# Intuitive Control of a Robotic Arm and Hand System with Pneumatic Haptic Feedback

Sihui Li*, Raagini Rameshwar*, Ann Marie Votta*, Cagdas Onal

***Abstract*—Robot teleoperation is a transformative field of study that can enable workers to safely perform tasks in dangerous environments. In this paper, we present our work towards a teleoperation system with safe, realistic force feedback for intuitive control of a robotic arm and anthropomorphic robotic hand as its end effector. The system interfaces with the user via a novel data glove. This glove detects the state of the hand using inertial measurement units (IMUs) and custom curvature sensors, and employs pneumatic muscles to provide force feedback. The glove itself weighs only 58 grams, and the glove combined with IMUs and tether weighs 213 grams. We use this glove to control a Kinova Jaco robotic arm and a custom 3D printed hand with embedded force sensors. We tested the functionality of this system in a grasp quality experiment and a full teleoperation test. With feedback, users were able to differentiate between good and poor grasps with 95% and 74% accuracy respectively, and some reported detecting objects slipping from their grasp. In user testing with the full system, all users were able to complete a series of pick-and-place tasks with only 5 minutes of training, with an average time of under 50 seconds per task.**

## I. Introduction

Robotic systems are becoming indispensable on factory floors [1], in hospitals [2], and for space and ocean exploration [3][4]. As robots become stronger and more durable, they are replacing humans for remote or dangerous tasks. State-of-the-art autonomy is often not sufficient to handle tasks in unpredictable environments. As such, these tasks benefit from teleoperation systems in which a human remotely and safely controls the robot [5][6]. The success of these teleoperation systems depends on both the control method and the existence of feedback [7][8].

In this paper, we propose a novel teleoperation system using soft robotic principles, building on our previous work [9]. A data glove system captures user movements using inertial measurement units (IMUs) and custom curvature sensors that detect finger bending using the signal between an infrared LED and receiver. The user movements are used to control a 6 degree of freedom (DoF) robotic arm (Kinova Jaco) and five-fingered anthropomorphic hand. The robotic hand is equipped with soft force sensors that detect grasp forces, which are transmitted to the user through soft pneumatic actuators. The result is a safe and intuitive system that can be used with very little training (Figure 1).

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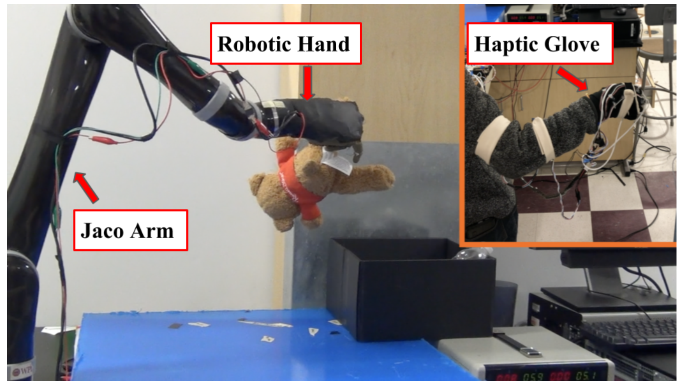


Fig. 1. In the proposed teleoperation system, a user wears the haptic glove and controls commercial 6-DoF robotic arm and a robotic hand as its end-effector.

### A. Existing Work

*1) Control Methods:* There are two main categories of control methods for teleoperation. One category uses small hand-held controllers such as joysticks, keyboards, computer mice, and touch screens [5]. Due to limited degrees of freedom, hand-held controllers pose a challenge when controlling robots with many degrees of freedom, such as robotic arms. In [10], joystick control of a robotic arm requires unintuitive mode changes between position, orientation, and gripping control.

The other category of controllers captures natural body movements to control a robot, resulting in a more intuitive system. Motion capture systems use cameras, body markers, and computer vision to detect user position [11]. While the measurements are accurate and the control seems intuitive, it results in a large, stationary, and expensive system. In contrast, data gloves are wearable devices that use sensors such as accelerometers and gyroscopes to track a users movement [12]. Data gloves are becoming an increasingly popular method of teleoperation for their potentially lightweight and portable form factors.

In [13], for example, the authors present a novel data glove using 18 IMUs to track a users arm and finger movements. The glove is relatively inexpensive and lightweight, but has several drawbacks. Firstly, the authors require that a users body stays stationary, which can result in an awkward user experience. Secondly, high-quality IMUs are expensive, and inexpensive IMUs are highly prone to drift. In contrast, our teleoperation system detects a user's palm position and orientation relative to their shoulder, allowing their body to adjust during teleoperation. In addition, using curvature sensors to measure finger positions reduces the number of IMUs to three.

Although controllers that capture users body movements seem more intuitive, [14] found that when relying solely on visual feedback, users performed better with the peg controller than with a data glove to control Cartesian pose of a non-anthropomorphic arm and end-effector for a peg-in-hole task. We hypothesize that when the controller more closely resembles a human body, users expect similar feedback sensations, such as touch, during the teleoperation experience.

*2) Feedback Methods:* Haptic feedback is an important aspect of an effective and usable teleoperation system [7]. There are several modes of haptic feedback, which vary in effectiveness depending on the application. Tactile feedback is transmitted using vibration, temperature, or pressure close to the skin and usually indicates initial contact with an object. Force feedback is transmitted by applying a force to a user's body and can indicate a resistive force, such as grasping an object [15]. In some cases, this force can stop a user's movement, for example by preventing their fingers from closing [16]. In others, the user's movements are not hindered by the force [17]. Force feedback is an effective way to transmit quality-of-grasp to a user, and enhances grasp stability and allows for more delicate manipulation [8].

In [18], the authors present the RML glove, used to control a mobile robot. As the robot approaches an object, the user's finger movements, which control the speed of the robot, are limited to prevent collisions of the robot with other objects. Another glove, presented in [19], uses three servos to provide 3-DoF feedback to one fingertip. In both these cases, the force feedback method is bulky and expensive. Additionally, attaching tendons to a users fingers poses a risk of injury if the system pulls the user's fingers past their comfort level. Our proposed force feedback method is pneumatically driven using very low pressures, making it a lightweight and safe alternative.

The ExoPhalanx [16] is a haptic glove that uses a shape memory alloy (SMA) driven brake to stop the user's fingers from bending once they pass a given threshold. This device is soft, wearable, and non-bulky, but locks the users fingers into a fixed position while transmitting feedback. Another glove, proposed in [20], uses soft inflatable chambers under the user's fingers to provide initial contact feedback. Our proposed system detects and relays contact for the duration of a grasp, enabling more accurate object manipulation.

Table I compares our current teleoperation system with many of the systems described above. We chose parameters that are important to a teleoperation system, such as weight, cost, time to learn, and capability. Some of the papers did not report pick-and-place test times, and others did not perform a pick-and-place task.

### B. Contributions

We present a novel teleoperation system that controls a 6-DoF robotic arm with an attached anthropomorphic robotic hand using an intuitive control scheme and safe force feedback. The system is lightweight (213g), inexpensive (less than $150), and user friendly, while still being effective. Using principles of soft robotics, it accurately reads external grasping forces and safely transfers them to a user. Our specific contributions are as follows:

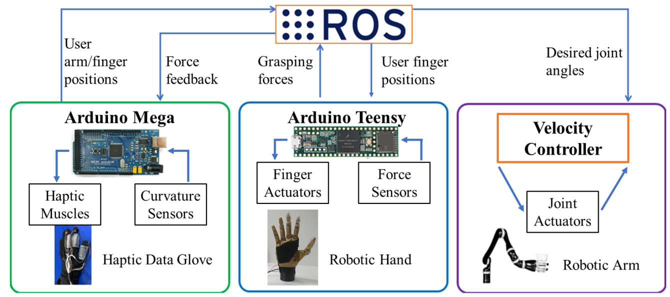


Fig. 2. The teleoperation system consists of three main subsystems connected through ROS (Robot Operating System). The haptic glove captures user movements and ROS passes this data to the Jaco arm and robotic hand. The robotic hand captures grasp forces which are passed back to the haptic glove.

1) Pneumatic haptic muscles that are lightweight, safe, and provide realistic kinesthetic feedback to a user.
2) Soft magnetic force sensors embedded in a compliant robotic hand used for teleoperation.
3) Custom optical curvature sensors that accurately detect finger curvature in a lightweight, cost-effective form factor.
4) An intuitive teleoperation system based on IMUs where the user may move freely and comfortably during operation.

In the remainder of this paper, we will present the system overview (II), design and validation of each subsystem (III), and user testing (IV).

## II. System Overview

The proposed teleoperation system consists of three major subsystems: a custom-built haptic glove worn by the user, a commercially available robotic arm, and a 5-fingered robotic hand mounted to the arm's end effector. The three subsystems are connected through ROS (Figure 2), which passes information across the whole system.

The haptic glove reads the user's hand position and orientation relative to their shoulder, as well as the curvature of their fingers. The pose is converted to joint angles for the robotic arm, and the finger curvatures map to joint angles on the robotic hand. As the user moves their arm and fingers, the robotic arm and hand mirror the user's movements.

The robotic hand contains soft force sensors at the fingertips that detect grasp forces during teleoperation. These forces are converted to signals that activate pneumatic actuators mounted to the haptic glove. As the actuators inflate, the user experiences a grasp sensation that mirrors the robotic hand's forces.

The system as a whole offers the user a telepresence experience, in which the movements and sensations of the robot system are directly associated with their own.

## III. Subsystem Design

### A. Haptic Glove

The haptic glove is a soft wearable glove system with sensors and actuators for data collection and force feedback. It consists of curvature sensors, IMUs (Adafruit BNO055),

| Name | Teleoperation Method | Feedback Method | Weight of Glove | Cost | Training Time Given | Avg Time to Complete Pick-And-Place |
|---|---|---|---|---|---|---|
| Joystick Modal Change [21] | Joystick | Visual Only | N/A | Not Reported | 5 minutes | ∼450s |
| Inertial Motion Capture [11] | CyberGlove, IMUs, Motion Capture | Visual Only | 540g | ∼$13,000 | Not Reported | Not Reported |
| IMMU Data Glove [13] | IMUs | Visual Only | >110g | $200 | Not Reported | Not Reported |
| RML Glove [18] | Exoskeleton with Encoders | DC Motor and Cable System | 180g | Not Reported | 5 minutes | N/A (Not Pick-And-Place) |
| ExoPhalanx [16] | Cyberglove, Motion Capture | SMA Brake | >540g | >$13,000 | Not Reported | N/A (No Pick-And-Place Performed) |
| CICG [22] | Commercial Data Glove, IMUs | Vibration Motors | 300g | ∼$3,500 | N/A | Not Reported |
| Electro-Tactile Teleoperation [23] | P5 Virtual Reality Glove | Electro-tactile Feedback | 28g | >$250 | 5 minutes | Not Reported |
| Pneumatic Haptic Glove (this work) | Custom Data Glove, IMUs | Pneumatic Haptics | 213g | <$150 | 5 minutes | 50s |

TABLE I
COMPARISON OF TELEOPERATION SYSTEMS

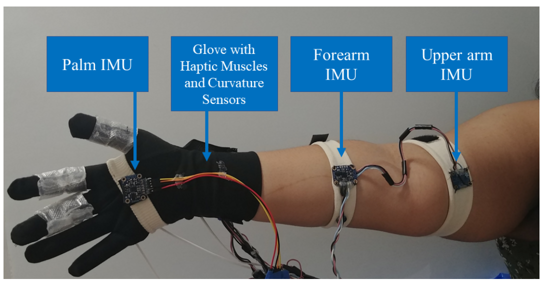


Fig. 3. The haptic glove system consists of curvature sensors and haptic muscles mounted to the glove and three IMUs secured with adjustable bands. The IMUs are placed on the user's palm, forearm, and upper arm.

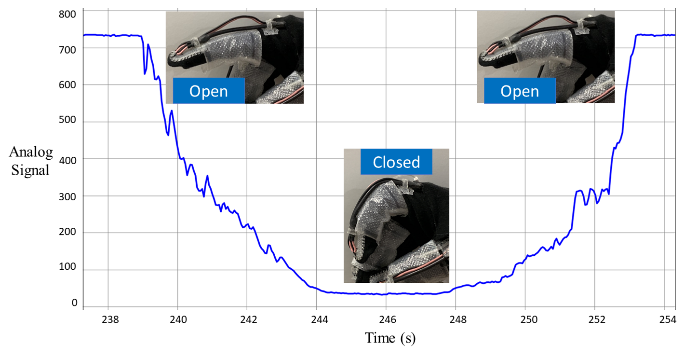


Fig. 4. When the user's finger is straight, light from the LED reaches the receiver, resulting in a high signal. As the user gradually curves their fingers, the light is blocked, resulting in a low signal. This provides an accurate reading of the user's finger curvature.

and pneumatic haptic muscles. The IMUs mount to the user's palm, forearm, and upper arm with adjustable bands and report the relative angles of the user's arm and wrist (Figure 3).

*1) Curvature Sensors:* To detect the curvature of the user's fingers, we use optical curvature sensors mounted to the fingers of the haptic glove. Each sensor contains an infrared LED and receiver connected by a black tube to block external light. When the user's finger is straightened, the LED and receiver are directly facing each other and the signal from the receiver is high. When the user's finger is curled, the signal is low, as shown in Figure 4. Because there is no resistive component to this sensor, the readings do not suffer from drift and other inconsistencies. We map the signal from each finger to a corresponding finger position on the robotic hand, thus mirroring the user's movements.

*2) Haptic Muscles:* The goal of our feedback system is to be as realistic as possible when conveying grasp forces. When a person picks up a cup, their fingers are prevented from closing past the cup's surface. This force that prevents a person's fingers from curling further is what the haptic muscles replicate.

The haptic muscles are pneumatic actuators manufactured from heat sealable plastic. The plastic is cut and sealed into a pouch, then rolled into a toroid shape to fit around the user's fingers. When deflated, the haptic muscles do not hinder the user's movements, as the plastic is fairly soft. As they inflate around the user's fingers, they exert a gentle force that straightens the knuckle and feels similar to the force exerted by a real grasped object (Figure 5. By regulating the pressure with solenoid valves and pulse-width modulation (PWM) control, we apply varying levels of pressure (from 0 to 5psi) to indicate a weaker or stronger grasp.

To measure the force exerted on a user's fingers, we mounted a haptic muscle to a 2-link 3D-printed finger with a freely rotating joint, and tied the fingertip to a load cell as shown in Figure 5(b). As we pressurized the haptic muscle by increasing the PWM input, the finger attempted to straighten and pulled on the string, applying a measurable force on the load cell. Figure 5(c) shows the force versus PWM values for one cycle of increasing and decreasing pressure. Because increasing the pressure involves pushing air into the actuator, and decreasing pressure lets the air leak into the atmosphere, the haptic muscle deflates slower than it inflates, causing the observed hysteresis. Given the results from User Study 1 (Grasp Quality Test) presented in Section IV, it is clear that this discrepancy is not noticeable during operation. Both the increasing and decreasing pressures were accurate enough to communicate grasp quality to the users.

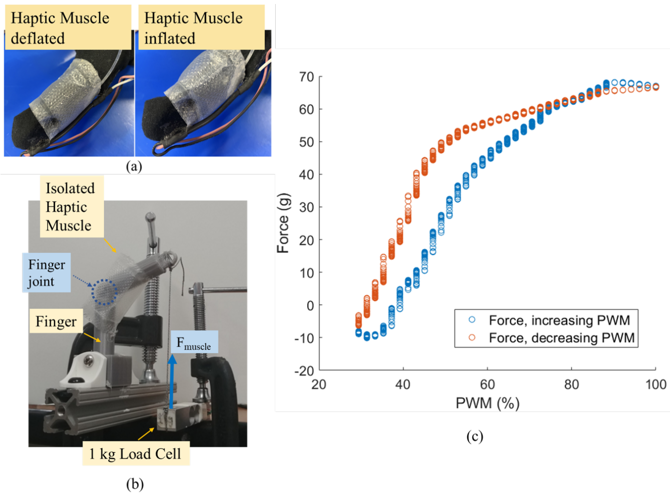


Fig. 5. (a) The deflated haptic muscles (left) are soft and do not hinder user movement. When inflated (right), they tighten around the user's finger and apply a gentle restoring force. (b) To measure the change in force from the muscle given a change in PWM signal, we tied the end of a 2-link 3D-printed finger to a load cell and incremented the PWM signal over time. When the muscle is deflated, the finger remains bent. When it inflates, the finger tries to straighten and pulls the string, applying an upward force on the load cell. (c) As the PWM signal is increased (blue) and decreased (orange), the force correspondingly increases and decreases.

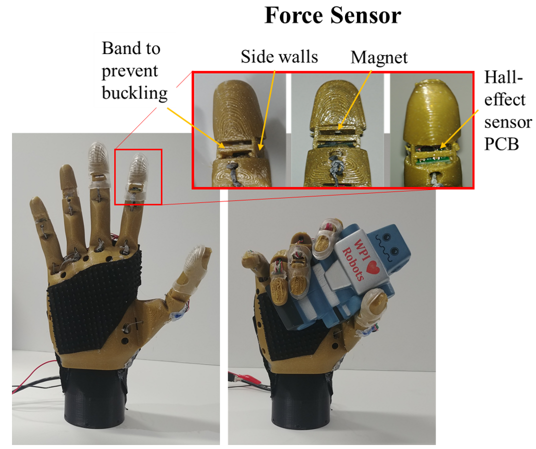


Fig. 6. Our 5-fingered anthropomorphic hand is printed out of PLA (black) and flexible Ninjaflex (gold). Embedded in each finger is a soft force sensor consisting of a Hall-Effect sensor and a magnet. As the fingers encounter grasping forces, the magnet shifts relative to the Hall-Effect sensor. Reading these shifts provides force measurements in three axes.

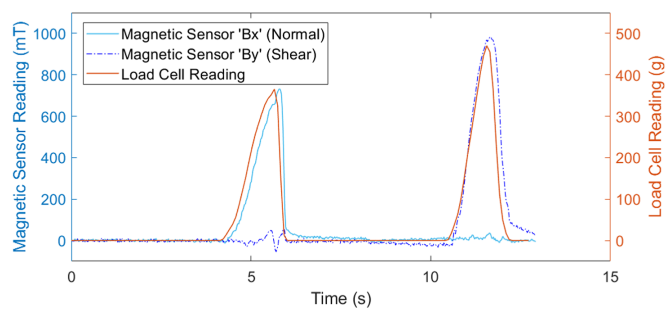


Fig. 7. Pushing the front of the fingertip in the normal direction against a load cell results in a linearly related change in force between the load cell and normal force. The result is similar when the side of the fingertip is pushed against the load cell in the shear direction.

## *B. 5-fingered Robotic Hand*

*1) Hand design:* The 5-fingered anthropomorphic robotic hand (Figure 6) is a modified version of the Open Bionics V1.1 Ada Hand, an open-source 3D-printable hand used as a research platform for prosthetic hands. The back of the hand is printed in PLA, while the palm and fingers are printed in Ninjaflex, a flexible filament produced by Ninjatek. The softer palm gives the hand some compliance while grasping, and the flexible hinges in the fingers allow for an underactuated tendon-driven system with realistic motions. Because the fingers are partially compliant, they conform to many object shapes without needing to account for various grasp types. Therefore, it is possible to grasp many different objects using only a few grasp motions. This decreases the complexity for the user, and the complexity of the system as a whole.

The hand uses four linear actuators (Actuonix PQ12-R) to flex its fingers: one each for the first, second, and third fingers, and one for both the fourth and fifth fingers. The fingers extend passively when tension is removed from the tendons.

*2) Soft Force Sensors:* We modified the original Ada hand for our teleoperation requirements by adding soft force sensors at the fingertips. These sensors, shown in Figure 6, are located in a small chamber embedded in the fingertip. At the bottom of the chamber is a custom PCB (developed in [24]) with a 3-axis hall-effect sensor, and at the top is a small magnet. As the finger tip deforms, the magnet moves in the x, y, or z direction, causing a change in the magnetic field read by the hall-effect sensor. As this deformation is caused by an external force on the fingertip, we can use this sensor to measure the relative force on each fingertip from grasping objects.

The sensor chamber has 2 walls on the left and right sides, and on the front and back a small ninjaflex band connecting the walls to prevent buckling (Figure 6). This geometry results in high stiffness in the normal direction and low stiffness in the shear direction. This was ideal for our purposes, as we wanted the normal direction to be strong enough to grasp heavy objects, and the shear direction flexible enough to still see a change in shear force when lifting lighter objects. In Figure 7, we pressed the tip of the finger against a load cell, first in the normal direction (front of the fingertip) and then in the shear direction (side of the fingertip). Due to the geometry of the hand and how it grasps objects, the shear force was much higher than the normal force during real grasping applications, so we chose to use the shear force to drive the haptic feedback.

## *C. Teleoperation Scheme*

To demonstrate the usability of our robotic hand and haptic glove, we designed a teleoperation scheme using the Kinova Jaco arm. The goal is to build an intuitive mapping between the Jaco arm (6 DoF) and the human arm (7 DoF). Existing work on teleoperating the Jaco arm falls into three main categories: teleoperation with a handheld device [10], teleoperation with motion sensors [25], and teleoperation with visual interface [26], [27]. In our previous work, we experimented

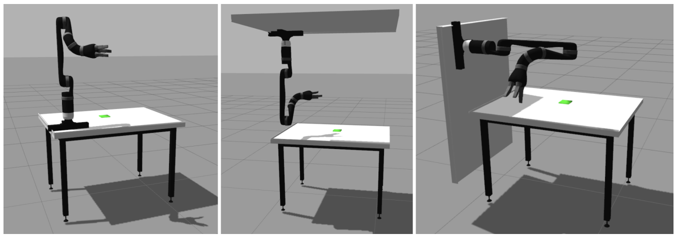

Fig. 8. We tested four teleoperation schemes using three mounting points in simulation (Gazebo). Users played a game in which they attempted to reach a given end-effector pose and orientation (green) as quickly as possible.

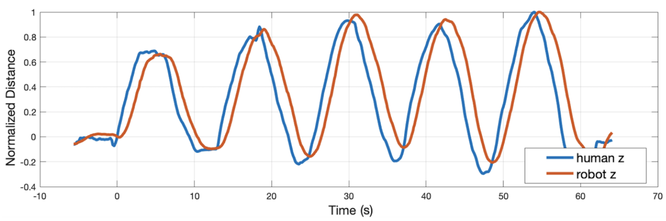


Fig. 9. To calculate the latency of teleoperation, we teleoperate the robot in one axis and find the time difference between the robot and user's highest and lowest points. The calculated latency is 1.07s.

with joint-to-joint mapping of Jaco arm, which requires users to limit their own motion because the Jaco has fewer DoF. In this work we explore end-effector (ee) mapping.

From a pilot study run in simulation testing various configurations and teleoperation schemes (Figure 8), we found that mounting the Jaco upright on the table was the easiest to use. We also found that ee mapping is fairly intuitive, since the user focuses more on the ee than the pose of the robot. We thus apply an end-effector mapping scheme to the physical robot using a table-top mounting position.

Since we have a different robotic hand from the Jaco arm's original gripper, Jaco's default inverse kinematic (IK) solver is no longer applicable. To solve the current IK, we use the $trac\_ik$ package [28] with a modified robot definition file to fit our needs. In our pilot study, sttesting with IMUs mounted to a user's arm, we found that separating the position and orientation for solving IK resulted in fewer invalid solutions. The first three joints of the Jaco arm are used to analytically calculate position and the last three joints are used to iteratively calculate orientation. After we have the joint angle solutions, the lower level control of joints is based on joint velocities for smoother results. A complete process of this IK mapping is described in the pseudocode in the Appendix.

To validate the teleoperation scheme and quantify possible delays, we collected data while teleoperating the arm to move up and down. Figure 9 compares the human and robot's trajectory along the z-axis. The robot's trajectory reaches further than the human's trajectory because of the extended length of the robot's wrist and hand. The robot trajectory follows the human trajectory with a time delay of 1.07 seconds, which is primarily caused by limited joint velocities, which were set for safety reasons. We set the first three joints velocity limits to 10 degrees/s and the last three joints velocity limits to 50 degrees/s.

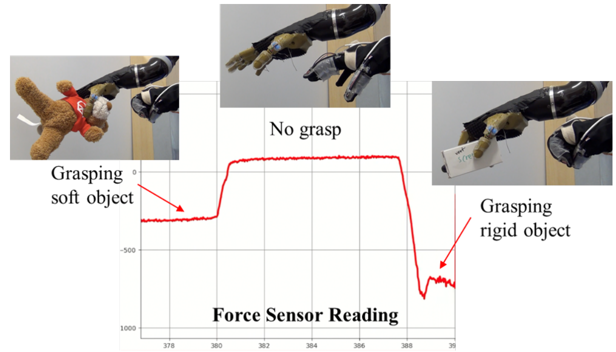


Fig. 10. When grasping a soft object, the force sensor reading is noticeably smaller than when grasping a rigid object.

## IV. Experiments

### A. Teleoperation with Grasp Detection Validation

To validate the functionality of the force feedback, we experimented with grasping both soft and rigid objects while plotting the force sensor readings from the hand. Figure 10 shows that as the robot's fingers contact the object, the magnitude of the force sensor readings increases. When grasping a rigid box, the force sensor readings are noticeably larger than when grasping a soft teddy bear. Additionally, the signal is more disturbed and we observe a peak at the start of grasping. This is due to the dynamics and compliance of the soft force sensors. When grasping a rigid object like the box, the sensors impact the object quickly, causing the first signal peak. Then, any small movements within the sensors or of the object result in observable signal changes. When grasping something soft like the teddy bear, the sensors sink into the object and experience less of an impact. After grasping, random movements of the object/finger are absorbed by the object and we see a smooth signal. These results show a potential to distinguish between soft and rigid objects during teleoperation.

### B. User Study I: Grasp Quality

We devised an experiment using only the data glove and the robotic hand to test the system's ability to convey grasp quality with the soft force sensors and haptic muscles. A user wore the haptic glove and looked at a computer screen, which showed live footage of a table surface. One of the authors held the wrist of the robotic hand, and the user could see the hand and some objects on the screen. The author placed the robotic hand over an object so the object was partially or fully occluded, the user closed their fingers to grasp the object, and we asked them whether the grasp was good or bad. After 1 to 3 minutes of practice, we recorded the true grasp quality and whether the user's guess was correct or incorrect. We repeated this test for four objects both with and without haptic feedback, performing a total of 12 grasps per object (6 with and 6 without feedback). We then turned off the camera to test a user's ability to determine grasp quality using only the pneumatic feedback. During the blind test, we asked users to rate the grasp between 1 and 3, where 1 was a poor grasp, 3 was a strong grasp, and 2 was a medium grasp, where the object would slip if a small disturbance was applied. Each

| | No Haptic Feedback | With Haptic Feedback |
|---|---|---|
| **Good Grasp, Correct** | 66/91 (72.53%) | 97/102 (95.1%) |
| **Good Grasp, Incorrect** | 25/91 (27.47%) | 5/102 (4.9%) |
| **Bad Grasp, Correct** | 54/106 (50.94%) | 71/96 (73.96%) |
| **Bad Grasp, Incorrect** | 52/106 (49.06%) | 25/96 (26.04%) |

TABLE II
GRASP QUALITY TEST WITH VISUAL FEEDBACK

| | Reported Grasp Quality | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| **Actual Grasp Quality** | | | |
| 1 | 49 | 23 | 10 |
| 2 | 2 | 11 | 14 |
| 3 | 2 | 8 | 61 |

TABLE III
GRASP QUALITY TEST WITH NO VISUAL FEEDBACK

object was grasped 6 times for this test. In all tests we tried to maintain an even balance of good and bad grasps.

### *C. Results of User Study I*

The results of the two experiments are presented in the Tables II and III. For the first test using the camera, we found that without feedback, users were able to identify good grasps 73% of the time and poor grasps 51% of the time. With feedback, they correctly identified good grasps with 95% accuracy and poor grasps with 74% accuracy. Users also responded more quickly and confidently with the feedback, and reported that without the feedback they were randomly guessing for many of the trials.

For the blind test, users were 60% accurate at identifying poor grasps and 86% accurate at identifying good grasps. They were also fairly accurate at reporting a middle-level quality of grasp; when users said the grasp was a two, the grasp turned out to be either a one or a two 81% of the time. For both a one or a two grasp, the object slipped at some point during the grasp, either upon initial lifting or after the object was lifted and experienced a small disturbance. Users were more likely to label a middle-level grasp as a 1 than a 3, which is ideal for teleoperation purposes.

During these tests, some users reported feeling an object slipping from their grasp, which highlights the capabilities of the soft force sensors as well as the haptic muscles. The soft sensors were able to detect slippage, and the corresponding pressure decrease in the haptic muscle conveyed the slip to the user.

### *D. User Study II: System Teleoperation*

To test the intuitive nature of the teleoperation system and effect of feedback on the entire system, we performed user testing with a series of pick-and-place tasks. Users were told to pick up a given object and place it in a nearby box as quickly as possible. After giving each user five minutes of practice time to become accustomed to the system, we tested them with five objects, each with and without haptic feedback, for a total of ten tasks. The five objects were a soft teddy bear, a robot-shaped stress toy, a paper cup, a cardboard box, and an empty plastic water bottle. These ten tasks were randomized

Fig. 11. To test our system, users picked up 5 randomly ordered objects, each with and without feedback, and placed them in a box. Objects are placed on the table one at a time.

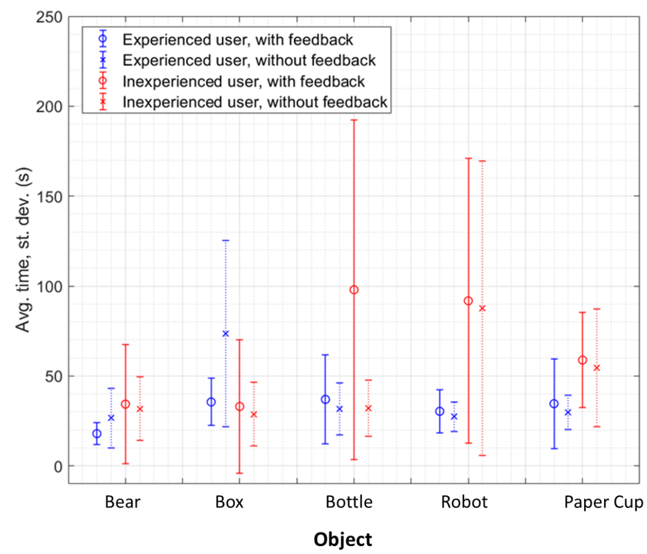


Fig. 12. User study results with/without feedback for experienced user and inexperienced user. The center point is the average time to complete the pick-and-place task for an object, and the error bars represent the standard deviation among users.

to account for user learning during the test, and the position and orientation of each object were kept constant for all trials. We recorded the time required to complete each task, starting from when we told the user to begin and ending when the object landed in the box.

*1) Results of User Study:* During the user study, all subjects completed every task. In the presented data, we define an inexperienced user as someone who was introduced to the system for the first time during user testing. An experienced user had worked with the system during development or for previous publications, and had about 30 minutes to 2 hours of practice before user testing. Analysis of the experienced and inexperienced user's data showed that subjects' teleoperation skills improve with practice.

When analyzing the time taken for tasks with and without haptic feedback, we found significant differences between the inexperienced and experienced users. The average task completion times were greatly reduced for some objects, as were the standard deviations. We also observe that in the experienced users, 2 objects benefited from the haptic feedback and the other objects had similar average times. The inexperienced users struggled more with controlling the robotic arm, so the benefits of the haptic feedback are less visible. The average time to complete a pick-and-place task for all users was 50 seconds.

## V. Discussion and future work

In this paper, we discuss the development and testing of a novel data glove with pneumatic feedback for intuitive teleoperation. The glove uses a combination of IMUs and optical curvature sensors to determine the user's hand and arm pose, and maps this to the position of a robotic arm and hand. The hand is equipped with soft hall-effect force sensors that provide force feedback to the user through pneumatic haptic muscles on the glove.

Through user testing, we found that the system is intuitive and usable with very little training. With only 1 to 3 minutes of training, users were able to use the haptic feedback to accurately judge grasp quality and object slipping. Additionally, both experienced and inexperienced users were able to complete a a total of 10 pick-and-place tasks with objects of various shapes and sizes, taking an average of 50 seconds per task.

One of the challenges in quickly completing the pick-and-place task was the configuration of the hand. The thumb is not opposable, and thus approaches objects at an angle. This makes grasping more difficult, as without practiced finger coordination the thumb can easily misalign the objects. This can be addressed in the future by adding an additional degree of freedom to the thumb, allowing users to adjust the angle of their grasp as desired.

The success rate of all users in completing pick-and-place tasks, as well as the accuracy of grasp quality detection, proves the effectiveness of our system. The next step in this project is to increase the capability of the robotic hand and explore different modes of feedback to add to the haptic glove. There is also potential to convey object size and stiffness, which would significantly improve a user's capacity to perform increasingly complex tasks.

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## VI. Appendix

**Algorithm 1** Teleoperation based on end-effector mapping with separated position and orientation

**Input:** Upper arm, Lower arm, and Wrist IMU readings.
**Output:** Joint angles of the Jaco arm.

```
Initialization :
Initialize IK and FK solvers, IMUs, and the joint velocity controller. Home the Jaco arm.
while not terminated by user do
    Get current robot joint angle readings, get current IMU readings.
    Calculate first three joints :
    Calculate human wrist position with upper arm length, lower arm length, upper arm IMU reading, and lower arm IMU reading.
    Map human wrist position to robot workspace to get robot ee position.
    Solve first three joints with robot ee position (analytical solution).
    Calculate last three joints :
    Calculate robotic hand ee orientation with wrist IMU reading and rotation matrix from human palm to robotic hand palm.
    Transfer robotic hand ee orientation from robot base frame to Jaco's third joint's frame with FK calculated from joints 1-3.
    Solve for last three joints in joint 3 frame with trac_ik solver.
    Send results to joint velocity controller :
    if first three joints and last three joints have solution then
        Send the target joint position to joint velocity controller.
    else
        Send zero velocities.
    end if
end while
return Joint angles of the Jaco arm.
```