We will be researching the ability to identify and replicate the action potentials through muscle contraction in the forearm. Utilizing data from a surface EMG sensor we want to demonstrate the control of a prosthetic hand. Applying the EMGs in specific locations on the forearm, we hypothesize that we can decipher different contraction signals for individual fingers, and in turn control a servo motor. This system has personal value since we have done extensive research into robotic prosthetic control and have actually designed and built a 3D printed prosthetic hand (Figure 1). That system takes user input from a glove and mimics the movement. Additionally, further research has been done in the field of Micro-Electrical Mechanical Systems (MEMS) involving replicating the feeling of touch in the fingertips. Utilizing haptic feedback sensors and machine learning, you can train a model to identify different materials and roughness using MEMS sensors in the fingertip of a robotic hand. All of these topics play a significant role in creating a more realistic prosthetic hand that can replicate contraction, feeling, and touch.

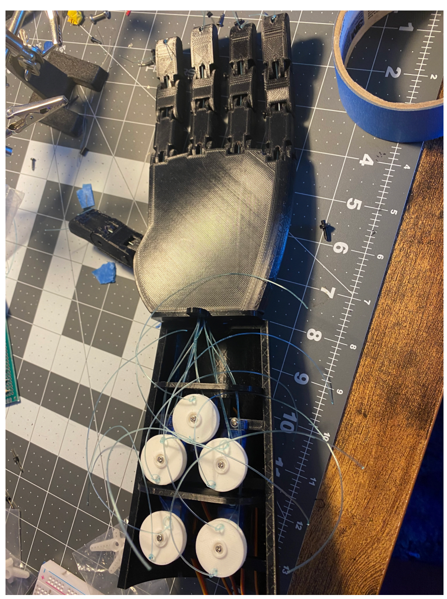

Figure 1. 3D printed robotic hand

This system is intended for amputees who require a prosthetic hand and want more functionality than a rigid prosthetic hand. By deciphering individual muscle contractions for each finger, the hand could become more dexterous than just a full hand contraction. We are utilizing EMG sensors with the aim to identify individual finger contractions through action potentials in the forearm muscles. We are considering muscle location and since the muscles are compact and intertwined, we are considering that some may have varying degrees of intensity due to the overlapping signals.

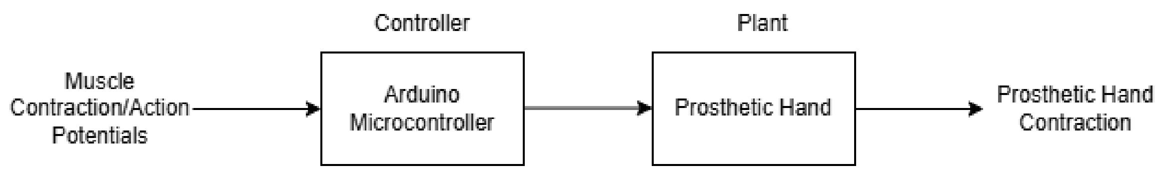

Figure 2. Control system block diagram

The intended output is going to be an electrical signal to the prosthetic hand, which will contract the fingers according to the intended input signal from the user. Additionally, to note further consideration, if further work is performed on this experiment, a haptic feedback sensor could be used on the fingertips to provide feedback to the controller, which would create a closed-loop system. This sensor would provide force feedback, preventing over-contraction and enabling finer movement control.

To begin, keeping our goal of initiating muscle contraction in mind, we did some testing with a tensor sensor. By placing two pads in different locations—typically higher on the forearm, inside closer to the elbow joint, as well as on and around the inside of the wrist—we used the tensor controller to send electrical signals of varying strength to each pad, stimulating the region of muscle/tendon underneath, resulting in contraction of the fingers and/or hand. It is important to note how, with a more intense electrical stimulus, a more intense contraction resulted, though individual muscular regions reacted differently. Similarly, we noted different feelings and results when the power and ground wires were switched between pads, alternating the direction of the current. It is similarly necessary to note that we chose this region based on the muscular anatomy of the human body in our effort to find and signal the region of muscle and/or tendon that contracts each finger (Figure 3).

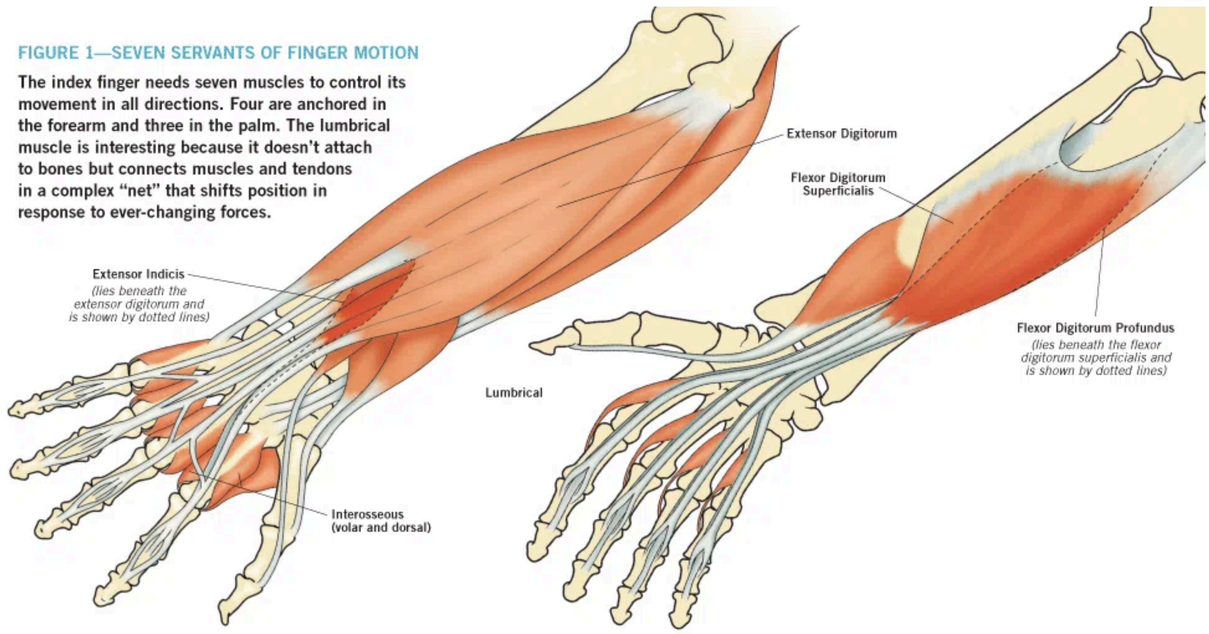

Figure 3. Muscle anatomy of the finger muscles [1]

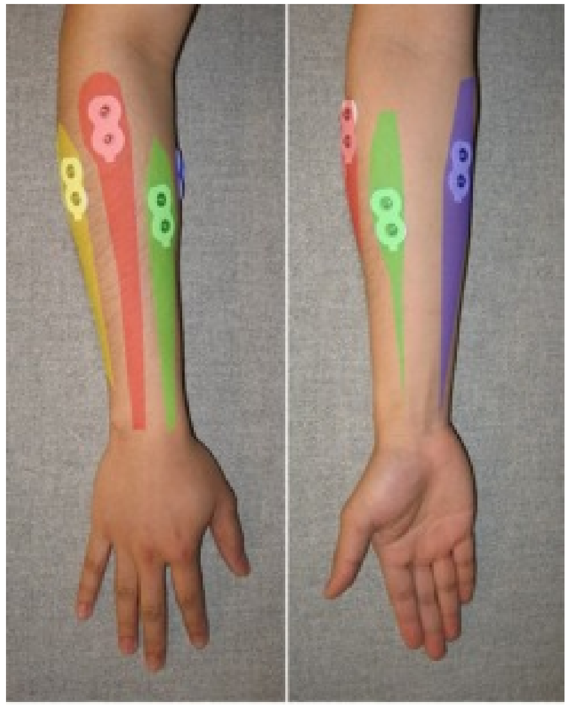

Figure 4. Experimental EMG placement [2]

Pictured below are the pad placements and the respective finger-triggered (Figures 5, 6, & 7). This is along the lines of what we were expecting, noting particularly coordinated regions, while keeping in mind the way the larger surface area of the pads decreased the accuracy of our results by stimulating larger areas than actually needed to contract individual fingers.

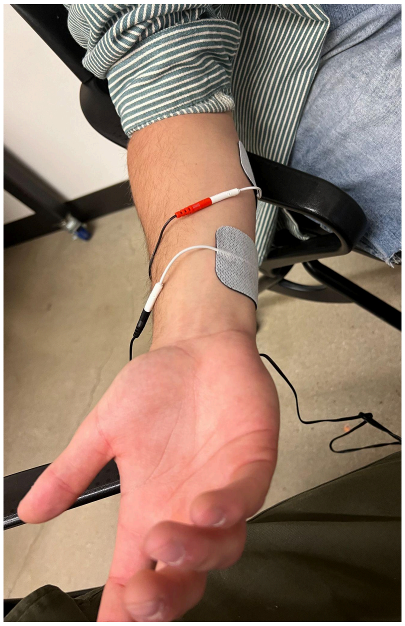

Figure 5. Pinky Contraction

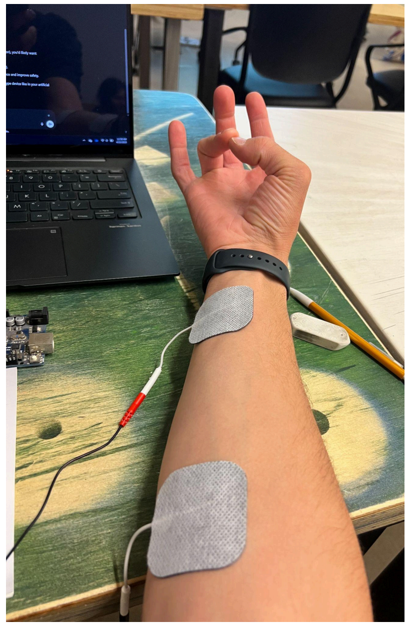

Figure 6. Ring Finger Contraction

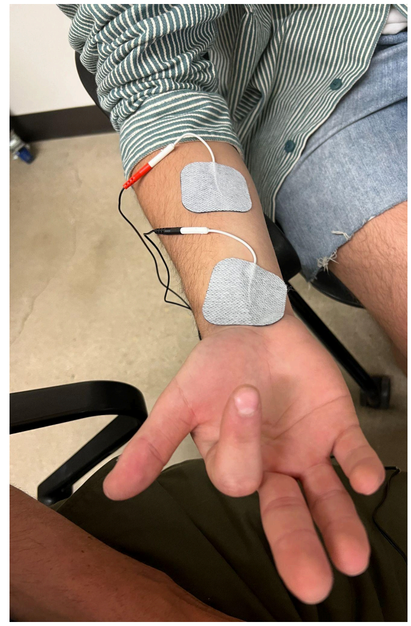

Figure 7. Pointer Finger Contraction

After determining the location of the forearm muscles, we decided to utilize the SparkFun MyoWare EMG sensor [3], which is an all-in-one EMG sensor to read the muscle excitation generated from the action potentials. We connected this to the Arduino and read the data through one of the Analog ports. Being limited to the distance between the electrodes, we conducted further research [4], and decided to place the sensor on the flexor digitorum profundus, which is a muscle in the forearm that controls the flexing of the digits in the hand as seen in Figure 8.

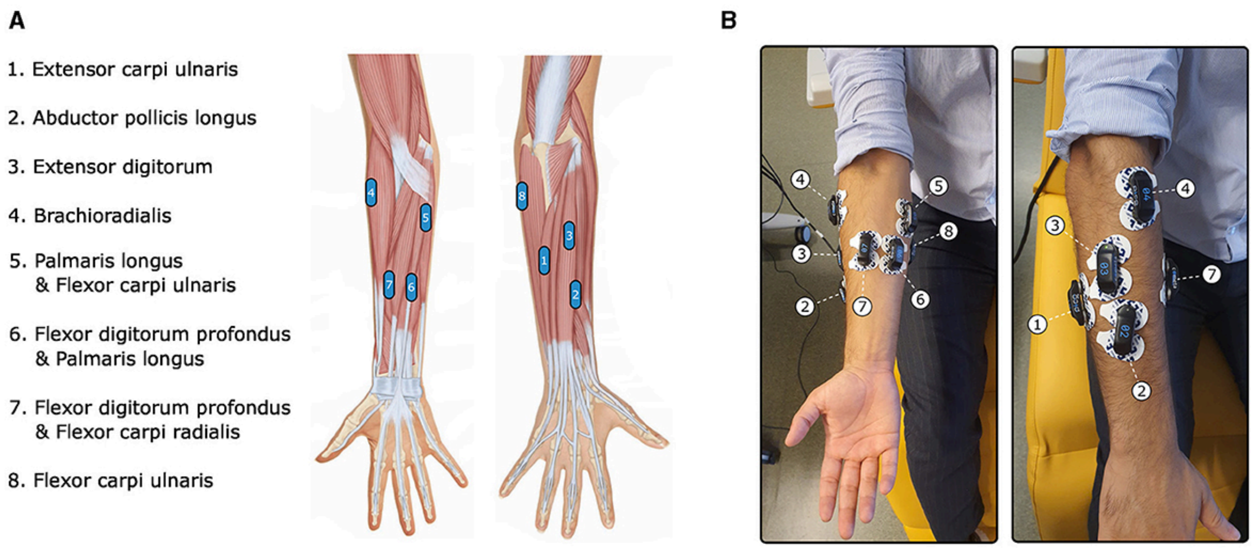

Figure 8. EMG Placement for Forearm Muscles [4]

Since we do not have a prosthetic hand to perform the high-level intended experiment, we decided to visualize the data through four LEDs wired in parallel to the Arduino. The intent is to turn on depending on thresholds met through the EMG during hand contraction. When the hand is in the relaxed position, no LEDs turn on, and as the contraction becomes more intense, the LEDs slowly turn on until the max threshold, when all are on. This translates to the higher-level experiment because if we turn this data into servo angles, we can map the intensity to the angle of the servo, so as it gets more intense, the servo rotates further, closing the robotic hand. In the end, this experiment demonstrated that we were able to take the muscle excitation read through the EMG sensor and visualize it through the LED array. The results of the experiment are seen in the images below (Figure 9 & Figure 10).

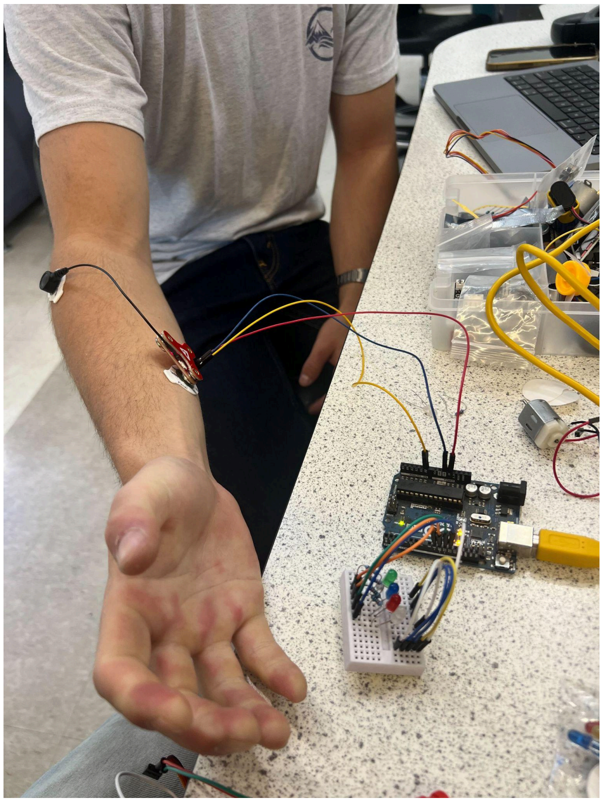

Figure 9. Relaxed hand

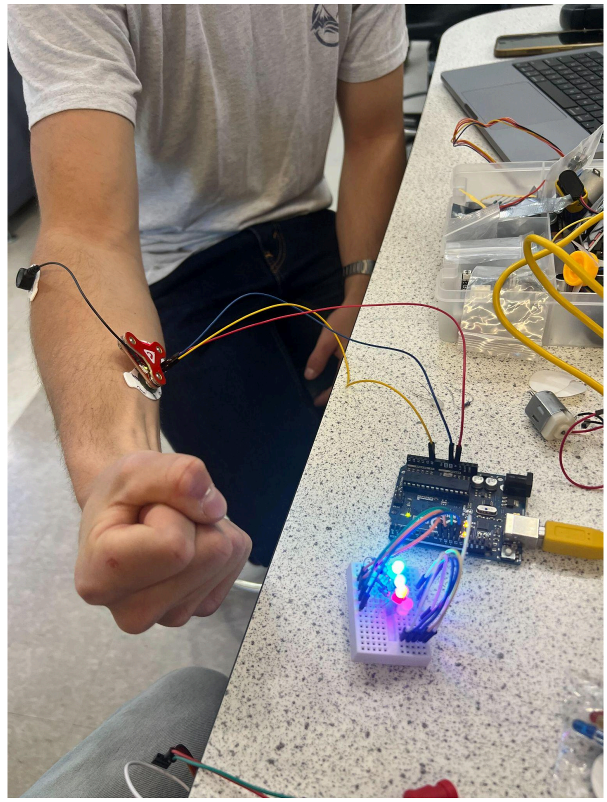

Figure 10. Fully contracted hand

In today's world, EMG sensors are surprisingly common and relatively easy to get one's hands on, though they do come with their limitations. From a quite literal surface-level view, gathering EMG data is quite easy; simply place the pads over the muscle, put one more in a region outside the desired muscle group, and so long as everything is wired properly, begin reading data as you flex and unflex the muscle. That is just it, though. The received data registers a localized region on the muscle, and so attempting to read specific signals, say from individual finger movements, is quite difficult. To do so, based on human anatomy, of at least the forearm for hand/finger movement, one would need intramuscular sensors and stimuli to accurately determine which muscles fire for any given action. While this inevitably affected which movements we looked to detect, it did not affect the stability of our system. Our proposed use case shifted from individual finger contractions to reading the overall force of a balled fist. To add further stability to our system, we introduced a Kalman Filter, helping to smooth out any noise and disturbance input within the system. Overall, the system worked as expected, correctly illuminating our homemade led strip with respect to the increased force outputted from an increasingly tightened fist. Excitedly, this correctly measured force allowed us to understand potential applications further. From our small exploration, we have provided ourselves with a better grasp of the potential applications within prosthetics and robotics when our movements are understood at a foundational level; what and where, when, and how aggressively, are our movements stimulated.

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[2] Tavakoli, M., Benussi, C., & Lourenco, J. L. (2017). Single channel surface EMG control of advanced prosthetic hands: A simple, low cost and efficient approach. *Expert Systems With Applications*, *79*, 322–332. https://doi.org/10.1016/j.eswa.2017.03.012

[3] *Getting Started with the MyoWare® 2.0 Muscle Sensor Ecosystem - SparkFun Learn*. (n.d.). https://learn.sparkfun.com/tutorials/getting-started-with-the-myoware-20-muscle-sensor-ecosystem/hardware-hookup

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