Effects of EMG Electrode Placement on a Closed-Loop Neural Interface

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Abstract— **Many people without lower arm function due to amputation or paralysis have trouble with everyday tasks required for autonomous living such as grasping, lifting, and moving objects. In this paper, we propose an electromyography (EMG)-based closed-loop neural interface that aims to restore these abilities to those without lower arm function and explore the effects that EMG electrode placement has on the performance of our system. Our neural interface uses a Kalman filter to decode EMG signals in order to control a simple grasper. We quantify the effects of EMG electrode placement on the system's performance in a control task that measures ease of use, speed, and accuracy. We found that EMG electrodes placed on the neck muscles provided the best performance on our control task. The neck muscles also are not part of the lower arm and could therefore be useful for potential neural prosthetics. Overall our results show promising data that can inform the placement of EMG electrodes for optimal performance of closed-loop neural interfaces.**

I. INTRODUCTION

Within the United States, more than 40,000 people are living with an amputated lower arm or hand and more than 160,000 people are partially or fully quadriplegic resulting in little to no lower arm function [1][2]. The loss of limb function not only directly impacts quality of life in terms of functionality, mobility, and autonomy, but also has significant psychiatric effects such as phantom-limb syndrome, depression, anxiety, insomnia, and suicidal ideas [3]. One method of addressing this problem is to develop a neural prosthetic that takes advantage of closed-loop control that aims to emulate the function of the lower arm as much as possible.

Closed-loop neural interfaces utilize feedback loops to allow a system to adapt to an individual and changes in underlying state. Past neural interfaces have taken advantage of closed-loop neural interfaces and shown that the accuracy and efficiency of such systems can be improved with the inclusion of feedback [4][5]. Closed-loop neural interfaces can use a variety of signals as input from the nervous system however, EMG is a commonly chosen signal that can be used for motor control tasks. EMG is heavily dependent on electrode placement over motor units and can affect the noisiness of the signal, activation dynamics, and ease of control of a neural interface [6]. While the usefulness of EMG as a control signal has been studied in the past and quantified in terms of its ease of use, speed, and accuracy in forearm muscles, the usefulness of EMG signals from a wider variety of muscles has not been explored [6][7]. Specifically, muscles not contained in the arm are of particular interest because many people in the population with need for neural prostheses may not be able to utilize neural interfaces that use EMG signals from the arm.

Our goal is to extend the study of EMG performance as a control signal to a closed-loop neural interface by experimenting with a variety of EMG electrode placements and identifying muscles that will result in the highest neural prosthetic performance. We aim to quantify performance based on the criteria of ease of use, speed, and accuracy. The results of our study will provide empirical data that can be used to determine the ideal EMG electrode placement in order to improve closed-loop neural interface performance and maximize the restored functionality of neural prostheses.

II. EXPERIMENTAL METHODS

A. *Signal Collection and Processing*

To find the most effective EMG electrode placement for controlling a closed-loop neural interface, we tested four separate muscle groups controlling a robotic claw while performing a behavioral task to assess performance. The EMG data was collected from each of the four muscle groups using a Muscle SpikerBox from Backyard Brains with two large muscle electrode stickers placed on each muscle for differential measuring. Ground electrodes were placed on bony parts of the body (elbow and back of neck on the spine). The EMG signal is sent to a computer using MATLAB to process the signal using a Kalman filter.

The Kalman filter uses the EMG signals to control the angle of the robotic claw. The Kalman filter uses the EMG signal along with the previous claw state to predict the new state: the rate at which the claw arm angles change. This corresponds to a Kalman filter controlling the velocity of a cursor rather than the position. This was found to be empirically more effective compared to controlling cursor position in lab 6. A study published in The Journal of Neural Engineering also explored different control system properties and found that the position of an arm recorded via Optotrak had much better performance controlling the velocity of a cursor rather than the position [8]. The Kalman filter outputs an integer ranging from 0 to 100.

The rate at which the angle changes is then converted to a pulse width modulation, which the robotic claw motor takes as input. The motor, the HS 422 Servo motor, takes a pulse train as input with a period of 20 milliseconds. The claw angle changes based on the pulse width, ranging from 0.9 ms to 2.5 ms, with the claw closed at full force at 0.9 ms and fully open at 2.5 ms. The Kalman filter outputted a range of 0 to 100, with 0 representing a pulse width of 1 ms (closed) and 100 corresponding to a pulse width of 2 ms (open). The signal is then sent through an Arduino Uno to convert the digital signal to an analog one, which sends the signal to the robotic claw motor. A block diagram of the entire closed-loop neural interface can be found in figure 1.

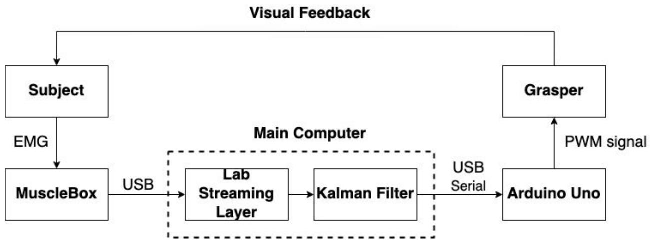

Figure 1*: Basic pipeline of the closed-loop neural interface.*

B. Behavioral Task

The task involves flexing muscles to open or close the claw. The subject tried to close the claw around a paper box, then pulled on a string to lift the claw holding the paper box. The subject must close the claw around the box without crushing it, move the box to the top without dropping it, and hold the box at the top for one second. Figure 2 shows the basic behavioral task setup.

The subject performed 10 trials for each muscle group tested. Four muscle groups were tested. A trial consists of the robotic claw starting at the bottom with the two arms surrounding the paper box. The subject closes the claw arms around the box and pulls the string, lifting the box when they feel like they have an adequate grip on the box. The subject moves the box to the top and holds the box for one second. Visual feedback is provided when the subject observes the claw closing and the box moving, closing the loop of the neural interface.

The first muscle group was the forearm muscles, the most basic muscle group used for many previous experiments in BIOEN 466 Lab. Specifically, electrodes were placed on the muscle that contracted when flexing the wrist and the muscle that contracted when extending the wrist. Flexing the wrist closed the claw while extending the wrist opened it. The next muscle group tested was the bicep/triceps pair, a larger muscle group with potentially more control as there is a larger range of movement. Flexing the bicep closed the claw while flexing the triceps opened the claw. Neck muscles were tested as well to simulate myoelectric prosthetic control for subjects with no arm muscles. Electrodes were placed on adjacent sides of the neck, so that tilting the head to the right closed the claw and tilting the head to the left opened the claw. Lastly, we placed electrodes on both pectoral muscles, a group of muscles that have been repeatedly used in the past for targeted muscle reinnervation [9]. Flexing the right pectoral muscle closed the claw while flexing the left pectoral muscle opened the claw. To rule out motion noise due to the subject using a single arm to both flex the pectoral and pull the string, we also performed 10 trials using both pectoral muscles while a third party pulled the string, for a final total of five experimental conditions and 50 trials.

There were four metrics used to assess performance of each trial. The quantitative metric was the time it took for the subject to close the arm around the box and lift the box to the top. Qualitative metrics included whether the subject was able to move the box to the top (success/fail), whether there was a successful hold (hold/drop), and the degree to which the box was crushed (low/medium/high).

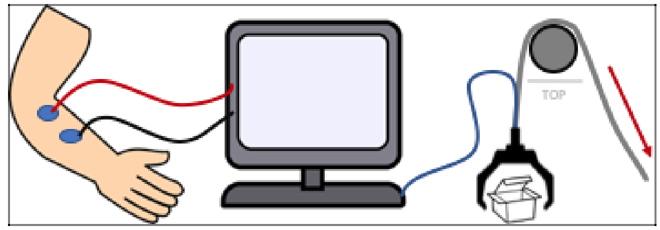

Figure 2*: Basic behavioral task setup. EMG signal comes from a muscle group (forearm pictured), is processed and sent to the robotic claw, which closes around a paper box in response. The subject pulls on a string to lift the claw and paper box to the top and holds it there for one second.*

III. RESULTS

A. Time to Task Completion

Our first test was to determine how quickly the subject was able to pick up the box for each of the five conditions. One team member was the subject while another timed each trial, starting the timer upon the utterance of “Go”, (from “Three, two, one, go”, and stopping the timer upon observing the box reach the top. These times were averaged across the 10 trials for each condition. In descending order from fastest average time to slowest, the results were as follows: pectorals with help -> neck muscles -> bicep/tricep -> forearm -> pectorals, with average times ranging from 2.82 seconds to 4.16 seconds. The amount of variation across trials as represented by standard deviation varied for each condition. In ascending order from lowest standard deviation to highest, the results were as follows: neck -> forearm -> pectorals with help -> pectorals -> bicep/tricep; with values ranging from .45 seconds to 1.53 seconds.

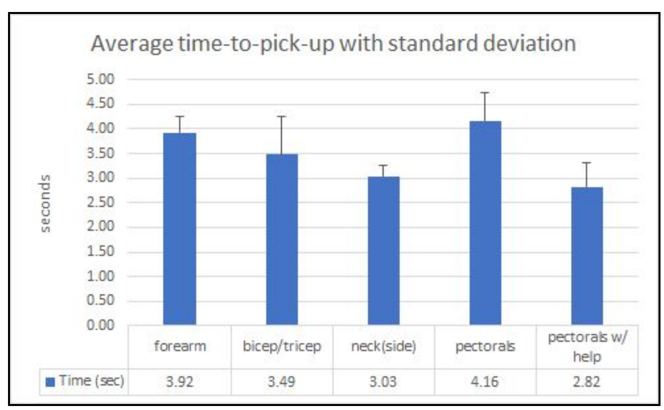

Figure 3: *Average time to pick up the box and bring it to the top in seconds for each condition, with standard deviation error bars.*

B. Success Rate of Task Completion

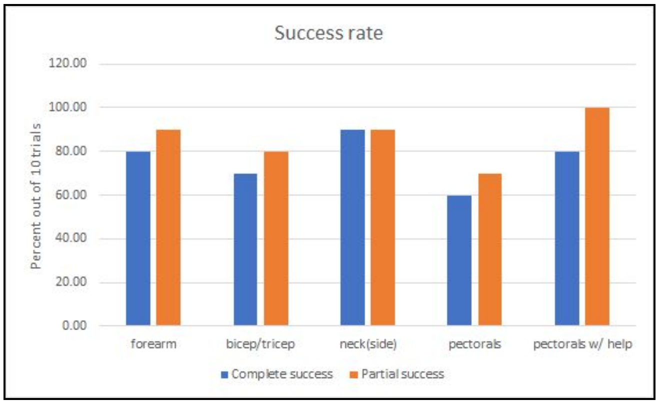

Figure 4: *Success rate of both partial and complete successes by percentage for all conditions.*

Our second test was to evaluate how successful the subject was at picking up the box and completing the task for each of the five conditions. Partial success was evaluated as picking up the box and bringing it to the top, but dropping it before voluntary release. Complete successes were evaluated as the latter plus voluntarily dropping the box after task completion. Note that partial successes were included in the time-to-pick-up calculations. In ascending order from lowest partial success rate to highest, the results were as follows: pectorals -> bicep/tricep -> forearm | pectorals with help -> neck. Likewise, for complete success, the results were as follows: pectorals -> bicep/tricep -> forearm | neck -> pectorals with help. For all conditions and success definitions, success rate ranged from 60 to 100%.

C. Evaluating Fine Control of Grasper

Our final test was to determine how delicately the subject was able to pick up the box as a method of evaluating how precise of fine control the subject had over the grasper in each condition. Crush was quantified for all trials with the exception of a single trial in the neck muscle condition where the grasper failed to make contact with the box. During each trial, the three team members evaluated the level of crush that the box experienced with reference to pictures taken during preliminary testing for consistency.

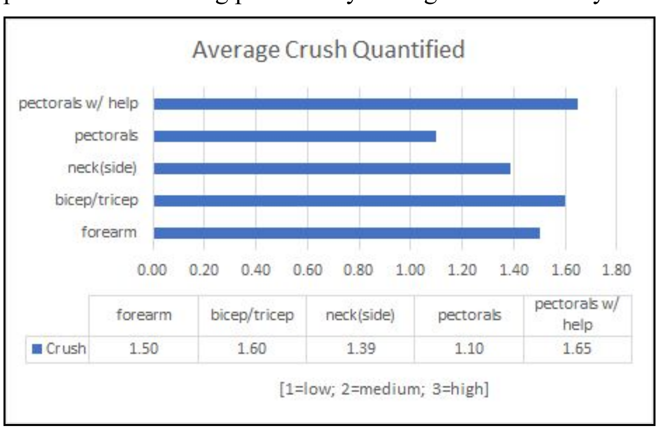

Figure 5: *Quantified crush averaged over the ten trials for all conditions.*

This low/medium/high evaluation was then converted to a numeric representation, [1, 2, 3], and then averaged for all conditions. Average quantified crush ranged from 1.10 to 1.65, or between low and medium, for all conditions. In ascending order from lowest to highest average crush, the results were as follows: pectorals -> neck -> forearm -> bicep/tricep -> pectorals with help.

III. DISCUSSION

A. Summary of Findings and Significance

Overall, controlling using the neck muscles was the best-performing condition. It was the fastest and most consistently successful independent condition (this excludes the pectorals with help condition). Between the fast task completion time, the lowest variation in completion time across all conditions, and a success rate of 90% for both partial and complete successes, this condition is very promising for future applications. An additional advantage to the neck muscles' high performance is that this condition is not dependent on a functional arm being present like the forearm and bicep/tricep conditions, making it a more feasible target for applications involving amputees or possibly quadriplegics.

The time to task completion being approximately two to four seconds for all conditions suggests that our system approaches the speed of doing the task by normal physiological means. The average crush level being uniformly between 1.10 and 1.65, or between low and medium crush, suggests that this system provides sufficient fine control to be applied to pick up a wide variety of objects, including potentially delicate ones. Empirically, there appears to be some negative correlation between crush level and success rate. This suggests that there may be a trade-off between delicacy of control and success rate that would need to be taken into consideration in future work.

This was a seemingly novel experiment, as our efforts to find papers directly comparing muscle groups with myoelectric prostheses yielded no results.

B. Limitations

One limitation of our study is the use of a single object to grasp. The box was very light, making it difficult to extrapolate the usefulness of our system to heavier objects.

Another limitation includes our additional trials with the pectoral muscles and a third party helping to pull the string. The trials performed with pectoral muscles and help also could be slower due to communication between the grasper and the puller. The third party pulling the grasper up may wait longer to make sure the grasper is secure than if the person controlling the grasper was controlling the string as well. Additional experiments would need to be performed to quantify these differences.

Our experiments were also performed with only one subject. Additional experiments with multiple subjects would allow us to generalize our results further to a broader population.

C. Future Work

In future work, we would like to fully mechanize our testing system. In this experiment, the grasper was controlled by EMG data but the act of pulling the box to the top was done manually by pulling on a string. An improved method could be a pulley system with a triggered action to pull up, or the up/down could also controlled by EMG data - although this would double the number of electrodes and muscles we would be measuring from and add additional complexity to the control task.

Another direction could be to directly attach the grasper to the subject and then ask the subject to complete more complicated pick-up tasks, such as picking up the box and then placing it in another container.

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