Improved Virtual Hand Grasping via Discrete, High-Gain Control Algorithm

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Amputees are frequently dissatisfied with their myoelectric prosthetic's grip control. Myoelectric prosthetics transform electromyographic activity into movement via a control algorithm. Here we introduce a novel, discrete high-gain control algorithm that outperformed the standard mean absolute value control algorithm on a grip control task. With the standard control algorithm a participant could grip a cylinder for 3.6300 ± 0.5567 s, whereas with the improced control algorithm they could grip a cylinder for 10.9192 ± 0.9745 s (N = 10, p < 0.001). These results indicate that the discrete high-gain control algorithm outperforms the the standard mean absolute value control algorithm in our measures of grip control. These results provide information to the myoelectric control field on ways to improve ease of grasping. These results may also aid the development of control systems powered by other bioelectric recordings.

I. Introduction

An estimated 400 thousand people in the U.S. are upper limb amputees [1]. The current standard of care is a prosthetic. However, many amputees are dissatisfied with their prosthetics due to poor comfort, appearance, sensory function, and control [2]. Upper limb myoelectric prosthetic users report that adaptability of grip strength and ability to prevent object slipping are high-priority complaints [2].

Myoelectric prostheses work by using surface electromyography (sEMG) to record the electrical activity of extrinsic muscles, which can provide insight into the intended movement [3]. A control algorithm reads the sEMG signals and produces a set of control values that direct the action of the prosthetic [3].

Current research in the field focuses on investigating the utility of multiple algorithms to derive control signals from sEMG recordings [4]. Critical efforts focus on improving prosthetic ability to mimic human hand gripping [4].

This proceeding aims to teach about the basis of control algorithms and how we can improve them programmatically. Its unique primary focus is maintaining relatively simple processing while reducing the effort required to grasp with a virtual hand. Importantly, we found that increasing the gain of a control algorithm through organizing a small range of EMG mean absolute values into discrete bins of control values improved grip control of a virtual prosthetic hand.

II. Methods

A. Participants

The presented data is from a single, healthy female participant who was 23 years of age at the time of data collection.

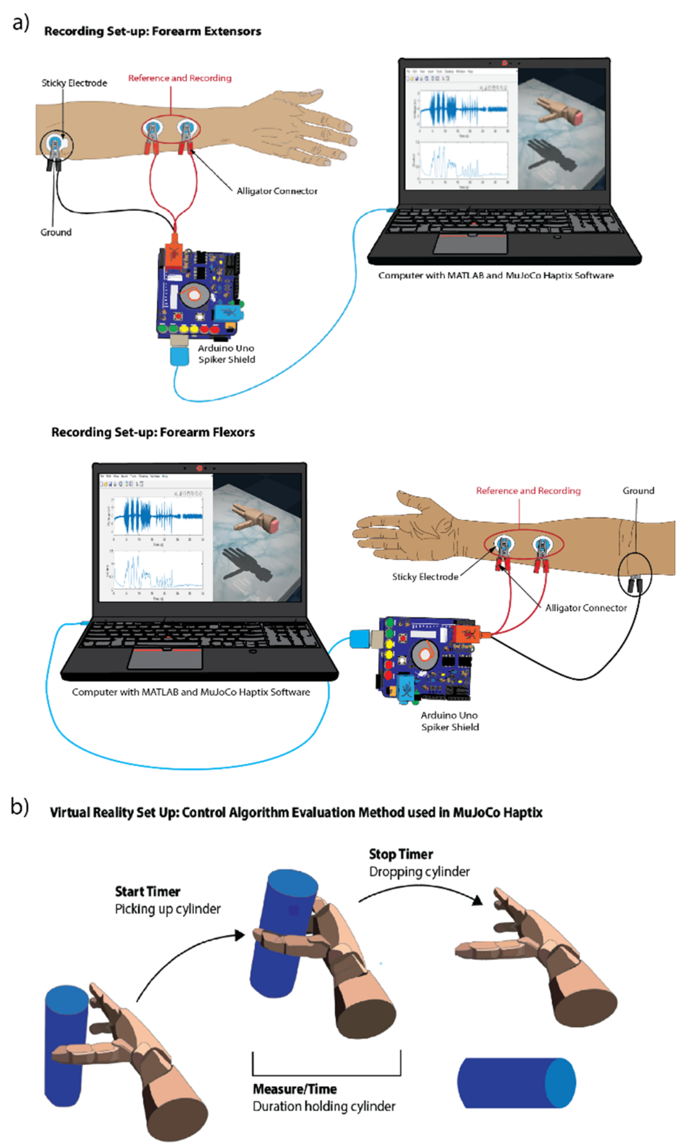


Figure 1. Three EMG electrodes were used to record muscle activity from the forearm flexors and forearm extensors, as well as control a virtual hand. **a)**

Schematic of EMG recording set up for forearm extensors (top) and flexors (bottom). **b)** Schematic of assessment used in virtual reality to control hand.

B. Signal Acquisition

3 Cardinal Health 22850 Kendall 850 Series Foam Electrodes were placed on the right arm for signal-to-noise ratio data collection. Signal-to-noise ratio data was collected using two single-channel electrode configurations (Figure 1). In the first electrode configuration, one recording electrode and one reference electrode were placed on the *medial* surface of the forearm. This electrode configuration was utilized to record from the extrinsic forearm flexors. In the second electrode configuration, one recording electrode and one reference electrode were placed on the *lateral* surface of the forearm,. This electrode configuration was utilized to record from the extrinsic forearm *extensors*. One ground electrode was placed on the skin over the olecranon for both electrode configurations.

For virtual hand control, the forearm flexor recording configuration was used electrode. Due to a shortage of the 850 Series Foam Electrodes, Cardinal Health Kendall ECG H124SG Electrodes were used instead.

In all sections of the experiment, surface electrodes were connected to an Arduino Uno Heart and Brain Spiker Shield via alligator connectors. The Arduino Uno Heart and Brain Spiker Shield is a microcontroller that sampled EMG voltage at a rate of 1 kHz, which was then amplified and frequency filtered before data transmission to a computer via a USB-A connector.

A MATLAB code recorded and plotted incoming data from the Arduino Uno in real-time. No modifications were performed by the software to change the raw signal.

Ten signal-to-noise ratio (SNR) measurements of raw signals were taken and calculated from each electrode configuration. Before running the MATLAB code, the participant's hand was held in a relaxed position. After starting the MATLAB code and EMG voltage = recording, the participant was instructed to keep their hand relaxed for three seconds. At the three-second mark, the participant was asked to perform and sustain a maximum voluntary contraction (MVC) of the forearm, with the hand grasped if the EMG electrodes were in the flexor recording configuration and the hand extended/splayed if the EMG electrodes were in the extensor recording configuration. The participant was instructed to hold the MVC for three seconds, at the end of which the MATLAB code was manually stopped by the user. The SNR in decibels (dB) was then derived via the following standard SNR equation for analog to digital conversions.

$$\mathrm{SNR\ (dB)} = 20\log\left(\frac{\mathrm{RMS}(\mathrm{Voltage}_{\mathrm{signal}})}{\mathrm{RMS}(\mathrm{Voltage}_{\mathrm{noise}})}\right) \quad (1)$$

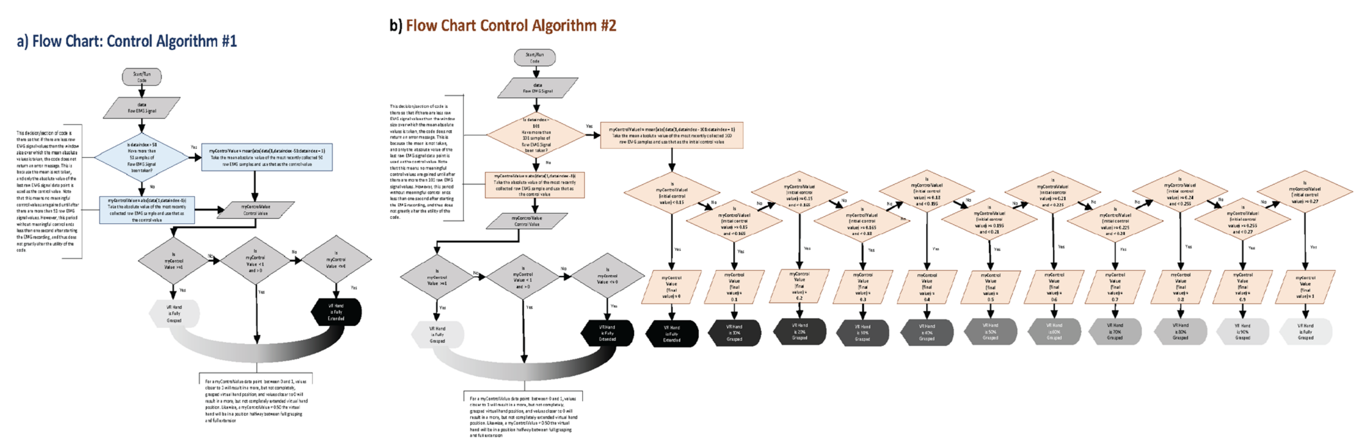
The root mean square (RMS) of voltages recorded after the three-second mark ($\mathrm{Voltage}_{\mathrm{signal}}$) was divided by the RMS of voltages recorded before the three-second mark ($\mathrm{Voltage}_{\mathrm{noise}}$). The logarithm base 10 of that value was then multiplied by 20 to yield the SNR in decibels. This process was repeated a total of 20 times, ten times per electrode configuration.

C. Control Algorithm

A control signal was derived and plotted from the raw EMG signal in MATLAB. The control signal was then transmitted to the MuJoCo Haptix software,
where the value of the control signal determined the positioning of a virtual prosthetic hand. A control value of 0 corresponded to complete extension of the hand's interphalangeal (IP) and metacarpophalangeal (MCP) joints (hand completely open with fingers/splayed/extended), while a control value of 1 corresponded to complete flexion of IP and MCP joints (hand completely closed/grasped). In contrast, values between 0 and 1 corresponded proportionally to intermediate hand positions.

The first control algorithm set the control value to the mean absolute value of the last 50 recorded voltages of the input raw EMG signals. This algorithm resulted in a continuous range of output values that spanned from the minimum mean absolute value (~0.05) of the last 50 raw EMG voltages at rest to the maximum mean absolute value of the previous 50 raw EMG voltages (~1.30) at the peak of an MVC. However, it is important to note that some submaximal voluntary contractions involving complete hand closure only resulted in a peak control

Figure 2. Flow chart of control algorithms logic **a)** Flow chart of control algorithm 1 demonstrating a simple mean absolute value transformation of the raw EMG data into the control value **b)** Flow chart of control algorithm 2 demonstrating how mean absolute values were placed into equidistant discrete bins to control the hand



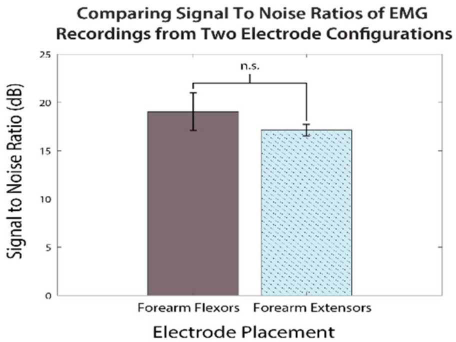


Figure 3. EMG recordings from forearm flexors and forearm extensors show no significant difference in signal to noise ratio. The dark grey solid bar represents the forearm flexor configuration data while the light blue striped bar represents the forearm extensor configuration data. Statistics: Forearm Flexor Configuration: 19.0379 ± 1.9406 dB Forearm Extensor Configuration: 17.1395 ± 0.5919 dB. Paired T-Test: N = 12, $p > 0.05$

value of approximately 0.38 and incomplete virtual hand closure. The second control algorithm also used the mean absolute value of the raw EMG signal (input). The mean absolute value of the last 100 recorded voltages was taken to achieve a greater smoothing effect. Additionally, all mean absolute values less than 0.15 were changed to a control value of 0, and all mean absolute values greater than or equal to 0.27 were changed to a control value of 1. Values between 0.15 and 0.27 were

separated into nine equal bins. Each bin was assigned a corresponding multiple of 0.1. The primary purpose of this alteration was to increase the gain of control value extraction so that sustainable sub-maximal contractions could result in the complete closure of the virtual hand.

D. *Evaluation*

The utility of the two different control algorithms was assessed by testing how long the participant could hold a virtual cylinder in the air with each control algorithm. The outcome measure, duration in seconds, was measured by starting a timer as soon as the virtual hand picked up the virtual cylinder off the virtual table. The timer ended when the virtual hand lost grip of the virtual cylinder. Twelve durations from each control algorithm (24 total) were collected. No subsequent processing was performed on the data.

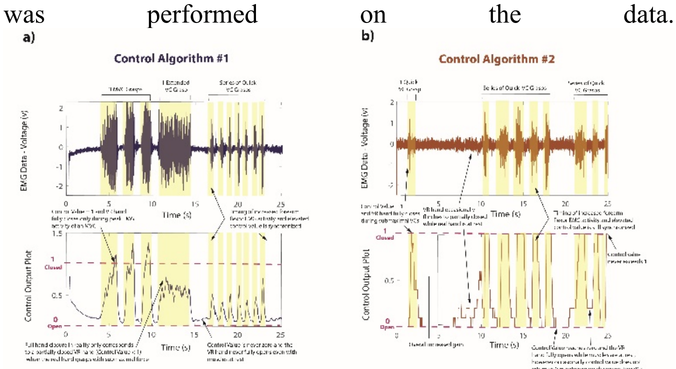


Figure 4. Control algorithm 2 (in dark orange on left) demonstrates higher gain, and discrete control while control algorithm 1 (in dark blue on right) demonstrates continuous control. Sample traces of raw EMG signals (top) are juxtaposed with their respective output control values (bottom).

E. *Statistical Analyses*

For both SNR and control algorithm assessment, histograms and Anderson-Darling tests were performed to assess if the data (N=10, both conditions) had a normal distribution. SNR data had a normal distribution and contained paired data, so a paired t-test was used to assess statistical significance. The control algorithm data (N=12, both conditions) did not have a normal distribution but did contain paired data, so a Wilcoxon Signed-Rank test was used to assess for statistical significance.

III. Results

A. *EMG Signal-to-Noise Ratio*

We first designed two EMG configurations. In the first EMG configuration, recording and reference electrodes were approximately 4 cm apart on the skin over the forearm flexors. In the second EMG configuration, recording and reference electrodes were about 4 cm apart on the skin over the forearm extensors. In both configurations, ground electrodes were on

the skin over the olecranon. We then assessed the two electrode configurations' signal-to-noise ratios (SNRs), using the following Equation 1 to calculate the SNR.

We obtained the signal's voltage by collecting the EMG voltage data of three-second maximum voluntary contraction (MVC) and the noise voltage by collecting the EMG voltage data of a three-second rest period. We then plugged the values for voltage into the above equation to calculate SNR. We repeated this process ten times per EMG configuration. For the forearm flexor EMG configuration, the mean SNR was 19.0379 ± 1.9406 dB. The mean SNR was 17.1395 ± 0.5919 dB for the forearm extensor EMG configuration. A paired t-test on the data yielded a p-value of 0.3658, indicating no statistically significant difference in the SNRs of the two electrode configurations (Figure 3).

B. *Control Algorithms*

We transformed the raw EMG signal into control signals to power a virtual robotic hand via two different control algorithms. A control value of 0 corresponded to a completely open virtual hand, while a control value of 0 corresponded to a completely grasped virtual hand. The first control algorithm took the mean absolute value of the last 50 raw EMG voltages and used that as a control value. The second control algorithm took the mean absolute value of the previous 100 EMG voltages and organized the values numerically into 11 bins with values ranging from 0 to 1 in increments of 0.1. While the control signals from the first control algorithm surpassed one and enabled full hand grasping, this only occurred at the peak of maximum voluntary contractions. Therefore hand grasping could not be sustained.

Additionally, with the first control algorithm, the control value was never 0, so the hand was never completely open. On the other hand, the second control algorithm has higher gain and achieves values of 0 at rest and one at submaximal forces.

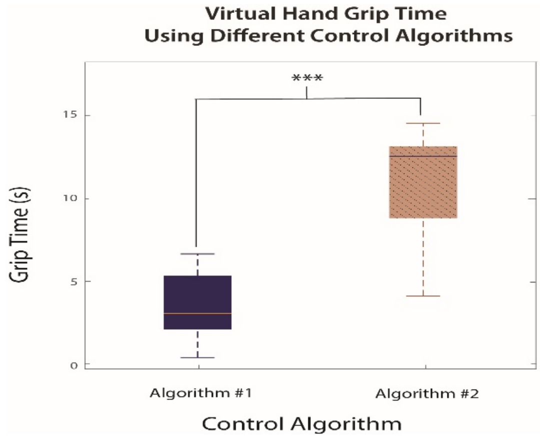


Figure 5. Control algorithm #2 outperforms control algorithm #1 on grip control task. The dark blue solid box represents control algorithm #1 performance while the orange striped box represents control algorithm #2 performance. Statistics: Control Algorithm 1: 3.6300 ± 0.5567 s Control Algorithm 2: 10.9192 ± 0.9745 s. Wilcoxon Signed-Rank Test: N = 12, $p < 0.001$

However, it lacks continuity of values and control and acts as discrete decoder (Figure 4).

C. *Performance Metrics*

We assessed the control algorithms on the ability of the user to control the virtual hand to sustain and control the grip on a cylinder in virtual reality using each control algorithm. We measured grip time in seconds as the time from picking the cylinder up from a virtual table to the time the cylinder dropped from the virtual hand. Control algorithm #1's mean grip time was 3.6300 ± 0.5567 s. For control algorithm #2, the mean grip time was 10.9192 ± 0.9745 s. The results of a Wilcoxon Signed-Rank test on the data yielded a p-value of 9.7656e-04, indicating that control algorithm #2 had a mean grip time significantly greater than control algorithm #1 (Figure 5).

D. *Subjective Impression*

It is important to note that while participant input is subjective, it still may be helpful. The participant noted that she had difficulty grabbing the cylinder with both control algorithms, but it was mainly due to the lack of friction in the virtual environment. She mentioned control algorithm #2 was easier and less fatiguing to use.

IV. DISCUSSION

The objective of this paper was to teach the scientific community about how we can improve control algorithms programmatically. We found that increasing the gain of our sustem and organizing a small range of EMG mean absolute values into 11 deterministic "bins" of control values improved grip control of a virtual prosthetic hand.

Prior work has shown that poor grip control is a critical factor in prosthesis dissatisfaction and that there is a need to design prosthetic hands that mimic human hand gripping. In contrast, we *implemented* a simple alteration in a mean absolute value-based control algorithm to reduce the effort required to sustain grasping.

The work presented here builds off prior works by Cordella et al., Tam et al., and Geethanjali et al.. They described and organized existing types of control algorithms, while also identifying limitations of existing control algorithms, such as grip control. In contrast, our work uniquely attempts to make a simple discrete system that increases gain and decreases the effort required to grasp. We accomplished this work by placing a narrow range of mean absolute values of raw EMG signals into 11 discrete bins of control values that allow the hand to open and close with less effort, albeit with less continuity.

Future work should replicate these findings with additional participants and amputees to further assess the utility of these control algorithms. Future work should also focus on improving continuity of control values and increasing degrees of freedom of hand motion while maintaining a low required effort to close the prosthetic hand fully. Engineers can implement these changes programmatically or in the hardware by developing a more sensitive multichannel recording setup. Additionally, future work should focus on creating a more complete and accurate evaluation system of the control algorithms. An improved evaluation system could involve analyzing several parameters aside from just grip control and increasing friction in the virtual reality system. Furthermore, scientists should eventually perform these assessments with actual myoelectric prosthetics after testing thoroughly with virtual prosthetics.

The results from this study provide the field of myoelectric control engineering with a simple and easily implementable solution to lowering the effort required for prosthetic hand gripping and increasing grip control. These results may be helpful to those studying EMG control and those interested in improving the gain and sensitivity while maintaining simplicity in other bioelectric recordings such as electrocardiograms, electrooculograms, electroencephalograms, and patch clamp electrophysiology. Most importantly, this work provides a foundation for improving myoelectric prostheses' grip control, which may ultimately lead to higher prosthetic satisfaction and less prosthetic abandonment among amputees.

AUTHOR CONTRIBUTIONS

DRL designed the control algorithms, wrote the manuscript, and generated the figures. IK implemented signal-to-noise ratio collection and calculation, executed control algorithm evaluation, and edited the figures.

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