Robotic Force Control with Acoustic Myography Interfaces

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***Abstract*— Acoustic myography, or AMG, is a technique for mechanically measuring the extent of a muscle's contraction, by detecting the sounds produced by muscle vibration. AMG has several advantages when compared to surface electromyography (sEMG), including less interference from external noise, the ability to detect activity in deep tissues, and a more direct relationship between the signal output and the force of contraction [1]. In this project, we tested the viability of using a commercially-available AMG sensor to provide force inputs to a robotic controller. We demonstrate that with a relatively simple data processing scheme, we can discern a significant nonlinear relationship between a user's subjective force of contraction and the rms signal amplitude, which appears approximately quadratic. Additionally, we report findings on our attempts to conduct force control with proportional feedback within a PyBullet simulation. Finally, we discuss ways in which we plan to directly connect force decoding with simulation control in real time.**

Fig. 1. The Myodynamik CURO, a commercially-available AMG system

I. INTRODUCTION

Robust force control of robotic manipulators is a major challenge when designing interfaces for human-operated systems. An ideal closed-loop force controller should be capable of identifying and tracking a human user's intended contact force, while immediately correcting for errors. The ability to adjust a robotic contact or grasp based on the applied contact forces has a multitude of applications, including the design of more flexible and responsive prostheses capable of grasping fragile objects safely [2], or surgical robotic systems capable of conducting operations with submillimeter precision [3]. While a user could theoretically input the desired force manually for all applications, this is neither efficient nor intuitive; instead, a simple solution is to develop a pipeline for decoding an operator's *force intent*, based on measurements taken from a more intuitive interface.

The choice of interface is the next hurdle. Recent work from Burden et. al. has demonstrated that muscle interfaces, which take measurements directly from muscle contractions, provide superior feedforward intent accuracy for users when compared to manual interfaces, such as screens or physical controls, allowing them to be used more effectively with motion-impaired users [4]. While many muscle interface techniques exist, the most prevalent by far is surface electromyography (sEMG), which records electric potential differences along the skin generated by muscle contraction. Thanks to its low cost, non-invasiveness and simplicity of implementation, sEMG has become the recent standard for clinical myography. However, it is by no means flawless: sEMG can be remarkably sensitive to external noise or signal cross-talk from neighboring muscles, and its restriction to the surface of the skin affords it very poor spatial resolution, and prevents reliable recording from deep tissues, or tissues protected by a thick layer of subdermal fat.

With the advancement of digital recording technology, one alternative that has recently become viable and affordable is acoustic myography (AMG), which directly measures the sounds produced by muscle vibrations during contraction. Harrison et. al. demonstrated that using AMG for muscle interfacing has many benefits as compared to sEMG, including a very low noise level during inactivity, signal stability unaffected by sweat, hair or unclean skin, and a signal parameter score that correlates directly and linearly with muscle output power [1] [5]. Additionally, Barry et al. demonstrated that AMG is a viable technique for the control of prosthetic devices, albeit with only binary open-close controls [6]. On the basis of these findings, we sought to perform proof-of-concept testing of the viability of commercially-available AMG sensors for providing real-time outputs that can readily be decoded into raw force intent. Currently, most robotic systems that utilize force control are autonomous and use sensor-derived feedback [7], but here we propose a robotic system with a human user as both the input and feedback source. For the purposes of setting up for future research, we attempted to model a force-controllable system in a 3D simulation using PyBullet. Ultimately, our goal for this project is to connect AMG-controlled inputs to a simulator, and provide real-time force control of a grasp using only muscle contractions as inputs.

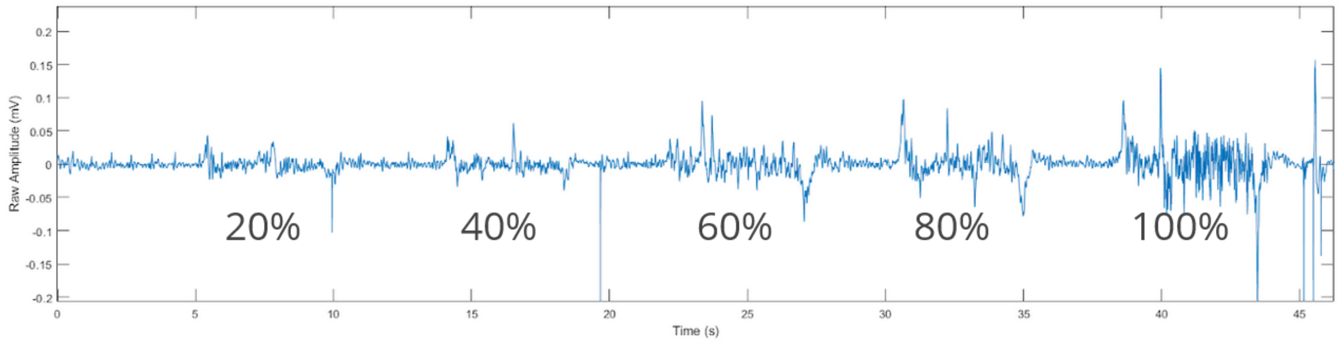

Fig. 2. An example trial recording. Note periods of contraction, with rest periods in between.

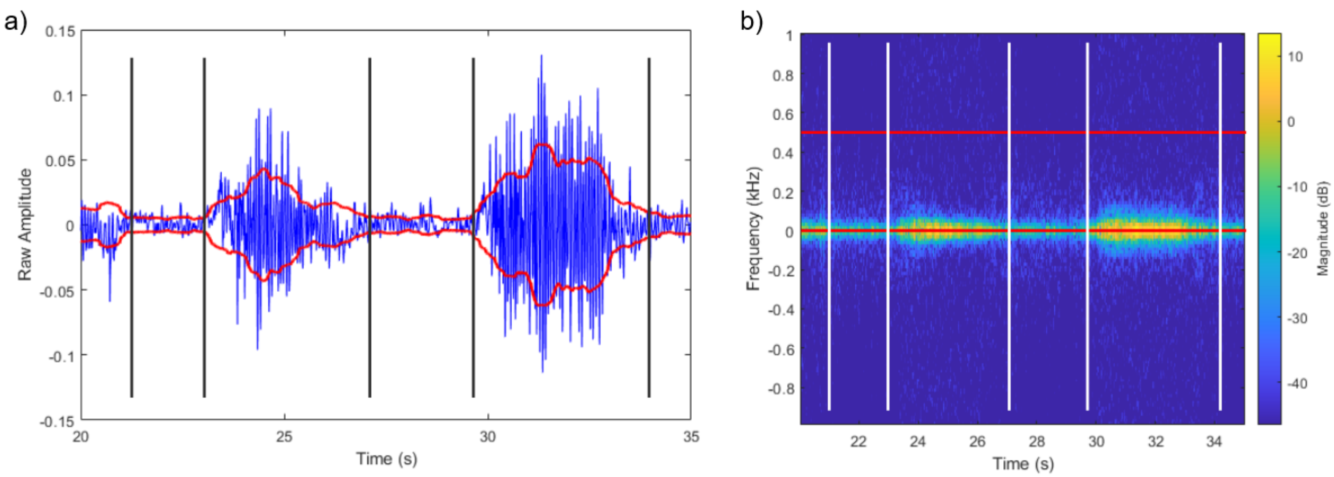

Fig. 3. A depiction of signal processing methods on a short recording segment. A) Amplitude detection via 0.5 s sliding rms envelope (red lines); black lines separate contraction periods. B) Frequency detection via averaging the mean frequencies between 2 and 500 Hz (red lines) at each timepoint; white lines separate contraction periods.

II. METHODS

A. Acoustic Myography Signal Collection

We performed all of our recordings using the commercially available MyoDynamik CURO (Figure 1), with the large equine AMG sensors depicted. For our recordings, we affixed a sensor to the center of the biceps, with ultrasound gel for noise insulation. Each subject was instructed to sit straight up with their elbow at a 90-degree angle, palms facing up. During the trial, subjects were told to perform isometric (motionless) contractions by pushing up against the bottom of a weighted table, using a subjective fraction of their total strength in increments of 20% for roughly 2-4 seconds, with 2-4 second rest periods in between contractions (Figure 2). We gathered a total of 25 trials from 8 subjects. All trials for any particular subject were taken back-to-back with a 1-minute rest period, without removing or replacing the sensor.

B. Digital Signal Processing

To identify a method for decoding force intent given a raw AMG signal, we decided to look at three parameters of the signal: amplitude, frequency, and the amplitude-frequency product. Signal amplitude was expected to relate to the spatial summation of muscle fiber firings (i.e. the number of fibers recruited), while frequency was related to temporal summation of muscle fiber firings, which controls the extent of muscle contraction. Software designed for the CURO is capable of calculating a proprietary ESTi score, which is effectively a product of spatial and temporal summation parameters, that has been shown to correlate linearly with muscle output power or force [1]. As a result, our hypothesized relationship is summarized in (1), where F_{out} is the muscle output force, n is the number of recruited fibers, F_{avg} is the average fiber output force, A is the amplitude, ν is the frequency, and α is a constant.

$$F_{out} = nF_{avg} = \alpha A \nu \tag{1}$$

For each of our 25 trials, we detrended the raw signal, removed outliers, and delineated the start and end of each contraction period manually. For the amplitude parameter, we took the difference between the upper and lower root-mean-square envelopes of the signal using a 1000-sample (0.5 s) window (Figure 3A), and calculated the mean amplitude for each contraction period. Due to individual variations in signal strength, we scaled each signal such that the mean amplitude at baseline (0% contraction) was set at 1.

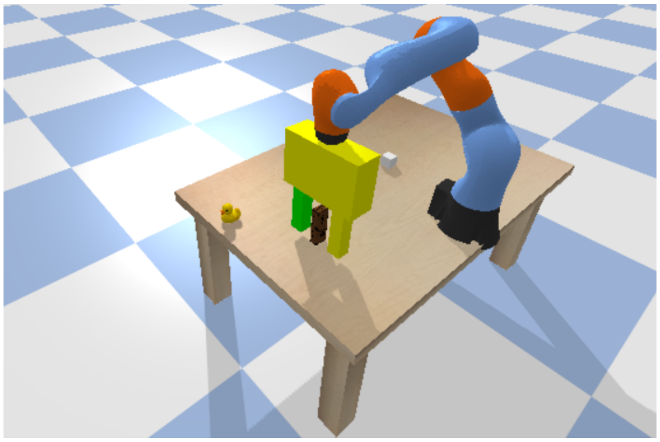

Fig. 4. Full simulation setup, with KUKA robot, gripper, and Jenga block shown.

To determine the frequency parameter, we took each individual contraction period, and multiplied it with a Hann window of the same length, to reduce spectral leakage around active frequencies. We then used MATLAB's meanfreq function to calculate the mean frequency of each contraction period between 2 and 500 Hz (Figure 3B), which encapsulates the full working frequencies of active muscle [1]. Because rapid spikes/outliers are strongly delocalized in the frequency domain, much care needed to be taken to remove them manually.

C. Force Control in Simulation

To determine if we could utilize a force input signal, *u(t)*, to control the contact forces on an object grasped by a robot's grippers, we utilized PyBullet as a simulation environment. We used a 7 degree-of-freedom KUKA robot situated on a table as the robot performing our grasp task in simulation. We also designed a custom gripper to be the end-effector for the KUKA robot, which simply consisted of a rectangular prism base with two gripper rods attached as shown in Figure 4. The gripper has two prismatic joints, allowing each one of the gripper rods to slide along the base freely until colliding with the other gripper rod.

The PyBullet simulator allows for position, velocity, and torque control of all robot joints, which extended to the gripper rods utilized to grasp an object. However, due to inconsistencies in the characterization of velocity and torque control, the latter of which would directly control the acceleration of the gripper rod since it is attached to a prismatic joint, we were not able to run experiments with velocity and torque control. As a result, we carried out two sets of experiments using position control of the gripper rods.

The first set of experiments characterized the average contact force exerted on an object using feedforward position control. The test simulation would first position the robot arm such that the attached gripper is 10 cm above the object to be grasped; here, we used a Jenga block that is 15 x 5 x 3 cm, and our robot was grasping along the 3 cm dimension. The combined setup is also depicted in Figure 4. From there, the arm would descend 10 cm, and begin to close the grippers until the gripper rods made contact with the Jenga block. After contact was made, position control was initiated by instructing the grippers to penetrate deeper into the block by x cm, where x cm is the feedforward position control input, also described as the gripper intrusion depth. At extremely small x values, the grippers would fail to maintain contact with the Jenga block, and at extremely high x values, the grippers would crush the Jenga block out of its grasp, which was the reasoning behind focusing the characterization on the range discussed in the results. We conducted three trials at each x value. While the gripper rods were in contact with the block, the contact forces would be measured by PyBullet at each contact point for each timestep, and the mean $\pm$ standard deviation of these contact forces was reported. During the measuring process, the wooden block was also raised up by 10 cm to the robot's original position to ensure that a stable grasp was achieved.

The next set of experiments utilized proportional feedback position control to track an input force signal $u(t)$. In this case, we specified a goal contact force in Newtons, and the gripper penetration depth from the previous experiment was varied as the feedforward input to achieve the target force. At each timestep, the error between the desired force and the current force is multiplied by 10^{-4} and this value is then added to the current gripper penetration depth. We utilized a variety of input force trajectories, ranging from sine waves to sawtooth waves and square waves. For each test, we utilized amplitudes, A, varying from 1 to 32 Newtons, and centered each wave at a DC value of $2A$. We performed most experiments with amplitudes at $A/4$, but also tested certain simulations with amplitudes at A. For each timestep in the experiment, the average contact force across all contact points was reported.

III. RESULTS

A. Force Decoding

The results of our 25 trials are depicted in Figure 5, with both individual and grouped data. We observed a significant nonlinear relationship between reported contraction strength and both signal amplitude and amplitude-frequency product ($p < 0.0001$), although the fact that we observed no similar relationship with frequency ($p = 0.2918$) suggests that the amplitude relationship is the only valid one. In addition to differences between signal features and contraction effort, two-way ANOVA on the individually-matched datasets also showed significant differences in signal features between users ($p \leq 0.0004$), as well as a significant effect of subject-effort interaction on signal features ($p < 0.0001$), for all three feature types. These results suggest that a high level of variation in system behavior between different users was present, which was no surprise, given the individual variations expected in user strength, anatomy, and sensor attachment location.

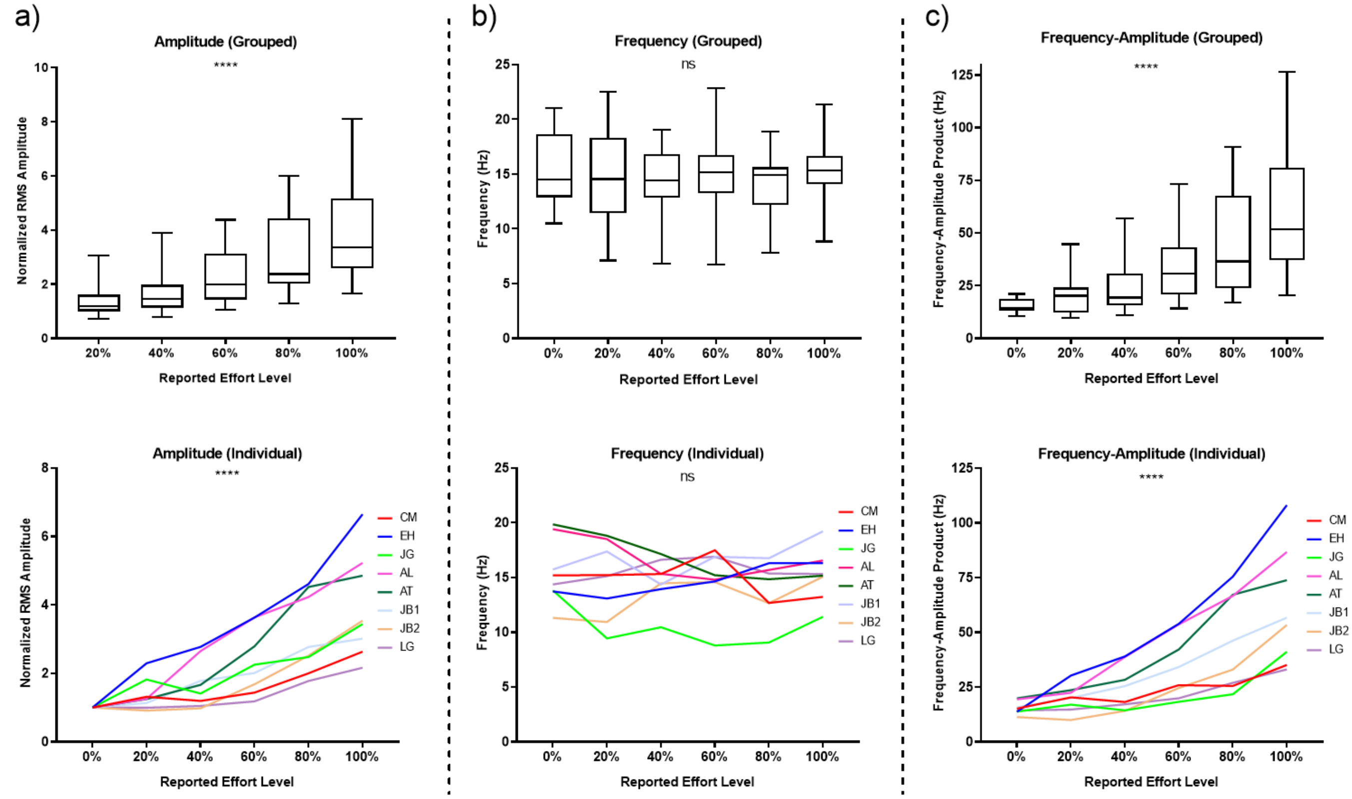

Fig. 5. Signal characteristics from 25 isometric lifting recordings, presented as both grouped (top) and individual (bottom). A) Normalized rms amplitude parameter (unitless). B) Frequency parameter (Hz). C) Amplitude-frequency product (Hz).

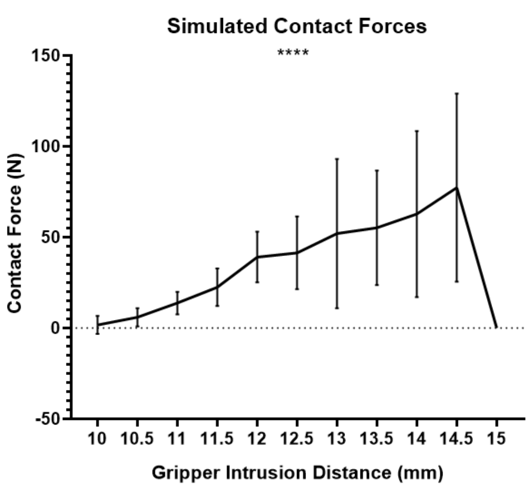

Fig. 6. Average contact force vs. gripper feedforward position control characterization.

B. Force Control in Simulation

The results from the feedforward position control experiment are shown in Figure 6. As the gripper intrusion depth increased from 10 mm, where it lost contact with the Jenga block, to 15 mm, where the block was crushed so hard that it flew out of the grippers, we saw a roughly linear increase in average contact force. Of note is that at very high contact forces, the variation in contact forces is extremely high. This is likely because some trials at these gripper intrusion depths involved the block getting squeezed out of the grippers' grasp. Other trials in this range likely had the block move ever so slightly, resulting in what would be small variations in contact forces at low gripper intrusion depths, but since the intrusion depth was so high for these trials, these slight changes in position caused huge fluctuations in the average contact forces on the block. Despite the large variations at higher forces, this set of experiments demonstrated that within a specific regime, we could directly and linearly control the contact forces experienced by a block by varying the gripper position, and that this control might be more accurate at lower contact forces.

Three example graphs depicting results of the proportional feedback position control experiment are shown in Figure 7. In these experiments, we made the desired input force trajectories sine, sawtooth, or square waves at 1 Hz with amplitudes A ranging from 1 to 32 Newtons centered at $2A$. We found that the average contact force generally tracks the desired contact force relatively well across each trajectory. The amplitudes and DC value are exactly as expected across the different amplitudes, ranging from the low force case of 1 N all the way to the maximum of about 100 N in the 32 N case. However, there is a bit of a discrepancy in the exact frequency of the output wave. Most of the waves appear to have a period of about 1.1-1.2 seconds, which means that the frequency of the experienced average contact force trajectory

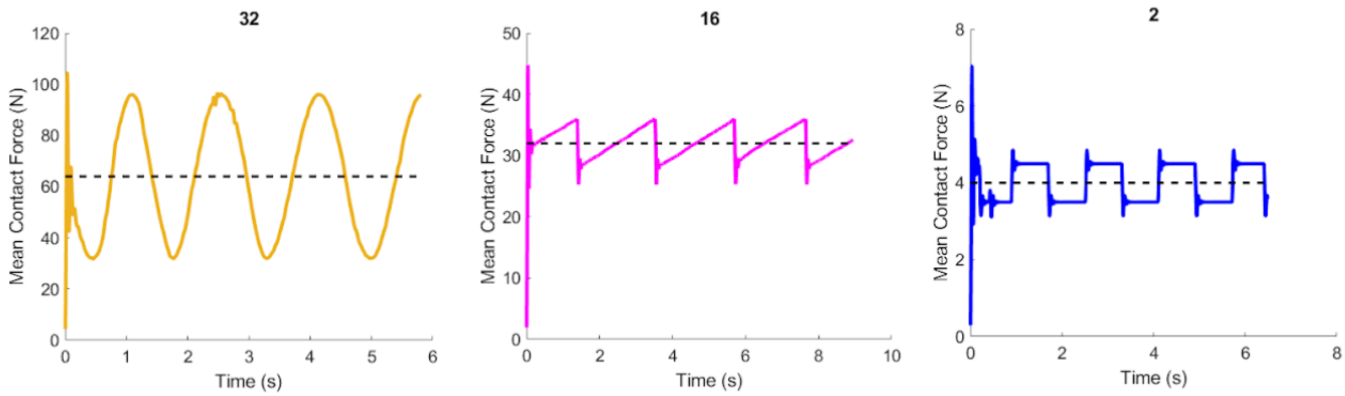

Fig. 7. Observed average contact force on block vs. time with proportional feedback gripper position control for Left: 1 Hz sine Wave with 32 N amplitude centered at 64 N, Middle: 1 Hz sawtooth wave with 4 N amplitude centered at 32 N, Right: 1 Hz square wave with amplitude 0.5 N centered at 4 N.

varies between 0.83 and 0.91 Hz, instead of the expected 1 Hz wave. However, since all simulations regardless of input force trajectory have this shift in expected frequency from 1 Hz to slightly less than 1 Hz, this suggests that this may be a discrepancy caused by simulation in PyBullet, or by intermediate calculations in the simulation causing a systemic slow-down effect.

Of special note are the square wave experiments because the sudden discontinuities in the square wave trajectory would largely mimic a human user's force trajectory when grasping an object remotely: they would start at a very low force, and quickly reach the force necessary to grasp the object and remain at that steady-state force value. We found that the measured force trajectory strongly matched the desired force input $u(t)$ with minor overshoot before settling to the correct steady-state value. In addition, the aforementioned minor changes in frequency and some transient stutters in the output force in the 32 N experiment were present. Overall, the simulation results suggest that the proportional feedback position control works very effectively both at maintaining steady-state forces and quickly adapting to sudden changes in desired force. In addition to the sine and square wave trajectories, we tested out sawtooth waves at the same amplitudes, in which we saw similar overshoot and settling as seen in the square waves.

IV. DISCUSSION AND FUTURE WORK

A. Discussion

Based on our force response characterization, we concluded that there is a roughly parabolic relationship between AMG rms signal amplitude and user-reported muscle force, and no relationship with frequency. Since our initial hypothesis predicted a linear relationship with the amplitude-frequency product, these results were a bit surprising. The fact that we see no difference in frequency could be due to an error in attaching the sensors during recording, or a lack of robust filtering during the data processing stage; as mentioned previously, the presence of even small spikes or impulses can quickly skew the entire signal spectrum toward higher frequencies, leading to inaccurate results if an originally low-frequency signal happens to contain many of them.

Originally, we planned to correlate AMG signal parameters with the actual magnitude of force exerted by the user. However, due to the difficulty of measuring muscle tension and output force in real-time, along with a lack of real-time support for the sensors, we ended up correlating the signal parameters to subjective effort levels instead, expressed as a percentage of the maximum voluntary contraction (MVC). While this approach prevents us from ascertaining any fixed relationship between AMG signal and output force, it has one major benefit: it allows us to gauge AMG characteristics with respect to the user's expected output force, instead of their actual output force, meaning that the approach naturally accounts for errors between these forces. This is particularly important because traditional psychophysics has found that the human perception of differences between sensory inputs can vary based on the magnitude of the inputs; this is known as Weber's Law. For example, it is much easier to detect the difference between a 1 kg versus 2 kg weight, than it is with a 19 kg vs 20 kg weight.

The parabolic relationship we observe in amplitude may be the result of a related phenomenon, since the difference between an 80% and a 100% contraction may be harder to judge on the user's part, leading to overapplication of force. Our approach allows us to determine a unique force intent curve for every user, such that the decoded force intents vary linearly with the user's *subjective* output force; in other words, the system *feels* linear to the user, even though their output force is actually parabolic. This has the added benefit of normalizing the force intents to the user and session, opposing the effects of variation due to differences in strength, physical anatomy, or sensor placement.

In practice, this requires an n-point calibration of the AMG signal response before the start of every real-time recording. The signal amplitude is calculated at n equally-spaced points between 0% and 100% MVC, and a quadratic curve fixed at the origin can be fitted to the points using least-squares. From there, real-time amplitude measurements can simply be plugged into the curve to determine the user's force intent, although more advanced techniques can also be used to separate true intent from error correction, as described in [4].

In seeking to actuate a force input signal $u(t)$, we designed a robust proportional feedback position controller in simulation. Across a variety of signal amplitudes and trajectories, the contact forces experienced by a grasped wooden block closely matched the desired input force trajectory, with the only minor drawback being that 1 Hz sine wave signals were output as slightly less than 1 Hz. Due to outside circumstances, we were forced to conduct these experiments in simulation, but there are several aspects of simulation that may prevent our results from working identically on similar robots in reality. Our proportional feedback utilized the difference between the desired force and the current average contact force to conduct error correction. However, in simulation, we have perfect knowledge of the average contact force because the simulator has the ability to retrieve that parameter without any error. In reality, we would require some sort of device attached to either the wooden block or the grippers to provide a real-time estimate of the current contact force the object is experiencing. Alternatively, we could find a way to retrieve the amount of force the gripper motors are exerting to maintain it in place. There will be some uncertainty in the real-time force value returned to the controller by either of these methods, which will make our controller less reliable in reality.

Another major area in which simulation fails to recreate reality is through the use of our custom-designed gripper. We chose to utilize the simplest gripper since our experiment was largely a proof-of-concept demonstrating that a human user's force intent could be used to actuate a gripper and control its force output. Since real grippers are more complicated than two prismatic joints, our simulation fails to capture those complexities. In addition, the gripper rods used in our simulation had a lateral friction value of 0.85, which may be significantly higher than in real grippers. All of these aspects of our proof-of-concept gripper greatly limit its validity in replicating real robotic grippers, suggesting that further experiments on real robots will be required to strengthen the validity of these simulation findings. Despite all these limitations, our simulation results do definitively demonstrate that proportional feedback control of contact forces is feasible and achievable in theory with a further developed version of our controller.

B. Future Work

Ultimately, our goal for this project is to be able to directly control the strength of a grasp force in real time using inputs decoded from AMG sensor recordings, both in simulation as well as on a physical robot platform. To this end, our intended next steps are to configure the AMG sensors in such a way that they can capture data in real time. While we initially attempted to gather real-time data by cutting open the sensor cables, isolating the signal-carrying wires, and reading them directly with an Arduino Uno, we ran into roadblocks with matching the 2 kHz sampling rate of the CURO, as well as significantly poorer signal quality. To address this, we would need to experiment with different preamplification gains, as well as other analog and digital filtering techniques.

If current circumstances persist and we are only able to use the simulator to test grasp force control, there are several improvements we could make to the simulator. The first improvement would be to test out larger objects. We did test out a small cube with similar mass and volume to the Jenga block used throughout our experiments, but if we tested grasps on significantly larger objects, we could examine what changes in force control might be necessary to resist larger gravitational forces. The next major step would be to sample human user AMG data after user calibration to feed into the simulator as the desired force input $u(t)$. If the robot is able to track the human user's intent without much modification to our current design, we would finally attempt to collect an AMG datastream, and use it to control the simulation robot in real-time.

V. ACKNOWLEDGMENTS

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VI. REPOSITORY/WEBSITE

Our (private) code repository can be found here: https://github.com/cmitch/final_proj_106b

A supplementary website with setup images, additional figures and simulation videos can be found here: https://cmitch.github.io/projects/robotics/amg/

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