Improved Prosthetic Grasping via Ensuring Movement Intentions

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***Abstract*—The long-term goal of this research is to improve the intuitive control of a prosthetic with the use of EMG recordings through a virtual hand control simulation. The number of Americans with limb loss is currently 1 in 190 and expected to double by 2050. Electrical properties of neuron communication, which controls muscle movements, can be measured less intrusively via EMG electrodes when compared to implantable electrodes and may be used in a similar manner to control prostheses. Results showed successful prosthetic grasping control with less intrusive techniques. Within the results, electrode location proved to be insignificant and an improvement for virtual hand jitters were made. Statistically significant outcomes were found for one of the two performance metrics and positive feedback was received from participants. The results provide a stepping stone in neuroprostheses towards achieving more intuitive bionic hand control with EMG signal acquisition. The algorithm and results may also be applied to adjacent fields, such as detecting regular vs. irregular heart beats for pacemaker devices.**

***Index Terms*—EMG, Signal Processing, Prosthetic Control**

I. INTRODUCTION

Currently, nearly one in 190 Americans live with limb loss. This number is predicted to double by the year 2050 [1]. As the number of individuals with this neurological impairment is likely to grow, it is important that efforts are focused on creating more intuitive tools to help these individuals adjust and improve their quality of life. Current clinical standards of care for these individuals focus on addressing pain treatment, exercise therapy, and educating these patients and their caregivers [2]. Although those aspects are vital, there are limitations when it comes to activities of daily life or leisure activities, and community integration [2].

Traditional prostheses have often been a useful tool for individuals with limb loss to regain some control over their daily lives. For further improvement, due to the electric spike behavior between the human brain's primary motor cortex and the body's muscles, engineers can take advantage of the electrical communication from the brain to a lost limb to animate control over a prosthetic device, providing the patients with more flexibility and functionality. One method for accessing and recording these neural signals are with electromagnetic (EMG) electrodes placed externally on the body where the target muscle is located. EMG signals contain two types of information, the timing of muscle activity and its relative intensity [3]. These two factors are the most prominent characteristics for characterizing intended movement, and transferring the intention into prosthetic control.

The methods for collecting and interpreting motor signals continues to be with the use of electrodes. Different types of electrodes may be used for different purposes. The most developed state-of-the-art method is with an implantable electrode array, such as the Utah array, which gets implanted directly into the muscle in which activity is to be measured, whether part of the peripheral or central nervous system [4]. Although high precision can be obtained, this is clearly a very intrusive procedure that still has room for improvement in device longevity for effective long-term applications.

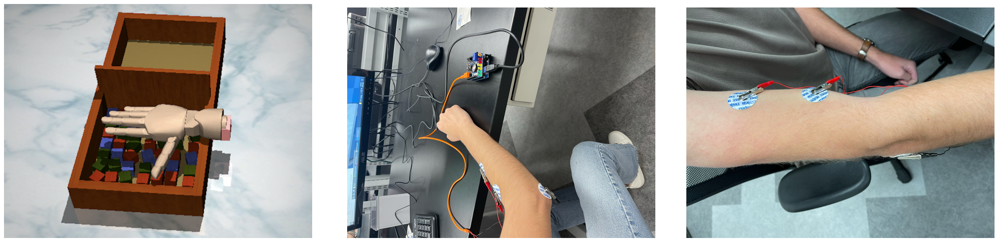
The objective of this paper is to develop a less intrusive form of neural data collection and analysis for the specific purpose of creating a more intuitive prosthetic hand control for upper limb loss. Due to the distance from the source of electrical activity, EMG signals have not been a common measurement tool for prosthetic control in the past. However, it is believed that if accomplished successfully, the non-intrusive and easy-to-use aspect of the EMG electrodes may provide a far more comfortable method for individuals with limb loss and may allow them more independence in their day-to-day life both in terms of every day abilities, and the ease of setting up their prosthetic. The findings from this paper conclude that the EMG electrode placement did not produce significantly different signal to noise ratios and that the second control algorithm developed was more successful in reducing the jittering motion of the virtual prosthetic hand by sending more definitive control signals. Between picking up a number of blocks and the success rate of picking up at least four blocks, the only performance metric that resulted in a statistically significant outcome was the number of blocks picked up. Overall, positive subjective impressions were received by the participants involved in the experiments.

II. METHODS

The following section reviews the specifications of this study outlined through a variety of subsections, including participants, signal acquisition, control algorithms, evaluation, and statistical analysis.

A. Participants

The research data acquired within this paper was conducted on four participants. The participant's ages ranged from 21 to 32 years old. The gender distribution of the group was 50% female and 50% male. In terms of neurological condition,



a. Virtual Hand Environment b. Forearm EMG placement c. Bicep EMG placement

Fig. 1. Test Environment Setup

all participants in the study were considered to be healthy individuals.

B. Signal Acquisition

Within this study, the BackYard Brains Muscle SpikerShield was used to sample and acquire the EMG signals. The device consists of a single channel and had a sampling rate of 330 bytes/ms, or 330 kHz. It had a surface-EMG electrode which was used to take measurements on both the fore-arm and biceps of the participants.

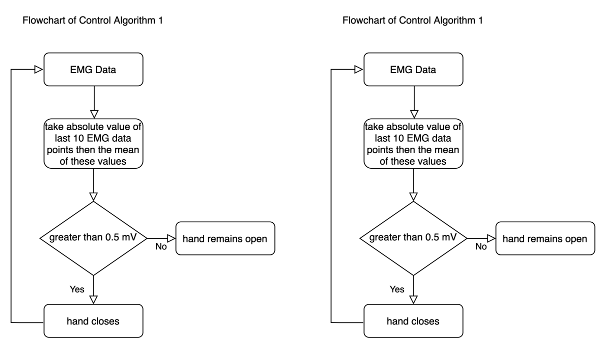
To acquire the data, two software systems were used. The Arduino platform was used to upload code to the on-board micro controller on the device and deliver the sampled data from the EMG electrodes to the computer. Overall, MATLAB was utilized to control the Arduino execution and serve as the interface between the data and the control of the virtual MuJoCo HAPTIX environment. The sampled data was amplified by a gain of ten and was offset by the mean of the sampled data. The modifications performed on the data were to counter some difficulties with the provided SpikerShield device and transition the raw data to be legible and centered around zero.

The signal-to-noise ratio (SNR) of the EMG was calculated by first finding the greatest peak of the noise and the lowest peak of the signal. The SNR was then found by dividing the signal amplitude by the noise amplitude.

C. Control Algorithms

The first control algorithm ran a moving average filter over the data and utilized threshold comparison for control of the virtual hand grasp. The input to the algorithm was the direct modified data described in the previous section. The running average was performed over the absolute value of the last ten data points for every iteration of the running while loop. The average value was compared to a threshold of 0.5 to produce a binary output control signal for the hand, e.g. if the average was above threshold, the control was set to one, and zero otherwise. The flow diagram for algorithm is depicted in Fig. 2-a. The threshold value of 0.5 was arbitrarily chosen by visually viewing the data waveform and deciphering a level that would differentiate noise from muscle activity.

The second control algorithm was designed to decrease the jittering affect seen on the virtual hand. A calibration time was introduced to obtain the varying noise and maximum muscle amplitudes that are present between individuals and trials. During calibration, the participants sat with their muscles relaxed until they heard a beep signal generated by the code. Upon the first beep, the participants flexed their muscles to max strength until they heard the second beep. After the second beep, the trials began. In a similar manner to the first algorithm, the second algorithm also took the modified data as an input and performed a running average of ten data points to compare against a threshold. In addition, the algorithm was implemented to activate a counter of twenty during the transition between grasping and releasing the virtual hand. The concept behind the counter is to help eliminate any accidental drops beneath the threshold when the muscle is contracted and intended to close the virtual hand. While the counter is still running, the hand control is held at one. If the counter finishes and the average value is still beneath the threshold, than the algorithm is more certain of the hand's release and will set the hand control to zero. The threshold value for this algorithm was also adjusted to reflect the noise level of each run. The flow diagram for algorithm is depicted in Fig. 2-b.



a. Algorithm 1 b. Algorithm 2

Fig. 2. Flow diagrams for the two control algorithms

D. Evaluation

The terminal device of the system was the virtual reality environment and the prosthetic hand. The virtual reality environment was a provided software environment that was made to set up realistic scenarios and mimic worldly affects, such as gravity. For the experiment, a virtual environment configuration was chosen which had a wooden box filled with smaller cubes. The prosthetic hand was a part of this virtual simulation and was the object of control within the trials. For this experiment, only the metacarpophalangeal joints of the hand were controlled to allow for a grasping and releasing affect. The terminal device setup can be seen in Fig. 1-b.

Within the experiment, the objective task was to see how many small blocks can be picked up within a minute. The two metrics that were gathered from the experiment were the number of blocks picked up in a minute and the success rate, in which a success was defined as picking up more than four blocks. For each algorithm, each participant went through six trials with the electrodes placed on the forearm, as seen in Fig. 1b. The experiment was repeated once more for algorithm 1 with the electrodes placed on the bicep, as seen in Fig. 1c, in order to statistically compare SNRs later one. For each trial, the number of blocks picked up and the success for that trial were reported right when the one minute time interval finished. Subsequently, the success rate metric per participant was derived upon the completion of the six trials.

E. Statistical Analysis

To begin the statistical analysis, a test of normality was conducted on the data from the two metrics for both algorithms. In addition, normality was tested separately for the SNR data from both locations as well. The normality tests revealed that only the success rate of algorithm 1 was parametric, therefore, all the data sets were treated as non-parametric moving forward. The statistical analysis for each metric was comparing two groups and the data was determined to be paired since it was conducted on the same participant with only the change of the algorithm type or electrode placement location. Due to these characteristics, the Wilcoxon Signed Rank test was used via the $signrank$ function in MATLAB. The statistical analysis for the success rate metric had 4 data samples per algorithm, one for each participant. The statistical analysis for the number of blocks picked up metric had 24 data samples per algorithm, due to the six trials per participant. The statistical analysis for the SNRs also had 24 data samples per location, due to the six trials per participant.

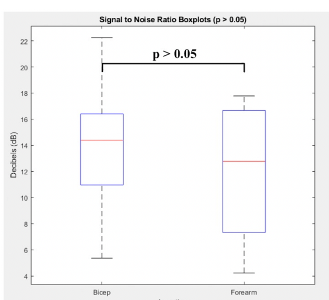
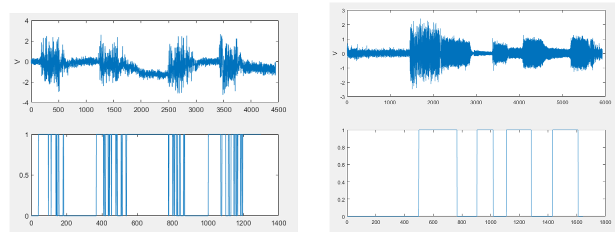


Fig. 3. Boxplot of Signal-to-Noise Ratio.

III. Results

A. EMG electrode placement did not produce significantly different SNRs

Within this experiment, the EMG signals were recorded from the bicep and the forearm, as seen in Fig. 1. From the collected data for each trial, the SNR was computed by



a. Algorithm 1 b. Algorithm 2

Fig. 4. Example traces of the time-sychronized EMG data and control output for each control algorithm

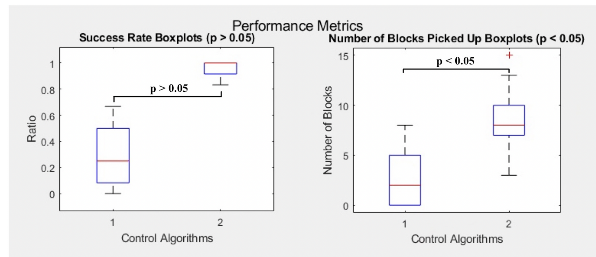


Fig. 5. Boxplots of Performance Metrics.

dividing the lowest peak of the signal by the greatest peak of the noise. The recorded values for the SNRs for each location are listed below.

Bicep = $[2.9046, 1.8912, 12.9483, 1.8517, 3.7871, 2.0912, 12.8259, 5.8840, 6.2392, 6.2069, 6.1709, 5.1824, 7.96543, 6.9438, 5.3010, 7.6952, 6.2946, 7.0841, 3.5145, 3.461, 3.5501, 3.5938, 3.5929, 3.6496]$

Forearm = $[2.3495, 2.3827, 2.8301, 2.3960, 2.2951, 2.0774, 7.1600, 6.4880, 7.5438, 6.6461, 7.7440, 7.3781, 6.9901, 6.1406, 6.0246, 6.1332, 7.1227, 5.2819, 1.6355, 1.8119, 1.7930, 1.6258, 3.4613, 3.5846]$

Fig. 4 displays example waveform traces from each algorithm. For the statistical analysis comparison, the SNR values were calculated using the traces from algorithm 1.

B. Control Algorithm 2 was successful in reducing the jitter of the virtual hand by sending more definitive control signals

The two control algorithms used in this experiment were based on the same underlying concept of a moving average filter and threshold comparison for binary control of the hand to be in full grasp or released. The first control algorithm was a straight forward attempt at applying a threshold. It simply ran a moving average filter over the data and utilized threshold comparison to determine if a grasp had occurred. The first algorithm did work, but was a bit jittery in its performance. The second algorithm was an attempt to improve upon the first by reducing jittering through the use of a timer that held the hand in a closed grasp position for an allotted time before recognizing a true release. From visual observation, the second algorithm did seem to reduce the jitter, however, the delay may have been too long as it often visibly lagged after a true release of the muscle. Fig. 4 displays example traces of both algorithms and clearly shows that algorithm 2 is more stable in its voltage signal. In addition, through the figure we can see a reduction in the definitive control signals sent to the hand, which correlates with the decrease in jitter.

C. The only performance metric that resulted in a statistically significant outcome was the number of blocks picked up.

The two performance metrics used throughout the experiment were the number of square blocks picked up in a minute and the success rate, where picking up at least 4 blocks is considered a successful trial. The outcomes showed that there was no statistical difference between the two algorithms for the success rate metric, with a p value of 0.1250. This may be due to the small sample size of data points for this metric. In contrast, there was a statistical difference for the number of blocks picked up metric, with a p value of 4.7063e-5. Algorithm 2 outperformed algorithm 1 for this metric. The outcome results can be visualized through the box plots in Fig. 5.

D. Positive overall subjective impressions were received by the participants.

A disclaimer should be stated that participant feedback is subjective, but can still be useful information for the improvement of future experiments. With this in mind, generally positive feedback was received from the participants. They felt the task had a quick learning curve, was an enjoyable challenge, and a good start to developing such a technology to aid in prosthetic control. One participant stated, "The experiments felt fairly intuitive in their nature. The second control method seemed to make the task at hand easier to accomplish, but there is still room for improvement to include more detailed hand movements."

IV. Discussion

This paper's objective was to develop a less intrusive form of neural data collection and analysis to guide in more intuitive prosthetic hand control for individuals with upper limb loss. The results from the algorithm development and experiments conclude the EMG electrode placement did not produce significantly different signal to noise ratios and the second control algorithm was more successful in reducing jitter of the virtual prosthetic hand by sending more definitive control signals. The only performance metric that resulted in a statistically significant outcome was the number of blocks picked up, not the overall success rates. Generally, subjective impressions by the participants involved showed positive interactions with the experiments and virtual prosthetic system.

Prior work has shown that more detailed signals can be obtained with implantable electrode arrays, for a variety of applications. However, prior work has also shown that these implanted devices will deteriorate in a way and loose their effectiveness over time, some lasting for only up to a maximum of 11 months [4], potentially leading to more risk and difficulty for device replacement. In contrast, here we show an alternate method for prosthetic control through the use of EMGs that is intuitive, as well as easy, cost effective, and low-risk to replace when necessary.

The work presented here builds off of prior works by establishing the same goal of interpreting neural motor data and using that data to control a virtual hand, then exploring alternative methods for data acquisition and algorithmic generation of hand control signals for grasping objects.

Future work should replicate these findings with a standardized testing environment to reduce the impact of external factors on experimental data. The alternating experiment environments within this paper introduced widely varying levels of noise on the acquired data, likely affecting the signal-to-noise ratios and the ease or difficulty of performing the task at hand. Doing so will allow for cleaner and more trustworthy data in the future. In addition, future work should expand the acquired data with additional participants to increase the data sample sizes, hence achieving a higher confidence in the statistical analysis results. Future work can also explore the realm of controlling individual finger digits and increasing the degrees of freedom in prosthetic movement.

The work accomplished in this paper has a direct impact on the field of neuroprostheses by providing an example where EMG signal acquisition and decoding can provide intuitive control over prostheses with positive results in terms of statistics and participant feedback. Doing so provides a basis to expand the possible use-cases for EMG signals for adjacent fields that require non-intrusive neural data acquisition and decoding. The algorithms developed may be used beyond the application for neural hand grasping control, and extend into decoding signals from other muscles, like detection of irregular heart beats. Clinically speaking, the development of this work provides a foundation for improvements in bionic arm control with non-intrusive methods of acquisition. Improvements in bionic arms can significantly impact the quality of life for amputees, providing a better approach for daily tasks and independence.

References

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