Vision-based, Low-cost, Soft Robotic Tongs for Shareable and Reproducible Tactile Learning

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***Abstract*— Recent research shows a growing interest in adopting touch interaction for robot learning, yet it remains challenging to efficiently acquire high-quality, structured tactile data at a low cost. In this study, we propose the design of vision-based soft robotic tongs to generate reproducible and shareable data of tactile interaction for learning. We further developed a web-based platform for convenient data collection and a portable assembly that can be deployed within minutes. We trained a simple network to infer the 6D force and torque using relative pose data from markers on the fingers and reached a reasonably high accuracy (an MAE of $0.548N$ at $60Hz$ within $[0, 20]N$) but cost only 50 USD per set. The recorded tactile data is downloadable for robot learning. We further demonstrated the system for interacting with robotic arms in manipulation learning and remote control. We have open-sourced the system on GitHub with further information. (`https://github.com/bionicdl-sustech/SoftRoboticTongs`)**

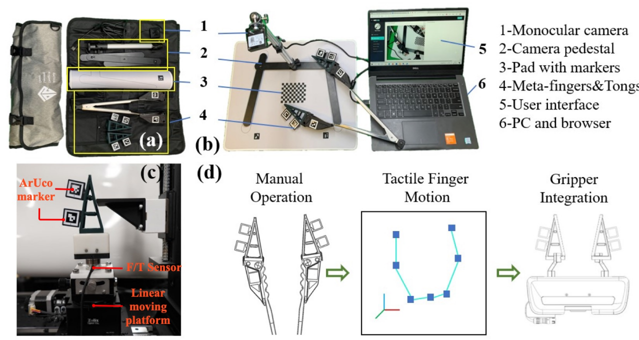

Fig. 1. **The vision-based, low-cost, soft robotic tongs for shareable and reproducible tactile learning.** (a) all components in a foldable fanny pack; (b) the assembled system on a tabletop connected to a laptop through USB; (c) the test rig for calibrating the 3D meta-finger's tactile performance; and (d) the working principle when integrated with the tongs.

I. INTRODUCTION

Collecting high-quality tactile data at the robot's fingertips complements learning dexterous interaction with the physical world. It is widely accepted that tactile perception offers complementary information about the physical properties of the objects and environment, which is not affected by occlusion or lighting, offering a reduced uncertainty in localized perception. Research literature has demonstrated various designs of tactile sensors. However, making it reproducible and shareable at a low cost remains challenging for an efficient collection of reasonably accurate, structured touch interaction data for learning.

A. Tactile Intelligence from Nature to Robotics

Skin is the largest organ of vertebrates, with a layer of usually soft tissue separating the internal organs from the physical environment, providing protection, regulation, and sensation as its main functions [1]. Tactile interaction between the skin and the object-centric environment has been well-recognized to provide perception for dexterous manipulation [2]. Recent research in robotic manipulation learning shows a growing trend in the adoption of touch-based tactile intelligence when dealing with challenging tasks, including the robotic Jenga player [3], magnetic skin with decoupled, super-resolution [4], as well as recent publication on the robotic flesh [5].

B. Tactile Sensorization of Force and Torque

The sensorization of tactile interaction is usually encoded as force and torque. A simple implementation is to fix a pressure or pneumatic sensor at the tip of the limb to detect binary contact*. One can replace it with a more advanced sensor to detect point-wise force and torque in 6D [6]. To detect tactile interaction in a distributed manner, an array of sensing units can be integrated to detect normal pressure over the contact surface [7]. Recent development shows growing adoption of optical [8], [9], [10], vision [11], [12], [13], and magnetic [4] modalities for more advanced tactile detection.

C. Soft Robotic Advantage for Learning Touch

The growing interest in soft robotics enables researchers to develop learning-based solutions to enable natural interactions with humans or the environment, showing closer resemblance to the skin. Interfaces with a soft design are usually challenging to model, especially when taking a complex physical form, but capable of providing feature-rich

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deformations for vision-based sensors [11]. Recent research uses magnetic sensors and machine learning techniques to show a high-performing design that detects decoupled tactile interaction between normal and tangential forces with super-resolution [4].

On the other hand, mechanoreceptive designs with soft structures also show promising performance in capturing tactile interaction. For example, the VESA actuator design uses optical sensors to detect external forces on the pneumatic soft actuator body to enable proprioceptive sensing [14]. Using 3D meta-materials with a soft design, similar optical sensors can be integrated either inside the soft structure [8] or on the contact surface [13] to provide rich, real-time data of physical interaction for learning-based object classification or contact prediction[15].

D. Towards Shareable and Reproducible Force Learning

The robot design paradigm is also experiencing changes to integrate sensing, planning, and actuation in one unit to address the shifting demand for learning, where force-related modalities become critically important instead of accuracy and speed. For example, the soft tactile finger design takes a different approach where the robot body provides sensory feedback while being capable of object grasping as a finger besides being part of the finger as a tip [13]. The recent design of the insight finger takes a rigid design comparable to a human thumb to provide high-performing tactile sensing while being capable of direct implementation as a robotic finger [16]. There is a growing trend in the robot learning community to include force-related modalities in learning-based robot control, such as Berkley's Blue Arm Project [17]. However, there remains a challenge in shareability and reproducibility at a low cost to implement tactile-based force learning in robotic manipulations.

E. Paper Summary and List of Contributions

In this study, we propose the design of soft robotic tongs fixed with a pair of 3D meta-fingers capable of generating omni-directional passive adaptation during physical interactions, as shown in Fig. 1, where vision-based pose tracking is used for collecting tactile data during object manipulation. The performance of the proposed design is verified using a multi-layer perceptron to benchmark its performance and validated in a series of object manipulation learning tasks. The contributions of this study are listed below.

- Proposed a shareable and reproducible design of the soft robotic tongs for collecting comprehensive tactile data in 6D with a web-based user interface;
- Validated the performance of the soft robotic tongs with a low cost that is at least 100X cheaper than commercial FT sensors, yet flexible for various manual demonstrations or gripper integration.
- Conducted a pilot study using this proposed design for teaching robot learning with positive student feedback.

II. Method

A. Shareable and Reproducible Design of Soft Robotic Tongs

Shareability and reproducibility are the priority of design considerations while developing the tactile data collection system at a low cost for robot learning. The overall hardware design is mainly mechanical, with a single monocular camera (720p/ϕ2.8mm/60Hz) as the sensing unit. Besides directly interacting with objects by hand, humans are also skilled at operating tools to manipulate objects. To make the system comparable with the standard parallel two-finger grippers used in the industry, we leveraged the existing design of regular kitchen tongs to systematically reduce the dimensionality of multi-fingered hand motion into two-fingered tongs. We used a soft, 3D meta-finger structure as the physical interface for interacting with the objects, which can be conveniently fixed at the tip of the tongs or the gripper. As shown in Fig. 2, the soft structure takes a unique design as a meta-material capable of generating passive geometric adaptation to object contact in any direction. This way, we can ensure a transferable interaction between the tongs or the gripper and the objects. The soft meta-finger passively deforms to the object geometry, enhancing its object grasping performance while providing a visible distortion that a camera can capture.

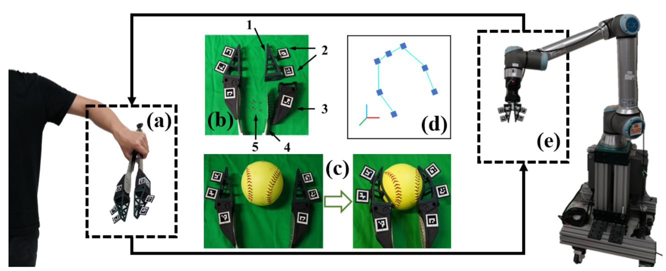

Fig. 2. **Integration of the 3D meta-fingers as soft robotic tongs.** (a) & (e) Example usages manually operated by humans as tongs or attached to grippers as fingers; (b) the soft robotic tongs with the left and right sides in assembled and exploded views; (c) demonstration of the meta-fingers' deformation and marker movements; and (d) the simplified model captured by the markers.

Previous work shows a promising performance of using vision-based tactile learning with this soft meta-finger by fixing a camera inside at the base, capable of inferring force and torque in 6D comparable to commercial F/T sensors [13]. In this study, we simplified the design by attaching two ArUco markers at the back of the finger surface for 6D pose tracking using a monocular camera. During physical contact, the 3D deformation of the meta-finger's front surface is translated to the backside, causing the relative pose between these two markers to change in 3D. By visually tracking such changes, we alleviate the need for hand-eye calibration to streamline data collection. We use this relative pose change to infer the 6D force and torque between the soft meta-finger and the objects for collecting the tactile interaction data. This process can be achieved with the fingers attached to the tongs or the gripper.

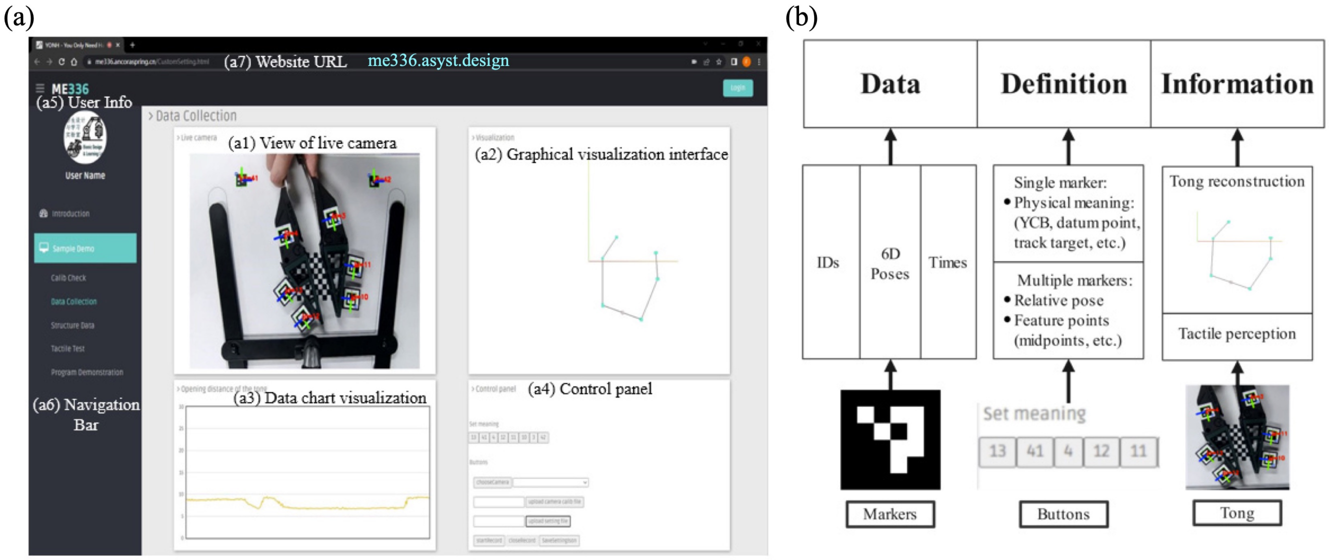

Fig. 3. **User interface for vision-based tactile data collection.** (a) The web-based user interface for collecting vision-based tactile data; (b) The pipeline of the web-based data collection software.

We further optimized the design to make it portable for storage as parts, which can be folded as a fanny pack, as shown in Fig. 1(a). One can set up the system within minutes by following simple instructions. A mouse pad with marks is also provided to help users place the camera stand quickly, and additional ArUco markers are printed on the pad for quick calibration of the scene plane. The next step is to connect the camera USB to a laptop for data collection in a browser.

B. A Web-based User Interface for Tactile Data Collection

While it is possible to train a machine learning model to infer force and torque from the meta-finger's structural deformation [13], in this study, we prefer to use fiducial markers instead for simplified and direct data processing. The highly distinguishable patterns of the fiducial markers are coded with geometric features for 6D pose and ID labels that can be readily extracted using existing APIs. To enhance reproducibility and shareability, we developed a web-based user interface for tactile data collection, which any user with a working laptop can access.

The user interface, illustrated in Fig. 3(a), consisting of a navigation bar on the left and four data screens stacked on the right for camera view, visualization screen, data recording, and control panel. The concept of this user interface is shown in Fig. 3(b). When markers are presented within the camera's view range, the users can define the labels of each marker in the control panel to assign physical meanings to each marker. For example, one can stick a marker plate to a YCB object and assign it using the control panel, which can be shown on the visualization screen with the object's model. When the physical object moves, the 3D model on the visualization screen moves accordingly, displaying its motion data on the data recording screen.

On the other hand, in this study, one can assign multiple markers to represent complex physical meanings, such as the soft meta-finger's distortion represented using two markers' relative poses. Accordingly, we prepared a simplified open chain representing the tongs' motion on the visualization and data recording screens. The data is recorded at $60Hz$ in a time-series format. One can export the recorded pose tracking data labeled with predefined physical meanings for convenient processing in robot learning. The data is recorded locally in the browser but not in the server.

C. Visual Tracking of Tactile Interaction at a Low-cost

Tactile sensor development usually focuses on leveraging a layer of soft material for physical interaction while using magnetic, visual, or electrical modalities for detecting tactile data, as shown in Fig. 4(a). However, further integration of these sensors into robotic systems remains a challenge. This study uses the soft, 3D meta-finger design with two extra marker plates fixed at the backside. These fingers can be rapidly prototyped using 3D printing, including the soft structure, the detachable plates for ArUco markers, and the base mount connecting the finger to the tongs. One can quickly redesign the base mount to fix the finger to different grippers to introduce passive adaptive compliance in omni-directions. The basic dimensions of the design are shown in Fig. 4(b).

The overall idea is to use the relative pose visually tracked by the markers on the soft meta-finger's backside to infer the 6D force and torque during tactile contact against baseline data collected from a high-performing F/T sensor at the finger's base, As shown in Fig. 4(c). A simple cube adaptor mounts the soft meta-finger on top of an F/T sensor (Nano 25 from ATI). The test rig can provide the loading flange with linear motions along the horizontal and vertical axes and rotary motion about the vertical axis. We adjust the camera viewing angle to face the soft meta-finger fixed on the test rig and use the web-based user interface to collect the relative pose of the two markers fixed at the finger's backside. Each time the push rod was fixed at different heights, the meta-finger was moved linearly toward the rod and rotated 10 or 20 degrees to mimic the real situations while grasping. The ATI sensor's force and torque readings were recorded as training labels. While the spatial distortion of the soft meta-finger at different contact states may not be perfectly mapped to the 6D force and torque readings at the finger's base, we intend to build a simple neural network for testing as a low-cost experiment.

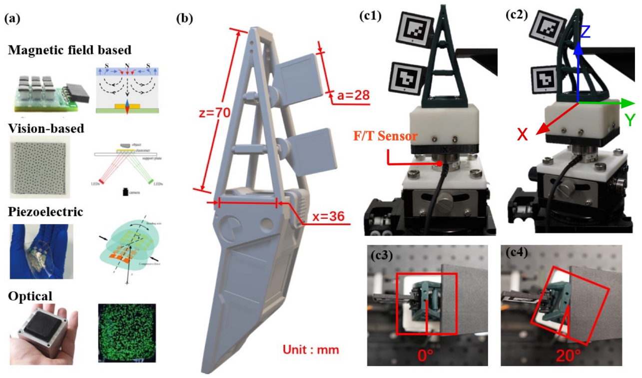

Fig. 4. **The 3D meta-finger design with two Aruco markers fixed at the back for vision-based tactile sensing at a low cost.** (a) Tactile sensors with different working principles such as magnetic field [4], vision [11], piezoelectric [18] and optical flow [19]; (b) Design of the 3D meta-finger; and (c) The front view of the test rig probing the 3D meta-finger in twisting motion is an example, and the top view is when the finger base rotates at 0 and 20 degrees.

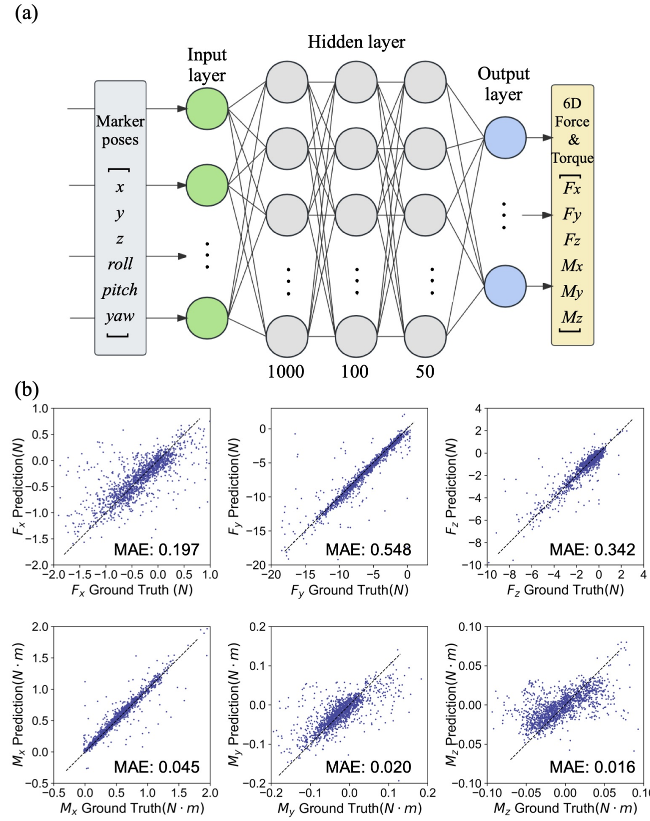

Fig. 5. **The tactile perception using the MLP.** (a) The architecture of the MLP model; (b) Results of the force-torque measurement on the 1500 testing samples. The black dashed line plots where the measurement meets the ground truth.

III. Experiment Results

A. Visual-Tracking Soft Fingers to Learn Tactile Interaction

We built a simple network of multi-layer perceptrons with three hidden layers of 1000, 100, and 50 neurons each, as shown in Fig. 5(a). The network input is the relative pose of the two ArUco markers with the bottom marker as the base reference, expressed in 6D as $(x, y, z, roll, pitch, yaw)$ and recorded as a time-series format at 60Hz. Compared with a direct reading of the absolute marker pose, the relative poses alleviate the need for external calibration. The output is the 6D force and torque estimated at the base of the soft meta-finger, also expressed in 6D as $(F_x, F_y, F_z, M_x, M_y, M_z)$, which is labeled using the ATI's reading recorded at 60Hz. We recorded a total size of 23,500 samples containing various finger deformations collected automatically. We randomly picked 22,000 samples as the training dataset, with the rest as the test dataset.

Fig. 5(b) shows the model performance in each dimension. Due to the experimental setup, F_x is within [-2,2] N, and F_y is within [0,20] N, along the direction of the tong's opening and closure. The MAE (mean absolute error) of F_x is 0.197 N, which is relatively large compared to its small force range. The prediction of F_y and F_z performs better with MAE of 0.548 and 0.342, respectively. The reason could be that F_x is related to the deformation characterized by the relative shift between the two Aruco markers along the Z axis of the camera. The marker detection has a lower accuracy in the depth direction. This also explains the worst performance in M_y with an MAE of 0.020 $N \cdot m$. From these results, mechanical information can be inferred from visually captured large deformations, replacing the need for more expensive F/T sensors.

B. Remote Manipulation with Soft Fingers

An essential problem in human-robot interaction is letting the robot follow human commands more intuitively and responsively. We demonstrated remote visual servoing of a UR10e robotic arm using the movements of human hand-held tongs in a structured way. The opening and closure of the HandE gripper matched the distance between the two soft fingers. In Fig. 6(a), the building cubes are transported by remote operators and stacked into a pyramid. As shown in Fig. 6(b), by controlling the opening width of the tongs, the operator completed the transport of the foam cylinders while keeping their original shape. In Fig. 6(c), the cylindrical foam was transported on a flat plate held by the robotic arm, and the foam did not roll and fall, which verifies the stability of the remote servoing. In Fig. 6(d), the robot arm successfully inserted a USB stick into a motherboard by remote control, reflecting the suitability for delicate tasks. The control is

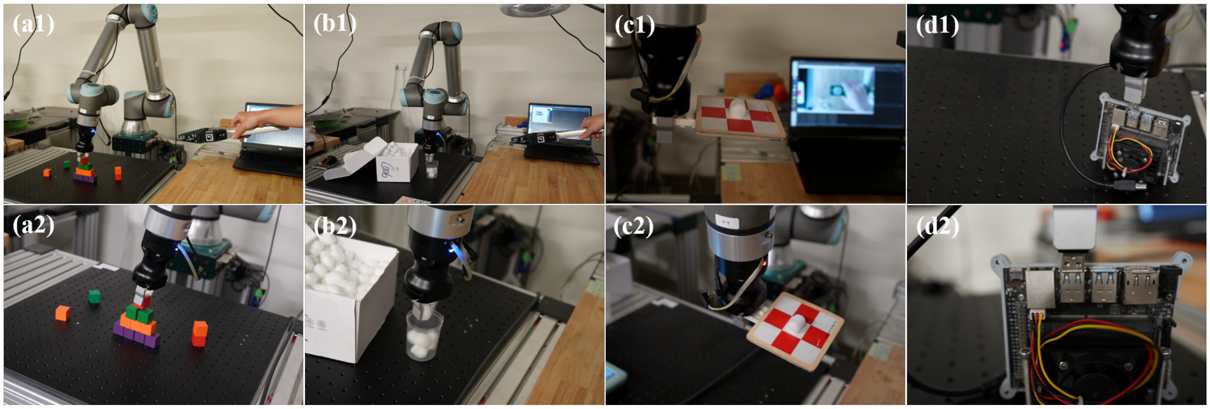

Fig. 6. **Results of remote manipulation control using the soft robotic tongs**, including (a) stacking YCB cubes; (b) transferring soft foam cylinders without damaging them; (c) balancing objects on a plate without falling, and (d) the assembly task is to insert a USB stick into an Nvidia Jetson Nano board.

intuitive to the human operator and does not require users to have a professional knowledge background. Users can understand the operation method after simple teaching, which reduces the difficulty of sharing and reproducing the learning results of the robot.

C. Applying the Collected Data for Gaussian Learning

Based on the data acquisition platform and the user interface of the web page, we selected an ArUco Code on the gripper as the pen tip on the web page, wrote letters on the data acquisition platform, and recorded the operator's entire movement information, including The 6D pose and the corresponding timestamp are formatted and saved. We then performed imitation learning using Gaussian mixture regression (GMR). Gaussian Mixture Regression (GMR) utilizes the Gaussian Condition Theorem to estimate the output distribution given input data. The first is the Gaussian Mixture Model (GMM) estimation, which encodes the joint distribution of input and output data points and then predicts the output given the observed input through a linear combination of conditional expectations. Therefore, GMR does not fit the region function but relies on the learned joint distribution.

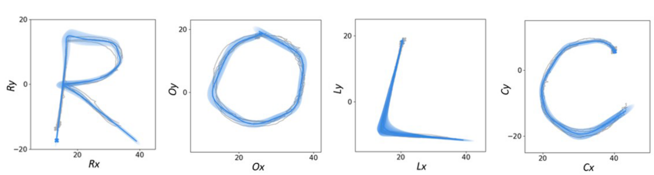

Fig. 7. **Gaussian learning using data collected by the proposed tools.**

In the experiment, we collected four sets of data and wrote four letters of ROLC (Robotics for Online Learning and Control) respectively. Each letter data set contains five sets of trajectory data and then extracts the x and y position information in the data as input. Refer to The method raised by Noemie Jaquier et al. [20]. uses the method of sampling at equal time intervals to complete the imitation learning based on GMR, and the output results are shown in Fig. 7.

D. Bi-manual Manipulation Demonstration with UR10e

In this experiment, we want to realize the cooperation between the human and the robotic arm to complete the task of double-arm operation. We symmetrically map the pose information of the tongs to the robot motion coordinate system, as shown in the sequence of Fig. 8. The robotic arm will take the central line as the central axis, and the movement of the tongs is symmetrically reproduced, thereby realizing the tasks of carrying the bag with two arms and opening, closing, and rotating the bag, which has an excellent prospect for the development of human-machine cooperation.

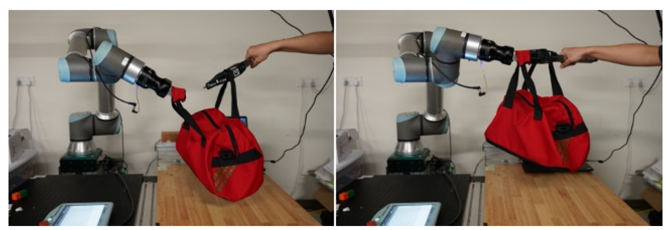

Fig. 8. **Demonstration of mirrored remote control where the soft robotic tongs collaborate with the robotic arm to perform a bi-manual bag handling task.**

IV. Discussions and Conclusion

A. Towards Shareable and Reproducible Tactile Learning

In this study, shareability and reproducibility are the primary design considerations while developing soft robotic tongs for tactile learning. The overall system takes a series of simplification during the design process: (1) we use the tongs as a tool with significantly reduced dimensionality for object manipulation, which is also transferable to robotic grippers; (2) we adopt the soft, meta-finger capable of omni-directional adaption to further reduce the uncertainties during physical contact with environmental objects, but functionally useful for both manual and robotic integration; (3) we further reduced the sensing burden by using only one monocular camera detecting common fiducial markers attached to the fingers, tongs, and objects for a structured representation of the object manipulation task environment; (4) the overall design further considers shareability and reproducibility by developing a portable bag at a low cost, which comes with a web-based browser interface that is easily accessible disregard of the operating system; (5) as shown in the demonstration, one can further develop APIs to remotely interact with robotic hardware in various ways for conducting learning-based research. The tactile model performs well along the direction of grasping with an MAE of $0.548N$ at a range of $[0, 20]N$.

B. Pilot Program for Teaching Robot Learning

We also conducted a pilot program using the proposed system to teach a robot learning course at the University level during Spring 2022, as shown in Fig. 9. While the lab session of this course was previously conducted on-site, the teaching team prepared the proposed design so that it could be fabricated at a low cost, accessed with ease of engineering, and provide relatively rich data so that students can use it for their training models. Although students returned to the campus during the second half of the semester, we kept using this proposed design for teaching purposes. We integrated four experiment sessions for students to practice collecting tactile data for robot learning.

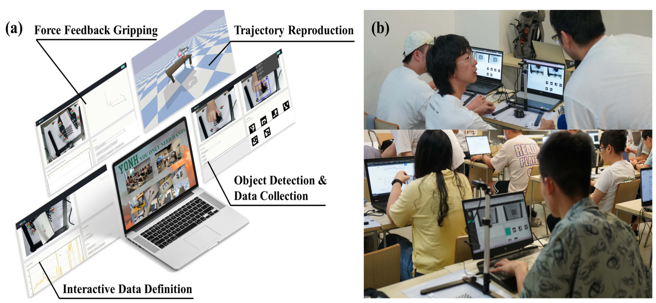

Fig. 9. **Pilot program implementation for teaching robot learning**, including (a) four lab projects online and (b) pilot testing with students.

V. Limitations and Future Work

While the resultant design shows interesting tactile interactions for robot learning, this study also has limitations. The system needs to be improved in its functionality and comprehensiveness to provide a rich data set for training, which requires further development. Although the presented system generally works, the ArUco pose estimation with the browser can only reach the level of many state-of-the-art pose estimations with filtering. Furthermore, the delays in communication limited the range and experience when conducting remote control.

In the future, we will focus on optimization in design and algorithm development with user interface improvement for tactile and movement data collection in human-robot interactions, including advanced techniques for better accuracy in determining the portable tong's 6D pose in real-time, improving our robotic learning processes and system capabilities. Further integration as a teaching tool is also a direction that we are working on, with updated information posted online for shareable and reproducible research[†].

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