Wrapping Haptic Displays Around Robot Arms to Communicate Learning

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***Abstract*—Humans can leverage physical interaction to teach robot arms. As the human kinesthetically guides the robot through demonstrations, the robot learns the desired task. While prior works focus on how the robot learns, it is equally important for the human teacher to understand what their robot is learning. Visual displays can communicate this information; however, we hypothesize that visual feedback alone misses out on the *physical connection* between the human and robot. In this paper we introduce a novel class of *soft haptic displays* that wrap around the robot arm, adding signals without affecting interaction. We first design a pneumatic actuation array that remains flexible in mounting. We then develop single and multi-dimensional versions of this wrapped haptic display, and explore human perception of the rendered signals during psychophysic tests and robot learning. We ultimately find that people *accurately distinguish* single-dimensional feedback with a Weber fraction of 11.4%, and identify multi-dimensional feedback with 94.5% accuracy. When physically teaching robot arms, humans leverage the single- and multi-dimensional feedback to provide better demonstrations than with visual feedback: our wrapped haptic display decreases teaching time while increasing demonstration quality. This improvement depends on the location and distribution of the wrapped haptic display. You can see videos of our device and experiments here: https://youtu.be/yPcMGeqsjdM**

***Index Terms*—Haptic Display, Learning from Demonstration, Tactile Devices**

I. Introduction

Imagine teaching a rigid robot arm to clean objects off a table (see Figure 1). One intuitive way for you to teach this robot is through *physical interaction*: you push, pull, and guide the arm along each part of the task. Of course, the robot may not learn everything from a single demonstration, and so you show multiple examples of closing shelves, removing trash, and sorting objects. As you kinesthetically teach the robot you are faced with two questions: i) has the robot learned enough to clear the table by itself and ii) if not, what features of the task is the robot still uncertain about?

While existing work enables robots to learn from physical human interaction [1]–[4], having the robot effectively provide *real-time feedback* to human teachers remains an open problem. Ideally, this feedback should not be cumbersome or distracting (i.e., the human must be able to focus on seamlessly guiding the robot) and should be easily interpretable (i.e., the human must be able to clearly distinguish between different signals). These requirements present a tradeoff as human fingertips provide the densest mechanoreceptors, but placing

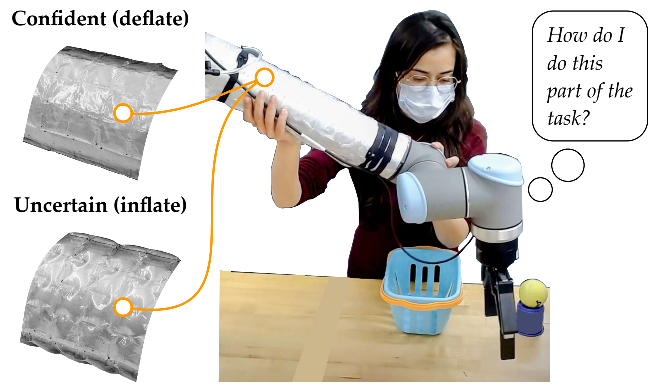

Figure 1. Human physically teaching a robot arm. We wrap a soft pneumatic display around the arm and render haptic signals by controlling the pressure of the display. The robot learner leverages this haptic display in real-time to communicate the parts of the task that it is confident about, as well as the parts where it is uncertain and needs additional guidance.

rigid devices at the hand will impact task performance. Recent research has created communication channels by instead wrapping *haptic devices* around the human's arm [5]–[7], but locating feedback at unrelated locations on the human's body can create a disconnect with the task.

Our insight is that — instead of asking the human teacher to wear a feedback device or watch a computer monitor —

We can take advantage of the preexisting physical contact between the human and robot through slim form-factor soft haptic displays that wrap *around the robot arm.*

Accordingly, in this paper we develop and analyze wrapped haptic displays for communicating robot learning based on soft robotic principles. We distribute these soft displays along rigid robot arms so that the human can physically interact with the robot to demonstrate a task while simultaneously perceiving the robot's feedback. We actively control the *pressures* of the pneumatic display to render where in the task and what features of the task the robot is *uncertain* about: the display inflates for regions and features of the task where the robot is unsure about its actions (and needs additional human teaching), and deflates where the robot is confident about the task (and does not need any additional human guidance). Our hypothesis is that — because the soft wrapped display creates a channel for communication on any surface without impacting the task — humans will be able to more intuitively and robustly use this feedback with a greater level of focus compared to other feedback modalities. We experimentally demonstrate that this pressure-based feedback enables humans i) to determine whether the robot has learned enough to be deployed and ii) to identify parts of the task where kinesthetic teaching is still required. Additionally, we demonstrate the importance of the location and distribution of the feedback on the robot arm for creating this improvement.

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Parts of this work were previously published in [8], which presented the experimental results for our one degree-of-freedom (DoF) haptic display. This current paper builds on that initial research by demonstrating the design, analysis, and application of *multi-DoF* spatial signals localized or distributed along the robot arm. Here we also present follow-up analysis for the psychophysics of the 1-DoF device. Overall, we make the following contributions:

Developing Wrapped Haptic Display. We design and build a compliant pneumatic haptic device that wraps around and conforms to the robot, providing haptic stimuli that are localized to the robot arm and distributed along its geometry. This device is manufactured using soft, flexible pouches that render haptic signals through pressure.

Measuring User Ability to Perceive Wrapped Displays. We perform a psychophysics study to find the range of pressures that humans can distinguish. We report the just noticeable difference (JND) for pressures rendered by the soft display.

Applying Wrapped Displays to Communicate Learning. We ask participants to kinesthetically teach a robot arm while the robot provides real-time feedback about its learning. We map the robot's uncertainty to the pressure of our wrapped display. When compared to a graphical user interface, rendering feedback with our wrapped haptic display leads to faster and more informative human teaching, and is subjectively preferred by human teachers.

Extension on Wrapped Displays to Multiple Degrees of Freedom. We extend and generalize the wrapped display design to create multi-degree of freedom displays. These displays can be configured to fit different robotic manipulator geometries and to change the interconnections between degrees of freedom.

Measuring Effect of Display Distribution on User Perception. We perform a psychophysics study to understand how the spatial distribution of the wrapped haptic display signals affects the accuracy and speed of signal identification. We demonstrate a tradeoff between speed of identification and accuracy as signals are spread further apart.

Measuring Effect of Display Distribution of Multi-Degree of Freedom Displays for Communicating Learning. We repeated kinesthetic teaching with three degree of freedom displays, confirming that users still improve demonstrations over baseline as signal complexity increases. When comparing different options to distribute feedback in 3-DoF displays, users performed better with and subjectively preferred wrapped display layouts where all feedback was displayed the small area where contact was already occurring instead of distributed in larger areas along the robot arm.

II. Related Work

In this paper we introduce a wrapped haptic display for communicating robot learning in real-time during physical human-robot interaction. We build on previous research for kinesthetic teaching, haptic interfaces, and soft displays.

Kinesthetic Teaching. Humans can show robot arms how to perform new tasks by physically demonstrating those tasks on the robot [1]–[4]. As the human backdrives the robot, the robot records the states that it visits and the human's demonstrated actions at those states. The robot then learns to imitate the human's actions and perform the task by itself [9]. One important output of the learning process is the robot's *uncertainty* about the task. The uncertainty can be measured as the robot's *overall* confidence in *what* to do at different states [10], [11], or also include measuring the robot's confidence on *how* to perform the task [12]–[15]. In this paper we explore how robots should *communicate* their learning uncertainty back to the human teacher. Keeping the human up-to-date with what the robot has learned builds trust and improves teaching [16]. Outside of physical human-robot interaction, prior research has developed multiple non-haptic modalities to communicate robot learning and intent: these include robot motion [17], graphical user interfaces [18], projections into the environment [19], and augmented reality headsets [20]. Within a teleoperation domain, our recent work suggests that *haptic interfaces* are particularly effective at communicating low-dimensional representations of robot learning [6]. Here we will leverage these results to develop a real-time feedback interface *specifically for* kinesthetic teaching.

Haptics for Information Transfer. When considering using haptic signals for communicating features of robot learning, the type of information being transferred is important to consider. While haptic devices have a general goal of stimulating the human sense of touch, haptics has also previously been applied to communicate *robot intent* or similar social features. For instance — when studying how humans and robots should interact in shared spaces — prior works have used haptics to explicitly convey the robot's intended direction of motion or planned actions [5], [21]–[23]. Recent work has shown that, given appropriate context, complex human-to-human social touch signals, like stroking [24], [25], hugging [26], dancing [27], and emotional communication [28]–[30], can be replicated and understood in a wearable format. Some other work has shown the use of haptic interfaces for high information tasks, like assisting navigation, by rendering patterns with a certain meaning, such as direction guidance or identification of points of interest [31]. Lastly, work has shown communicating alerts with different urgency levels in car driving settings [32], [33] and communicating contact events in teleoperation and AR/VR through hand-held devices with haptic feedback [34], [35]. These past works suggest that a wide range of social and collaborative information can be transferred using haptics with appropriate design of the interface and signals.

Soft Haptic Devices. Soft haptic devices offer an attractive option for human-robot communication due to their compliance and adaptability, either through the *flexibility* of the interface or the *compliance* of the actuators themselves. Soft haptic displays have been shown with a range of compliant actuation types: pneumatic actuation [36], [37], shape memory alloys [25], dielectric elastomers [38], and fluidic elastomers [39]. Soft devices can target smalls areas of stimulation. Soft wearable fingertip devices have successfully targeted a range of stimuli in the skin [40], such as vibrations [41]–[43], indentation [44]–[46], skin-stretch [47], [48], or some combination of those [49]–[52]. Soft haptic approaches scale easily to increased areas of stimulation; work on developing haptic surfaces out of arrays of actuators and sensors show scaling to fit varied areas. These developments have typically used rigid elements embedded in cloths and silicone layers to create bi-directional interfaces that can cover large areas: actuation has included NFC electronics [53], thin-metal film strain sensors [54], and piezo films [55]. These rigid elements can limit the flexibility of the device, and lead to issues with wear over time and comfort. Some tabletop haptic displays have used pneumatically actuated soft composite materials [56] or combined particle jamming and pneumatic actuation [57] to control the shape and mechanical properties of surfaces, leading to highly complex signals and comfortable interaction.

Soft haptic interfaces also easily support a range of device types distinguished by the method of interaction: graspable, wearable, or touchable [58]. This method of interaction can have a large impact on the usability of the devices. Many haptic interfaces are designed to be wearable. Fingertip worn devices serve as an obvious choice for providing high fidelity and interpretable signals [40], [43], [49]. These devices are popular for virtual reality where physical contact with the real world is unlikely but in other applications they can reduce the user's ability to use there hands during the target task. This motivated wearable devices for body areas other that the fingertip, such as hand dorsal [59], [60], wrists/forearms [25], [36], [37], or gloves that cover the whole hand [61]. Placing haptic signals *directly on the human body* enables the human to move about the space while receiving real-time feedback; but as feedback is moved away from the fingertip and physically separated from the task it potentially requires additional mental energy to decode the intended message. A different approach has focused on developing touchable haptic surfaces consisting of arrays of actuators and sensors [53]–[55]. These devices use the fingertip mechanoreceptors without burdening the user's hands. Soft touchable displays allow installation of haptic interfaces in common touch areas, like car steering wheels [32]. While not a haptic display, recent work showed pneumatic actuators wrapped around robot arms to visualize the weight load carried by the robot [62]. Based on this past work, we target a touchable device placed at the point of human-robot interaction, and use soft pneumatic actuation to maximize the flexibility and transparency of the display.

III. Developing a Wrapped Haptic Display

We first aim to design a soft haptic display that can be wrapped around a robot arm, conforming to the surface and effectively adding a haptic interface to existing points of contact between the human and robot. This section describes the identification of three critical requirements for the design of the haptic displays (low volume, fast inflation, and textured surface). With these requirements in mind, we outline two designs of wrapped haptic displays built on the same underlying principle. We first discuss the design of a simple 1-DoF display with a large area for contacting the device. Then, we discuss how the lessons learned from the 1-DoF device were used to create a more complex N-DoF design, consisting of multiple reduced width "ring" sleeves placed side by side in a smaller area than the first 1-DoF sleeve design. Finally, we describe the implementation of these wrapped haptic displays in the experimental setting.

A. Requirements

While designing the wrapped haptic display concept we considered three key requirements, linked both to the operation and to improving the haptic sensation: low volume, fast inflation, and textured surface. First, we wanted to design a display that would clearly show inflation without using either large volumes of air or large volumes of static materials. This requirement is linked to keeping the haptic display flexible enough to easily wrap around target objects like the robot arm and to limiting the effect the display had on the users interaction with the surface, especially when deflated. Limiting the volume of air that the display holds also helps with the requirement for fast inflation and deflation. This is an important design feature since fast transitions between inflation levels would allow for faster changes in the signals that the display is producing. An additional requirement was to create an inflatable surface that would produce textured tactile sensations. Our hypothesis is that a textured surface would help users to quickly identify pressure changes in the display since there are more surface features to explore with their hands. Since the target application of the wrapped haptic display is robot learning, an additional design constraint was the need to fully wrap the display around robot arms without constraining motion or impairing demonstration.

B. Soft Haptic Display Concept

To summarize our requirements, the goal was to conceptualize a soft haptic display that is relatively flat and conformed to a surface while not actuated, but that features low volume, fast inflation, and textured surface when actuated. To pursue this concept, we use thin heat-sealable and relatively inextensible materials that can be formed into air-tight pouches. These pouches are then heat-sealed with patterns to generate a textured surface and constrict the volume of the bag when inflated. Initial testing showed that having a single inflatable pouch without heat-sealing to add texture did not provide enough surface change to assist users in identifying pressure changes, as well as being slow to inflate. Additionally, while initially being flat when deflated, these pouches generated a large restorative moment against bending when inflated, making it difficult to wrap them around objects. Adding heat sealed patterns subdivides the bag, limiting the volume, adding additional texture, and allowing the overall surface to remain flexible when inflated and deflated. The final soft wrapped haptic display design consists of an array of 2.54 cm square-shaped cells patterned into a low-density polyethylene (LDPE) plastic tube using a linear heat sealer (H-89 Foot-Operated Impulse Sealer, ULINE). The cells are interconnected to allow for smooth and fast inflation of the array via a pattern of gaps in sealing. A repeated and homogeneous pattern across the entire length allowed for even and reliable inflation of the display. If the pattern was not homogeneous, we found that issues such

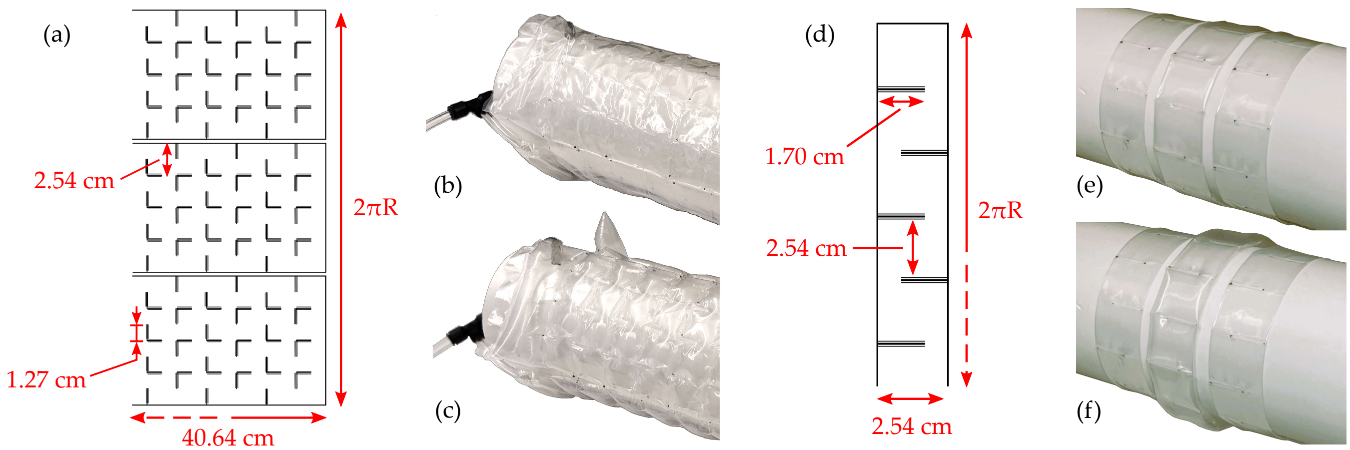

Figure 2. Overview of the soft wrapped haptic display design. (a) Detailed view of square-cell array implemented in the 1-DoF sleeve display. The thick lines indicate places where the LDPE plastic tube was heat-sealed. The sleeve is composed of 3 pouches taped together to form a sleeve with circumference $2\pi R$. The sleeve display is shown (b) deflated and (c) inflated. (d) Detailed view of the square-cell array implemented in the 1-DoF ring display. Grouping multiple individually-actuated pouches, placed side by side, forms a N-DoF wrapped haptic displays. A 3-DoF ring display is shown in two states: (e) deflated and (f) one of the DoF (center) is actuated, while the others are deflated.

as superfluous contraction and unintentional airflow blocking would stop some cells from inflating consistently. The square-array design is shown in Figure 2 in two form factors. The dimension and shape of the display can be varied to fit different applications and conform to varied surfaces. A unit of a soft wrapped haptic display consists of one or more patterned pouches attached to the same pressure source, forming a single degree of freedom (1-DoF) and multiple degrees of freedom can be attached together to form an N degree of freedom (N-DoF) display. Given this general descrption of the soft haptic display, we will next describe the specific 1-DoF and 3-DoF displays that were used in experimental testing.

C. Large Surface Display

We first experimented with a simple 1-DoF display with a large surface area for humans to interact with. The 1-DoF soft wrapped haptic display is made from a set of three connected pouches made from a 10.16 cm flat-width LDPE plastic tube (S-5522, ULINE). The plastic tube was cut to fit the length of one of the sections of a UR-10 robotic arm (40.64 cm). As previously mentioned, the square pattern was manufactured into the LDPE tube using a heat sealer. The sealed lines are 1.27 cm long, alternated in rows and columns to create the 2.54 cm-squares. Figure 2(a) shows the design with the dimensions in more detail. Through-wall straight connectors (5779K675, McMaster-Carr) were attached to one of the sides of each bag strip to allow for individual inflation. The circumference of the robot arm segment ($2\pi R$) was found to match the width of three bags placed side by side, as shown in Figure 2(a). The display was made of three bags taped together using viscoelastic adhesive tape (MD-9000, Marker Tape) to construct a sleeve that entirely wrapped the cylindrical surface. The bags were then connected using tee-adapters to inflate the three bags using a single pressure line, essentially creating a 1-DoF soft wrapped haptic display in the shape of a sleeve. Tests showed that the 1-DoF soft wrapped haptic display can be inflated quickly; pressures above 1.5 psi (10.43 kPa) inflate the display in 0.86 seconds, and it can variate inflation pressure from 1 to 3 psi (6.89 to 20.68 kPa) in 0.72 seconds, and deflate back to 1 psi in 0.18 seconds. The display can operate to a maximum of 3.5 psi (24.13 kPa). Above that pressure the heat-sealed edges begin to tear, producing leaks.

D. Multi-Degree of Freedom Display

We next aimed to increase the signal complexity while maintaining the design requirements by building on the design of the 1-DoF display. We did this by grouping multiple individually-actuated pouches placed side by side, forming a N-DoF wrapped haptic display, as shown in Figure 2(d) and (e). For this design, each of the pouches consisted of a 2.54 cm flat-width LDPE plastic tube (S-11155, ULINE), cut to fit the circumference ($2\pi R$) of varied segments of a target segment on a robot arm. This way, the length of the pouch guaranteed that the haptic display fully wrapped around the cylindrical surfaces of the segments, forming a ring-shaped soft wrapped haptic display. The pattern is modified from the one used in the 1-DoF displays to better fit the available off-the-shelf LDPE tubing. The 2.54 cm square cell grid was achieved by heat sealing 1.7 cm long lines across the length of the tube, alternating sides as shown in Figure 2(c). The pattern allowed ring displays to conform to a cylindrical surface better, while providing a textured surface and restriction of excessive inflation. Silicon tubing (0.66cm OD) was attached to an end of the individual ring display to inflate. For the studies described in Sections VI and VII, three ring displays were placed side by side. The ends of the displays were taped with a 1.9 cm separation between each. Grommets were placed in the ends of the group of displays, and elastic bands tied the device around the cylindrical surface. The separation between pouches is intended to assist in making the identification of each easier. This design allows the rendering of multiple signals in a smaller area than the 1-DoF sleeve design. For example, N ring displays can be placed in a single location to render N individual signals. Individual actuation of ring displays in sequences can further increase the complexity of haptic signals rendered by a set of N-ring displays. Since the N-DoF display covers a smaller area, it is easier to mount it in different places of the robot arm. The geometry of

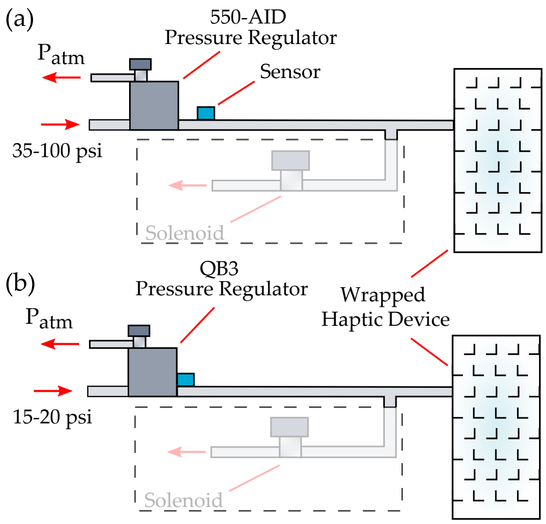

Figure 3. The actuation of the soft wrapped haptic displays consisted of (1) a pressure regulator that supplied an electronically controlled pressurized-air supply and (2) a pressure release feature for deflating the displays. (a) Pneumatic arrangement implemented for the studies described in Sections V and VII, which uses a 550-AID pressure regulator and an electronic pressure sensor. (b) Pneumatic arrangement implemented for the studies described in Sections IV and VI, which uses a QB3 pressure regulator, which has an integrated pressure sensor. In both cases, if faster switching between inflation and full deflation is needed, on-off solenoid valves can be implemented.

Figure 4. Experimental Setup. The participants were instructed to sit in the desk right in front of the curtain and put on hearing protection headphones.

these ring displays influenced its actuation performance when compared to the 1-DoF sleeve design. Since the width of these displays (and therefore their radius when inflated) is small, they have smaller volume when inflated and resist higher pressures, therefore producing faster inflation/deflation speeds. These ring-shaped soft wrapped haptic displays can be inflated to pressures above 1.5 psi (10.43 kPa) in 0.55 seconds, and withstand a maximum of 5 psi (34.48 kPa). This design also allows for faster variations in inflation pressure, switching from 1 to 3 psi (6.89 to 20.68 kPa) in 0.38 seconds, and deflate back to 1 psi in 0.12 seconds.

E. Implementation

As mentioned in Subsections III-C and III-D, the haptic displays were mounted on cylindrical surfaces for the studies outlined in the remainder of this work, either sections of the robot arms or a PVC pipe acting as a passive stand-in. The mounting arrangements fixed the wrapped display in place, restricting it to less than 10% contraction. Figure 3 shows the basic pneumatic control systems used to actuated the wrapped haptic displays. In summary, the implementation of the actuation was (1) a pressure regulator that supplied an electronically controlled pressurized-air supply and (2) a pressure release feature for deflating the displays. Two different electronically controlled pressure regulators were used for the studies described in this paper. A pressure regulator (QB3, Proportion-Air, McCordsville, Indiana) was used for the studies outlined in Sections IV and VI. The regulator was controlled using an Arduino Uno via MATLAB. The Arduino sent analog signals to the pressure regulator, which provided accurate pressure values needed for the studies. This pressure regulator has a built-in sensor and exhaust line. For the user studies described in Sections V and VII, a pressure regulator (550-AID, ControlAir, Amherst, New Hampshire) was controlled using either the UR-10's I/O controller or an Arduino Uno. This pressure regulator does not have a built-in sensor, but does have an exhaust line. The inflation pressure was measured using an electronic pressure sensor (015PGAA5, Honeywell Sensing, Gold Valley, Minnesota). For both of the pressure regulators, we initially used on-off solenoid valves (ASCO Z134A, Emerson, St. Louis, Missouri) to switch the air supply and allow air to escape for deflation. The exhaust valves in the pressure regulators are not capable of deflating the display to zero-volume, but just to zero-pressure leaving some air in the display. However, since the experiments did not involve complete deflation of the haptic displays, we determined solenoid valves were not needed. If faster switching between inflation and full deflation is needed, on-off solenoid valves can be implemented. It is important to note that each 1-DoF device (either the 1-DoF sleeve or the individual rings in the 3-DoF display configuration) are connected to individual pressure supplies. For the case of the 3-DoF display, one can configure the device to effectively act as a 1-DoF device by connecting the individual rings to a single pressure, or have 3-DoF control if three pressure regulators are used.

IV. Measuring Human Perception of 1-DoF Wrapped Haptic Displays

Understanding the human sensory perception of the soft display, especially as it compares to rigid haptic displays, is essential in determining how to apply and control the wrapped haptic display. To that end, we conducted a psychometric user study to measure the basic ability to distinguish touch sensations outside of the context of the target application scenario and to obtain qualitative data of how users perceive the display. Participants physically interacted with the 1-DoF display and were asked to distinguish between pairs of pressures. We focused on studying the user's ability to differentiate pressure inflation levels in the display to understand the minimum pressure differential that can produce clear haptic signals.

A. Experiment Setup

The 1-DoF inflatable haptic display was mounted on a PVC pipe of identical diameter to the UR-10 used in Section V. The pipe was placed lying flat and secured to a table. As shown in Figure 4, we placed a curtain to block the user's vision and instructed users to wear hearing protection to ensure the perception study was focused entirely on tactile sensations.

The study was conducted as a forced-choice comparison where participants were asked to identify the higher pressure. The pressures were shown in pairs (i.e., reference pressure, P_o, vs. test pressure, P) to the user, distinguished as "Pressure 1" and "Pressure 2". We selected 2 psi (13.79 kPa) as the reference pressure, and the test pressure values of 1.5, 1.75, 1.875, 2.0, 2.125, 2.25, and 2.5 psi (10.34, 12.07, 12.93, 13.79, 14.65, 15.51, and 17.93 kPa) since these pressures are a safe range of pressures for the operation of the display. Each pressure was compared against the reference ten times. We randomized the order in which the P_o and P pairs would be shown to the participant, as well as the order in which the reference and test pressure would be shown in each pair. We also showed the reference pressure against itself to measure bias on whether participants preferred choosing the first or the second pressure when unsure.

The participants were instructed to sit at the desk, positioned in front of the curtain, and put on hearing protection headphones. Before beginning the experiments, we demonstrated the display function to the participants by inflating the display to three pressure levels and allowing them to interact with it. Each experimental trial started by inflating the display to the selected "Pressure 1". Once the display reached a steady-state, constant pressure, the participants were asked to touch and interact with the display for an unrestricted period of time and then release it. There was no restriction on how the participants could grasp or touch the display; however, they were allowed to interact only while the device had a constant pressure. Then, the display was inflated to "Pressure 2". Again, the participants were asked to touch the display and then release it. Once they interacted with both pressure levels, we asked which one felt like a higher inflation pressure. The subjects were not told the correct answers during the experiment. This procedure was then repeated until all pairs of pressures were tested ten times. Since seven different pressures were tested against the reference pressure, we had a total of 70 pairs in the study.

After completing the interaction portion of the experiment, the participants were given a post-experiment questionnaire. The questionnaire asked about the overall experience during the study (clarity of instructions, sense of safety during the experiment) and about their previous experiences and familiarity with haptic technology, robotics, and video games. The entire experiment took approximately 35 minutes, with an optional break after the first 35 experimental pairs.

B. Results

A total of 10 participants (5 female or nonbinary, average age 20.6 years, age range $18-23$ years) participated in this experiment after giving informed consent. Out of the group, 9 participants were right-handed, and 1 was left-handed. The Purdue Institutional Review Board approved the study protocols. Figure 5 shows a single subject's responses to the experiment. Each dot shows the percentage of times the test pressure was selected as higher when compared against the reference pressure. The just noticeable difference (JND) was calculated by first fitting a sigmoid function to the data:

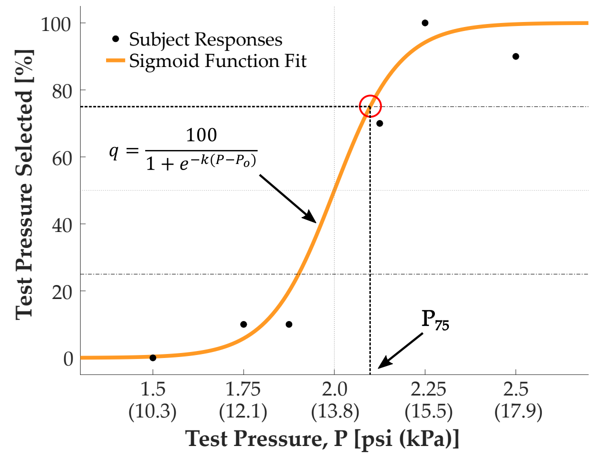

Figure 5. Raw data and sigmoid function fit for a single participant. The percentages represent the times this subject selected the test pressure, P, as higher. The JNDs were calculated using the sigmoid function to solve for the pressure value corresponding to the 75% threshold, and subtracting it from the reference pressure.

$$q = \frac{100}{1+e^{-k(P-P_o)}} \tag{1}$$

where q is the modeled percentage of times the user choose the test pressure (P) as higher, k is the steepness factor for fitting a sigmoid curve, P is the test pressure, and P_0 is the reference pressure. Using this fit, the JNDs are calculated by finding the pressure value corresponding to the 75% threshold, P_{75}, and subtracting the reference pressure, P_0:

$$JND = P_{75} - P_o = -\frac{1}{k} ln\left(\frac{100}{75} - 1\right) \tag{2}$$

Figure 6 shows the sigmoid function fit for each of the subjects, as well as the fit for the collection of responses from all subjects.

C. Analysis

The experimental results show that the k steepness factor for the overall sigmoid fit (shown as the orange line in Figure 6) was 4.678, with 95% confidence bounds between 3.605 and 5.751, giving a JND of 0.235 psi (1.62 kPa). Table I summarizes the JNDs for each of the participants. Individual JNDs ranged 0.099-0.444 psi (0.68-3.06 kPa). The mean JND was defined as the mean of the values obtained for all participants, which was found to be 0.228 psi (1.57 kPa), with a standard deviation of 0.109 psi (0.75 kPa). The Weber fraction (WF), calculated as the ratio of the JND and the reference pressure, ranged between 4.9% and 22.2%, with a mean value of 11.4%. Although there was no restriction on how the user could interact with the display, multiple users reported (via post-experiment questionnaire) using active interaction with the inflation to explore the display. This means that users explored reactive force sensing to explore the dynamics of inflation and determine how much pressure was used to inflate the display. Additionally, the users reported they mainly used their fingertips. Previous studies on fingertip

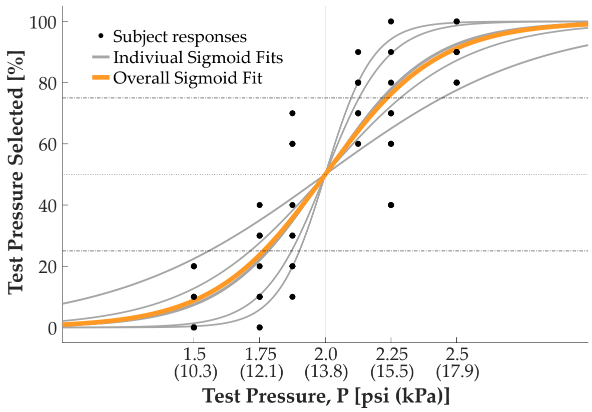

Figure 6. Sigmoid function fit for each of the subjects (grey), and the collection of responses from all subjects (orange). The dots represent percentages associated with individual subject responses. The k steepness factor for the overall sigmoid fit was 4.678, giving a JND of 0.235 psi. The individual steepness factors ranged 2.477-11.15, with JNDs varying between 0.099 and 0.444 psi (0.68-3.06 kPa).

Table I
EXPERIMENTAL RESULTS FOR PSYCHOPHYSICS STUDY.

Subject	k	JND (psi)	WF (%)
1	5.048	0.218	10.88
2	11.15	0.099	4.927
3	3.846	0.286	14.28
4	2.478	0.443	22.17
5	4.989	0.220	11.01
6	8.557	0.128	6.419
7	2.477	0.444	22.18
8	5.008	0.219	10.97
9	4.574	0.240	12.01
10	5.102	0.215	10.77
Mean	4.810	0.228	11.42
St Dev	2.524	0.109	5.431
Overall	4.678	0.235	11.74

psychophysics tests show similar values for JNDs and WF. Frediani and Carpi [63] conducted psychophysical tests for a fingertip-mounted pneumatic haptic display, reporting JNDs varying in the range of 0.12-0.33 psi (0.8-2.3 kPa) for driving pressure between 0.58 and 2.90 psi (4 and 20 kPa). The WF found for this experiment was 15%. Another study evaluating a haptic jamming display found fingertips WF to be 16% (σ = 7.4%) and 14.3% (σ = 2.6%) for stiffness and size perception, respectively [64]. A different study testing stiffness perception for a rigid vibrotactile, fingertip-mounted haptic device reported WF between 17.7 and 29.9% [65]. The results of this study demonstrate that our wrapped haptic display performs according to the psychometric baselines found in the literature. The JNDs and Weber fractions obtained show that the display produced detectable signals and matched previously developed rigid or soft haptic devices in performance.

As mentioned in Section IV-A, the reference pressure was shown against itself 10 times to the subjects to measure bias on whether users had a preference for choosing "Pressure 1" or "Pressure 2". Overall, the results showed that there was no bias on their choices. The subjects chose "Pressure 1" as the higher pressure 45% of the time, and "Pressure 2" 55% of the time. Two subjects had a large preference for choosing "Pressure 2" as the highest when shown this pair of identical pressures (80% of the time). Looking at the qualitative data, one of these subjects mentioned that they were unsure about their answers throughout the experiment, which may explain the discrepancy in their bias relative to the average bias shown by the complete pool of participants.

The qualitative data collected from the post-experiment questionnaire shows that, besides the participant already mentioned (who had the highest JND), no other participants struggled to identify the pressures. A majority of the participants (7 out of 10) mentioned that they could detect the differences and that they "more or less agree" or "completely agree" that they were sure about their answers throughout the experiment. Additionally, 9 out of the 10 participants said they felt safe interacting with the haptic display. It is also worth noting that the subjects with the highest correctness rates when comparing pressures mentioned they have dexterity-related hobbies or skills. For example, subject 2, who had the smallest JND and Weber fraction, mentioned that they play multiple string musical instruments. This activity requires them to vary contact pressure, which explains their high performance in the experiment. Other hand-related activities mentioned by high-performing participants include knitting, piano playing, and American Sign Language proficiency.

This study shows that the sensations produced by our wrapped haptic display match the psychometric measures for other haptic devices. The fingertip JNDs were in close agreement with those found in the literature. Additionally, qualitative data showed that users felt safe interacting with the display. The users were able to distinguish pressure changes without a specific task context and visual feedback. The qualitative and quantitative data show that the wrapped display fulfilled the requirements outlined in Section III-A. Overall, we demonstrated that the soft wrapped haptic display can perform as well as other haptic devices (both rigid or soft) in displaying tactile signals without encumbering interaction.

D. Follow-Up Study

As timing became a significant factor during the later studies in Sections V-VII, a follow-up study was conducted, replicating the wrapped haptic display experimental procedure with the addition of a graphical user interface (GUI). The purpose of the GUI was to enable participants to control the pace of the experiment without the influence of the experimenter. The GUI allowed for accuracy in recording the time spent by the user exploring each pressure. By evaluating time, we can better understand later result on timing and difficulty of interpreting haptic signals.

A total of 12 participants (6 female or nonbinary and 6 male, average age 21.9 years, age range 21 - 23 years) participated in the follow-up experiment after providing informed consent. Due to technical difficulties in data collection, 2 participants were removed from the study. 1 additional participant was excluded from analysis as an outlier since they performed equivalently to guessing. Of the remaining 9 participants, 7 were right-handed, and 2 were left-handed.

The results show a JND of 0.279 psi (1.923 kPa). Individual JNDs ranged 0.114-0.674 psi (0.788-4.650 kPa), with a mean JND of 0.310 psi (2.136 kPa) and standard deviation of 0.173 psi (1.195 kPa). The WF ranged between 5.7% and 33.7%, with a mean value of 15.5%. These findings are consistent with those of the initial study.

Participants spent an average of 13.84 seconds on the first pressure (σ = 7.323 seconds), an average of 11.27 seconds on the second pressure (σ = 5.746 seconds), and an average of 25.11 seconds per pressure pair (σ = 10.855 seconds). By one-way ANOVA, total time spent per pressure pair was found to significantly impact correctness ($p = 0.024$). Subjects answering incorrectly spent significantly more time on average assessing the haptic device than when answering correctly. In particular, participants spent an average of 26.84 seconds assessing the pressure when answering incorrectly, and an average of 24.56 seconds when answering correctly. Notably, it was determined that mean time itself did not have a significant influence on overall accuracy ($p = 0.973$).

V. Applying Wrapped Haptic Displays to Communicate 1-DoF Robot Uncertainty

So far we have studied the precision with which humans can perceive the 1-DoF wrapped haptic display. Next, we apply this display to convey robot learning from physical interactions. In this experiment, participants kinesthetically teach a UR-10 robot arm to perform a set of cleaning tasks. We apply an existing learning algorithm to measure the robot's uncertainty [11] and then convey that uncertainty back to the human in real-time. We highlight two key differences from the experiment in Section IV: the robot arm is *moving during interaction* (i.e., the wrapped haptic display is not stationary), and the haptic display *now conveys a specific signal* that the human must interpret and react to during interaction. We recognize that — because participants are now interacting with a moving robot arm — they will experience both the forces they apply to the arm and the pressure rendered by the haptic display, which will also be changing to represent uncertainty. We anticipate this will make changes in pressure easier to recognize compared to the perception study, where participants interacted with constant signals.

Independent Variables. We compared three different types of feedback (see Figure 7):

- A graphical user interface (**GUI**) that displayed the robot's uncertainty on a computer monitor.
- Our soft haptic display placed **Flat** on the table.
- Our proposed approach where we **Wrapped** the haptic display around the robot arm.

All three types of feedback showed the same information but used different modalities. Within the **GUI** baseline we displayed uncertainty on a computer screen that was located in front of the user. Here uncertainty was shown as a percentage, where numbers close to 0% meant that the robot was certain about that specific part of the task, and numbers close to 100% indicated that the robot was uncertain about what it had learned. The **Flat** and **Wrapped** interfaces used the 1-DoF soft haptic display from Section III. Uncertainty was linearly

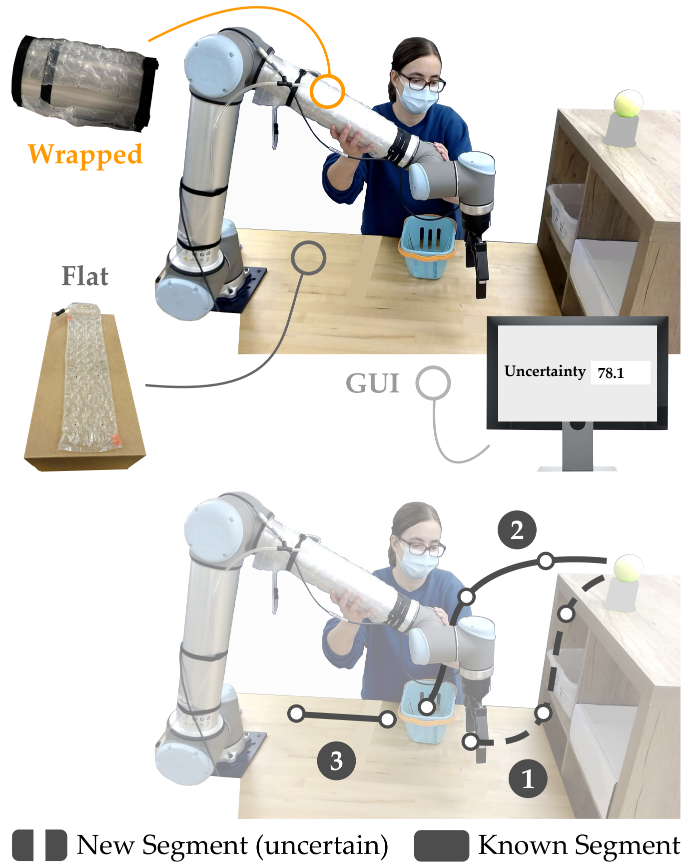

Figure 7. Participant kinesthetically teaching the robot arm the *Cleaning* task. (Top) We compared our proposed approach (**Wrapped**) to two alternatives. **GUI** displayed the robot's uncertainty on a screen, while in **Flat** we placed the haptic display on table. (Bottom) We initialized the robot with data from known segments. During their first demonstration the human attempted to identify the region where the robot was uncertain (i.e., the new segment). The human then gave a second demonstration where they only guided the robot through the region(s) where they thought it was uncertain.

scaled on the haptic display from $1-3$ psi ($6.89-20.68$ kPa). Here 1 psi (deflated bags) corresponded to 0% uncertainty and 3 psi (inflated bags) corresponded to 100% uncertainty. The **Flat** haptic display was placed in a designated area next to the human, such that participants could periodically touch it while guiding the robot.

Experimental Setup. Participants completed three different tasks with each of the three feedback conditions (i.e., nine total trials). In the *Organizing* task participants were asked to guide the robot to close a drawer, pick up a ball, and then place the ball in the basket. In the *Shelving* task participants kinesthetically taught the robot to close a drawer and then pull an empty container from the shelf. Finally, in the *Cleaning* task participants taught the robot to pick up a ball from the top of the shelf, place it in the basket, and drag the basket to a marked location (Figure 7 shows *Cleaning* task).

Before conducting any experiments we first initialized the robot's uncertainty. We collected five expert demonstrations of each task and trained the robot with a behavior cloning approach [11]. This approach outputs the robot's uncertainty at each state (i.e., uncertainty was a function of the robot's joint position). We purposely *removed* segments of the expert's demonstrations from the training set: specifically, we trained

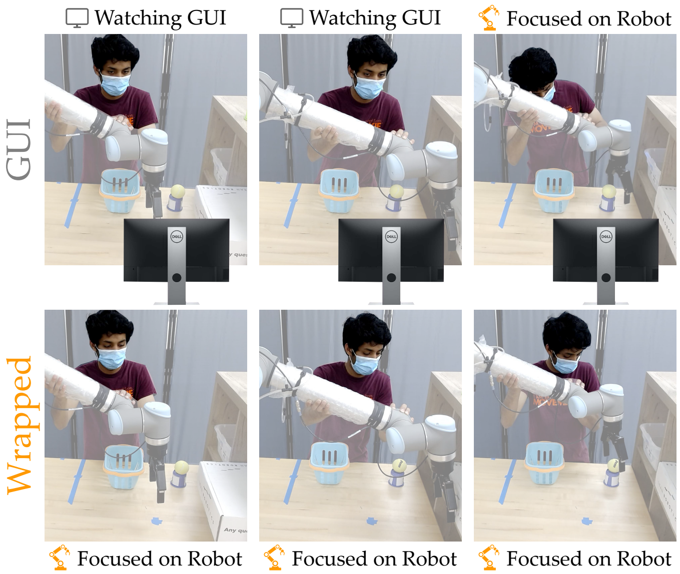

Figure 8. Participant teaching the same task under two different feedback conditions. (Top) When working with **GUI**, participants must occasionally look at the visual interface to monitor the robot's uncertainty. (Bottom) Wrapping the feedback around the robot arm enables the human to seamlessly teach the robot without having to remember to check an external interface.

the robot without showing it how to perform either the first segment or the last segment of the task. As a result, when participants interacted with the robot, the robot was uncertain about either the start or the end of the task.

For each trial the participant provided *two demonstrations*. First, the participant kinesthetically guided the robot throughout the entire task while receiving real-time feedback from **GUI**, **Flat**, or **Wrapped**. Based on this feedback, the participant attempted to identify the region of the task where the robot was uncertain (and needed additional teaching). During the second demonstration, the human *only taught the segment* of the task where they believed the robot was *uncertain* (i.e., the region they identified in the first demonstration). If the feedback is effective, participants should only reteach segments where the robot is confused without repeating parts of the task that the robot already knows.

Participants and Procedure. We recruited ten participants from the Virginia Tech community to take part in our study (5 female, average age 22.9 years, age range $19-26$ years). All subjects provided informed written consent prior to the experiment. Only one participant had prior experience physically interacting with a robot arm. Before starting the trials, we allowed participants to familiarize themselves with each task and feedback method. We used a within-subject study design: every participant interacted with all three feedback conditions. To mitigate the confounding effect of participants improving over time, we *counterbalanced* the order of the feedback conditions (e.g., different participants start with different feedback types).

Dependent Measures – Objective. Our objective measures were based on the user's *second demonstration* (i.e., the demonstration where they tried to reteach the uncertain part of the task). We recorded the amount of time users spent on this second demonstration (*Teaching Time*) and the percentage of this second demonstration that overlapped with the segment where the robot was actually uncertain (*Correct Segment*). Offline, we retrained the robot using the participant's second demonstration. We then measured the percentage reduction in uncertainty due to the user's demonstration (*Improvement*). Let U_1 be the robot's uncertainty after the first demonstration, and U_2 be the uncertainty after the second demonstration. Here $\textit{Improvement} = \frac{U_1 - U_2}{U_1} \cdot 100$.

Dependent Measures – Subjective. Participants filled out a 7-point Likert scale survey after completing all three tasks with a given method. Questions were grouped into six multi-item scales: was the user able to recognize parts they needed to repeat (*informative*), did the robot's feedback have any effect on the user's ability to demonstrate the task (*easy*), was the user able to fully *focus* on teaching the task, did the robot's feedback seem *natural* to the user, did the user find robot's feedback *intuitive* and understandable, and did the user *prefer* this current feedback method to the alternatives.

Hypotheses. We had two hypotheses for this user study:

> **H1.** *Participants will most efficiently teach the robot with wrapped haptic displays.*
>
> **H2.** *Participants will subjectively prefer our wrapped haptic display over other methods.*

Results – Objective. We report our aggregated results in Figure 9 and show an example interaction in Figure 8.

We first ran a repeated measures ANOVA, and found that the robot's feedback type had a statistically significant effect on *Teaching Time*, *Correct Segment*, and *Improvement*. Post hoc analysis revealed that participants spent less time teaching the robot with **Wrapped** than with either **GUI** or **Flat** ($p < .05$). Participants also better focused their teaching on the region where the robot was actually uncertain: **Wrapped** resulted in a higher *Correct Segment* than **Flat** ($p < .05$). However, here the differences between **Wrapped** and **GUI** were not statistically significant ($p = .287$).

Recall that *Improvement* captures how much more confident the robot is about the task after the participant's demonstration. This metric is especially important: we want to enable humans to teach robots efficiently, and *Improvement* quantifies how much the robot learned from the human's teaching. We found that the robot's confidence improved the most in the **Wrapped** condition as compared to either **GUI** or **Flat** ($p < .05$). Overall, these results support **H1**: when users get real-time feedback from a haptic display wrapped around the robot arm, they provide shorter duration kinesthetic demonstrations that more precisely hone in on the robot's uncertainty and efficiently correct the robot.

To better explain why **Wrapped** outperformed **GUI**, we show an example interaction in Figure 8. Notice that — when the feedback was not located on the robot arm — participants had to periodically turn their attention away from the task to check the robot's uncertainty. For **Flat**, this required taking a hand away from the robot and feeling the haptic display on the table; for **GUI**, participants had to look up and check the computer monitor. The key difference with **Wrapped** is that this haptic display is located at the point of interaction, so

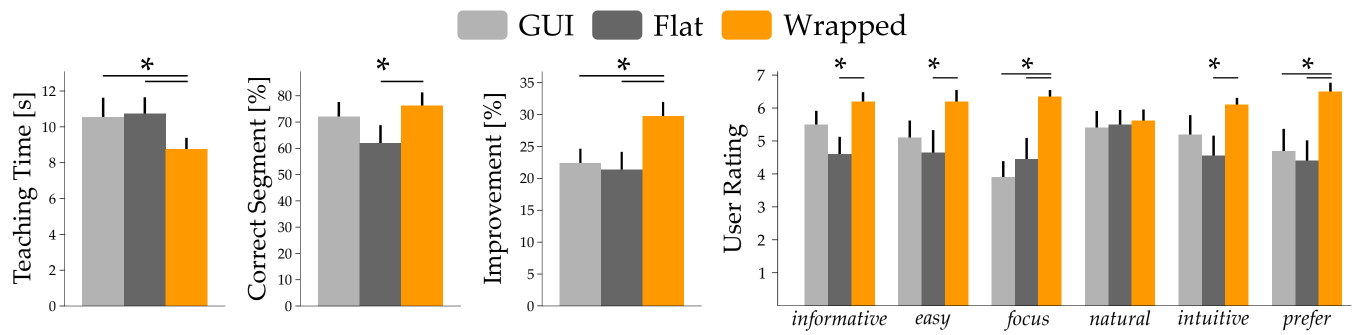

Figure 9. Objective and subjective results when communicating 1-DoF robot uncertainty in real-time with **GUI**, **Flat**, and **Wrapped** feedback. Participants taught the robot three tasks; we here report the aggregated results across tasks. Error bars show standard error of the mean (SEM), and $*$ indicates statistically significant comparisons ($p < .05$). (Left) Wrapping the haptic display around the robot arm caused participants to spend less time teaching the robot, focused their teaching on regions where the robot was uncertain and improved the robot's understanding of the task after the human's demonstration. (Right) Participants thought that the wrapped display best enabled them to focus on the task, and they preferred this feedback type to the alternatives.

participants could experience feedback while still remaining focused on the task and their physical demonstration.

We were initially surprised that — although users with **Wrapped** and **GUI** scored similarly for *Correct Segment* — the results for *Improvement* were significantly different. However, we believe the explanation for this lies in the quality of the participants' demonstrations. Returning to Figure 8, we recognize that with **GUI** participants often had to pause and check the uncertainty, breaking up their demonstration (and causing the demonstration to include multiple stops). Our subjective results support this explanation: as we will show, participants reported that they were more distracted with **GUI** than with **Wrapped** feedback.

Results – Subjective. Figure 9 depicts the results from our Likert scale survey. After confirming that our six scales were reliable (using Cronbach's α), we grouped these scales into combined scores and ran a one-way repeated measures ANOVA on each resulting score.

Participants perceived each of the feedback methods as similarly natural. But post hoc analysis showed that participants thought that **Wrapped** was more informative, easier to interact with, less distracting, and more intuitive than either one or both of the alternatives ($p < .05$). Participants also indicated that they preferred **Wrapped** over **GUI** and **Flat**. When explaining this preference, one participant said, *"I definitely prefer **Wrapped** over other methods. I was able to clearly focus and the other methods were distracting."*. Our subjective results support **H2**, and indicate that users perceived wrapped haptic displays as preferable when compared to alternatives like visual interfaces.

VI. Measuring Human Perception of 3-DoF Wrapped Haptic Displays

Having explored the human perception and application of the 1-DoF wrapped haptic display in the shape of a sleeve, we next pursue a study that will expand to a multi-degree of freedom display and help us understand how the spatial distribution affects the perception of multiple-DoF soft haptic displays. Both temporally and spatially varying signals can help us add complexity when we need to communicate multiple haptic signals within the space that a human might contact. We also seek to understand how the spatial distribution of signals might affect the effectiveness of the display in terms of accuracy of identification and the time needed to identify signals. To do so, we conducted a user study to measure the ability to distinguish haptic signals in different spatial distributions and outside of the context of the target application scenario. We select pressure levels considering the psychometric baselines (JNDs) obtained in Section IV, and designed a study in which participants physically interacted with 3-DoF displays. The displays were arranged in two ways: (1) a 3-DoF ring display placed in a single location, and (2) three 1-DoF displays, made up of three rings each (by interconnecting the individual rings) and placed at three different locations. We called these arrangements **Global** (for the 3-DoF display), meaning all information was available at the single point of contact, so it would be "globally" available, and **Local** (for the three 1-DoF displays), meaning the information for each degree of freedom was only available locally. In each display, the user was asked to identify the signal with the highest pressure out of the three, and we hypothesized that distribution of the signals (whether three in a single location or spread over a distance) would affect performance. As a note, these same methods are later used in the experiment in Section VII, but there three of the **Global** displays are used instead of one to keep the total area of the display on the robot constant and allow different users to contact at different locations based on preference while still receiving the same feedback.

A. Experiment Setup and Procedure

The 3-DoF wrapped haptic displays were mounted on passive stand-ins. For the **Local** method, three stand-ins with a 3-DoF configured as a 1-DoF each were placed on the table, with a separation in between each. For the **Global** method, a single stand-in with a 3-DoF display was used. Both methods essentially have 3-DoF, but the difference is the spatial distribution of each of the degrees of freedom; for **Global**, all signals are located in a small space, while for **Local** the signals are distributed in a 1 m space. The three degrees of freedom were named *Left*, *Center*, and *Right*, for both methods. The setups are illustrated in Figure 10. Participants were instructed to wear hearing protection and safety glasses

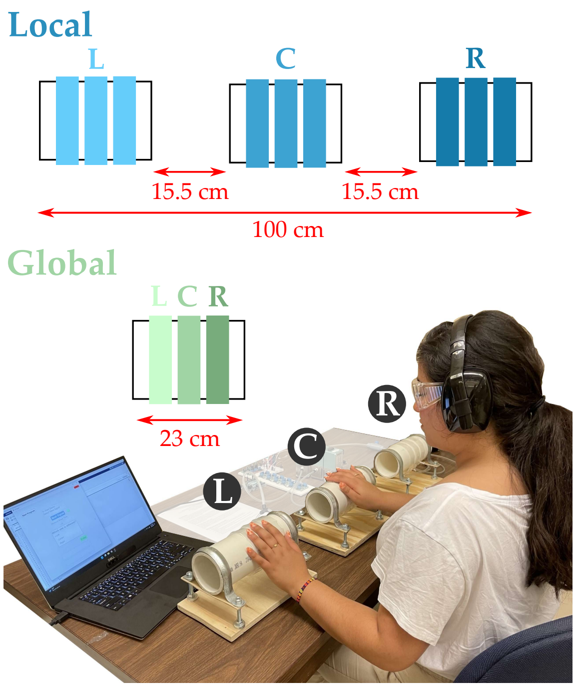

Figure 10. Experimental Setup. (Top) The **Local** setup consists of three sets of 3-DoF displays configures as 1-DoF each, with a separation in between each. (Middle) The **Global** setup consists of a single 3-DoF display. Both methods essentially have 3-DoF, but the difference is the spatial distribution of each of the DoF. The three DoF were named *Left*, *Center*, and *Right*, for both methods. (Bottom) Participants were instructed to sit in front of the setup; here we show a participant interacting with the **Local** setup.

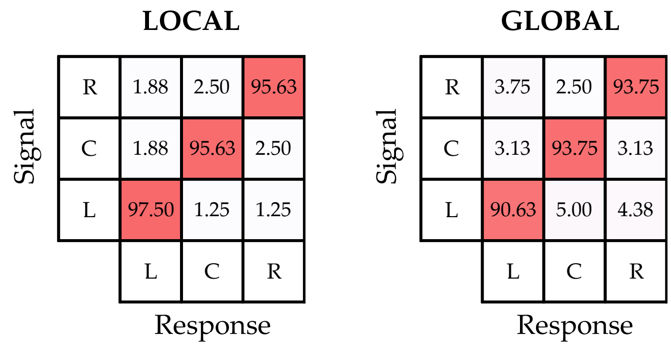

Figure 11. Confusion matrices showing the mean accuracy for each signal rendered (*Left*, *Center*, *Right*) in both methods (**Local** and **Global**).

during the study. The task was to identify which of the signals, *Left*, *Center*, or *Right*, was inflated to the higher pressure. Two of the degrees of freedom were inflated to a reference pressure P_o (2psi) and one to a high pressure P_H (2.75 psi). Subjects were not told that two degrees of freedom had the same pressure, they were just instructed to identify the one inflated to the different pressure. We selected the P_o and P_H values based on the findings of the previous pyschophysics study and taking into consideration that there is an increase in the complexity of haptic signals for this new study. As reported in Section IV-C, the average JND found in the previous study was 0.228 psi. However, some of the participants had JNDs almost double of the mean (i.e. Subjects 4 and 7, see I). With that in mind, we determined that a difference between the signals of ΔP = 0.75 psi was a large enough so that we could guarantee all subjects could perform to an adequate level in this study.

Each of the DoF (*Left*, *Center*, and *Right*) were rendered to the participant as the P_H a total of 16 times each, for a total of 48 trials. The process was performed for both **Global** and **Local** methods. Half of the participants completed the procedure with **Global** first then **Local**, and the other half the opposite. The study was conducted as follows. Participants were instructed to sit in the desk right in front of the arrangements. They interacted with a GUI developed in MATLAB to navigate through the study. The GUI first guided the participants through a demo to demonstrate the study procedure. The GUI shows a red light that would turn green to indicate the times when the participant was allowed to touch the displays. For each of the trials, the GUI asked the participant to click a "Next" button to continue. Once clicked, the red light would turn to green once the displays have reached their corresponding steady-state pressures. The participants were then allowed to touch the displays for a unrestricted period of time. There were also no restrictions on the way participants could explore the displays, and they were allowed to use both hands if desired. Right after the light turns green, the GUI displayed the question *"Which one has the different pressure?"*, and showed options for selecting *Left*, *Center*, and *Right*. After the participants selected an option, they were instructed to click an "Enter" button to answer, and the GUI showed if they were correct, and if not, what the right answer was. It is important to note that the GUI was configured to measure the participants' response time in the background; a timer would start when the light turns green, and would stop when the participants answered the question. To continue with the next trial, the participants then had to "Next." The procedure was repeated until the 48 trials were completed for the first method, and then for the second method. Participants were granted a break in the middle of each method's study, and another break in between methods. After completing the interaction portion of the experiment, the participants were given a post-experiment questionnaire. The questionnaire asked about how distinguishable the signals were, if they were often unsure about their answers, and if they were increasingly confident about their answers as the study progressed. We also asked about the overall experience during the study (clarity of instructions, sense of safety during the experiment) and about their previous experiences and familiarity with haptic technology, robotics, and video games. The study was 45 minutes long.

B. Results

We recruited 10 participants (4 female, ages 22 ± 3 years) from the Purdue community. All participants completed the study after giving informed consent. The Purdue Institutional Review Board approved the study protocols (IRB #2021-1283). Out of the group, 9 participants were right-handed, and one was left-handed.

The confusion matrices in Figure 11 summarize the accuracy of participants. Overall, participants' accuracy was higher for the Local method (average $\bar{x}$ = 96.25%, standard deviation σ = 3.88) than Global ($\bar{x}$ = 92.71%, σ = 7.17). Participants spent an average of 15.09s (σ = 7.55) using the Local method,

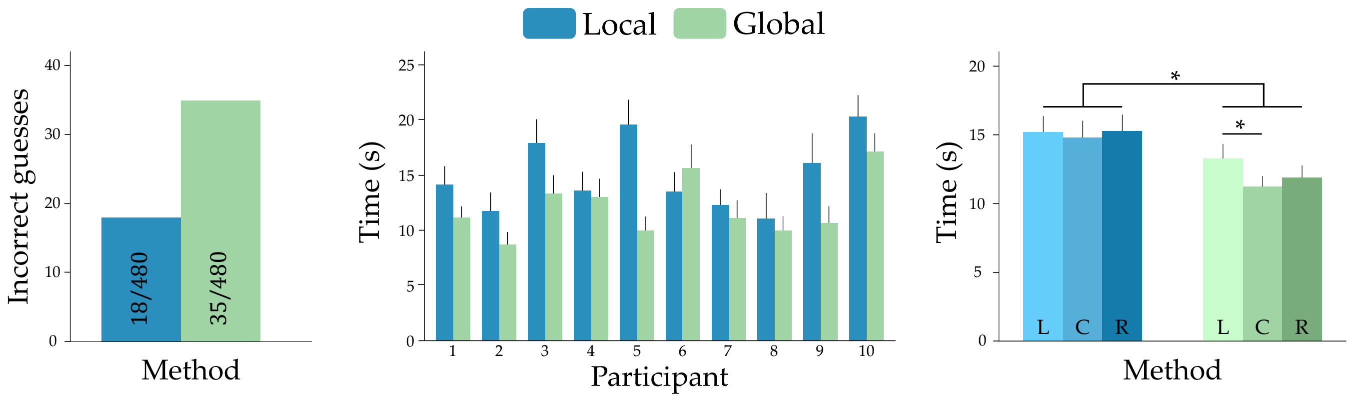

Figure 12. Experimental results. (Left) Count of incorrect guesses for each of the methods. A Wilcoxon signed-rank test showed that there is a significant association between participants' accuracy and methods (Z = -2.335, p < .05). (Center) Mean response time of individual participants for each method. Nine out of ten participants had a higher response time using the **Local** method. (Right) Mean response time for both methods, displayed by signal type (*Left*, *Center*, *Right*). Signal type had a statistically significant effect on response time (p = .047) but to a lesser extent than the method type (p < .001). For **Global**, participants spent more time responding the question when the *Left* signal was the highest pressure than when it was *Center* (p < .01) or *Right* (p = .078).

and 12.12s (σ = 5.877) for Global. Interestingly, looking at the complete pool of participants' responses (whether global or local), we found that participants had a greater response time when they responded incorrectly ($\bar{x}$ = 16.89s, σ = 7.68s) than when they answered correctly ($\bar{x}$ = 13.41s, σ = 6.83). Figure 12 shows the average time spent by each participant for both **Local** and **Global** methods.

C. Analysis

The two quantitative measures that we used to understand the results are *Accuracy* and *Response Time*. To further analyze the accuracy of participants, a Wilcoxon signed-rank test was conducted to understand the relation between accuracy and the methods used. The results showed that there is a significant association between participants' accuracy and methods (Z = -2.335, p < .05). This means that although participants responded faster to the task while using **Global** as shown by the mean response time values, participants were not as accurate at detecting the higher pressure as when they were using **Local**. Figure 12 shows the count of incorrect guesses for both local and global methods. Another Wilcoxon test was conducted to determine whether the order in which the experiments were conducted (Local first, then Global, or vice-versa) affected subjects' accuracy. The results showed that there was no significant association (Z = -0.143, p = .886), suggesting that subjects did not benefit from learning to improve their accuracy for the second half of the study.

To analyze response time, we used a one-way repeated measures ANOVA. We found that the method type had a statistically significant effect on response time. Post hoc analysis revealed that participants spent less time identifying the target signal with **Global** as compared to **Local** (p < .001). This observation matches the mean values for response time previously mentioned, and also the mean response time for each participant as shown in Figure 12. Nine out of ten participants spent more time using **Local** compared to **Global**. We also found that the rendered signal (whether *Left*, *Center*, or *Right*) had a statistically significant effect on answering time (p = .047) but with a smaller effect size than the method type. Data shows that while using **Global**, participants spent more time responding when the *Left* signal was the highest pressure than when it was *Center* (p < .01) or *Right* (p = .078). For **Local**, we did not find any statistically significant distinction between signals and their mean response time. These results can be observed in Figure 12, where we show the response time of participants for each signal type (*Left*, *Center*, *Right*) when using **Local** and **Global** methods.

This study shows that the spatial distribution of soft wrapped haptic displays is an important factor to consider, since it has an effect in both accuracy of detection and response time. Using the psychometric measures found in the previous study, we showed that participants were better able to identify the highest pressure out of a set of three when the signals were spatially distributed/separated (**Local**) than when the signals are condensed in a smaller space (**Global**). However, the response time for the spatially distributed signals was higher; this makes sense because participants had to move around a larger space to interact with the places where the haptic signals were located. The results of the post-experiment questionnaire show that participants thought the pressure differences were detectable, they were sure about their answers throughout the experiment, and that they felt safe interacting with the displays. Some participants mentioned that during the **Local** portion of the experiment, they wished they could place the displays together to make the exercise easier; this suggests that users consciously thought that having displays dispersed in different locations was an inconvenience, even though the results show participants were slightly more accurate with this method than with **Global**. As a summary **Global** method had the fastest response time, but **Local** had the highest accuracy. These observations show the trade-off between response time and accuracy when we increase the complexity of haptic signals in a smaller space or distribute them in a larger space.

VII. Using Multi-DoF Wrapped Haptic Displays to Communicate 3-DoF Robot Learning

In Section V we demonstrated that robot arms can leverage a haptic display to communicate with human teachers. However, this haptic device only had 1-DoF: the same pressure was rendered along the entire robot arm. One degree-of-freedom

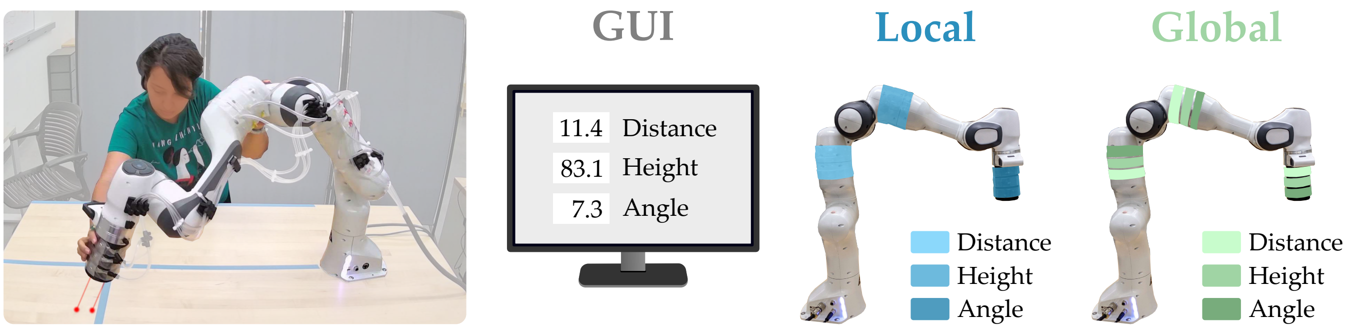

Figure 13. Experimental setup and independent variables for the user study from Section VII. (Left) Participants physically demonstrated a mock welding task to a Franka Emika robot arm. We mounted two lasers to the robot's end-effector: the robot prompted human teachers to keep the end-effector and lasers at the correct distance, height, and orientation. (Right) The robot indicated which feature(s) it needed help with using three different feedback modalities: **GUI**, **Local**, and **Global**. For **GUI** the robot printed its percentage uncertainty about each feature on a computer monitor placed in front of the workstation. Both **Local** and **Global** leveraged our wrapped haptic displays. In **Local** we attached three 1-DoF displays, and the location of the display indicated the desired feature. By contrast, in **Global** we used three 3-DoF displays such that each row of the displays corresponded to a separate feature.

is sufficient when the robot learner wants to convey whether or not it is uncertain — but what if the robot needs to communicate more complicated feedback? For instance, the robot may want to indicate *what* it is confused about or *how* the human teacher could improve their demonstrations.

In our final user study we wrap multiple 3-DoF haptic displays around a Franka Emika robot arm. Participants physically teach the robot to perform a mock welding task, and the robot applies multi-dimensional feedback to indicate what aspects of the task the human teacher must emphasize. From Section VI we know that the speed and accuracy of humans' perception of 3-DoF haptic displays depend on the distribution of the degrees of freedom. Here we build on these psychophysics results: we use the same haptic design and pressure differences as in Section VI. But we also highlight the differences between these studies — now the human is interacting with a moving robot arm, and the human must interpret the robot's feedback in real-time to actively change their own behavior.

Overall, our goal is to compare two different feedback distributions shown in Section VI and understand how they impact humans kinesthetically teaching a task to the robot. Remember that we are wrapping haptic displays along the robot arm. One option is to *localize* different signals to different parts of the arm, such that the place where the bags inflate helps indicate and remind users what the robot is uncertain about. Our second option is to *distribute* all three signals along the entire arm; here the human perceives the same haptic rendering no matter where they grasp the robot. In this user study we explore how human teachers perceive and leverage multiple displays that use both feedback layouts.

Independent Variables. The robot learner was confused about various parts of a mock welding task. We compared three different types of feedback for communicating when the robot was uncertain and what motions it needed the human teacher to emphasize (see Figure 13):

- A **GUI** baseline where the robot showed its numerical uncertainty on a computer monitor.
- Three 3-DoF, each configured as 1-DoF, wrapped haptic displays with signals localized to different regions of the robot arm (**Local**)
- Three 3-DoF wrapped haptic display with signals distributed across the entire robot arm (**Global**)

All conditions provided the same information to the participants. Similar to Section V, in **GUI** the robot displayed its uncertainties as a percentage: values close to 100% meant that the robot needed assistance. For **Local** and **Global** we actuated three separate wrapped haptic displays with pressures between $1-3$ psi ($6.89-20.68$ kPa). In **Local** each location of the haptic display had a single pressure signal; i.e., bags at the end-effector were one pressure, bags at the base of the arm were another pressure, and bags in the middle of the arm were a third pressure. In **Global** each haptic display location rendered all three of the potentially different pressures using three independent degrees of freedom, and all **Global** displays rendered those same three pressures — participants could feel the same feedback at the base, middle, and end of the robot arm. **GUI**, **Local**, and **Global** each provided a total of 3-DoF feedback. The difference was whether that feedback was wrapped around the robot, and if so, how the feedback was distributed along the arm. We emphasize that with **Global** participants had to discern which segments of the 3-DoF haptic display were inflated, while with **Local** participants needed to determine at which parts of the robot arm the haptic displays were inflated. Based on the results of our study in Section VI, we anticipate that participants using the wrapped haptic displays will discern the robot's feedback signals faster and more accurately during the teaching process.

Experimental Setup. Participants physically interacted with a 7-DoF robot arm (Franka Emika) to complete a mock welding task (see Figure 13). We mounted lasers to the robot's end-effector: participants kinesthetically guided the robot across a table while the lasers marked where the robot was "welding."

The welding task consisted of three features: how close the end-effector was to the edge of the table, the end-effector's height from the table, and the orientation of the end-effector. When the task started participants would guide the robot arm towards the fixed goal position. As they moved, the robot would leverage its feedback to notify the human *which feature* they needed to emphasize. For example, during the first third of the task the robot may prompt the human to keep the lasers close to the table; in the middle of the task the human

Figure 14. Participant teaching the welding task with **GUI**, **Local**, or **Global**. We show task progress in 5 second intervals. (Top) With **GUI** users need to look at the computer monitor to obtain feedback. The monitor is placed on the near side of the table: this participant is looking at the **GUI** at times $t = 5$, $t = 10$, and $t = 25$ seconds. (Middle) With **Local** participants must move their hands — and change their grasp — to sense the different wrapped displays. This participant keeps one hand on the end-effector, and then moves their other hand between the haptic displays at the middle and base of the robot arm. (Bottom) Finally, with **Global** the participants receive feedback through 3-DoF Haptic displays. **Global** helped this user remain focused on the task: notice that they are continually looking at the welding task, and keep both hands on the end-effector (where a 3-DoF haptic display is located).

should move the end-effector to the table edge; and during the final third of the task the human might need to align the robot's orientation. Participants had to dynamically determine *what* feature the robot currently needed help with and then *modify* their motion to emphasize that feature. Note that the robot asked for assistance with all three features at different segments of the task — we randomized these segments so that participants could not anticipate the robot's feedback.

Participants and Procedure. We recruited 12 participants (5 female, ages 28 ± 5.6 years) from the Virginia Tech community. All participants provided informed written consent consistent with university guidelines (IRB # 20-755). None of the participants for this study took part in the previous study from Section V. Three of the twelve participants reported that they had physically interacted with robot arms before.

Each user completed the welding task four times. First, we asked users to demonstrate the task without any feedback from the robot. We used this initial demonstration as a baseline to measure their improvement. Next, participants completed the welding task with **GUI**, **Local**, and **Global**. We counterbalanced the order of these feedback conditions: four participants started with **GUI**, four participants started with **Local**, and four participants started with **Global**. Overall, we followed a within-subjects design where all participants worked with every feedback condition. Prior to the experiment we explained and demonstrated each condition to the users so that they understood how to interpret the robot's feedback.

Dependent Measures – Objective. We measured the total time it took for participants to demonstrate the welding task (*Teaching Time*). This includes idle time where the human has paused and is not moving the robot; for instance, the human may have stopped to feel the different haptic displays or to carefully read the **GUI** feedback. We also measured the *Improvement* between the human's initial demonstration and their demonstration under each feedback condition. Let $e(\xi)$ be the total error between the correct feature values and the current features along trajectory ξ. Intuitively, $e(\xi)$ is the distance between the ideal demonstration and the human's actual demonstration. We defined *Improvement* as $\big(e(\xi_{initial}) - e(\xi)\big)/e_{max} \cdot 100$, where e_{max} is the maximum possible error for the welding task. *Improvement* captures the percentage change in demonstration quality for each feedback condition: positive *Improvement* reveals that the human is demonstrating the task more accurately.

Dependent Measures – Subjective. Participants responded to a 7-point Likert scale survey after each feedback condition. Our survey was composed of four multi-item scales and one single-item scale (see Table II). We asked participants how *easy* it was to understand the robot's feedback, whether they could *focus* on the task, how *distinguishable* was the robot's feedback, if the feedback was *intuitive* for this task, and to what extent they *prefer* this condition as a communication modality. Finally, after participants had finished working with all the conditions they responded to a forced-choice comparison: "Which method did you like the most?" Here users had to select one of **GUI**, **Local**, or **Global**.

Hypotheses. We had two hypotheses for this user study:

> **H3.** *Distributing multi-DoF haptic feedback along the robot arm (**Global**) will lead to improved demonstrations and lower teaching time.*
>
> **H4.** *Participants will prefer distributed feedback (**Global**) as compared to localized feedback (**Local**).*

Results – Objective. The results from this user study are summarized in Figure 15. To get a sense of the users' experience, we also show participant demonstrations in Figure 14.

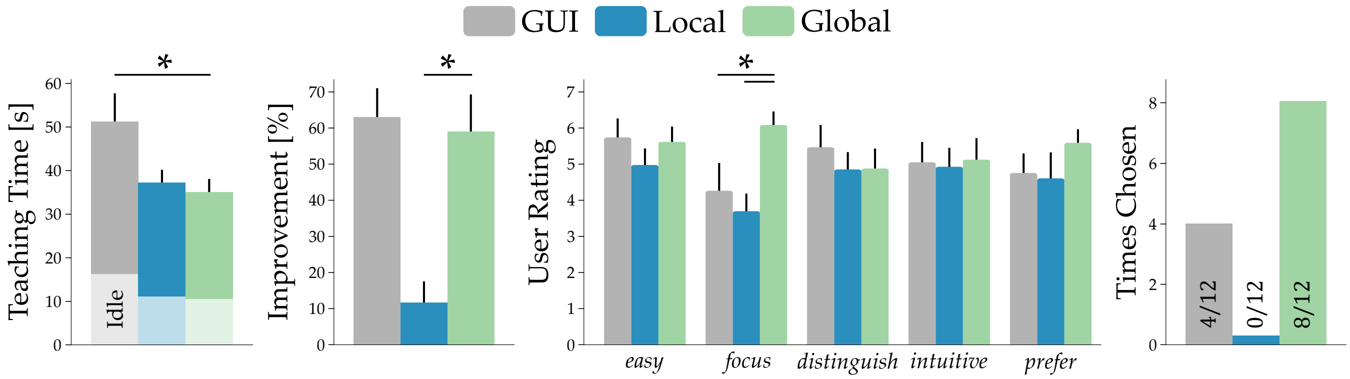

Figure 15. Objective and subjective results when communicating multi-dimensional robot feedback. We compared using a computer monitor (**GUI**), localizing wrapped haptic feedback to specific parts of the robot (**Local**), and distributing 3-DoF feedback along the arm (**Global**). Error bars show standard error of the mean and an $*$ indicates statistically significant comparisons. (Left) Participants spent less time teaching the robot with **Global** as compared to **GUI**: shaded regions show the amount of time where participants stopped moving the robot to think about their next actions. The human's demonstrations improved more with **Global** feedback as compared to **Local** feedback. (Middle) Participants perceived the multi-DoF wrapped haptic display as similar to the alternatives, but indicated that **Global** enabled them to focus on teaching the robot. (Right) At the end of the experiment users were asked to choose their favorite method. Of the 12 total participants, 8 selected **Global**, 4 selected **GUI**, and none selected **Local**.

Let us start our analysis by looking at the objective results. Using a one-way repeated measures ANOVA, we determined that feedback type had a significant effect on *Teaching Time* ($F(2, 22) = 3.423$, $p < .05$). Post hoc tests revealed that participants spent less time demonstrating the task with **Global** than with **GUI** ($p < .05$), while the differences between **Global** and **Local** were not significant ($p = .675$). To explain these results we measured the amount of idle time during the demonstration. We found that with **GUI** users needed to stop, look at the monitor, and think about their next action: shifting attention back-and-forth between the monitor and the welding task contributed to the increased *Teaching Time*.

So with **Global** participants taught the robot more quickly — but did they provide accurate, informative demonstrations? Remember that to measure *Improvement* we first collected a demonstration without any feedback, and then compared that initial demonstration to the user's behavior under each feedback condition. The type of robot feedback had a significant effect on *Improvement* ($F(2, 22) = 12.707$, $p < .001$). With both **GUI** and **Global** the participants made similar improvements to their teaching ($p = .769$). However, *Improvement* was significantly lower for **Local** as compared to **Global** ($p < .01$). To illustrate why we turn to Figure 14. When participants received **Local** feedback they frequently had to change their grasp and move their hands across the three haptic displays; by contrast, in **GUI** and **Global** the participants could maintain a fixed grasp. When **Local** participants did not constantly check all three haptic displays missed out on the robot's signals (and failed to emphasize the corresponding features).

Overall, our objective results support **H3**. Distributed, multi-DoF wrapped haptic feedback enabled users to teach robots more seamlessly than **GUI** and more accurately than **Local**.

Results – Subjective. Table II and Figure 15 outline the results of our Likert scale survey and forced-choice comparison. We first checked the reliability of our four multi-item scales: *easy*, *focus*, and *intuitive* were reliable (Cronbach's $\alpha > 0.7$) but *distinguish* was not. We then grouped each scale into a combined score and performed a one-way repeated measures ANOVA on the result. Note that we did not check for reliability in *prefer* because we only had one item (i.e., one question) on this scale.

Table II

QUESTIONS ON THE LIKERT SCALE SURVEY FROM SECTION VII. WE GROUPED QUESTIONS INTO FIVE SCALES AND EXAMINED THEIR RELIABILITY USING CRONBACH'S α. QUESTIONS EXPLORED WHETHER PARTICIPANTS THOUGHT THE ROBOT'S FEEDBACK WAS *easy* TO INTERPRET, IF THEY COULD *focus* ON TEACHING, HOW *distinguishable* THE ROBOT'S SIGNALS WERE, WHICH METHODS WERE *intuitive*, AND THEIR OVERALL *preferences*. FOR *preference* WE DID NOT CHECK FOR RELIABILITY SINCE THERE WAS ONLY A SINGLE ITEM. WE THEN PERFORMED A ONE-WAY REPEATED MEASURES ANOVA ON THE GROUPED SCORES: HERE AN $*$ DENOTES STATISTICAL SIGNIFICANCE.

Questionnaire Item	Reliability	$F(2, 22)$	p-value
– It was hard to figure out what the robot was trying to convey to me. – I could **easily** tell what the robot wanted.	.75	1.699	.206
– I could **focus** on the robot's feedback without having to look up or move my hands. – I had to physically go out of my way to get the robot's feedback.	.74	6.266	$< .01^*$
– It was easy to **distinguish** the different feedback signals. – I had to think carefully about what I was seeing / feeling to determine the signal.	.64	1.733	.215
– The way the robot provided feedback seemed **intuitive** to me. – I thought the robot's feedback was unintuitive and hard to understand.	.86	.081	.923
– Overall, I **prefer** this communication modality.	–	5.189	.191

We found that participants perceived **GUI**, **Local**, and **Global** to be similar along several axes. For instance, users did not think that any of the feedback types were more distinguishable ($p = .215$) or intuitive ($p = .923$) than the others. However, users reported that they were better able to *focus* on the task with **Global** than with **GUI** ($p < .05$) or with **Local** ($p < .001$). This result matches Figure 14, where we see examples of a participant shifting their attention during **GUI** and **Local** conditions. After the experiment was finished we asked users to select their favorite feedback type: eight of the twelve participants chose **Global**, and the remaining four selected **GUI**. These subjective results support **H4**. We were particularly interested to find that participants preferred **Global** feedback compared to **Local** feedback — it seemed that the convenience of having the same three signal available at different contact points along the entire arm outweighed the potential difficulty in interpreting those signals and determining which parts of the bag were inflating. One participant mentioned that "*I liked **Local** the least, since it requires repositioning hands to get feedback.*"

VIII. Conclusion

In this paper we presented a novel approach for communicating information about a robot's internal state during physical interaction. Specifically, we introduced a class of soft, wrapped haptic displays that are mounted on the robot arm at the point of contact between the human and robot to communicate the robot's uncertainty. We designed and manufactured these pneumatic devices using flexible pouches that render one or more pressure signals, and then wrapped the soft displays around rigid robot arms (Section III). We finally performed psychophysics and robotics experiments with (a) 1-DoF displays and (b) multi-DoF displays.

Starting with the 1-DoF setting, our results suggest that humans can accurately distinguish between different pressures rendered by the wrapped haptic display (Section IV), and that the wrapped display provides more informative feedback about robot learning than the current alternatives (Section V). User study participants physically taught the robot in less time while making larger improvements when the 1-DoF display was wrapped around the robot arm.

We next explored whether multi-DoF haptic displays could be leveraged to communicate more detailed and fine-grained feedback. We compared two approaches: localizing separate 1-DoF haptic displays to different regions of the robot arm, or distributing identical 3-DoF displays along the entire arm. From a psychophysics perspective, we found that localized feedback resulted in more accurate communication but at slower speeds: because these signals were spatially distributed over a larger surface area, humans could distinguish them more accurately, but it took longer for participants to move their hands, perceive each region, and recognize the signal (Section VI). We next applied both types of haptic displays to a robot learning task. Here we found that distributed 3-DoF signals were preferable to localized 1-DoF signals in terms of teaching time, demonstration improvement, and subjective responses (Section VII). Participants needed to use their hands to kinethetically teach the robot arm — but because the localized feedback required humans to continually change their grasp and feel along the robot arm, this localized feedback conflicted with the human's teaching. In the context of learning from demonstration we therefore found that using multi-DoF haptic displays to concentrate signals in a smaller space resulted in more seamless communication and teaching.

Limitations. This work is a first step towards wrapping pneumatic displays to convey the robot's internal state during physical human-robot interaction. One limitation of our work is that — without written or verbal explanations — human users do not know how to interpret the robot's feedback. For instance, we had to explain to users that increased pressures corresponded to increased robot uncertainty. Although it seems reasonable to provide operators with an instruction manual, moving forward we want to ensure that the robot's signals are as intuitive as possible.

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