

# Developing PID control for Robots to Mimic Human Haptic Response

A thesis submitted by

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# 1 Abstract

Humans and animals alike are capable of complex, coordinated movements, and comparatively, robots are far behind. Biomimicry is often seen in robotics, such as robots with fish tails that use less energy than with propellers, [1] or robots inspired by snakes that can navigate through tight spaces. [2] Could biomimicry of human motor control be employed to improve robot capabilities, enabling robots to dance, play sport, or work in tandem with humans?

To explore this, I analyzed a simple haptic response scenario: palm-to-palm contact with one agent leading another. Twenty-five participants were asked to follow a robotic arm equipped with a force sensor and prosthetic hand. The goal was to determine whether a common haptic response pattern exists across individuals and whether it could be modeled in robotic software.

The data displayed a notable degree of uniformity across subjects. The standard deviation of force at each time point, averaged across all trials, ranged from 1 to 2.5 Newtons in all directions — relatively small compared to overall force variations of up to 15 newtons. Consistent behavioral trends were also observed: all participants anticipated the robot’s motion and led ahead of the prosthetic hand’s velocity when they could recognize and predict the trajectory, despite explicit instructions to follow the arm. This anticipatory behavior was statistically significant at  $\alpha = .05$  for a one tailed T-test. All participants also exhibited signs of fatigue over time, often resulting in downward force drift.

The consistency suggests the potential for a generalized control model. However, I began by testing basic PID control, which failed to capture key human tendencies like shape anticipation, fatigue, and variable impedance. As a result, only 32% of participants felt the robot’s movements were human-like. Based on these findings, I propose future work incorporating compliant joints, variable arm impedance, and analyzing broader haptic interaction scenarios.

## 2 Acknowledgments

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This thesis is also a reflection of the immeasurable support from Kat Allen, who helped me solve my ROS issues and acted as an academic mentor and role model, for which I am eternally grateful.

To my colleagues in the CEEO, thank you for your advise, support, and sharing your research with me. The hackathons you all organized helped inspire my learning.

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## 3 Introduction

### 3.1 Background

Even with the state of modern technology, humanoids (human-shaped robots) remain few and far between. This is mostly due to high costs associated with their manufacturing, but should humanoid usefulness reach a certain point, it could justify the cost. A precedent for this exists in industrial robotics, where robotic arms have become indispensable in large-scale manufacturing. In contrast, humanoids, at least within publicly recognized commercial applications, have remained largely confined to research settings.

A possible avenue for humanoids to reach a usefulness threshold significant enough to create a large uprising in popularity could come from breakthroughs in their ability to mimic human action. The obvious implication of human action capabilities include the ability to replace physical labor, or at least work in tandem with human labor. However, it could also lead to humanoid dance partners, physical assistants, or athletic training partners.

Such applications require humans to communicate with each other haptically, through physical touch and sense. For example, a golf instructor guiding an athlete may feel their athlete attempt to swing too slow and apply a corresponding force to speed up their swing. The haptic input communicates not only to the instructor what the athlete is doing wrong but also to what degree and in what direction. One can imagine a similar manner of conveying knowledge between a physical assistant and their patient, or a dancer with their partner.

Despite the fundamental role of haptic communication in human interaction, research on how humans respond to haptic input remains limited. Human motor control is highly complex; it does not operate through a simple feedback loop but instead involves predictive and adaptive mechanisms within the brain. Furthermore, psychology and neuroscience have yet to develop precise models

for the decision-making processes underlying human motor responses. As a result, the current state of human-robot interaction (HRI) lacks human-like haptic response capabilities.

### **3.2 Problem Overview**

There are two main problems. Firstly, how can we collect data on and characterize the human behavior involved with haptic response, and second, can this be modeled and incorporated into robotic software? Both of these main problems contain many further challenges.

For the first problem, an experimental setup is required that provides both sufficient range and accuracy of motion while incorporating sensors capable of capturing detailed haptic information comparable to human skin sensitivity. Ensuring the fidelity of this data collection is essential for meaningful behavioral characterization.

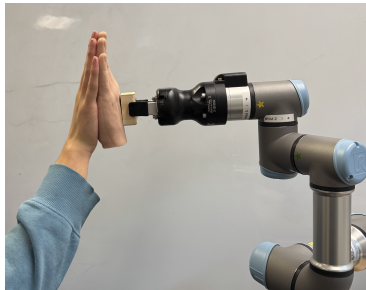
For the second part, a solution requires some sort of consistency to human responses to be expressed in the data in order for one consistent model to be made. Even should different people have consistent enough responses, how should the position and force data be analyzed to create a control system model that provides motion commands based upon force input? There are a vast range of variables that make the relationship between input force and response motion difficult to model: time of day, distance from the robotic arm, physical fatigue, cognitive focus, dominant hand choice, reaction time delay, and more. Addressing these variables requires a structured and targeted approach to ensure meaningful and generalizable findings.

### 3.3 Thesis Organization

I have broken down human haptic response into a fundamental interaction: palm-to-palm leader and follower motion. A prosthetic hand was attached to the end effector of a robotic arm (UR3e), palm out. (pictured below) To eliminate the need to compensate for gravity vector changes on the force sensor, only linear end-effector motion was considered, with no rotation. The robot arm translated the hand through a series of shapes and motions, and a human with palm to robot-palm contact attempted to follow, minimizing changes in force between the two hands. With this setup, forces recorded by the force sensor were due to inaccuracy of the human following the robot arm, and were measured over time and analyzed to see if patterns could be found.

PID parameters were derived from human responses. The robot arm then attempted to follow a human using these same PID parameters that defined human response. Study subjects reported on whether the arm felt human-like in its haptic response. They were also free to comment on if they would prefer a model which minimizes force changes between their arm and the robot arm, (objectively a better follower model) or one that acts more as humans would. (imperfections included)

A more thorough description of the experimental setup and procedure can be found in the methodology section.



**Figure 1:** Palm-to-palm setup

### **3.4 Objectives**

My hypothesis is that different humans all have a uniform approach to their haptic responses. By analyzing force data, we aim to determine whether such uniformity exists and assess the feasibility of modeling human haptic response using a PID control system. Even considering a lack of success in implementing a human-like model in robotic software within this study, identifying response patterns will provide valuable insights into human motor behavior and guide future research on robotic haptic response. At the very least, this study will contribute to building intuition about which parameters and modeling approaches for human motor control are most effective.

## **4 Literature Review**

### **4.1 Introduction**

In this thesis I will model human closed-loop feedback response. It is important to contextualize this within the field of human robot interaction (HRI), but just as importantly, to the current state of psychological research surrounding human motor control.

In order to organize such previous research, its logical to follow the flow of information in a human haptic response. The brain synthesizes a response, sends information to the muscles, and (in this case of this study) the human force is exerted on a robotic entity. Likewise, research surrounding human motor control leads to research covering human kinesiology, which leads to research about human-robot interaction. Therefore the three previous topics are what will be focused on, in that order.

## 4.2 Previous Research on Human Motor Control

Prior research acknowledges the challenge of achieving reproducible human motor movements and forces, even under identical conditions. [3] Given this complexity, many studies focus on qualitative theories to explain why humans move the way they do. Todorov and Jordan, in their 2002 paper *Optimal Feedback Control as a Theory of Motor Coordination* [3], propose the “Optimal Feedback Control” framework, which suggests that the brain allows for variability in task-irrelevant dimensions while applying feedback and control toward goal-directed motion [3]. For instance, if many people are asked to tighten a screw, the turning motion will likely be similar across humans, but the height at which the screwdriver is held may vary. This implies that minimizing variability requires ensuring that all motion directions are task-relevant — a condition I attempt to establish in this study.

A similar work, Schmidt’s (1975) Schema Theory [4], serves as a foundational reference for understanding how humans plan and execute movements. It was critical in seeing human motor control as centered about how humans accomplish their movement goals. Specifically, Schmidt’s work challenged reflex-based models by proposing that motor control relies on generalized motor programs (GMPs) and schemas rather than fixed movement patterns. According to his theory, the brain stores abstract representations of movements, which are adapted to different contexts based on sensory feedback and prior experience. This paradigm was influential in shaping later computational models of motor learning, as it introduced the idea that humans use stored rules to generate and refine movements rather than relying solely on direct sensory feedback. This raises a critical question: do individual differences in experience lead to variations in haptic response patterns? If so, how could these patterns be mapped and translated into robotic control models? Would such an approach resemble

a traditional structured control system, or would it necessitate a more complex, black-box learning model? Uncovering the degree of motor control uniformity across people through this study will help answer these questions.

Other research also uncovered important characteristics to human motor control that are critical in contextualizing findings to this study. Burdet et al. (2001) showed that humans learn to stabilize unstable dynamics by creating an internal model of a given system's dynamics. This is an impressive feat for the human brain, but it makes sense when we consider the multitude of tasks that humans complete that have unstable systems, such as the same tightening a screw example, where any parallel force to the axis of the screw causes the screwdriver to slip out of the slot. [5]

Moreover, rhythmic activity plays a crucial role in motor control. Specifically, Mcauley et al. show that "the motor output from the central nervous system (CNS) is modulated by rhythmic activity at certain frequencies" [6]. It was found that humans have an intrinsic inclination for movements around 3 Hertz for finger movement and 10 Hertz for eye tracking. It is unlikely that humans will favor these frequencies for tasks that require the movement of their entire hand, as in this study. However, the work shows how the central nervous system is modulated by rhythmic activities, so it will be interesting to see if any common frequencies become apparent to human responses in this study.

Still, noting some numerical patterns within human motor response is far from a complete understanding of the human brain. Should we be able to track information from the subjects' nerves, through the brain, out to the subjects' muscle fibers, a complete and perfect model of human motion could be formed that could be incorporated into robotic software for perfect human mimicry. In order to see why we haven't already done this, its necessary to look at the state of research on mapping individual nuerons within the brain.

Since the brain’s computational power to energy consumption ratio is superior to computers, “neuromorphic” systems are being studied in an attempt to improve computational power. “Neuromorphic engineering’ looks at how the brain uses the physics of biological synapses and neurons to ‘compute’.” [7] However, we are still far from a complete understanding of how information travels through the human brain. “The human brain is an enormous scientific challenge. Knowledge of the complete map of neuronal connections (connectome) is essential for understanding how neuronal circuits encode information about how the brain works. Nanoscale connectomes are created for a few small animals but not yet for the human.” [8] The most restricting factor is the pure amount of data that would need to be collected. Models have predicted that it could require over 5 million exabytes. [8] (Each exabyte is a million terabytes). Even should this be stored, the computational power required to analyze this volume of data isn’t yet available.

Given these constraints, a direct, neuron-level model of haptic response is currently infeasible. Instead, the most viable approach is to apply mathematical modeling techniques to observed human behavior, identifying patterns in haptic response through experimental measurement. In this study I follow that approach, seeking to characterize human haptic responses and explore their potential applications in robotic control.

### 4.3 Kinesiology

Once sensory information is processed by the brain, the next step in human haptic response is muscular movement. In this study, participants will be moving their hand and arm in response to haptic sensory input, so relevant research will focus around upper-limb precision movements.

R.G. Martenuik and C.L. MacKenzie’s paper *Constraints on human arm*

*movement trajectories* provides a good introduction to the biomechanical constraints to human hand motion and accuracy. Specifically, they show how final trajectory paths of the arm are both a function of task related constraints (e.g., accuracy requirements, environmental factors) and internal constraints (e.g., muscle dynamics, joint mechanics). [9] They show that the speed of a trajectory is inversely related to the required accuracy of the task. Martenuik's work was built upon the work of 1954 Psychologist Paul Fitts, who originally showed that "time required to move to a target depends on the distance to it, yet relates inversely to its size". [10] However, this only applied to feed-forward control, (pre-planned movement execution based on prior experience). In most tasks, users combine feed-forward control and feedback control (where users make adjustments based on sensory input to correct deviations). The lack of knowledge on where the robot arm will lead in this study will likely leave participants almost entirely relying on feedback control.

More recent research has shown that for more difficult feedback control motor tasks, humans often use co-contraction of agonist-antagonist muscles. In the arm for instance, tightening both the bicep and tricep can provide corrections to unexpected disturbances by increasing muscle impedance. Christopher M. Saliba et al. [11] note that the increase in metabolic effort without any increase in force initially seems a waste. However, the increase in stiffness and damping provides an immediate negating impact to disturbances without delays due to neural control. They show how performance is also improved in a tracking task where a participant tracks a target that moves at a constant speed back and forth with their finger. "Participants were asked to perform the task with and without active antagonistic co-contraction of the muscles spanning the elbow. We found a clear improvement in the performance of participants when the co-contracted." [11] Burdet in his 2001 paper *The central nervous system stabilizes unstable*

*dynamics by learning optimal impedance.* goes one step further and shows how this muscle coactivation is used as the second step of a typical human response to unstable dynamics he calls “Three phase muscle activation”. The first phase is typical agonist activation, characterized by feedforward control. In the second phase humans incorporate antagonist muscle coactivation to adjust impedance, and finally there will be a period of feedback control for error correction and movement refinement. [5]

It is also of worth to note that contemporary research may suggest that varying limb stiffness can improve haptic sense. “When two connected individuals carry out a task together, they exchange haptic information about their motion plan to combine with their own visual information to improve their accuracy. Critically, haptic information transferred by the mechanical connection is modulated by their muscle coactivation (Fig. 1B). Could individuals regulate their muscles’ activation to adapt the limbs’ stiffness and better sense the partner’s movement?” [12]. For robots to gain human like movement capabilities for joint tasks, such as being a physical assistant or dance partner, it will be important to incorporate adaptable impedance in to robot joints, and to study humans’ use of muscle coactivation to vary arm impedance.

However, differences in the goals of these studies with mine may make co-contraction less relevant in my study. For example, the movements in Saliba’s study were predictable and relatively simple, allowing participants to anticipate and adapt their responses. In contrast, my study requires participants to maintain continuous palm-to-palm contact with a robotic arm while following its movements without prior knowledge or prediction of its trajectory. In this context, a lower-impedance response is more advantageous, as it enables the human arm to more easily track the robot’s motion before voluntary motor adjustments can take effect in response to mechanical disturbances.

Because of this and its difficulty to measure, this study will not record whether participants engage in co-contraction of the arm muscles. The narrow focus of this study is in the resulting equations, models, and trends of how accurately humans follow the robot arm palm-to-palm. We felt it was not a requirement to take into account how humans specifically utilized their muscles, and if there are potential strategies for them to do better. The only focus is in finding a model for what humans actually do, not knowing how they do it. Future work will be required to determine this.

#### 4.4 Human Robot Interaction and Human Motion Mimicry

As far back as 23 years ago researchers such as Christopher Atkeson worked to demonstrate that “Being able to generate human-like movements for virtual characters and humanoid robots helps create engaging human-machine interactions”. [13] In his study *Robot Catching: Towards Engaging Human-Humanoid Interaction*, he showed that mimicking human motion plans provide clever solutions for activities that require complex motor control. Others also argue that as human machine interfaces become more common, robots need to become more fluent in the language of physical communication, as this is a gateway to an elevated level of intuitive user experience. [14]

However, implementation of human like movement and haptic response has not only been shown as an enabler for more intuitive user experience, but as a requirement for joint physical labor with humans; [15] It’s required in order for people to predict behaviors and intentions, which is essential for collaborate work relying on haptic communication. As shared in the paper *A Human-like Upper-limb Motion Planner: Generating naturalistic movements for humanoid robots*, “In joint action tasks, the consequent motor simulation of an action allows the observer to timely select an adequate complementary behavior. There

is a growing body of experimental evidence suggesting that robot motion can activate the action resonance mechanism as well if it shows human-like characteristics.” [15] So, it is increasingly important to understand human haptic response in order to incorporate models into robotic software if there is to be humanoid-human joint physical labor, object manipulation, dance, and more. This research demonstrates the importance of this study, and why human biomimicry specifically is required for future robot tasks.

Safety concerns surrounding HRI also must be addressed, as this study has a powerful robot arm closely interacting with human subjects. There is much research on HRI safety techniques. In a paper titled *Collision Detection and Isolation on a Robot using Joint Torque Sensing*, Bimbo et al. develop algorithms to answer that very question solely using joint torque sensors already contained on robotic joints. [16] Other researchers are designing new robots characterized by low inertial properties with load to weight ratios similar to other humans, and adding human skin like padding to joints. [17] That way, it is hard to argue more danger is present than already present with humans working together. Although these techniques have promise for future domains, this study relies on Universal Robotics’s collision detection software which automatically turns off the arm if a collision is detected.

Finally, an underlying goal of this study is to promote the future use of more complex robots such as humanoids. With that in mind, its important to briefly note some research surrounding the state of social interaction with robots, which is rapidly developing due to the newfound advances in artificial intelligence. Without having likable and friendly characteristics, humanoids suffer from a negative stigma, which will provide yet another barrier to their rise in popularity. Much research has understood this and attempted to develop rules and patterns for what one paper called “Robotiquette” [18]. Other papers

have shown that robots adapting human behaviors has a concrete impact on human mood. “[Study] participants exhibited high favorability, feeling of relief, and willingness to continue interaction with robots that exhibited appropriate reactions to the touch of participants.” [19] Some are attempting to incorporate human facial expressions into robots. [20] Although there is great nuance to human touch and human facial expressions, the success of large language models and artificial intelligence has shown it is possible to break down another highly nuanced communication method (human language) into statistical models; what is preventing these areas from coming next?

## 5 Methodology

### 5.1 Experimental Procedure

Upon arrival, participants completed a Qualtrics survey on either their own computer or the test administrator’s. The survey provided an overview of the study, explained the procedures, and requested consent to use the collected data for academic purposes, including video recording. Video recordings were solely used to reference whether participants chose to sit or stand and whether they used their left or right hand.

The survey then presented three questions, each rated on a sliding scale from 0 to 100:

- 1) How comfortable are you with robots completing tasks for you?
- 2) How comfortable are you with robots physically interacting with you?
- 3) How comfortable are you with robots making decisions for you?

These questions were included as a precaution to help explain potential outlier data.

Participants were then introduced to the two phases of the experiment:

**Test 1:** Participants placed their palm against a robotic arm’s prosthetic hand and attempted to follow its movements as accurately as possible. The robot’s motion plan is detailed in the following section.

**Test 2:** Participants became the leader, guiding the robot arm through palm-to-palm contact. The robot used PID control based on force sensor measurements to generate accelerations for its end effector, enabling it to follow the participant’s movements.

After completing the survey, participants were instructed to begin **Test 1** and were encouraged to ask any questions. The test administrator started the video recording, and participants followed the robotic arm through a predefined motion plan lasting approximately 90 seconds. This process was repeated for three identical trials.

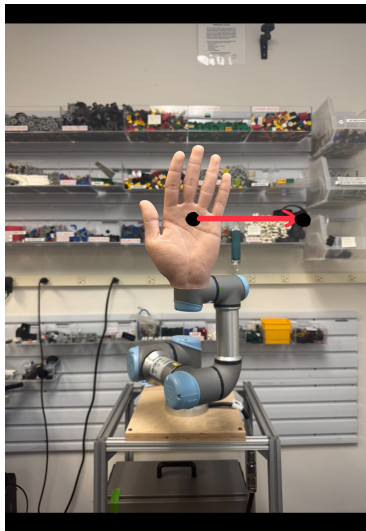
Following **Test 1**, participants had the opportunity to provide feedback through an open-ended survey response before proceeding to **Test 2**.

For **Test 2**, participants were instructed to lead the robotic arm in any motion of their choosing for ten seconds while maintaining palm-to-palm contact. They were informed that exceeding a certain range would trigger the robotic arm’s auto-stop function. If triggered, the arm was reset, and the participant was given another ten-second trial.

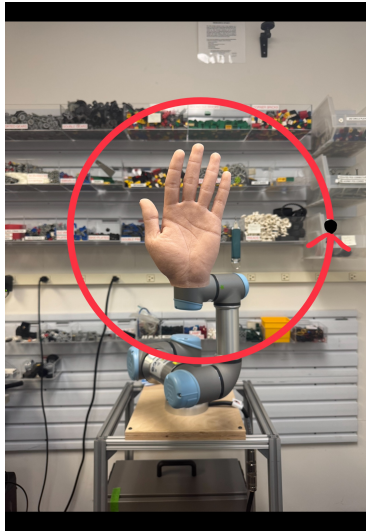
Finally, participants answered an open-ended question: “Did this experience feel similar to having a human arm follow you? Why or why not?”

### 5.1.1 Motion Plan

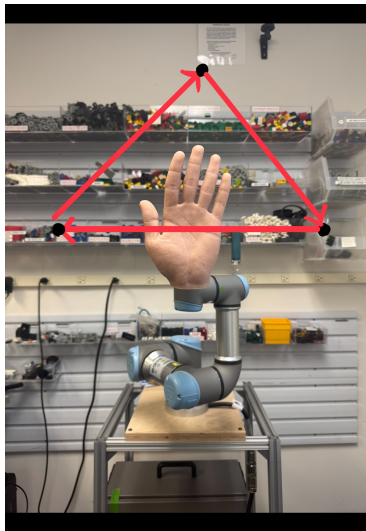
For the three trials where the robot arm acted as the leader, there was a specific motion plan that had twelve separate “movements”. Each movement lasted less than 10 seconds with a 0.25 second pause before moving on to the next movement. The movement order was not randomized and was the same in every trial. Possible impacts from participants remembering previous trials were negated by using just the first trial for much of data analysis. Note that all directions below are given with respect to the subject as the reference frame. All velocities were below 0.15 m/s.



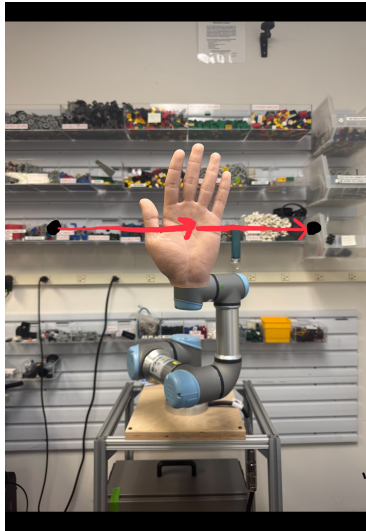
**Figure 2:** Movement #1 – constant velocity movement to the right by 0.05 meters



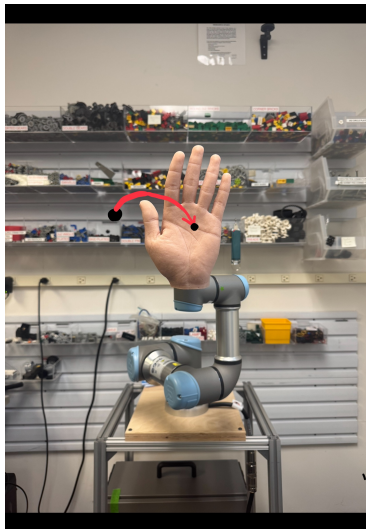
**Figure 3:** Movement #2 – Circle Clockwise with radius 0.5m starting at the end of the last movement



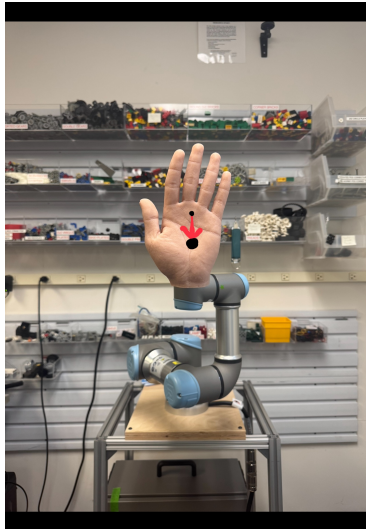
**Figure 4:** Movement #3 – Triangle with constant velocity steps



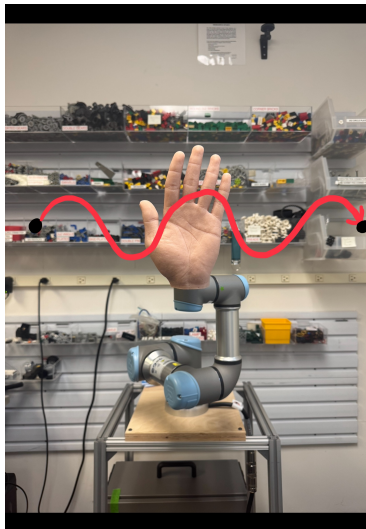
**Figure 5:** Movement #4 – constant acceleration to middle, then deceleration from left to right



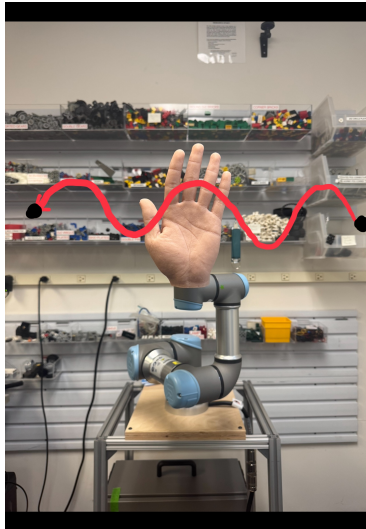
**Figure 6:** Movement #5 – constant velocity away from subject by 0.03 meters, staying in the middle



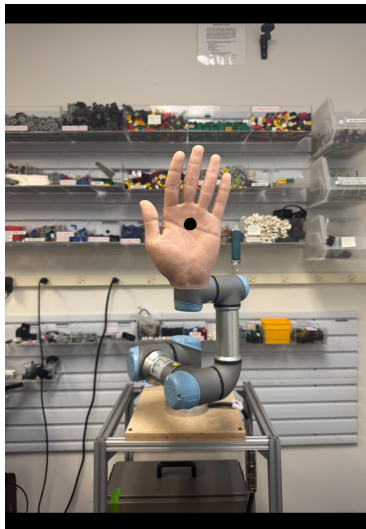
**Figure 7:** Movement #6 – Constant acceleration back to starting position



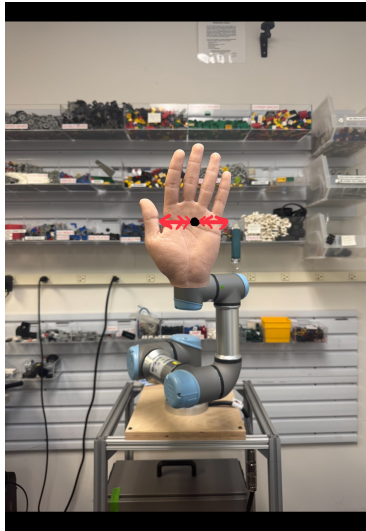
**Figure 8:** Movement #7 – Move to the left then make sin wave motion up and down traveling to the right



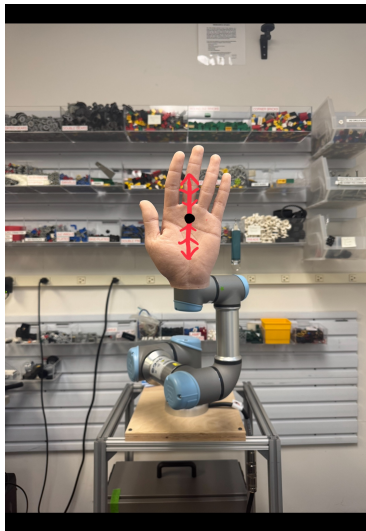
**Figure 9:** Movement #8 – Sin wave motion up and down back to the left



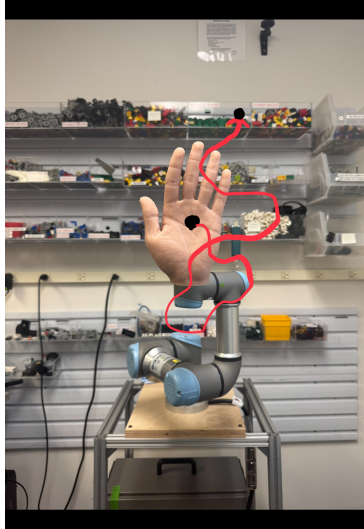
**Figure 10:** Movement #9 – move back to start and then stay still for 4 seconds



**Figure 11:** Movement #10 – Move left and right about middle, only traveling 0.03 meters from start, repeating 5 times



**Figure 12:** Movement #11 – Move up and down about middle, only traveling 0.03 meters from start, repeat 5 times



**Figure 13:** Movement #12 – Random motion (not a specific shape) less than 10 seconds and with no hand accelerations beyond 0.1 m/s. The motion in the image was not necessarily the motion completed, as it was randomized every trial.

### 5.1.2 PID model used for Test 2

For test 2, where the robot arm followed the test participants' motions, PID control was used to solve for end-effector acceleration at each time step:

$$\text{Acceleration}_s = \text{Force}_s \times K_p + \int \text{Force}_s dt \times K_i + \frac{d\text{Force}_s}{dt} \times K_d \quad \text{for } s = x, y, z \text{ directions} \quad (1)$$

Where,

- $K_p$  is the proportional gain coefficient,
- $K_i$  is the integral gain coefficient,
- $K_d$  is the derivative gain coefficient.

A time step of  $T_s = 0.002$  seconds was used, as a faster time step made

robot movements more smooth and fluid. Although it is hard for humans to notice changes at 500 Hz frequencies, it was found that at a lower rate of update time, the discontinuous changes in velocity were noticeable. At faster update rates the software wouldn't be able to calculate and send new velocity values over ROS2. Once x, y and z accelerations were calculated, desired end-effector velocity was determined using:

$$\text{Velocity}_s = (\text{Previous Velocity})_s + \text{acceleration}_s \cdot Ts, \quad \text{for } s = x, y, z \text{ directions} \quad (2)$$

Once desired end-effector velocity was determined, joint velocities were solved for using the Newton-Raphson approach to solve inverse kinematics:

$$q_{k+1} = q_k + J^+(x_d - x_k) * Ts \quad (3)$$

Where,

- $q_k$  is the joint configuration at iteration  $k$ ,
- $x_d$  is the desired end-effector position,
- $x_k$  is the current end-effector position,
- $J^+$  is the Moore-Penrose pseudoinverse of the Jacobian.

Peter Corke's Robotics-Toolbox python library [21] was used to solve for inverse kinematics within python, however I built many python libraries in order to neatly calculate PID updates and communicate them to a ROS2 velocity controller. These libraries are referenced here: [https://github.com/houlton888/UR3\\_HandHold](https://github.com/houlton888/UR3_HandHold)

### 5.1.3 Sampling Method

Convenience sampling was used in this study. Subjects were friends and colleagues of the test administrator, but all had no expertise in the subject area or background information on the study. There were 25 study participants, roughly 50% male and 50% female, within the ages of 19 to 30.

### 5.1.4 Experimental Equipment

The robotic arm used is Universal Robot's UR3e arm.



**Figure 14:** UR3e Robotic arm

A FT 300-S Force Torque Sensor was attached to the arm. The noise was experimentally determined to be within 0.3 Newtons.



**Figure 15:** FT 300-S Torque Force Sensor

Tooling weight	0.44 kg (1 lb)
Measuring range	300 N (FX, FY, FZ) / $\pm 30$ Nm (MX, MY, MZ)
Overload capacity	500%
External noise sensitivity	Immune
Data output rate	100 Hz
Ingress protection (IP) rating	IP65
Operating temperature	15 to 35°C (59 to 95 °F)
Cobot compatibility	Omron, Techman Robot, Universal Robots

**Figure 16:** FT 300-S Torque Force Sensor Specifications

The end-effector used was the Robotiq Hand-E - Adaptive Parallel Gripper for Harsh Environments



**Figure 17:** Robotiq Gripper

A realistic silicone human hand was mounted to the end-effector.



**Figure 18:** Silicone Hand

## 5.2 Data Collection Method for Test 1

Data was collected using the force torque sensor and Universal Robotics's joint state broadcaster ROS2 node. Measurements for x, y, and z axis force, x, y, and z axis end-effector position, and time were collected while study subjects attempted to follow the robot arm's motions as closely as possible. Measurement collection rates varied movement to movement, but were all between 20 Hz and 100 Hz. The data was saved in .xls file format using the pandas python library and then stored on a secure server.

Video data was also collected throughout the study. Video data did not include subjects' faces for privacy, and was not used in analysis except to record what positions subjects were in while following the arm. (which hand they used, and if they were sitting or standing) Video data was deleted after use.

## 5.3 Analysis Methods

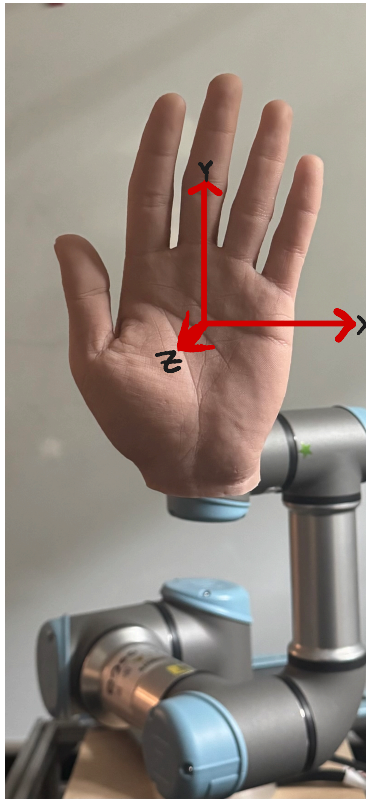
Data was imported into Matlab to be analyzed. Each subject received a numbered ID, 1-25, and participant names were deleted to decrease bias and further protect subject privacy. Analysis methods linked with each result are explained in the results section.

Data was analyzed for trends in force with respect to position, velocity, and acceleration in both the time and frequency domain. However, considering the limited analysis methods employed, it remains plausible that there are significant findings that were missed.

## 6 Results

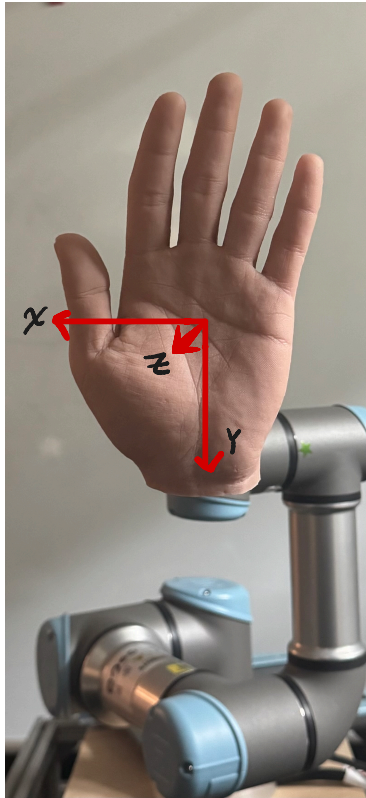
### 6.1 Frame of Reference

The following will be used as the reference frame when discussing motion in the experiment. Note that Z goes out of the page.



**Figure 19:** Coordinate Reference Frame for UR3e end-effector motion

The force sensor had a different reference frame than the motion of the UR3e arm - the X and Y-axis were flipped. The force reference frame is shown below. Z is out of the page.



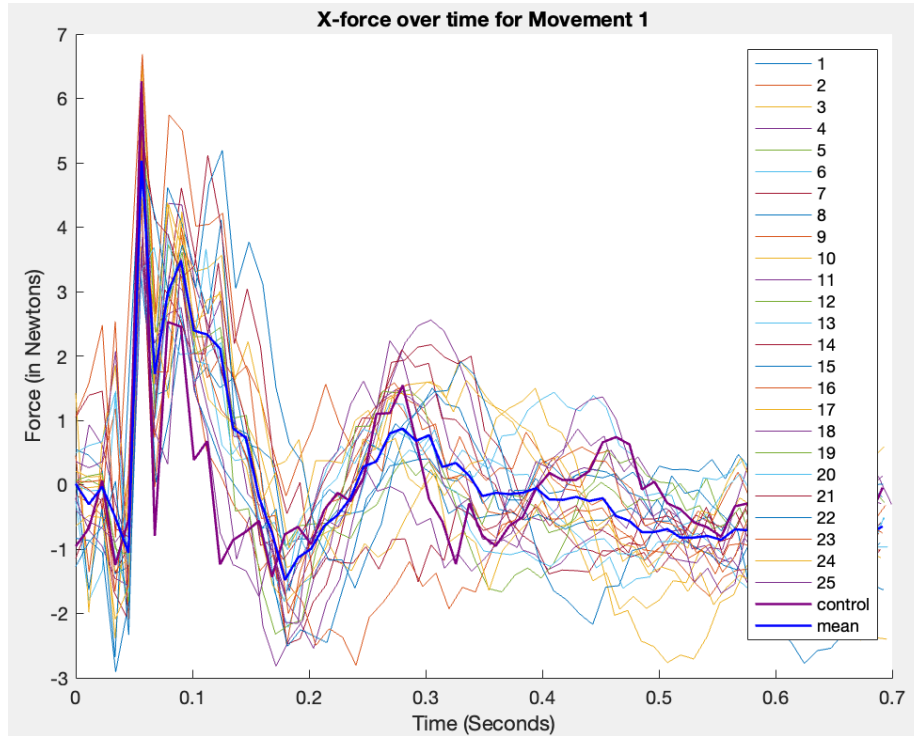
**Figure 20:** Coordinate Reference Frame for force data

## 6.2 Responses are similar across people and trials

Creating an all encompassing model for human haptic response relies on some consistency across different people. This study showed that such consistency exists. Below is a plot of the force over time responses (Fig 21) to the robot arm end-effector starting at a constant velocity in the x-axis direction. The force shown is also in the x-axis direction, and the acceleration impulse occurs at time=0 seconds.

Force effects due to inertia of the hand and end-effector were found by running the same motion path and measuring force with no subject in contact with the hand. This **control trial** is plotted along with the data and is shown in

purple. The mean force value for all study participants at each time step is plotted in blue:



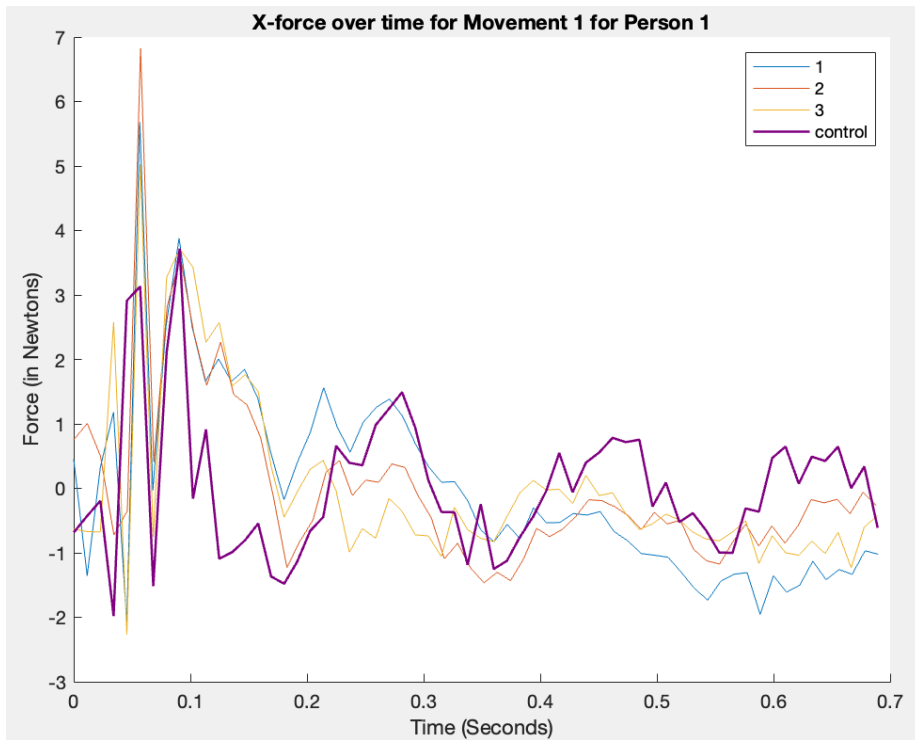
**Figure 21:** X-direction force response to starting a constant velocity in the X-direction for each person’s first trial

In Fig 21, the direction of the movement and the force are opposite. A positive force therefore indicates that the person is behind the arm’s movement, and a negative force shows that a person is ahead of the arm’s movement.

You can see how the study subjects’ arms initially fall behind, but then we see how the work from the robot arm’s motors accelerates the human arms until they catches up. It is most likely that inertia and not the motor response of the person causes this affect, as previous literature shows human response time to typically fall over 0.2 seconds [22]. We then see how around 0.2 seconds human motor control kicks in, and subjects seem to oscillate from ahead to behind as

they attempt to align their hand's velocity with the robots hand. By .5 seconds, we see close alignment, if slightly ahead.

It is apparent that there is at least a certain degree of uniformity from the shape of the graph. It is also of note that there was consistency across one person's separate trials. Below is the same graph as above but containing each trial for one person. The trial without a human subject (control) is still denoted in purple:



**Figure 22:** X-direction force response to starting a constant velocity in the X-direction for participant ID #1

This person has a slightly different force shape as a response to the acceleration impulse. They notably had a higher force to their initial lag behind the motion around time=.08 seconds than the mean (displayed in previous graph). Since this is before the period where human motor control can adjust to an

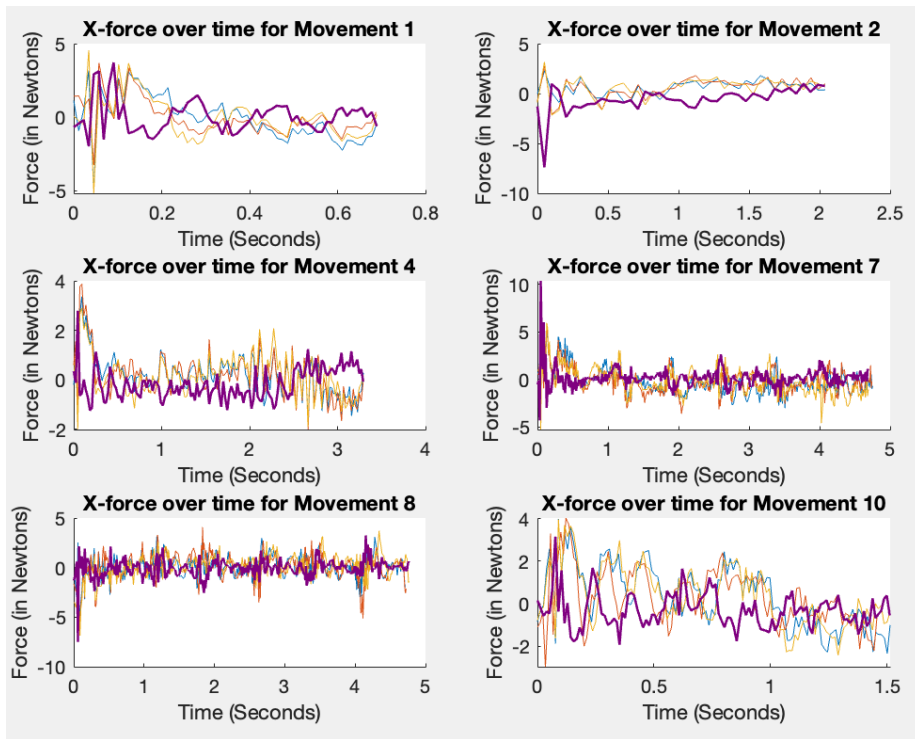
input, it is likely due to the person's pose, the size of their arm/hand, and how taut they keep their arm muscles in anticipation, as covered in the kinesiology section in the literature review. It is also assumed that the participant didn't learn the pattern after the first trial, as similarities across trials suggests.

The key takeaway is that there was consistency amongst trials of the same person (average standard deviation of 0.526 Newtons for one person) and amongst different people. (average standard deviation of 1.8 Newtons for multiple people) It is also a key takeaway that this study suggests roughly a 0.2-0.3 second reaction time, as this is when they start to differentiate from the control and even-out the system oscillations shown in the control trial. This finding is consistent with findings from other research.

Notably, standard deviation is not a perfect metric to answer just how unified responses were. This is discussed in detail within the discussion section.

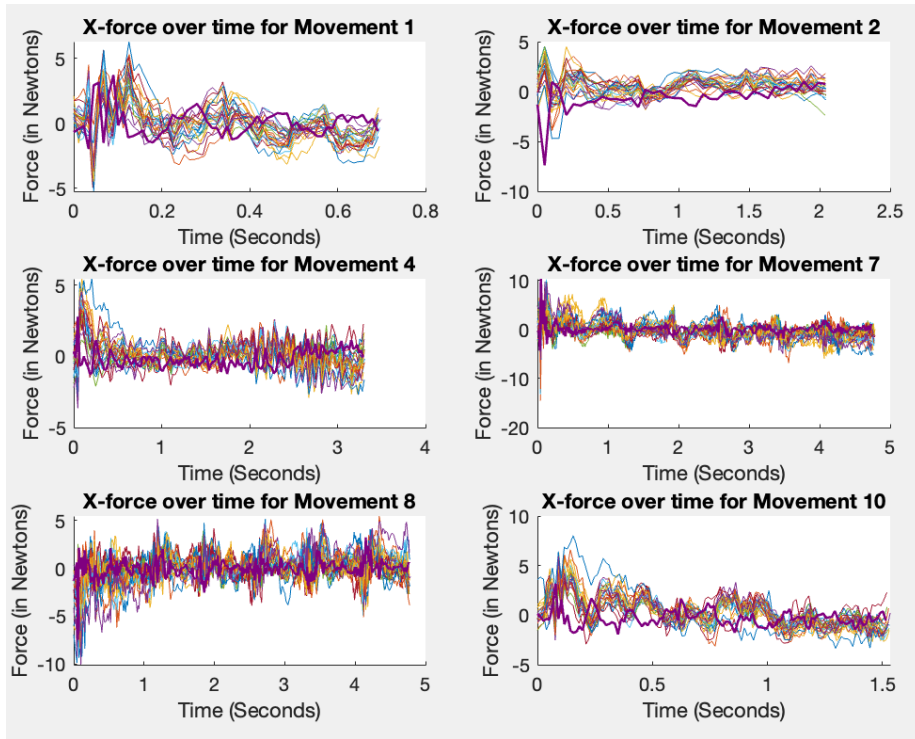
Also of note is that the haptic responses above only last for half a second. Much of the force response in this time is likely due to natural dynamics and the inertia of the human subjects' arm.

To better display consistency in human motor control we need to illustrate subjects having similar responses that vary from inertial effects. To do this we need to look at longer lasting movements. Below is the force responses in the X-axis direction for a bunch of different motions for person #1. As displayed on the time axis, these movements are sufficiently long for human motor response to kick in:



**Figure 23:** X-direction force response of person 1 to many different shapes

Fig 23 displays specifically how people follow trends independent of the inertial effects displayed by the control, shown in purple. This signifies that the consistency shown in motor response across trials is not just due to consistency in inertia's effects. There is shown to be this same motor response consistency across different people. Fig 24 (below) displays the responses of each persons' first trial to the same shapes as above:



**Figure 24:** X-direction force response of each person in their first trial to many different shapes

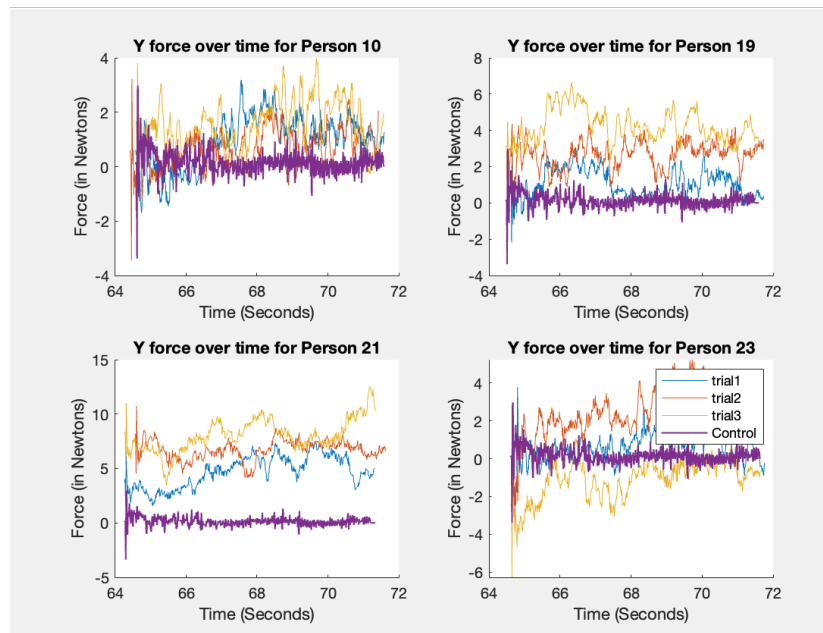
The rest of the shapes and data also display a degree of consistency amongst different humans in what forces they apply in response to haptic input. The outlier person for motion 10 was due to a participant readjusting their arm, as was seen in the video footage. The data shows that human haptic response had similarities sufficient enough to create models for it.

### 6.3 Following worsens as people tire

The one notable area where study subjects were inconsistent was their response to their shoulders getting tired. Some people start to pull down on the robot arm as the trial progresses, and the magnitude of force with which they pull down usually progressed each subsequent trial. There were a few comments in

the survey where people noted that their arms were tired during the study, with one person even noting that they purposefully pulled down on the robot arm for support, but for the most part this reaction seemed to be subconscious. This, however, is an outlet for future research.

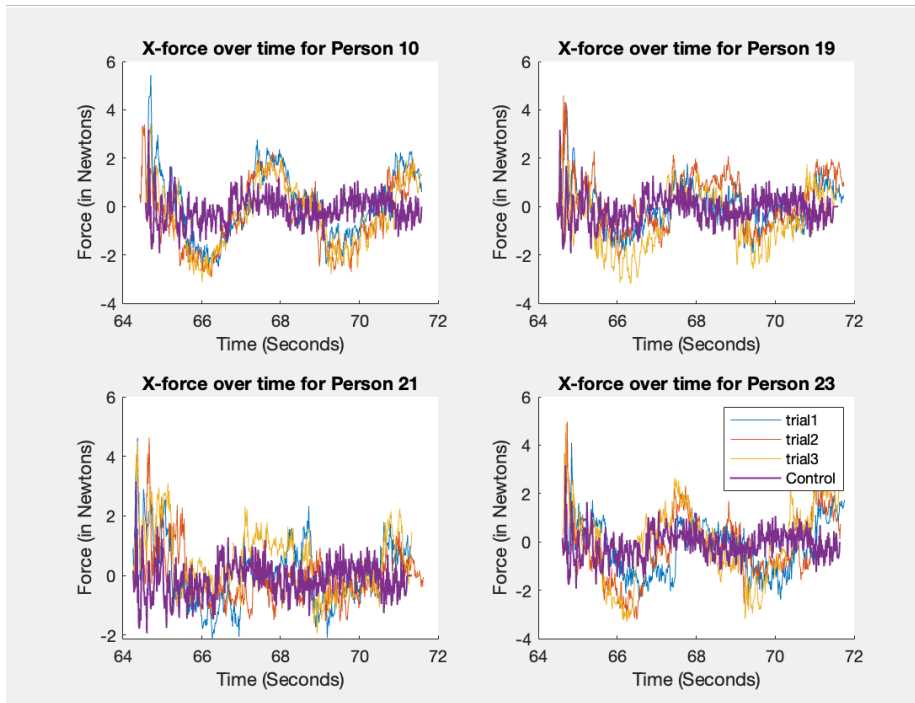
Fig 25 displays the Y-axis force for four different people for movement #10 (.5 Hz X-axis wiggles about a middle point). A downwards pull shows-up as a positive Y-axis force. Gravity is also in the positive Y-direction, but has been zeroed out. Notice how the downward force from participants' arms tends to be above control (shown in purple), and to increase with each subsequent trial.



**Figure 25:** Y-direction Force of 4 different people during movement #10

There is clear inconsistency trial to trial and person to person. Person #23 even overcompensated on the last trial and pushed upward on the arm. Yet, for the same movements, it can be shown how there was consistency on the X-axis dimension, the one aligning with changes in acceleration and controlled

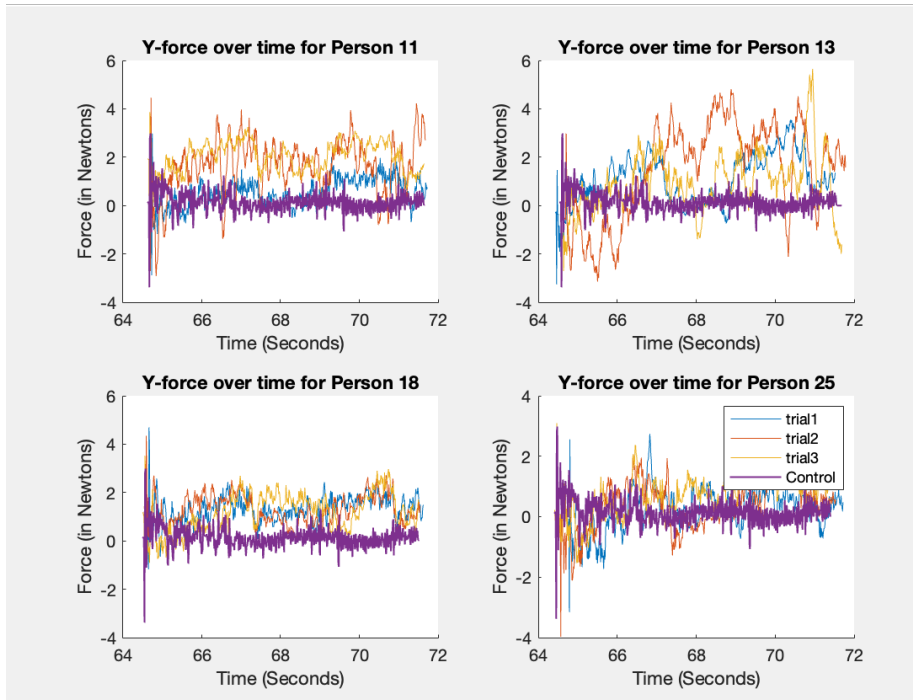
by human motor response rather than fatigue. Below is a plot of the same motion for the same people, but displaying their X-axis forces rather than Y-axis (control still denoted in purple):



**Figure 26:** X-direction Force of 4 different people during movement #10

Clearly this fatigue inconsistency is only effecting the direction aligning with gravity, as Todorov's paper from 2002 would likely predict [3]

The inconsistency in this fatigue person to person is noticeable to the point that some people display relative resistance to it, whether it be from having more muscular endurance or trying harder to keep even with the arm:



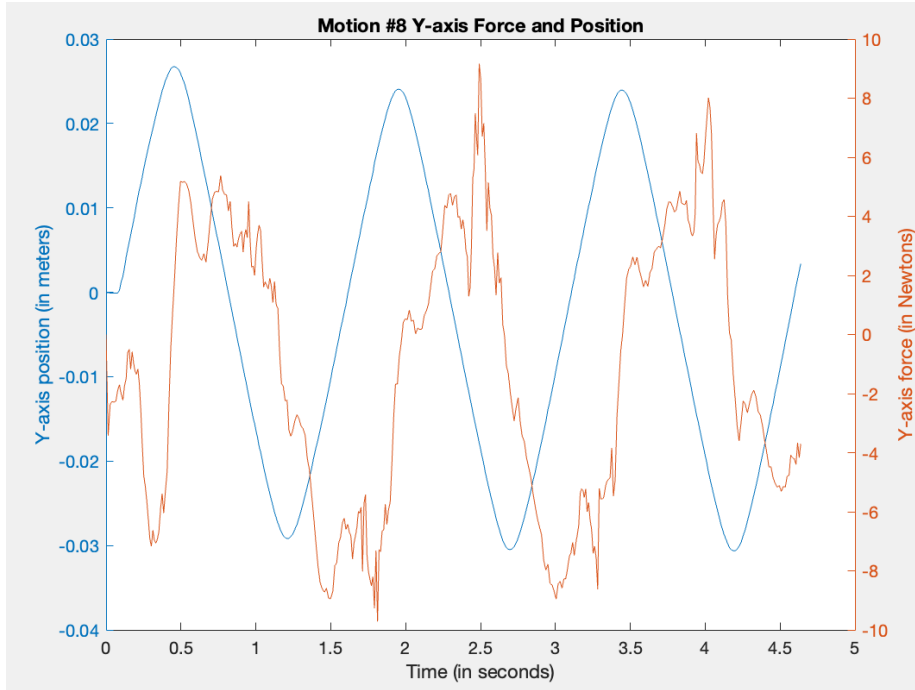
**Figure 27:** Y-direction force of 4 different people during movement #10

These people were far closer to zero force difference in the Y-axis than the other four people displayed in the same plot above. This gives merit to previous research discussed in the literature review, suggesting that the brain focuses on feedback and control for goal-directed motion. [3] There is a chance that since there was no motion in the Y-direction for this movement, people considered it less important to match position with.

#### 6.4 People tend to lead ahead once they identify a known shape

It became immediately apparent upon analyzing data that it would be difficult to create a PID control model that accurately mimics human haptic response to palm-to-palm following. The main restricting factor was human shape recog-

dition. Once humans recognized that the arm is making a specific pattern or shape, they had a tendency to lead ahead of the shape, forcing the robot arm to do negative work in order to stay on its pre-planned motion path. In retrospect, this makes sense, as humans are impatient, but the consistency of this trend (all participants expressed it) was striking. For instance, below is a graph of the Y-axis position and force over time for movement #8. This movement features an up down sinusoidal movement while moving right to left that is easy to recognize. Note how whichever way the arm is moving, the sign of the participant's force on the hand is opposite (aligned directionally). For upward movement, (positive Y-direction) there is a negative force, indicating an upward force - the participant "aids" the arm by pulling the way the arm is moving, and vice versa for downward force. This shows up as 90 degree phase lag in the chart. I also believe there is very little delay in how long it takes for someone to recognize the slope because the sinusoidal pattern repeats at even intervals. People can predict when the slope will change and change the direction of their pulling force at the exact right time:



**Figure 28:** Y-direction Force and Position of Person #1 during movement #8

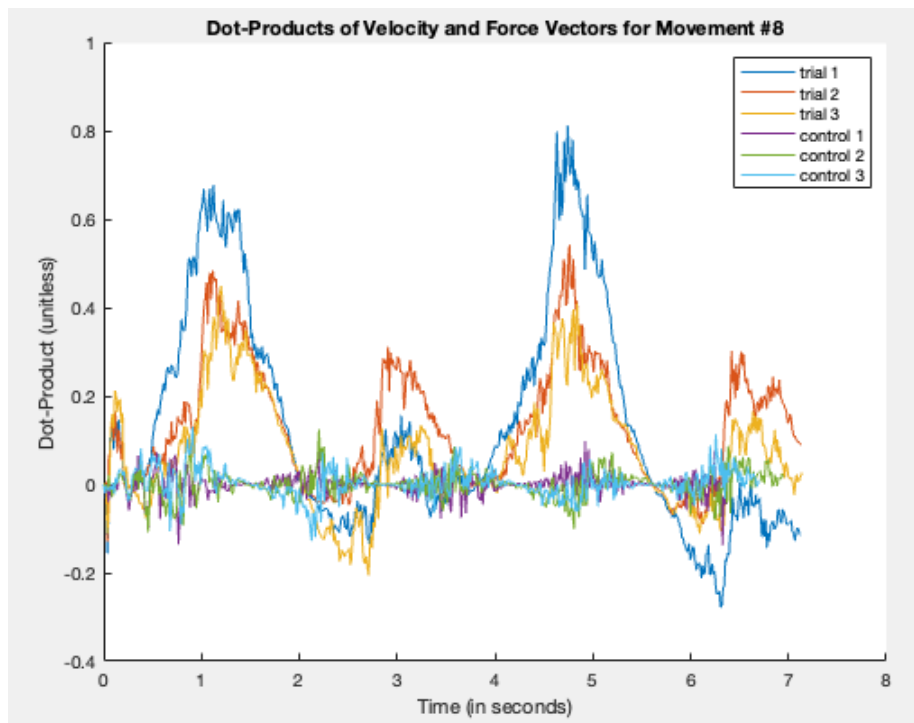
The presence of this leading ahead phenomenon becomes very clear by taking the dot product of the velocity vector with the force vector. Since movements and forces could occur in any direction in 3-D space, this metric is a good representation of the alignment of the force and velocity vectors. The dot product of the force and velocity vectors is given by:

$$\vec{F} \cdot \vec{V} = |\vec{F}||\vec{V}| \cos \theta = V_x F_x + V_y F_y + V_z F_z$$

A positive dot product would indicate that the test participant was pulling in the same direction as the movement, leading ahead of the robot arm. A negative dot product would indicate that the person is behind the movements of the arm. A zero value dot product would indicate that the person's force is orthogonal to the velocity vector, or close to zero.

It is similar to expressing the angle between the two vectors, which could be analyzed by dividing the dot product by the vector magnitudes and taking the inverse cosine. However, the dot product is more useful to see this trend, as small forces opposite to (lagging behind) the direction of motion can be more aligned with the direction of movement than a huge force aligned with the direction of the movement vector. This small negatively aligned force may show up as a larger angle than a large force that is slightly less aligned with the direction of movement. Because of this, it is important to keep the vector magnitudes to negate the impacts of such chance and noise.

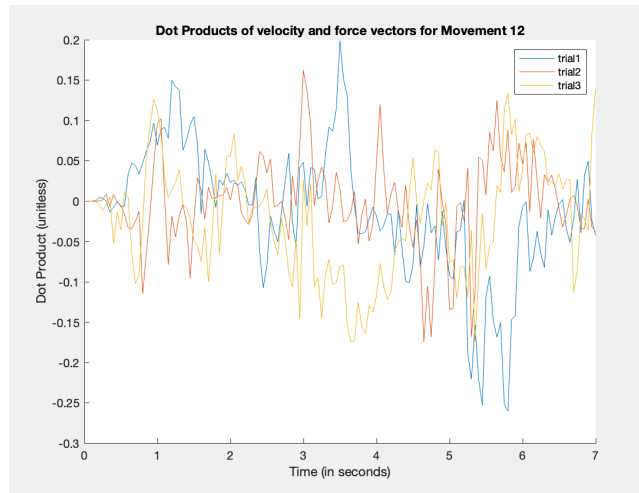
A plot of the dot products over time for the same sinusoidal motion discussed above is displayed below:



**Figure 29:** Dot Product of Force and Velocity of person #1 during movement #8

The positive values maintain that the test participant was pulling in the same direction as the arm was moving. The results from the control trials display how this effect was not due to inertial forces.

Fig 31 (below) displays the dot products over time for motion #12 for the same person. Since motion #12 is the random motion (random accelerations at each time step) there is no pattern for humans to recognize and follow. The lack of a positive dot-product trend therefore supports the theory that people lead ahead of recognizable shapes.



**Figure 30:** Dot Product of Force and Velocity of the arm during movement #12 for Person #1

Below is a table with the mean dot product values of each shape. The mean displayed is an average of all trials of all participants. Next to it is displayed the means and standard deviation of the dot products for the control trial, where no subject was in contact with the robot hand.

Motion	Mean	Standard deviation	Control Mean	Control STD
Motion 1	0.0232	0.0155	-0.0448	0.0111
Motion 2	0.113	0.115	0.00879	0.0206
Motion 3	0.0346	0.0460	0.000211	0.00299
Motion 4	0.0306	0.103	0.0348	0.00724
Motion 5	0.0373	0.0541	-0.00446	0.00545
Motion 6	-0.0257	0.0264	-0.0263	0.00282
Motion 7	0.147	0.177	-0.0396	0.0108
Motion 8	0.272	0.202	0.0713	0.0117
Motion 9	4.56E-06	5.83E-05	3.16E-06	3.93E-06
Motion 10	0.0369	0.0353	0.00185	0.00171
Motion 11	0.1015	0.0405	0.00798	0.00688
Motion 12	0.000336	0.0433	NA	NA

**Table 1:** Dot product of Force and Velocity for Every Movement

#### 6.4.1 Statistical Analysis of the Force and Velocity Dot-Products

The following table summarizes the previous one by displaying the results for a one-tailed Welch’s T-test comparing the mean dot-products from the subject trials to the mean dot-products from the control trials for each shape.

Motion	Description	t	df	p-value	result
Motion 1	Constant Velocity to the right	15.9	7219	1.64E-05	significant
Motion 2	Circle	7.63	5536	0.843	
Motion 3	Triangle	5.72	4138	0.045	significant
Motion 4	Acceleration then Deceleration	-0.68	13630	1.64E-05	significant
Motion 5	Velocity Away from Subject	11.1	8212	0.00265	significant
Motion 6	Acceleration towards subject	0.146	4135	0.385	
Motion 7	Sin left to right	22.4	33616	0.000399	significant
Motion 8	Sin right to left	18.0	33616	2.58E-24	significant
Motion 9	No movement	-0.055	27376	0.189	
Motion 10	left/right waves about middle	13.8	51766	6.17E-17	significant
Motion 11	up/down waves about middle	4.16	1723	0.236	

**Table 2:** Results of Welch’s t-test for each motion

Where,

- $t$  is the scaled difference between the two sample means,
- $df$  is the degrees of freedom,

- *p* – *value* is the chance (0-1 scale) that the observed differences between the subject and control data happened by chance,
- *result* signifies whether the motion was statistically significant at  $\alpha = .05$ .

For the significance level of  $P < .05$ , only motions #2, #6, #9, and #11 failed to reject the null hypothesis that the sample means between the control and subject trials are the same. Motion #12 does not have a control trial so the test was skipped, but it was previously shown that there was no positive trend within its mean dot-product, as motion with random accelerations has no shape for people to anticipate and lead ahead of. It would also fail to reject the null hypothesis. For motion #2, the circle, the high p-value was due to the large variance in dot-product values. Different people responded to this shape differently. People pulling down on the arm due to fatigue (discussed in previous section) may have had an impact on this. For motion #6, the mean dot product was actually negative. My intuition here is that a movement inward towards the body is uncomfortable due to human biomechanics, and so people don't want to lead ahead in that direction. However, future work should be done to test this hypothesis further. Motion #9 was a period of still that acted as a control, so the test results say little about leading ahead behavior. Motion #11 was also likely influenced by people pulling down due to fatigue, as its direction of motion was up and down. For every other motion contained in this study, subjects displayed the tendency to pull ahead of velocity to a degree statistically significant at  $\alpha = .05$ .

A permutation test was then performed to compare the mean dot-product of every motion with that of the control. (Motions #9 and #12 were excluded). Although this is similar to the T-test, it doesn't assume a normal distribution for the data. It also combined every motion into one, so it was a good representation of how different a complete human trial was from the control. For 10,000

permutations, the test concluded that there was a .59% ( $P=.0059$ ) chance that the observed difference would occur randomly.

Finally, a repeated measures ANOVA test was conducted to examine the effect of the shape on the mean dot-product. The means and standard deviations for each shape are reported in Table 1.

Mauchly's test was inconclusive due to the high number of conditions, so the degrees of freedom were corrected using the Greenhouse-Geisser estimates of sphericity to be conservative. The effect of which motion was being followed on the dot-product was significant at the  $\alpha = .05$  level,  $F(10, 230) = 18.468$ ,  $p = 4.8402e-08$ . This indicates that differences in the leading motion had a significant impact on the mean dot-product.

Post-hoc pairwise comparisons with a Bonferroni adjustment indicated that dot-products were significantly higher for some shapes than others (some above  $p = .05$ ). With 55 pairwise comparisons, the data has been left out, but this confirms that which shape was being followed had an impact on the force and velocity dot-product.

This test also showed that the interaction between subject and motion was significant,  $F(10, 230) = 6.9071$ ,  $p = 0.0077$ . This suggests that the effect of shape varied across subjects, but that the subjects were far more similar to each other within the same motion than their responses across different motions, signifying that the motion had a greater impact on the mean dot-product than which subject was following. So, although there were notable differences in following between test subjects, a baseline level of uniformity within human haptic response is supported. The full results from the repeated measures ANOVA test are displayed below:

	SumSq	DF	MeanSq	F	p-value	p-valueGG
(Intercept):Motion	3.82	10	0.382	18.4	1.19e-24	4.84E-08
Subject:Motion	1.43	10	0.143	6.90	1.9e-07	.0077
Error(Motion)	4.7	230	0.0207			

**Table 3:** ANOVA Table with Greenhouse-Geisser p-values

#### 6.4.2 Dot products of Force and Acceleration

It is not intuitive that it is velocity, rather than acceleration, that creates this pattern.  $F=m*a$  typically suggests a force should be proportional to an acceleration, and that humans should attempt to align their force with the direction of acceleration, but the data did not show any significant correlation between the two. The same table but for the dot products of acceleration and force is shown below:

<b>Motion</b>	<b>Mean</b>	<b>STD</b>
Motion 1	0.046	0.105
Motion 2	-0.09	0.092
Motion 3	-0.023	0.036
Motion 4	-0.017	0.027
Motion 5	0.003	0.023
Motion 6	-0.055	0.088
Motion 7	-0.139	0.224
Motion 8	0.053	0.205
Motion 9	0	0.001
Motion 10	-0.077	0.03
Motion 11	-0.413	0.374

**Table 4:** Mean and Standard Deviation of the Dot Products of the Force and Acceleration vectors for each Motion

The lack of a positive correlation between the directions of the acceleration and force vectors as shown below is likely because human pattern recognition involves extrapolating position to get velocity, as it is too complex to track acceleration. However, this is discussed in greater detail in the Discussion section.

## 6.5 Test 2 Survey Responses

To incorporate this human phenomenon where people anticipate and lead ahead of shapes into a control paradigm, a model would not only have to be dependent on the force difference between human and robot hand, but also the velocity direction of the leader. It would be difficult for a PID model to incorporate this. Each shape would have to be individually analyzed and a corresponding constant force would need to be applied in the direction of motion. This constant may change shape to shape, and even at different parts within the shape.

However, the goal of this study was to develop a PID model, so rather than tune control parameters based off data from the human following portion of the study, parameters were tuned experimentally, until the best “feel” was found. First,  $K_p$  was slowly increased until the arm felt too responsive. Then  $K_i$  was increased until the arm felt too “boomerang” like. Finally,  $K_d$  was increased until the motions began to show signs of instability. The  $K_p$ ,  $K_i$ , and  $K_d$  values were found to be .1 [1/kg], .0002 [1/kg\*s], and .00001 [s/kg], respectively. Since finding a quantitative method to tune PID parameters based on human responses wasn’t possible, at least an intuitive feel for participants’ thoughts on a rough model utilizing PID could be developed as a baseline for future work.

The resulting feedback from the survey was not very conclusive. The answers to the question, “Did this experience feel similar to a human arm following you?” were contradictory person to person. Some, like the first two participants, didn’t even answer the question asked. The answers are shown below for each of the 25 participants:

- No, I did not necessarily feel completely in control; it felt like an equal amount of leading and following.
- It felt like I was driving it a lot more but I felt like it was still in control. When following, the motion was definitely more smooth.

- When the resistance is too low, it didn't feel like a human arm; it felt way too responsive. With higher resistance it did but I still felt like it was hard to hold on to it so I think some hyperparameters need to be tuned in order to deal with resistance, acceleration, pressure, etc to ensure that A) I'm not trying too hard to hold on to it, B) it doesn't respond too quickly beyond my natural anticipation.
- Not really, because I am kind of expecting it to follow me, it feels a little fake. It is cool how it tracks and keeps pressure with you however. It was also smoother than I expected it to be.
- Yes and no, pressure is different and hand texture, but in terms of following, reaction is more robotic.
- It felt similar. The arm was very responsive to very little movement which was similar to human interactions.
- At some points it did. I felt like when the robot moved smoothly and changed directions with less of the jerky, immediate stops and movements, it felt more human-like. With the very calculated and 'start-stop' movements, it felt like a robot or machine but with the smooth ones it was human-like.
- Yes, felt similar to following a human arm. The robotic arm makes sure to keep the pressure between my hand and the robotic hand the same, and so as I guide the arm, it naturally follows where I am slightly putting more pressure. I was initially skeptical, as my test run of this portion ended within a second as the robotic arm went straight down, but more smooth and controlled movement on my real test through went smoothly, and felt very natural.
- Yes. It felt really natural, because it actually followed me.

- Not really, humans move more continuously but this felt robotic.
- A little, the movements felt a little too erratic and was moving too quickly at times or was pushing my hand when I didn't intend for it to be pushed.
- It feels more responsive than a human arm, I think a human would push back a little more. However, the overall experience is similar.
- Yes, it is very responsive. It feels very realistic, especially when moving forward/back/sideways at the same time.
- Yes, except for any sharp direction changes. When it moved in a zigzag up and down it felt sharper than it would following a human hand. I think the softness/bending of the attached hand helped to dampen motion and make it feel more human.
- Yes in the sense that the force back felt a bit more unpredictable.
- Similar forces to a human hand and response time. When I was following it, the movements were twitchy. When it was following me, it would overcorrect to the force I was putting on it (pushing on the hand, it sent the hand flying all the way back past the neutral point).
- It did not.
- Sort of, the movement is human-like but the pressure/force it produces is like a robot.
- This experience felt somewhat similar to a human arm because it was able to follow the movement of my hand when pressure was placed.
- Not really, but it was very smooth. The reason it didn't feel like a human arm was because of how steady its motion was the whole time (for the first

part) and because it was difficult to keep the arm in one place without the force sensor adjusting the position constantly (for the last part).

- Kind of, more so yes than no, it felt like a mix of me leading the arm and the arm leading me. It definitely felt a lot smoother than when I was following it.
- Yes. I felt like I could feel the robot continuously testing the magnitude and direction of the force I was inputting. I feel like this is similar to how a human would determine how to follow a hand.
- I feel like the pattern was a little confusing because I did not know what to do with the hand once it was following me. I did find it easier to follow the hand over making it follow me. I feel like one confusing part was the pressure.
- No, not yet.
- In a very limited range, it did. However, its constant pushing is a little too forceful to be fully accurate.
- No, because it felt like it was anticipating what my movements were going to be, which isn't very familiar. Usually, following a human arm is much slower because the other person gives you more of an opportunity to react to them.

Results were roughly categorized as follows:

Yes	Indecisive	No
8	8	9

**Table 5:** Survey Responses

## 7 Discussion

The data showed that different humans have some uniformity to their haptic responses to the palm-to-palm following scenario. It also became apparent that a simple PID control schematic is only an okay model for human haptic response in these scenarios.

Yet, there are still important unanswered concerns central to the investigation. Many of these are addressed in the remainder of this section.

### 7.1 Can one control model encapsulate all humans?

This question is central to discerning whether the goal of a humanoid robot haptic interaction should be for it to feel like a human, or for it to feel like humans. For instance, when I go palm-to-palm with my friend, (lets call him John) is his response inherently “John”? Are my underlying thoughts, “that feels like a person responding to me”, or are they “that person responds like John specifically, but I know its a person because John moves similarly to other people I’ve interacted with in the past”?

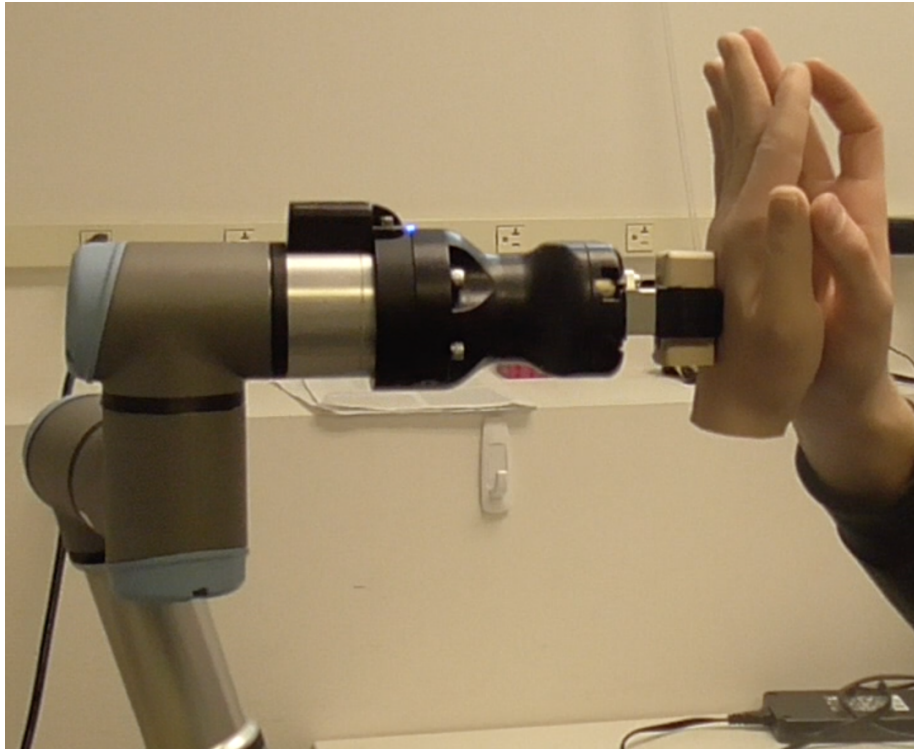
By displaying a certain degree of uniformity within subject responses, we provide proof of concept that one model may stay true for all of humanity. However, discerning whether a model should be designed to mimic human patterns, or whether a model should attempt to feel like at least one human depends on the degree of uniformity. Just how uniform were the results?

There is likely not one metric that defines the degree of uniformity. The average of the standard deviations of force at each point in time is a good starting point, but it does not incorporate overall pattern and shape. Two people may respond with the same overall pattern or shape, but apply a little more force in some areas and less in other areas. Another may follow this same pattern but have a slightly slower response time, causing standard deviations to

spike for high frequency force changes although the general shape is the same. This can be seen in movement #7. As such, it is possible for someone to follow the same pattern or use the same motor control strategies, and end up with a smaller standard deviation than the person who had the same intrinsic model but fell behind at certain points. In addition, all forces were small in this study, considering a human could apply far more than 100 Newtons of force if they wanted to. So, what should be used to consider a standard deviation high or low? The highest force differences in this experiment were around 15 Newtons, so perhaps this could be a reference, but it changes motion to motion.

Yet, even beyond this, we need to uncover whether discrepancies in response are due to discrepancies in human behavior, or due to errors in measurement, differences in sitting position, or other variables that were unaccounted for. These may include but are not limited to subject sleep levels, subject fitness levels, room temperature, type of chair, size of robot's hand, subject hunger levels, whether subject's friends are present, subject focus levels, and more.

Many of these variables are outlets for future work, but one that is worth pointing out specifically is subject attitude during the study. This would have a large impact on "how hard the subject tries". Some of the survey responses were very short (shown in results section) which may indicate lack of care about survey findings. In the video recordings, one subject was seen flicking a finger of the robot hand during a trial.



**Figure 31:** Subject flicking a finger of the robot hand during movement #10

If it is the case that these behaviors indicate a lack of seriousness in the study environment, it is certainly possible to suggest that study participants may give in to impulses telling them to apply a random force, or play around with the arm on impulse. Due to natural low frequency variations in human motor response, it is difficult to tell if the more subtle of these impulses are purposeful decisions or part of normal haptic response.

Because of this and the emphasis on patterns and shape over exact closeness in magnitude, it is most useful to simply look at the data graphically when looking for uniformity. In conclusion, it is challenging to draw quantitative conclusions on just how unified human responses are, as the important output is “feel” based. An alternative method is needed to answer whether haptic

response software should mimic one human or all of humanity. One method may be a future experiment designed to question whether people can tell someone apart from their palm-to-palm following response alone.

## **7.2 Should algorithms incorporate human imperfections?**

Another important question for future research is whether people would prefer human imperfections in a robot counterpart, or a more perfect following algorithm. As mentioned in the previous section, people get impulses to stray from their optimal motor response performance. These impulses, and how often they are given into, are seemingly random, but work could be done to study them. Would a robot incorporate any of these random impulses? There are other human activities that are sub-optimal for performance as well. Should a robot incorporate adjusting its arm position after a period of time where a human would get tired? Should it start to drag down, as seen in this study? Should it complain and give up when a human would? Or do we want to model the best case-scenario of human responses, even though this may result in a less human experience? Likely, it will vary depending on the goal and application of the robot.

As far as this experiment's application goes, the goal of the follower was to minimize force differences between their palm and the palm of the leader. I would likely design the robot software to use a best-case scenario human's response, ignoring all possible imperfections. If the goal was to interact with children, entertaining and introducing them to society and how other people may act, introducing human tendencies may be more important.

### **7.3 Implications on other haptic response scenarios**

A major weakness to the findings of this study is the difficulty of applying findings to other human haptic response scenarios. Uncovering similarities and differences in motor responses across different movements requires data to be collected on other haptic response scenarios, and is a part of future work.

### **7.4 Why do people lead ahead of velocity rather than acceleration?**

The data was analyzed comparing position, velocity, and acceleration to force, and the only statistically significant correlation in direction was between velocity and force. This trend, where people lead ahead when they identify a shape makes sense, but it is non-nonsensical that they lead ahead of velocity rather than acceleration. For any deceleration movement, “speeding up” the movement means applying a force opposite the direction of the velocity.  $F=m*a$  tells us that any force we apply will administer an acceleration on the robot hand opposite to the robot’s goal, “slowing down” the motion. Yet, the force people tend to lead ahead with was shown not to depend on the acceleration of the leader, but the velocity. This is puzzling and there is no clear answer as to why this occurs. Likely it is just an area where human intuition does not align with the laws of nature. Still, models depicting human haptic responses will need to compensate for this phenomenon and it was useful for this study to quantify this effect.

## **8 Conclusion and Connection to Research**

This study received feedback of only 32% of participants feeling that the robotic haptic control model felt “human-like”. A future where robots can mimic human

motor control requires far more work put in to collecting data on human motor control and organizing optimal techniques for its implementation into software. Other haptic interactions beyond the simple one analyzed in this study should be analyzed. Since all these interactions will involve different muscle groups, body orientations, masses, and moments of inertia, it would be near impossible to create a simulation predicting an all-encompassing human haptic response model. Without this, a new empirical study would be required for each situation a robot may find itself in. For instance, the data from a human pulling a humanoid robot through a dance spin would likely not be able to inform models on robots performing human-like handshakes. With different models for different situations, robotic software would need to be able to categorize different situations and apply the correct haptic response model.

As a result, the work required of a robotics company to create a fully functional humanoid mimicking all of human motor response is daunting. However, most of this work will likely come from the data collection requirement. If there is a good method for mass amounts of human haptic response data to be collected, artificial intelligence will likely be helpful in analyzing and creating applicable software. This suggests that there should be a focus put on identifying sensors equipped to capture this data effectively, and methods developed to make these sensors non-disruptive so they can mass collect human data.

In this study, I began collecting such data for the most elementary haptic response scenario. Although the PID model utilized in this study was not able to encapsulate the feel of human motor response, many interesting patterns were observed. A proof of concept for modeling human motor control as applied to haptic response was provided, and the uniformity in the data collected suggested that one day robots may be just as capable of human dance as they are of human speech.

## 9 Future Work

Perhaps the most significant finding of this study was not in its results, but in the questions it has raised. Many of these questions provide perfect outlets for future research on the topic. Some of the questions raised in the discussion, and suggested experiments to answer them, are organized below:

- Can people tell someone apart by their palm-to-palm response?
- How would people's responses change following with two hands at the same time?
- A test designed to answer whether one model can be applied to many different following situations. A good starting point could be whether a model created to work for the following scenario in this study also works for elbow-to-elbow contact. Or, joint manipulation of an object held by both human and robot hand together.
- Should these studies suggest that new models must be designed for each scenario, future work must be done studying sensors and methods that best fit a large-scale study of human haptic responses in many different situations. Perhaps this data can be used to create motor response artificial intelligence.
- Attempt to create models to enable robots to have adaptable impedance. Humans do this using antagonistic muscle co-contraction. (explained in literature section) Methods for robot arms to mimic this should be explored.
- An experiment to quantify how humans change their impedance in different scenarios, and when they utilize feedforward vs. feedback control.

- Test the feel of a robot following people using robots with compliant joints to see if it feels more human.
- What constitutes a simple enough shape for a human to lead ahead of? What shapes do humans recognize?

### **9.1 How can we identify when the motion path is a shape?**

After building an intuition by analyzing data from this study, I suggest two possible methods for this last question specifically. The first possibility is to train a neural network capable of predicting whether a movement is part of a simple shape, and select what shape it is part of. The other is to Fourier transform the velocity. For all the shapes in this study where people were capable of following, the power spectral density plot of the velocity would express only significant power for low frequencies, as shapes humans can identify have simple velocity profiles with no high frequencies. After a normal human response time (roughly .2 seconds) the program can check to see if the motion is “simple” by doing a Fourier transform. If a vast majority of the power spectrum (the exact percentage should be experimentally determined) is low enough (this exact number should be experimentally determined as well) then the program could have the robot arm that is following add a force in the direction of the leader’s velocity.

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