Decreasing the effects of fatigue on EMG signal decomposition for prosthetic control using MAV

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Many different conditions, including diseases, accidents and congenital defects, can lead to the use of a prosthetic hand. Since there are several different causes that can lead to the use of prosthetics, the population of patients is ever growing. With this expanding population group comes more innovation in the technology, such as the ability to not only control the hand with brain signals, but also get feedback sensation such as touch. Although the developments of prosthetics have come a long way, they still face some big issues, such as the impact of muscle fatigue on reliable control. As a patient's muscle becomes fatigued, the EMG signal declines and can cause all control to be lost if it requires high spiking. To address this, we developed a control algorithm that aims to maintain meaningful control under fatigued conditions. This was done by using two iterations of a control algorithm and simulating short term fatigue in our participant. The second control algorithm, which uses mean absolute value (MAV), is able to more closely follow the contractions done by the participant and has lower signal decline due to fatigue. Control algorithm 2 also showed less false positives than control algorithm 1 (46% error versus 10%) and is able to maintain the opened state up to 5 times longer. Algorithm 2 also required less force output to maintain the spiking needed to open the hand, even during the fatigued tests. These results allow for more reliable prosthetic control when using EMG as the control signal. These findings could also be applied to human-robot interactions in order to assist humans who are becoming fatigued regain control of themselves or a prosthetic [1].

Keywords—Fatigue, EMG decomposition, prosthetic control

I. Introduction

The human hand is one of the most complex parts of the human body. It is able to move in up to 21 degrees of freedom and complete some of the most sophisticated movements in the body. When a person loses their hand, they lose the ability to interact with the world at this high level. In 2005, 1.6 million people were living with limb loss and this number is projected to double by 2050 [2]. The need for more sophisticated prosthetics that more closely emulate natural movement and control is more important than ever. On top of the increase in projected patients, the number of diseases and conditions leading to limb loss and prosthetic use continues to increase [3].

Current advancements in the field, such as the creation of electronic skin, which allows for sensory feedback [4], show great improvements in the use and function of prosthetics, but still lack in some of the reliability. The issue of muscle fatigue is a recurring one in prosthetic control and can cause poor response or even unwanted movement [5]–[7].

To address the impact of fatigue on prosthetic control, we develop two control algorithms and test them in both fatigued and non-fatigued conditions. Our objective is to decrease the effect fatigue has on the ability to open and close the virtual prosthetic hand. Other papers addressing fatigue in muscle control emphasize the decrease in force [5], so we will look at the decrease in meaningful control.

II. Methods

The virtual environment used to simulate a prosthetic hand was MuJoCo. For this paper, we focused on the EMG signal decomposition caused by fatigue, so we just used the basic MPL.xml simulation. This just shows the hand as either opened or closed by manipulating the metacarpophalangeal, proximal interphalangeal , and distal interphalangeal joints.

A. Participants

The participant in this study was between 18-24 years old, male and of healthy neurological condition. There was only one participant in this study because of the high variance of fatigue among people. In order to have one algorithm applied to the non-fatigue and fatigue conditions without making adaptations to the threshold values, we had to use recordings from the same person.

B. Recording Hardware

The hardware used in this study consists of an *Arduino* Uno with an attached BackYard Brains Muscle SpikerSheild. One channel of EMG recording was used. This was done using a sampling rate of 1 kHz on analog input pin 1. The hardware used in this study consists of an *Arduino* Uno with an attached BackYard Brains Muscle SpikerSheild. Two disposable surface electrodes were placed approximately 2-3 centimeters apart on the flexor carpi radialis muscle and one on the bony part of the elbow to act as the ground.

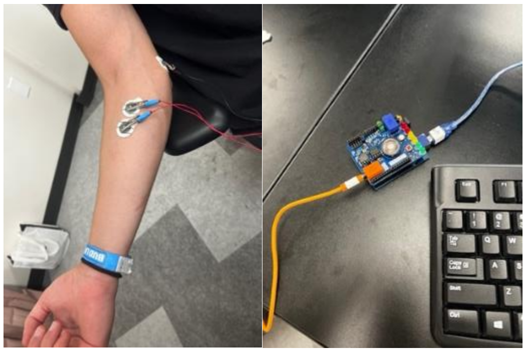

Figure 1: Electrode placement and recording set up on the participant. The electrodes are placed on the flexor carpi radialis muscle and the ground on the elbow. The hardware shows the Arduino with the attached BackYard Brains Muscle SpikerSheild with the cables for the electrode leads (orange) and the USB for power and communication (blue).

C. *Signal Acquisition*

Recording the EMG signals and processing them was done using MATLAB. First a connection to the virtual environment, MuJoCo, had to be established, then a connection to the Arduino. Since the hardware implemented two filters: high pass (~15 Hz) and low-pass (~375 Hz) to filter out motion, heart rate, and high frequency noise, we did not do any filtering in the code. The only preprocessing we did was to remove the defined noise from the signals so we could lower the threshold of spiking.

D. *Control Algorithms*

Control Algorithm 1 was our first attempt at deriving meaningful control values from the raw EMG signal. Our first thought was to take the most recently recorded EMG value (a single value), compare it to a threshold, and assign it a value of either 0 or 1 based on the threshold. This algorithm gives an output of either 0 or 1, which corresponds to the close (0) and open (1) states of the hand.

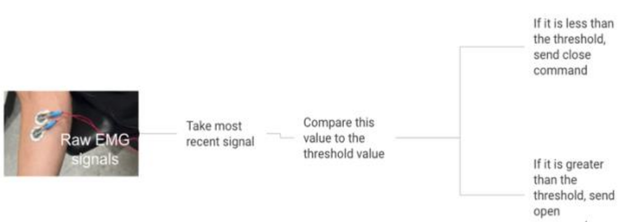

Figure 2a: Flow chart for control algorithm 1 showing the flow of data, the input, and the output of the algorithm.

Control algorithm 2 built off of control algorithm 1 in the sense that it also used a threshold, but we realized that a single raw value wasn't enough to give meaningful control. To address this, we used a sliding window of 800 to pull the 800 most recently recorded EMG signals. We then averaged these together and took the absolute value. This mean absolute value was then compared to the same threshold as control algorithm 1 (0.5) and assigned a value of either 0 or 1. [8]

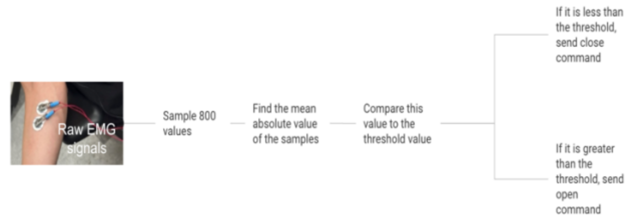

Figure 2b: Flow chart for control algorithm 2 showing the flow of data, the input, and the output of the algorithm.

E. *Signal-to-noise ratio*

To define noise, we assumed the first 500 samples of EMG recordings were the noise. We made sure not to produce a contraction in this timeframe, and if we accidentally did, the calculated signal-to-noise ratio for that run was thrown out. Once we measured the amplitude of the noise, we then produced a contraction and measured the amplitude of the signal. The variance of the noise and the signal were calculated and we defined this as the noise power and signal power [9]. Finally the signal-to-noise ratio was calculated using equation 1.

$$SNR = 10 * \log \frac{Signal\ power}{Noise\ power}$$

Equation 1: calculation of the signal-to-noise ratio where the signal power is the variance in the signal strength and the noise power is the variance in the noise strength.

F. *Evaluation*

We conducted tests of the algorithms in both fatigued and non-fatigued states. We defined the fatigued state as holding the contraction for 30 seconds and the non-fatigued state as holding for only 10 seconds. These times were inspired by similar tests conducted using short term fatigue techniques [5]. To quantify the impact of fatigue, we compared the number of spikes to the hold time (expected versus observed) and asked the participant preference based on hand response. We conducted tests for each state and algorithm, totaling to 4 different data points. We could not run more than one trial for each test because the participant would become over fatigued and this would decrease the signal even more than expected.

G. *Statistical Analysis*

We ran our statistic tests on the SNR data because the way the trials were conducted for the EMG data did not gather the data needed for traditional evaluation methods. For the SNR, we ran a Shapiro-Wilk test to check normality [10]. Based off of this, we chose to run an unpaired t-test [11]. The total number of samples (N) for these test was 4: 2 from the first algorithm and 2 from the second algorithm. They are unpaired because the values from each algorithm are not related.

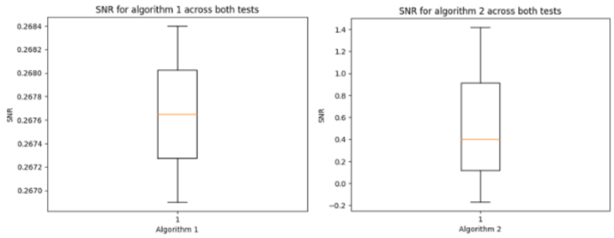

Figure 3: Boxplots for algorithm 1 and 2 SNR values. Each show a fairly even distribution, with more variation in algorithm 2 due to the final reading when the participant was highly fatigued.

III. Results

A. The addition of more signals and use of MAV in the control algorithms shows a decrease in the effect of fatigue on control

Control algorithm 1 takes one sample of EMG signal and applies it to the threshold value (0.5), while control algorithm 2 samples 800 signals, applies MAV, then compares to the threshold. The raw incoming data for each algorithm is the same: EMG signals from the participant. Although they have the same incoming signals, which can be seen in the top graph of figures 4a-d, they vary in the hand response. This is due to the adjustments made to algorithm 2 which allow it to be more robust in the event of fatigue (figure 4d).

B. Algorithm 2 has less false positives in the expected versus observed hand behavior.

In order to quantify the results for each algorithm, we look at the expected versus observed values during the contractions. This allows direct comparison for each algorithm and for each trial, unlike some other metrics that would need multiple trials and more data. Since we had very limited chances to collect data due to the nature of the research question, we also take into account the participants input. Algorithm 2 is able to hold the open state longer than algorithm 1 and more closely resembles the expected behavior (figure 5d), despite being the last trials. The participant states they were experiencing greater fatigue during the algorithm 2 trials.

C. The participant prefers the responses shown from algorithm 2.

While participant impressions are subjective, they are necessary in this case. Only the participant can tell us how much fatigue they are feeling for each trial. In this case, the level of fatigue they feel has a direct correlation on the results. We are still able to see algorithm 2 outperform algorithm 1 on both the qualitative and quantitative measures, but given the fatigue the participant states they are feeling, we would expect if the trails were repeated in a different order or after a more significant break, the results would be more clear.

D. The Signal-to-noise ratio across trials is consistent.

The data does not show a significant departure from normality ($p = 0.088$, $W(4) = 0.76$). This allows for the use of an unpaired t-test, which shows no significant difference between the values ($p = 0.3319$, 95% confidence -2.82 to 1.54). These findings show that the signal to noise ratio between trials had no significant variance and did not play a role in the outcomes of the algorithms.

*Figures for time-synchronized EMG data for all trials is shown. Due to space, only the fatigue trials for algorithm 1 and expected vs. observed graphs are shown.

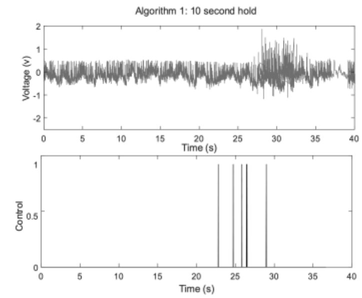

Figure 4a: Raw EMG recording of time-synchronized data for algorithm 1, trial 1 (non-fatigued). The lower graph shows the open and close commands sent to the MuJoCo hand. False positives can be seen as well as inability to hold an open condition.

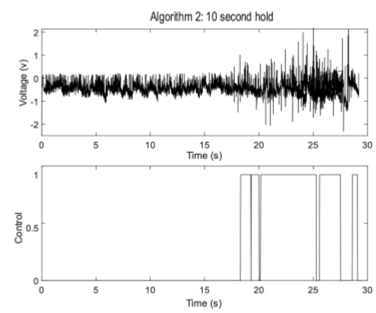

Figure 4b: Raw EMG recording of time-synchronized data for algorithm 2, trial 1 (non-fatigued). The lower graph shows the open and close commands sent to the MuJoCo hand. This shows much better response and the ability to hold the hand open.

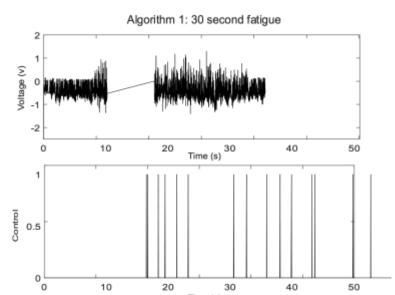

Figure 4c: Raw EMG recording of time-synchronized data for algorithm 1, trial 2 (fatigued). The same issues as trial 1 are seen.

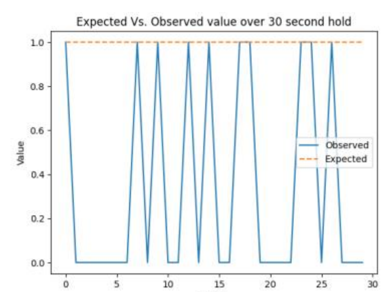

Figure 5a: Representation of expected value versus observed for algorithm 1 fatigued. For the 30 seconds, there are 14 instances of being in the wrong state (46%).

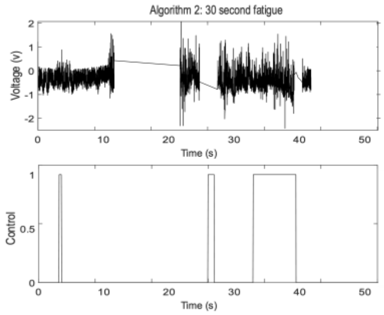

Figure 4d: Raw EMG recording of time-synchronized data for algorithm 2, trial 2 (fatigued). There is less correlation than the 10 second trial, but still much better tracking than algorithm 1.

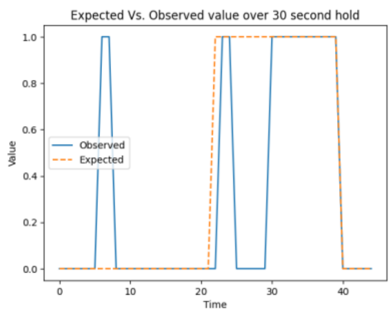

Figure 5b: Representation of expected value versus observed for algorithm 2 fatigued. For the 30 seconds, there are 3 instances of being in the wrong state (10%).

IV. Discussion

The impact of muscle fatigue on meaningful prosthetic control can be catastrophic, as we see with control algorithm 1. The updates in control algorithm, like the sliding window of samples and use of mean absolute value, allow for much closer behavior to that expected. Control algorithm 2 is able to hold the open state up to five times longer (figure 5c versus 5d). Prior work has been done on the impact of fatigue of grasp force [5] and specifically on the bicep muscle [6]. In contrast, we focus on the forearm muscle, which shows less interference for EMG signals [12] and on the impact on prosthetic control, rather than grip force.

The work presented here builds off the prior works on muscle fatigue by Wang et. all and Ahmed et. all and works on EMG signal decomposition. Novel from this work is the focus on control algorithms and prosthetic control. Future work should address the algorithm and threshold to make it more robust and able to handle more participants. Another direction could be looking at effects of more long term fatigue or different protocol for causing short term fatigue.

These results provide a basis that the adjustment of the control algorithm can decrease the negative effects of muscle fatigue on prosthetic controls. This can allow for a wider use of prosthetics on varying conditions or muscle definition that may not have been feasible before. This work also opens the door for the study on the impact of muscle fatigue in other fields, such as in robot-human interaction as assistive technologies.

V. Author Contributions

RM calculated signal to noise ratio, developed control algorithms and wrote the manuscript. CA helped with design. GO helped with design and performance metrics. KR worked on the algorithm iterations with RM and project scope. All authors contributed to figure generation.

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