdotool mousemove 0 500")  # Move mouse out of the way
1244     print("DISPLAY CONFIGURED")
1245
1246 def switchDisplay():
1247
1248     switchDisplay.display ^= 1           # toggle variable between 0 and 1
1249     os.system("xdotool key ctrl+Tab")
1250
1251     return(switchDisplay.display)
1252
1253 switchDisplay.display = 0               # initialize static variables
1254
1255 # Initialize
1256 if __name__ == '__main__':
1257     init()
1258
1259     # sleep(1)
1260     # switchDisplay()
1261     # print("Attempting to change display")
1262     # sleep(5)
1263     # print("Attempting to change display")
1264     # switchDisplay()

```

## F. moveMotor.py

```

1265 '''
1266 AUTHOR: Aditya Patel and Jim Ramsay
1267 DATE CREATED: 2018-04-05
1268 LAST MODIFIED: 2018-04-07
1269 PLATFORM: Raspberry Pi 3B, Raspbian Stretch Released 2017-11-29
1270 PROJECT: EMG Human Machine Interface
1271 ORGANIZATION: Bradley University, School of Electrical and Computer Engineering
1272 FILENAME: moveMotor.py
1273 DESCRIPTION:
1274     Script to move the connected servo motor to a specific duty cycle.
1275
1276 NOTE:
1277
1278     CW --> INCREASE PWM
1279     CCW --> DECREASE PWM
1280
1281     20% --> +90 deg
1282     80% --> -90 deg
1283
1284 USAGE:
1285
1286     ssh emgPi_1 'python /home/pi/scripts/moveMotor.py PWMdir isLastTime'

```

```

1287
1288     Command Line Arguments:
1289
1290         PWMdir           integer      0 --> CW           1 --> CCW   others --> not recognized, do nothing
1291         isLastTime      boolean      True --> execute IO cleanup   False --> do not cleanup, run normally
1292
1293     '''
1294
1295     import RPi.GPIO as IO
1296     import sys
1297     import time
1298
1299     global initialDuty
1300     initialDuty = 50
1301
1302     class Motor:
1303
1304         global initialDuty
1305         def __init__(self, PWMdirection, startPWM):
1306
1307             IO.setwarnings(False)
1308             IO.setmode(IO.BOARD)
1309
1310             IO.setup(12, IO.OUT)                                # set GPIO pins to Output mode
1311             self.p = IO.PWM(12,350)                             # set pin 12 to 350Hz pwm output
1312             self.PWMdir = PWMdirection
1313             self.duty = startPWM
1314             self.p.start(startPWM)
1315
1316         def ccw(self):
1317             if (self.duty >= 20) and (self.duty <= 70) :
1318                 self.duty += 10
1319                 # print("ccw")
1320                 # print(self.duty)
1321                 self.p.ChangeDutyCycle(self.duty)
1322                 time.sleep(0.01)
1323
1324         def cw(self):
1325             if ( self.duty >= 30 ) and ( self.duty >= 80 ) :
1326                 self.duty -= 10.0
1327                 # print("cw")
1328                 # print(self.duty)
1329                 self.p.ChangeDutyCycle(self.duty)
1330                 time.sleep(0.01)
1331
1332         def cleanup(self):
1333             self.p.stop()
1334             IO.cleanup()
1335
1336     if __name__ == '__main__':
1337
1338         # moduleName = sys.argv[0]
1339         startPWM = float(sys.argv[1])
1340         PWMdir = int(sys.argv[2])
1341         isLastTime = int(sys.argv[3])
1342
1343         # print("PWM Direction: ", type(PWMdir))

```

```
1344
1345 mtr = Motor(PWMdir, startPWM)
1346 time.sleep(1)
1347 # if (PWMdir == 0):
1348     # mtr.cw()
1349     # time.sleep(1)
1350 # elif (PWMdir == 1):
1351     # mtr.ccw()
1352     # time.sleep(1)
1353 # if (isLastTime):
1354     # mtr.cleanup()
1355
1356
1357 # t_end = time.time() + 10
1358
1359 # if (isLastTime == 1):
1360     # mtr.cleanup()
1361
1362 # while (time.time() < t_end):
1363     # if (PWMdir == 0):
1364         # mtr.cw()
1365     # elif (PWMdir == 1):
1366         # mtr.ccw()
1367
1368
1369
```