Towards smooth human-robot handover with a vision-based tactile sensor*

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Abstract. Cooperative human-robot interaction often requires successful handovers of objects between the two entities. However, the assumption that a human can reliably grasp an object from a robot is not always valid. To address this issue, we propose a vision-based tactile sensor for object handover framework that utilises a low-cost sensor with variable sensitivity and pressure. The sensor comprises a latex layer that makes contact with the object and a tracking marker that registers the resulting changes in position. By pre-processing this information, a robot can determine whether it is necessary to open the gripper. Our approach is validated through an exploratory user study involving ten participants who completed handover tasks involving eight objects of varying shapes and stiffness, including rigid and deformable objects like raspberries and dough. The study results demonstrate the effectiveness of our approach, with a success rate of 94%. Additionally, users reported less difficulty performing the handover tasks when the sensitivity value was decreased. Overall, our vision-based tactile sensor framework offers a promising solution for the challenging problem of human-robot handover in cooperative settings.

Keywords: Tactile sensing · Human-robot handover · Robotics

1 Introduction

In recent years, there has been remarkable progress towards more direct collaboration between humans and robots, enabled by technological advances in robot hardware [1]. The current trend of Industry 4.0 envisions shared environments, where robots interact with their surroundings, humans, and other agents [2]. In addition, the recent COVID-19 pandemic has increased the demand for autonomous and collaborative robots in environments such as care homes and hospitals [3]. Human workers can potentially benefit from robotic assistants due to several advantages, such as transferring repetitive, low-skill, and ergonomically unfavourable tasks to robots. In this context, robot handover is of great significance [4].

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The human-robot handover task has been studied in several works. One of these pioneering works is [5], in which the authors proposed a system that comprises a three-finger gripper attached to a robot that makes decisions regarding when to open the gripper, close it or adjust one of the fingers in case the contact between the gripper and the object is lost. This approach uses a combination of information regarding joint angles, contact with the object, and kinematics to assess the grasping stability. The authors showed that handover is closely related to grasp stability since the robot must hold the object until the human is ready to receive it. In contrast, Edsinger and Kemp demonstrated that humans adapt how they hand objects over to a specific configuration of the robot's gripper [6].

There are handover approaches based on using the user's hand velocity to determine when the robot should release an object [7]. However, visual information can be unreliable if the object is occluded or the lighting conditions are not appropriate. Besides that, some objects, such as soft or irregularly shaped objects, may be challenging to hand over. On the contrary, tactile sensors provide more precise and accurate information to the robot, enabling it to adapt according to the object's physical properties. This allows the robot to perform the handover of a broader range of objects with varying shapes, sizes, and textures and ensures a more robust grasp of an object whose surface friction is unknown [8]. Despite the benefits of tactile sensing and its implementation under various operation principles (e.g., pressure, vibration, temperature, texture, or shape), the use of vision-based sensors for human-robot handover tasks has not yet reached its full potential.

In this paper, we present a vision-based tactile sensor for object handover framework[1], aiming to solve the problem of coordination and timing in human-robot handover. The framework is based on a sensor comprising a latex rubber layer with a marker on the interior surface, a camera, and a chamber with variable pressure. The contact movement is estimated by tracking the marker on the latex skin's surface. This information is then used to decide if opening the robot's gripper is required. We investigate several aspects of the framework, such as success rate with an exploratory user study in which ten participants complete the task of handing over eight objects. Each object has a different size, shape, and stiffness. For our experiments, we built an interface for experiments that allows the user and the robot to interact during the handover tasks. Our contributions are summarised as follows: (i) a framework that allows human-robot handover with a vision-based tactile sensing principle, and (ii) a method for calibrating the sensor's sensitivity based on the user's experience.

The rest of the paper is organised as follows. Section 2 discusses related work on tactile sensors and human-robot handover. Then, Section 3 presents our vision-based tactile sensor for the object handover framework. In Section 4, we explain the experimental setup used to validate the framework. Section 5 discusses the results. Finally, we conclude this paper and propose potential future work in Section 6.

[1] `https://github.com/FranciscoMunguiaGaleano/TactileSensorHandover`
Demo available at `https://youtu.be/qP54j6ZPKLk`

2 Related Work

A handover is defined as a collaborative joint action in which one agent (the giver) gives an object to another agent (the receiver). The physical exchange begins when the receiver first touches the object held by the giver and ends when the giver completely hands over the object to the receiver. Human-robot handover, a frequent collaborative action among humans, requires a concerted effort of prediction, perception, action, learning, and adjustment by both parties. Implementing an object handover that is as efficient and fluent as the exchange among humans is an open challenge in robotics [9].

There is a significant amount of literature on human-robot object handover with the potential to enhance robot capabilities performed from a range of aspects, such as visualising robot intent [10], adaptiveness to user preference [11], visual perception for handover [12], affordance-based handover [13], and gripper effort control [7]. These approaches are based on specific aspects, such as the human hands, objects, contact points, and contact pressure. On the other hand, our framework does not depend on contact force estimation. Instead, it utilises the direct measurement of the object's movement by tracking the dot placed on the internal face of the layer.

Among the different robotic applications and tactile sensing types, slip detection is a typical application [14]. An important early approach in this area was proposed in [15], where the authors describe grasping behaviours and grip forces. Similar vision-based optical tactile sensors have been studied in [16, 17], with the purpose of detecting slip. For example, the sensor proposed in [18], covered with an opaque surface skin made of latex, provides slip detection by producing high-resolution force arrays. Another popular device for tactile sensing is the BioTac sensor [19]. For example, in [20], two BioTac sensors are used to detect slip. BioTac sensors are also used in [21], where the authors defined three types of tactile estimation: finger forces-based, slip detection-based, and slip classification-based.

Despite the success of the aforementioned approaches, the most commonly used object shapes to test are cylindrical (i.e. bottle) or rectangular (i.e. box). These objects are easier to hand over than deformable and fragile objects; Hence, the generalisation of handovers to a variety of objects with different shapes and stiffness has not yet reached its full potential.

3 Vision-based tactile sensor for object handover framework

In this section, we present the vision-based tactile sensor for object handover framework (Fig. 1), which aims to solve the problem of human-robot handover. The framework comprises the following modules: segmentation, dot tracking, and decision.

The **segmentation module**'s input is the video stream image captured by the camera inside the sensor. This module is in charge of segmenting the dot

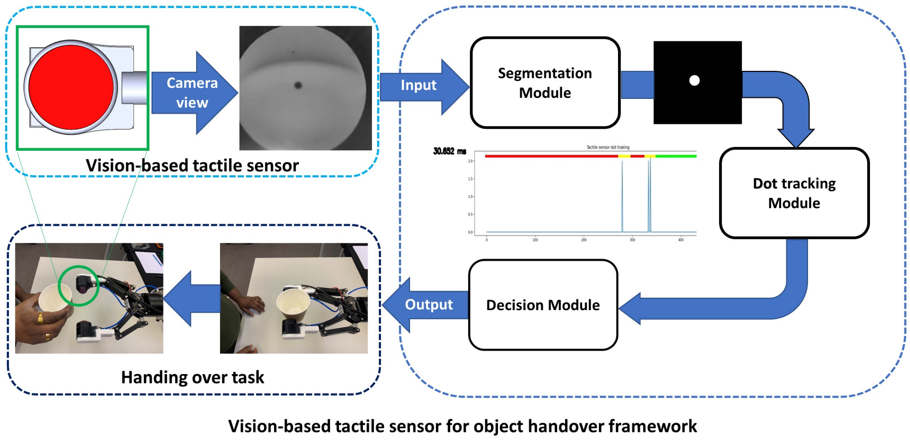

Fig. 1. Vision-based tactile sensor for handover framework

printed at the centre of the latex layer. For this purpose, the original image is transformed into a negative version of it and then into grayscale. This module is implemented using Python and OpenCV.

The **dot tracking module** utilises the output of the segmentation module as input and transforms the image into coordinates of the white dot's centre. First, the dot tracking module sets an initial position once the gripper has closed and is holding an object. Then, the centre coordinates of the dot moving with respect to the initial position are stored in the vector v, which is the output of this module.

The **decision module** controls the sensitivity-pressure pair of the sensor and the open and close actions of the gripper. The accumulated displacement of the object being pulled by the user while the gripper holds it is given by the following :

$$M = \sum_{i=T-n}^{T} \left| \frac{||v_i - v_{(i-1)}||}{(t_i - t_{(i-1)})} \right|, \tag{1}$$

where t_i and $t_{(i-1)}$ denote the current and past time, and v_i and $v_{(i-1)}$ are the current and past positions of the dot, respectively. Here, i takes values within the range $(T-n, ..., T)$. The value of M increases proportionally to the accumulated displacement of the dot, and the bigger the value of n, the more past information is considered. The decision module can decide if opening the gripper is necessary based on the following:

$$Gripper_{action} = \begin{cases} \text{Open}, & M > S \\ \text{No action}, & \text{otherwise} \end{cases} \tag{2}$$

where S is the sensitivity and acts as a threshold that determines when the robot should release an object.

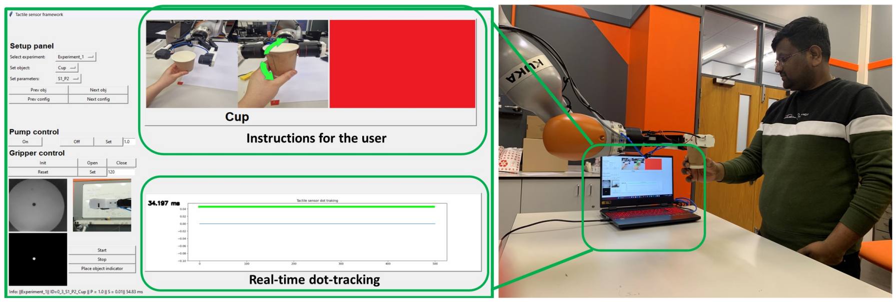

Fig. 2. The image displays the experimental setup, in which the robot is handing over a cup to a user.

4 Methodology

To investigate the optimality of the sensitivity-pressure pair that is more comfortable from the user's perspective when using our framework, we conducted an experiment in which users rated how easy or difficult it was to hand over an object from the robot. Additionally, users rated the degree of damage the object sustained after completing the task. The time taken by the user to attempt to take the object from the gripper until it was released (sensing time) was also measured for all the handover tasks. The experimental setup (Fig. 2) consisted of a KUKA® LBR IIWA 14 robot arm with 7 degrees of freedom and a Robotiq® 2-finger gripper with a vision-based optical tactile sensor attached to its fingers. Moreover, the user followed instructions displayed on a screen placed next to the robot, indicating when to place or take the object from the gripper.

4.1 Participants

We asked 10 participants from Cardiff University, including 8 males and 2 females aged 24-30, to do the experiments. There was no compensation for the participants. Among them, 2 participants had previous experience with robots, while 8 participants had never interacted with a collaborative robot.

4.2 Experimental Procedure

The experiment took place at the Robotics Lab of Cardiff University under the supervision of our 2 experimenters. Participants stood in a designated position before a robotic arm and started the object handover task. Participants first read

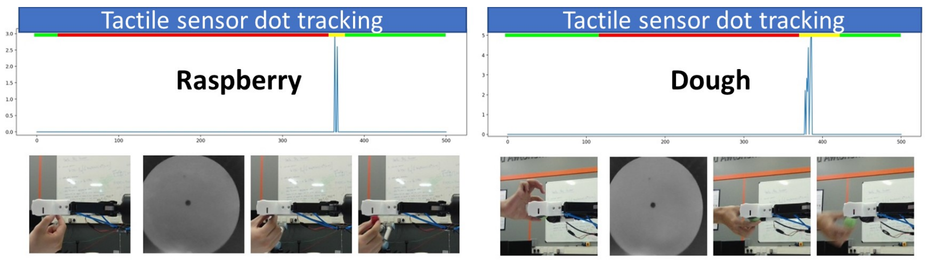

Fig. 3. A human and a robot are performing a handing-over task with raspberry (on the left) and dough (on the right) during the experiments. In the dot tracking plot, when the colour of the line is red, the gripper is closed. The yellow colour indicates that the user is trying to get the object. The green colour indicates that the gripper is open.

the instructions and then signed the consent form. After reading the instructions, the experimenter provided information about the experimental process by reading from a script and collected basic demographic information, such as gender, through a short questionnaire.

Table 1. Parameters used for the sensitivity-pressure pairs during the experiments.

Parameter	**Sensitivity-pressure pair**								
	S_1P_1	S_1P_2	S_1P_3	S_2P_1	S_2P_2	S_2P_3	S_3P_1	S_3P_2	S_3P_3
S	0.01	0.01	0.01	0.005	0.005	0.005	0.001	0.001	0.001
P	0.8 psi	1.0 psi	1.3 psi	0.8 psi	1.0 psi	1.3 psi	0.8 psi	1.0 psi	1.3 psi

For the experiments, we set nine sensitivity-pressure pair values, as shown in Table 1, and used eight objects with different shapes and stiffnesses (paper, fabrics, a cup, dough, strawberries, raspberries, a cable, and a prism). Aiming to investigate several aspects of our framework, we designed a questionnaire (Table 2) that consists of two questions. **Q1** has a scale of 0-10, where 0 - too sensitive, 5 - ideal, and 10 - too difficult. **Q2** has a scale from 0-10, where 0 - the object is intact, and 10 - the object is damaged. The participants perform the following experiments:

1. Each participant performs the handover tasks in a random order without knowing the sensitivity-pressure pair values.
2. After each handover, the participant answers **Q1** (Table 2) for the object in turn.
3. After each handover, the participant answers **Q2** (Table 2) for the object in turn.
4. If the robot fails to hand over the piece, the participant marks the experiment as invalid and is not required to answer questions **Q1** and **Q2**.

For each experiment, in turn, we aim to answer the following research questions:

1. Despite the random order of objects and sensitivity-pressure pairs in which the participants are asked to perform the handover tasks, is it likely that the participants will agree on which sensitivity-pressure combination results in a more pleasant handover?
2. Which sensitivity-pressure pair produces a more pleasant human-robot handover from the participant's point of view?
3. Which sensitivity-pressure pair reduces or increases the damage to the objects after handing them over?
4. What is the success rate of the proposed framework?

To validate the questionnaire, we conducted a pilot study at the beginning with three participants who carried out the experiments and answered **Q1** and **Q2**. For this analysis, the Cronbach's alpha value of each question was calculated, such that the statistical output was 0.775 and 0.852 for **Q1** and **Q2**, respectively. Since both values are greater than 0.7, the questions are considered good [22].

Table 2. Questionnarie used for the exploratory user study.

Questionnarie		Cronbach's alpha
Q1	How easy was to hand the object over?	0.775
Q2	How damaged is the object after hand it over?	0.852

The described experiments involve the use of a screen placed on the side of the participants to provide instructions for handling various objects, as shown in Fig. 2. Once the participants verbally indicate they are ready, the researchers manually start the robot program. The positioning of the screen is strategic, as it allows the participants to receive clear visual guidance while completing the handover task (see Fig.3). The screen will show red, indicating that placing an object is unsafe and may cause damage or harm. In this case, the participant will be instructed to refrain from placing the object and wait for further instructions. When the user indicator displays orange, it signifies that the participant can place the object between the gripper. Once the object is in place, the experimenter can close the gripper, and the participant can continue the task. Once the indicator displays a green signal, the participant can attempt to take the object.

Moreover, the instructions are essential to ensure that the participants follow the correct procedure for each object, which is critical to ensure the safety of the objects and the participants involved.

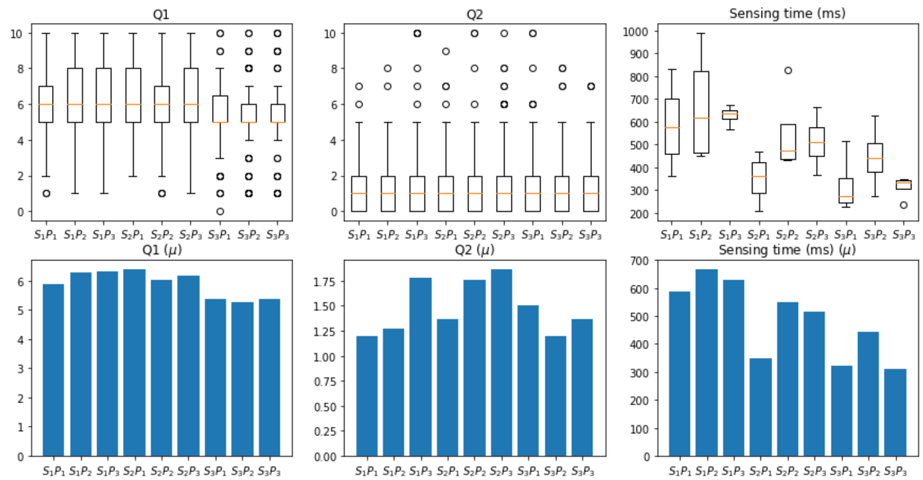

Fig. 4. This figure displays the results of each sensitivity-pressure pair for **Q1** and **Q2**, as well as the sensing time for all objects. The box plots are displayed in the upper row, while the means are shown in the bottom row.

5 Results and Discussion

5.1 Results

We have organised the data in a hierarchical order to evaluate the experimental results. First, we sorted the participants' ratings for **Q1**, **Q2**, and the sensing time for all the objects. Then, we analysed the results of **Q1** by considering each object type. Lastly, we examined the findings of **Q2** by considering the different categories of objects.

Table 3 summarises the results of **Q1**, **Q2**, and the sensing time for all the objects (Fig. 4). For **Q1**, the results show that the participants found the handover task more comfortable for S_3. At the same time, the score deviates from 5 (5 being the ideal score as defined in the questionnaire), which indicates that the scores increase proportionally to the value of S. At this point, the pressure value P does not seem to have a significant impact on the participants' sensation of fluency during the handover tasks. For **Q2**, the participants scored higher values that correspond to higher pressure values. In terms of sensing times, the participants perceived a more comfortable handover when the time is below 500 ms. However, the high values for the standard deviation indicate that the time measurement requires improvement.

In Table 4, the participants' ratings for **Q1** with respect to each object are summarised. Among all the objects, raspberries and cables received the highest scores for being difficult to hand over. On the contrary, the rest of the objects obtained a rating of around 6. For all objects, the score is closer to 5 when the sensitivity value S is lower.

Table 3. This table displays the results of each sensitivity-pressure pair for **Q1** and **Q2**, as well as the sensing time for all objects and participants.

	Q1		**Q2**		**Sensing time** (ms)	
	μ	σ	μ	σ	μ	σ
S_1P_1	5.89	1.94	1.2	1.51	586	205.1
S_1P_2	6.28	2.11	1.27	1.62	669	259.59
S_1P_3	6.32	2.22	1.78	2.55	628	45.03
S_2P_1	6.41	1.68	1.37	1.85	348	113.53
S_2P_2	6.04	2.03	1.76	2.29	550	186.88
S_2P_3	6.18	2.43	1.87	2.4	514	125.47
S_3P_1	5.37	2.01	1.5	2.21	322	130.79
S_3P_2	5.27	2.23	1.2	1.85	445	145.41
S_3P_3	5.36	2.12	1.37	1.71	312	51.03

Table 4. The table displays the results of each sensitivity-pressure pair for **Q1** obtained in the experiments.

Q1	**Paper**		**Fabrics**		**Cup**		**Dough**		**Strawberry**		**Raspberry**		**Cable**		**Prism**	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
S_1P_1	5.8	1.75	6.33	1.22	4.8	1.93	6	1.56	5.7	1.42	5.5	3.25	7.11	2.52	6	1.25
S_1P_2	6.6	2.12	6.88	2.03	5.5	2.12	6.11	0.93	5.8	2.57	6.57	1.99	7.14	2.12	6.11	2.67
S_1P_3	6.9	2.02	6.11	2.47	5.6	1.51	5.2	2.3	5.89	2.26	6.88	2.23	9	1.53	5.8	1.93
S_2P_1	6.8	1.81	5.9	1.85	6.5	1.72	5.8	0.92	5.7	1.64	7.5	2.17	6.78	1.39	6.3	1.42
S_2P_2	5.8	2.2	6.2	2.1	5.5	1.84	5.3	1.95	5.7	1.25	7.3	2.5	6.8	1.99	5.7	2.06
S_2P_3	5.8	2.66	6.78	1.86	5.3	2.41	5.2	2.04	5.56	2.13	8	1.66	7.78	2.59	5.4	2.67
S_3P_1	6.1	2.28	5.4	1.71	5.5	0.85	5.5	2.64	5.22	1.56	4	1.51	5.75	2.71	5.3	2.26
S_3P_2	4.9	1.73	5.89	2.8	4.9	2.23	4.8	2.3	4.8	2.3	5.9	2.6	6.62	2.0	4.7	1.77
S_3P_3	5.8	2.04	5.7	2.26	4.67	2.06	4.7	1.89	4.9	1.1	5.8	2.2	6.25	2.96	5.2	0.0

Table 5 shows the participants' ratings for **Q2** with respect to each object. It can be observed that as the pressure increases for P, the participants tend to rate a higher value for **Q2**, indicating that the object is more damaged after the handover. Among all the objects used during the experiments, raspberries had the highest rates of damage, suggesting that the handover task using our approach is more challenging to execute with a fragile object like a raspberry.

In terms of success rate (Table 6), the cable got the lowest success rate, followed by the Raspberry with 86% and 90%, respectively. While the rest of the objects obtained a similar success rate of above 95% despite their shapes or sizes.

5.2 Discussion

Based on the above results, it was found that, from the participants' perspective, a lower value of S ($S_3 = 0.001$) produces a more comfortable handover. Additionally, a higher pressure value of P caused more damage to the objects after being handed over. However, there is no clear indication that the change in pressure

Table 5. The table displays the results from the experiment of every sensitivity-pressure pair for **Q2**.

Q2	**Paper**		**Fabrics**		**Cup**		**Dough**		**Strawberry**		**Raspberry**		**Cable**		**Prism**	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
S_1P_1	1	0.87	0.78	1.09	1.11	1.05	1.12	0.99	1.22	1.48	3.11	2.62	0.56	0.73	0.67	1.12
S_1P_2	0.6	0.84	0.5	0.71	1.4	1.43	1.44	1.13	1.44	1.51	4	2.51	0.57	0.79	0.6	0.7
S_1P_3	1.11	1.9	0.56	0.88	0.89	0.78	1.5	1.08	2.2	3.05	5.7	3.74	0.62	0.52	1.11	1.54
S_2P_1	1.2	1.93	0.3	0.67	1.1	1.1	1.5	1.43	1.3	1.42	3.9	2.96	1	1.32	0.6	0.7
S_2P_2	1.33	1.73	0.78	1.64	1.44	1.67	1.89	1.05	1.44	1.88	5.44	3.4	0.67	0.71	1.11	1.62
S_2P_3	1.56	2.01	1.33	2.18	1.67	1.87	2.22	2.05	1.5	1.77	4.67	3.46	1.33	2.55	0.67	1.0
S_3P_1	1.3	1.89	0.8	1.55	1.4	1.96	1.8	1.55	1.1	1.2	4	4.18	1.22	2.05	0.6	0.84
S_3P_2	0.7	1.06	0.5	0.85	1	1.25	1.5	1.08	0.6	0.7	3.8	3.39	1.2	1.81	0.3	0.67
S_3P_3	1.49	1.49	0.5	0.71	1.22	1.09	2.2	2.1	1.4	2.22	3	1.89	1	1.5	0.6	0.0

Table 6. Success rates of the proposed framework for each and the total of the objects.

Paper	**Fabrics**	**Cup**	**Dough**	**Strawberry**	**Raspberry**	**Cable**	**Prism**	**Total**
100 %	96 %	99 %	99 %	98 %	90 %	84 %	99 %	94 %

enhanced the user's sensation of fluency while handing over the objects during the experiments. In terms of success rates, our approach encountered more difficulty with reduced-diameter objects, such as the cable, because, depending on the object's initial position while being grasped, the dot at the centre of the latex layer did not move as it did with the other objects. As a consequence, the dot-tracking module could not detect any movement of the object. Other challenging objects were the raspberries because, among all the objects, the participants noticed damage to them after performing the task, which also reflected in the success rate. Despite the shortcomings, the robot using our framework managed to hand over different objects with different sizes and stiffness with a 94% success rate.

6 Conclusion and Future work

In this paper, we proposed an object handover framework using the vision-based tactile sensor. Overall, the experiments achieved a success rate of 94%. The exploratory user study revealed that users found the handover task more comfortable when the sensitivity value was lower. The limitations of this paper, found during the experiments, are related to reduced diameter objects (e.g., cables) and highly fragile objects (e.g., raspberries), which seem to be the most challenging objects to hand over using our approach. However, the reliability of our framework and sensor was demonstrated for handing over objects such as paper, fabrics, dough, and strawberries. For future work, we plan to improve the sensor by adding more markers to the latex layer and exploring the effects and benefits of using tactile sensing with variable pressure.

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