PREDICTING MUSCLE FORCE OUTPUT USING EMG ACTIVITY

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INTRODUCTION

The fundamental goal of hand prosthetics is to accurately mimic human function. As the technology behind these devices has progressed, the ability to simulate human function has improved as well. In hand amputees with intact forearms, using information from the forearm muscles has been shown as an effective method of prosthetic control [1]. Because these muscles are still functional, electromyography (EMG) can be used to record the electrical activity in the muscle. Through understanding how EMG activity correlates to hand movement in healthy individuals, we can use forearm muscle activity to drive hand prosthetics in a more realistic and functionally useful way.

An important step in this process is understanding how EMG activity is correlated with the force output of the muscle. Research groups using surface electrodes have addressed this topic with reasonable success [1][2][3]. Unfortunately, surface electrodes suffer from many practical use problems, many of which are solved by intramuscular electrodes. However, no consensus exists for the most effective way to process EMG data recorded using intramuscular electrodes. The goal of this project was to adapt popular motor unit sorting methods to analyze intramuscular EMG activity and then predict muscle force output within the limitations of the experimental setup for our main project.

METHODS

The study involved a healthy adult male with no upper limb impairment. The participant was implanted with 16 intramuscular electrodes in the forearm and several surface electrodes on the upper arm. In addition, the participant wore a custom made glove fitted with Hall Effect sensors to measure movement kinematics such as finger position and joint velocity.

The subject completed 217 trials with each lasting approximately 30 seconds. During these trials, forearm EMG activity and hand/wrist kinematics were recorded as the participant completed a wide variety of finger and wrist movements. The focus of this study involved trials where the participant was tasked with pressing a button with a designated target force and then maintaining that force once the specified threshold was reached. The button press was repeated 6 times in each trial, and a separate trial was conducted for 2N, 5N, and 10N target force.

DATA PROCESSING

The majority of this project focused on processing and analyzing the data collected during the experiment. The first component of our analysis was filtering. The Hall Effect sensors used to measure hand kinematics were a significant source of noise in the raw EMG data. To remove this noise, a custom filtering protocol was developed and applied. In addition to magnetics noise filtering, the EMG signal was also high-pass filtered using a 4^{th} order Butterworth filter with a 500 Hz cutoff frequency to remove movement artifacts.

After the identifiable noise in the EMG signal was filtered, we sought to extract the contribution of individual motor units that compose the overall signal. To sort the motor units, we used the two most prominent sorting programs currently available: Offline Sorter and EMGLAB.

Offline Sorter is most commonly used to sort action potential waveforms in the brain, but for the purposes of this project it was used to sort spikes in the motor units of the forearm muscles. After configuring the sort parameters in the program, it was determined that the automatic K-Means sort method verified by a 3D cluster plot of the first three principal components would optimally fit our experiment.

EMGLAB is a Matlab based program and is currently the standard for sorting EMG activity recorded from the periphery [4]. EMGLAB automatically sorts the input signal based on waveform templates it identifies over a user selected time interval. EMGLAB required less effort to configure because it's intended purpose more closely fit our desired functionality.

Both Offline Sorter and EMGLAB output the sorted units with each timestamp where the unit's waveform was identified. With this information, the overall fire frequency was calculated by summing the number of spikes across all units that occurred within 2ms time bins. To determine how well this fire frequency rate corresponded with muscle force output, we ran a cross correlation with the force data recorded from the button during the trials.

RESULTS

Overall, the correlation between fire frequency and force output was disappointingly inconsistent. Our analysis yielded correlations as high $r = 0.75$ but as low as $r = 0.06$, with the average correlation across all trials being $r = 0.27 \pm 0.15$. There was no clear evidence that one sorting method was more effective or yielded higher correlations than the other. Figure 1 illustrates the variability in the correlation as a result of the sorting methods.

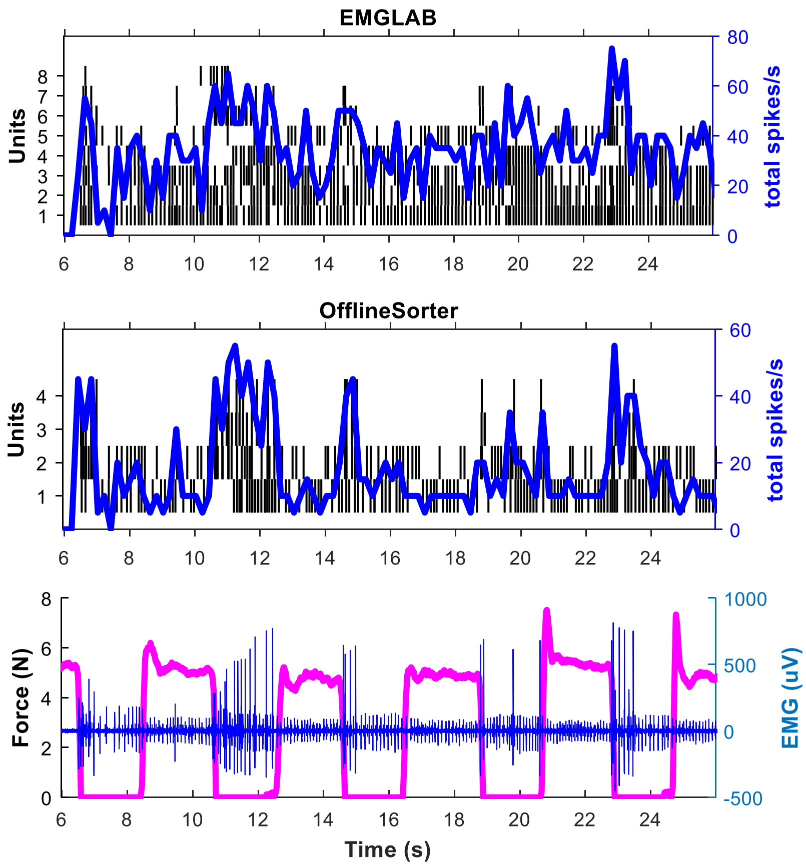

Figure 1: All graphs share the same 6-26 second time interval from one trial. The top two graphs show the result of sorting the same data with different sorting methods. Both show the spike times for each identified motor unit (black) and the resulting fire frequency (blue). The bottom graph shows the raw EMG signal (blue) mapped over the force exerted on the button (pink). The distinct differences in the top two graphs explain the inconsistent r values.

DISCUSSION

Two main problems limited the consistency of our results. Our experimental setup did not lend itself to robust motor unit sorting, and our sort methods were unreliable. Because our project was an offshoot of a larger overall project, the experimental setup was not designed with high accuracy motor unit sorting in mind. Whereas the studies we referenced had multiple electrodes in each muscle, our experiment had just one electrode which made it impossible to compare and confirm the quality of our unit sorting.

The sorting methods implemented in this study also presented problems. Offline Sorter had difficulty aligning spike waveform shapes which lead to errors in the unit sorting results. Some difficulty was expected because Offline Sorter is not optimized for EMG data, but the inconsistent results across trials made it difficult to mitigate this error. EMGLAB also had drawbacks in the context of our experiment. EMGLAB is no longer maintained, so many Matlab version compatibility problems arose which hindered the performance of the program. This most notably affected the automated sort feature, which was largely ineffective at template matching waveforms and resolving superpositions. The inconsistencies in both sort methods required manual sorting which introduced error and inconsistency, and explains a large degree of the variability in correlations.

Despite being unsuccessful in our effort to predict muscle force output with fire frequency, this project helped determine the limitations of our experimental setup. Moving forward we plan to examine more robust methods of predicting muscle force output and reconsider the methods by which data is recorded from the experiments.

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ACKNOWLEDGEMENTS

This work was supported by the Swanson School of Engineering and the Office of the Provost.