

# Characterizing Input Methods for Human-to-robot Demonstrations

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**Abstract**—Human demonstrations are important in a range of robotics applications, and are created with a variety of input methods. However, the design space for these input methods has not been extensively studied. In this paper, focusing on demonstrations of hand-scale object manipulation tasks to robot arms with two-finger grippers, we identify distinct *usage paradigms* in robotics that utilize human-to-robot demonstrations, extract abstract *features* that form a design space for input methods, and characterize existing input methods as well as a novel input method that we introduce, the *instrumented tongs*. We detail the design specifications for our method and present a user study that compares it against three common input methods: free-hand manipulation, kinesthetic guidance, and teleoperation. Study results show that instrumented tongs provide high quality demonstrations and a positive experience for the demonstrator while offering good correspondence to the target robot.

**Index Terms**—Human demonstrations; Robot programming; Design space; Input methods; User experience

## I. INTRODUCTION

Demonstrations—examples of users performing actions—are used as input for a range of purposes in robotics, including programming, guiding, and controlling robots. Several methods exist for providing these demonstrations, such as using a joystick or kinesthetically operating the robot by physically moving it. Different input methods have different features, benefits, and drawbacks, making them more or less appropriate for any particular demonstration scenario. However, there is no framework to assess this fit towards choosing appropriate methods or determining specifications to design new input methods that better address the needs of a given scenario.

Our contribution through this work is twofold. First, we articulate a framework for discussing input methods used for providing demonstrations in the context of hand-scale object manipulation tasks carried out by robot arms with two-finger grippers. Second, to exemplify the utility of this framework, we present and assess the design of a novel input device for such demonstrations, *instrumented tongs*.

We begin by considering a range of *usage paradigms* in robotics, such as real-time control or learning from demonstration, that require human demonstrations. From this

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list of usage paradigms, we derive a set of *features* for input methods, each useful in at least some of these paradigms. These features provide a *design space* in which we can map existing input methods in order to characterize them. In the context of this design space, we also situate the design of a new input device, instrumented tongs, to support scenarios where inexperienced users provide demonstrations of object manipulations as input to inform robot execution of these tasks. Such scenarios require input methods that are easy for users, provide natural and efficient movements, support easy instrumentation, and achieve good correspondence to robot motions. We present a user study that assesses the extent to which instrumented tongs support these goals by comparing it to other commonly used input methods.

## II. RELATED WORK

We draw on prior work to develop two levels of abstraction that serve as the basis for our framework: paradigms for the use of human-to-robot demonstrations (*usage paradigms*), and desirable qualities of demonstrations and the methods to input them (*features*). We then use these abstractions to characterize existing and new input methods.

Prior work has compared specific input devices for learning from demonstration [1]–[3] and for real-time control [4]–[6]. We look for other broad categories in the robotics literature that utilize demonstrations and list them as *usage paradigms* in Section III-A.

Prior research in HRI has considered either multiple implementations of a single input method such as kinesthetic guidance or teleoperation (e.g., [3]–[8]) or compared multiple input methods including GUI, space mouse, and haptic interface (e.g., [1], [2], [9]–[12]). At a high level, these studies indicate that input methods affect the experience and quality of the demonstrations provided by users. We build on this body of work to identify desirable *features*, as listed in Section III-B.

Many studies provide evidence of features and tradeoffs of specific input methods, which we take into consideration when generating the design space. For example, Muxfeldt et al. [10] suggest that extracting human assembly strategies from kinesthetic teaching leads to distorted results as compared to more natural input methods. Fischer et al. [1] discuss issues such as performance, physical exertion, and naturalness across input devices. Prior work that identifies drawbacks of input

methods also contributes to our understanding of useful features of input methods. For example, Akgun et al. [7] show that kinesthetic demonstrations suffer from extraneous movement, and Pervez et al. [13] highlight the problems associated with inconsistent demonstrations from teleoperation.

We also draw insights for generating our framework from work in human-computer interaction that involves systematizing human-machine input devices [14], [15], and designing specialized devices to address input needs, most notably to support teleoperation [16]–[18].

### III. A FRAMEWORK FOR CHARACTERIZING INPUT METHODS

In this section, we present a framework for characterizing input methods used for demonstrations in robotics (Figure 1). The framework emerged from our experiences designing new input methods. We realized the need for a more formal framework to provide a tool for identifying requirements and understanding existing methods. To create the framework, as described in Section II, we distilled insights from prior work into the abstractions of *usage paradigms* and *features* that allow us to characterize commonly used demonstration methods. As a starting point, we focus on scenarios where demonstrations are provided to a robot arm with a two-finger gripper that performs hand-scale object manipulation tasks. Such scenarios are frequent in current robotics applications.

#### A. Usage paradigms

We identify distinct categories in robotics that use demonstrations and have different needs from them. We refer to the categories as *usage paradigms*.

1) *Direct Replay*: In direct replay, the robot executes the demonstration as it was recorded, with minimal processing. It is commonly used to program industrial robots and to assess demonstrations in other usage paradigms (e.g., [7]).

2) *Real-time Control*: Demonstrations can enable an operator to control a robot in real time. This is also important for Wizard-of-Oz prototyping [19]. This usage paradigm requires robot execution that is faithful to the demonstration and that retains the expressiveness of the demonstration.

3) *One-shot Learning*: A single demonstration can be used to inform the generation of actions. This usage paradigm differs from direct replay because the robot will not execute the exact demonstration. Unlike more traditional, multi-demonstration learning, one-shot learning relies heavily on the properties of that single demonstration.

4) *Learning from Demonstration (LfD)*: We use LfD to refer specifically to scenarios that generalize from *multiple* demonstrations. Here, demonstrations are not directly executed by the robot but rather combined to create robot movements.

5) *Incremental Learning from Demonstration (ILfD)*: ILfD refers to a special case where the demonstrations are provided during the learning process. ILfD has similar needs to LfD, but may require demonstrations that are responsive to problems identified by the user (e.g., [20]) or partial task demonstrations.

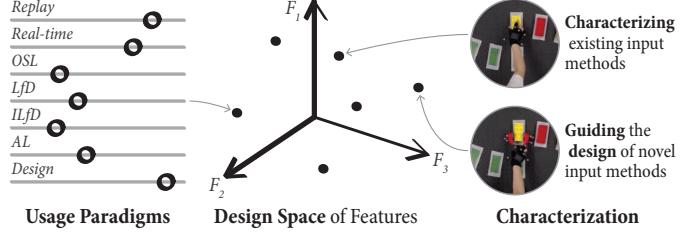


Fig. 1. Our framework and its three components: usage paradigms, design space of features, and characterization of input methods.

6) *Apprenticeship Learning (AL)*: We use this term for scenarios where demonstrations are only part of the input into the learning algorithm. For example, demonstrations can guide reinforcement learning [21] either for reward shaping or as starting points for guided exploration. AL has different needs because of the less direct use of the demonstrations.

7) *Design*: Demonstrations may be used for intermediate steps toward design goals such as identifying reusable primitives for preprogramming robots (e.g., [22]) or understanding human performance to inform robotics tasks (e.g., [23], [24]). This is a distinct usage paradigm because the demonstrations are not translated into robot motions but rather used to gain insight on demonstrator behavior or performance.

#### B. Features

Each usage paradigm suggests features that it needs from demonstrations and the methods to input them. The union of these features provides a list of desirable qualities for input methods. The features are often interconnected (i.e., are not orthogonal). For example, usability concerns may lead to demonstration quality effects. However, the extended set of features is valuable because there may be multiple ways to achieve a particular feature, and a feature might serve different goals. We organize our discussion by groups of feature types, and label specific features with numbers for later reference.

*Qualities of the Resulting Demonstrations* — Input devices influence the qualities of the resulting demonstrations by providing affordances that encourage particular properties. Even if it is possible to add properties to a demonstration *post-hoc*, such improvements come at a cost of reducing how much information is kept from the original demonstration.

1) *Efficient*: Many scenarios require demonstrations that have desirable quantitative measurements, such as being short in distance or time, low in energy consumption, or low in jerk. Efficient demonstrations may lead to more effective robot executions when replayed or built into learned behaviors.

2) *Subjective performance*: Many scenarios benefit from demonstrations that have properties that are difficult to measure directly. For example, they may seek demonstrations that are *natural* (performed in a manner that a person would normally perform the task), or *recognizable* (the demonstrator should see that the movements are similar to what they provided). Naturalness may be important if the robot's performance needs to be interpretable by collaborators [25], to train robots to

make human-like movements (e.g., for communication [26]), or if the goal is to understand how people perform tasks.

3) *Desired demonstrations*: Usage paradigms often need certain types of demonstrations. For example, they may require *successful executions* of tasks (although failed demonstrations can also be learned from [27]). In some cases, meaningful *variance* in executions is useful to understand how to generalize beyond the provided demonstrations (e.g., [28], [29]). In contrast, extraneous variance such as differences between executions because of false starts, inflections, mistakes, or inaccuracies, are less often useful, although some analysis techniques might exploit such information (e.g., [30]).

4) *Amenable to analysis*: Different downstream data processing algorithms may require different input data properties. For example, some scenarios need continuous trajectories while others employ only keyframes. Different input devices may have different affordances for different data types, such as being more or less easy to create continuous movements [7] or providing the ability to capture meta-data to inform analyses such as segmentation and keyframe determination.

*Qualities of the Demonstrator Experience* — The input device affects the experience of giving a demonstration. The importance of the demonstrator experience varies, e.g., scenarios with casual users may place more emphasis on the subjective experience than methods designed for experts performing critical tasks.

5) *Affords quality demonstrations*: As described above, the input device may facilitate a person to give demonstrations *naturally* (as they would in the real-world task), *confidently* (to know that they are achieving their goals), and *expressively* (to achieve other demonstration goals such as speed).

6) *Facile*: The input method should place low mental and physical demands on the demonstrator beyond the task itself. For example, expecting a demonstrator to lift a heavy robot or attend to collisions of the robot’s joints in the environment may distract them from performing a challenging task.

7) *Easy to learn*: Experience in using a device often leads to better performance. However, some devices allow demonstrators to achieve good performance with less training.

8) *Preference*: Many scenarios value input methods that demonstrators like. For example, in casual user scenarios, methods that are novel or fun may encourage users to try an application. Conversely, casual users may stop using things they dislike when they aren’t being compelled.

9) *Feedback*: The input method must provide the demonstrator sufficient feedback to perform the actions they intend. Visual, haptic, tactile, and even auditory cues can be important to helping a demonstrator perform a task.

*Correspondence with Robot* — In many usage paradigms, demonstrations are used to create robot actions, requiring them to be relevant to how the robot will perform the actions. This correspondence can be challenging when the demonstrator has different abilities than the robot, such as the different kinematic and dynamic properties of human and robot arms.

We distinguish correspondence for demonstrations into two types: *plausible* and *feasible*. *Plausible* demonstrations

match the capabilities of the target robot, whereas *feasible* demonstrations can be executed by the robot. For example, in a pick-and-place demonstration, an implausible demonstration may involve grasping the object with multiple points of contact on a single finger, using dexterous in-hand manipulations to orient the object, or using fine haptic sensing to determine where on the object to grasp. Even with a plausible demonstration, e.g., performing the above task using a pinch grasp and a wrist movement to correctly orient it, the robot may not be able to feasibly follow the paths of the fingers due to kinematic constraints, collisions, or singularities.

10) *Plausibility*: It is often valuable that the basic strategy of performing a task is a plausible one for the robot to use. While it may be possible to transform an implausible demonstration into a plausible one, these transformations are necessarily complex (because they involve changing strategy). Even if the transformation is possible, it may change the demonstration enough to disturb other properties such as recognizability.

11) *Feasibility*: Feasibility ensures that a specific demonstration can be executed on the robot. Feasible demonstrations are enforced by methods that involve physically moving the robot. However, given a plausible end-effector path, feasible trajectories can be generated through optimization (e.g., [31], [32]), and near-feasible trajectories can be made feasible through trajectory optimization (e.g., [31], [33]–[36]). Such computational methods for creating feasible motions are necessary in scenarios that generalize demonstrations because even if the demonstrations are feasible, the trajectories generated by a learning method may not be.

*Practical Qualities* — Practical concerns make up the final category of features, that is if the device can be built and deployed in an effective manner. We focus on one specific aspect of practicality that concerns input devices.

12) *Instrumentable*: All usage paradigms require measurements of demonstrations using appropriate sensors, including positions, orientations, and applied forces and torques. Different scenarios may require different types or fidelity of measurements. For example, understanding human task strategies may only need coarse timing data, while a method to infer constraints from a demonstration may require precise position, orientation, force, and torque measurements [37]. Different input devices afford different instrumentation. For example, positioning a robot provides precise kinematic information whereas tracking the position of the demonstrator’s fingers may be challenging.

### C. Characterizing Input Methods

In this section we first discuss two points about usage paradigms and features that are applicable to the process of characterizing input methods.

*How do usage paradigms relate to features?* Different usage paradigms may require different features from demonstrations. Within this discussion, we look at binary weightings of these features, that is whether a feature is prioritized or not. For instance, direct replay and real-time control require robot execution to be faithful to the demonstration

and retain the expressiveness of the demonstration (e.g., [38], [39]). These paradigms would benefit from efficient (Feature 1), recognizable (2), plausible (10) and feasible (11) demonstrations. In addition, specific scenarios will require the presence of other features. Scenarios involving repetition or complex tasks are likely to benefit from having input methods that are facile (6), for instance to provide multiple knot tying demonstrations for LfD [29]. An easy to learn (7) input method may allow non-expert users to confidently (5) provide demonstrations for one-shot learning (e.g., [40]). In Bajcsy et al. [20], demonstrations are required in the form of corrections as input for incremental LfD. Some of the prioritized features are sporadic demonstrations (3), plausibility (10), feasibility (11), recognizability (2), capturing corrections (12) and feedback (9). It is also possible that certain features are intentionally de-prioritized, for instance failed demonstrations are encouraged in Grollman and Billard [27] for improving LfD algorithms.

*How can features be used in the process of characterization of input methods?* Each feature can be evaluated using different measures. For instance, in Fischer et al. [1], length of demonstrated paths and interaction times are used to measure efficiency (Feature 1). Kramberger [2] used standard deviation of the learned trajectories to measure repeatability (3). Muxfeldt et al. [10] and Rakita et al. [4] use decreasing interaction time of repeated trials as an indication of ease of learning (7). A detailed discussion of the measurements for each feature is beyond the scope of this paper. However, Section V-A provides an example of a broad set of measures that may be used to measure the quality of demonstration and demonstrator experience.

Below, we theorize from prior studies referred to in Section II about three input methods commonly used to provide demonstrations across a range of robotics applications. Our empirical evaluation of these input methods is part of the user study described in Section V-A.

1) *Kinesthetic Guidance (KG)*: In KG, the demonstrator physically moves the robot. Such an input method requires that the demonstrator has access to the robot system and that the robot can be “back-driven” to be posed manually. Because robots can typically sense their configurations, KG inputs provide precise kinematic measurements and, in some cases, force information (Feature 12). KG provides plausible (10) and feasible (11) demonstrations, as the use of the robot to create the movements ensures that it is capable of performing them.

User experience with KG depends on the implementation; some robots are easier to move (e.g., due to better gravity compensation) while others have kinematic properties that are hard to understand. At a high level, KG requires the user to consider how the robot moves during the demonstration, particularly to create feasible movements. The need to physically move the robot can negatively affect user preference (8), ease of learning (7), facileness (6), and demonstration qualities (5). While KG generally offers good visual feedback, it does not provide users with a complete haptic sense of the robot’s performance (9). Although prior studies [8], [10] have shown user preference toward KG over traditional input

methods (e.g., joystick or teach pendants), these studies do not include more natural input methods as we will in Section V.

The qualities of movements obtained with KG are hard to assess *a priori*. We expect the unnatural mode of input and the need to consider the robot’s kinematics to be a challenge in creating demonstrations that are efficient (1), natural (2), or of the desired type (3), particularly for inexperienced users. Motion artifacts, e.g., irrelevant starts and stops to change grip on the robot, can make analysis challenging (4).

2) *Free-Hand Manipulation (FHM)*: In FHM, users perform demonstrations with their hand. Unlike in KG, obtaining precise kinematic measurements and force information of these demonstrations is difficult (12). Instrumented gloves are also expensive and uncommon. Robustly tracking fingers from video or optical data is challenging because of occlusion. Because the hand is so capable, the resulting demonstrations may not be plausible or feasible for robot execution (10, 11).

Our inherent skill and lifelong experience at using our hands to perform actions leads to high quality demonstrations (5) with little extra effort (6) and no learning (7). We expect people to also show higher preference (8) toward using this inherent ability. The hands provide considerable amount of sensing (9). People’s inherent skill in using their hands also ensures that the movements will be efficient (1), natural for them (2), and controllable to achieve desired goals (3).

3) *Teleoperation (TO)*: In TO, the demonstrator is physically separated from the space where the demonstration is performed. TO often involves real-time remote control of a robot or its virtual representation for real-time or future use. Unlike in FHM, the movements are used to control a robot, and therefore perform tasks indirectly. The specific input device used to control the robot can vary; see Rakita et al. [4] for a comparison of various options.

Feedback (9) is a critical issue in TO, as the operator is unable to directly observe the action. Prior work has explored techniques for visual [41] and haptic feedback [42]. Similar to KG, TO is naturally instrumented to record kinematic information (12) and provides plausible (10) and feasible (11) movements (assuming that the actual robot is used). Prior work has explored natural interfaces for teleoperation control and compared it to other standard interfaces [4]. While this interface has been shown to have usability and performance advantages relative to other TO input devices [4], its performance relative to other non-TO demonstration approaches is unknown.

#### IV. DESIGN OF INSTRUMENTED TONGS

Our vision is to enable inexperienced users to teach robots to perform physical manipulation tasks and this highlights the need to satisfy the following design goals.

##### A. Design Goals

1) *Obtaining High-Quality Demonstrations*: Efficiency is valuable (1) as we seek to execute demonstrations (or programs derived from them) on the robot. Natural movements (2) will enable the demonstrator to easily verify robot actions. Most scenarios we consider require successful demonstrations, and some benefit from meaningful variance (3).

**2) Improving User Experience:** Because we are interested in supporting inexperienced users, we are concerned with the qualitative experience of providing demonstrations. We want to enable inexperienced users to provide quality demonstrations of potentially complex tasks. Our input device must be facile (6), easily to learn (7), and liked (8). Tactile feedback is valuable to complete complex manipulation tasks effectively (9).

**3) Trajectory Quality:** Because demonstrations may be executed on the robot, we require plausibility (10), and to a lesser degree, feasibility (11). We can use optimization to create feasible trajectories from end-effector paths.

**4) Precise Measurement:** Many robot control algorithms require precise measurement of position and orientation as well as applied forces and torques during the demonstration (12).

Unfortunately, existing methods do not serve this set of desired features. Free-hand manipulation offers the desired user experience and movement qualities, but is too difficult to instrument and does not encourage plausible demonstrations. Kinesthetic demonstrations offer easy instrumentation and enforce plausibility. However, we were concerned that its unnaturalness would not provide the desired user experience and would lead to poor quality movements in the demonstration.

## B. Design Details

Our design is inspired by kitchen tongs. We observe that tongs restrict manipulation to a clumsy form of pinch grasp that is simpler than most robot grippers. Despite this limited capability, people use tongs adeptly to perform a wide range of manipulations (e.g., patrons at a salad bar or a parent pulling a splinter from a child with tweezers). Therefore, tongs serve as a metaphor for the limitations of a robot gripper.

The design details in this section are specific to the prototype shown in Figure 2 and used in the experiments of Section V. The specific details may be adapted based on the sensors available and the size of objects to be manipulated. Full construction plans, including shape files for 3D printing and assembly suggestions, are available under a non-restrictive open-source license.<sup>1</sup>

**1) Basic Construction:** The instrumented tongs consist of two rigid, 3D printed arms made from PLA plastic. A hinge consisting of a steel pin with plastic bushings holds the arms together. The tongs are held open with a flat *spring steel* spring. On the grasping side of the tongs, two inset mounting surfaces enable attachment of force-torque sensors. Multiple prongs provide locations to attach motion capture markers.

**2) Size and Mechanism:** Our tongs are sized to be similar to kitchen tongs. We felt this size fit comfortably in the hand and provided the ability to manipulate hand-scale objects. Our tongs retain the single hinge design from kitchen tongs, which is a simpler mechanism than the parallel jaw, compliant, or under-actuated designs commonly seen in robot grippers. The simple hinge design has advantages; it is easy to design and build, requires few parts, is familiar to most users (as it mimics common tools such as pliers, tweezers and kitchen tongs), and provides for direct haptic feedback.

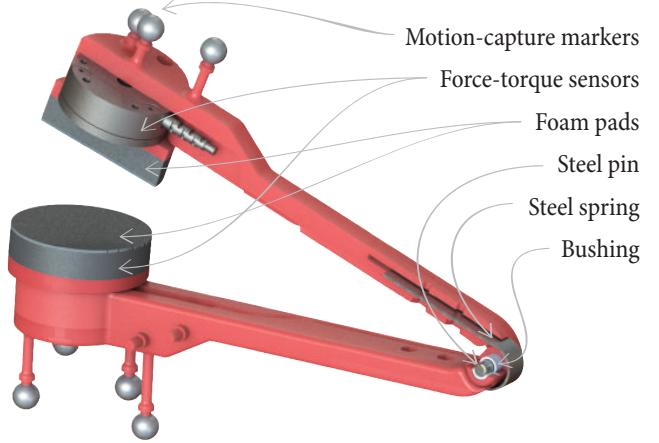


Fig. 2. Design of the current prototype of *instrumented tongs*.

**3) Gripper Surface:** The hinged geometry described earlier makes the jaws parallel in only one position. Rigid objects contact the gripper at two points. To mitigate this issue, we build compliance into the tongs by padding the contact surfaces with dense foam to provide enough contact area to manipulate rigid objects such as blocks in Section V, yet firm enough to provide good tactile cues. A plastic plate is attached directly to the tool side of the force-torque sensors to provide a mounting surface for softer padding. The plastic plate is wedge shaped to accommodate a relatively parallel grasp of large objects. The padding consists of a low-density thick foam layer (~10mm) followed by a high density thin foam layer (1mm). A final layer of 3M Gripping material (3M TB400) was used to provide sufficient friction to hold objects in place.

**4) Sensors:** The current version of the tongs uses an Optitrack motion capture system which employs reflective markers that are rigidly attached to the tongs and cameras to record the motion of these markers. We track both arms as independent rigid bodies. A pair of ATI Mini40 force-torque sensors, one in each arm, provide accurate measurement of the applied forces and torques when grasping objects. The current sensors provide precise measurement of forces and torques applied by the tongs to a manipulated object. While force-torque sensors are highly accurate instruments (which directly reflect on cost and durability), many applications may not need the accuracy or may require a different kind of measurement (e.g., temperature, vibrations).

## V. ASSESSMENT

This section describes a study to validate that instrumented tongs meet the design goals listed in Section IV-A by comparing the tongs against three methods commonly used in human-to-robot demonstrations discussed in Section III-C. The study aimed to determine whether the tongs could provide the demonstration quality and user experience of free-hand manipulation with the mapping and practicality benefits of kinesthetic demonstrations. We developed a set of object-manipulation tasks and asked participants to demonstrate these tasks with four input methods: free-hand manipulation,

<sup>1</sup><https://github.com/uwgraphics/HRI2019Tongs>

kinesthetic guidance, and teleoperation as described in Section III-C; and instrumented tongs as described in Section IV-B.

### A. Study Design

**Experimental Design** — We designed a  $4 \times 1$  within-participants experiment in which novice participants provided demonstrations of three tasks with all four input methods—*Tongs*, *Hand*, *Kinesthetic*, and *Teleoperation*—in a counterbalanced order. Movements during the demonstration were recorded using an Optitrack motion capture system that tracked reflective markers. Synchronous video was captured by a ceiling-mounted Logitech C920 Pro webcam. Participants filled out questionnaires after using each input method.

**Participants** — We recruited 24 participants (13 male, 11 female) from the University of Wisconsin–Madison campus between the ages of 21 and 27 ( $M = 23.75$ ,  $SD = 1.54$ ). Participants reported some familiarity with robots ( $M = 3.17$ ,  $SD = 1.39$ , measured on a 7-point scale). Five participants reported an interaction with a robot in prior robotics research studies. The study took 90–120 minutes, and all participants received USD 20 as compensation.

**Methods of Demonstration** — We used representative implementations of the methods discussed in Section III-C that allow us to assess general properties of each method.

**Hand:** Participants wore a glove that did not interfere with the dominant hand’s functional dexterity. All participants wore the glove on the right hand (23 participants were right-handed, and one participant was ambidextrous). Motion-capture markers were attached to the back of the glove to track hand movement but not finger movement, allowing us to assess the amount of arm movement but not the details of manipulation.

**Kinesthetic:** Participants used a UR5 robot arm from Universal Robots equipped with a Robotiq 85 two-finger gripper. The robot was placed in “freedrive” mode that allowed for it to be moved freely with gravity compensation. A separate button was provided on a wireless remote to open and close the gripper. While the joint angles of the robot can be recorded, we tracked the end-effector position and orientation using the same motion capture markers as with other devices.

**Teleoperation:** Participants used the system described by Rakita et al. [4] to teleoperate the UR5 robot. The participants held an HTC Vive controller that tracked the position and orientation of their hand, which the system mapped to the robot end-effector in real time, causing the robot to mimic the natural arm motions of the participant. A button on the controller operated the robot gripper. To ensure safety, participants stood outside the working radius (850 mm) of the robot.

**Instrumented Tongs:** Participants used their dominant hand to provide demonstrations, and motion-capture markers on the tongs were used to record them.

**Setup, Tasks, & Procedure** — Tasks involved manipulating  $5 \times 2.5 \times 1.5$ -inch ( $L \times W \times H$ ) blocks in a workspace across various locations identified by the letters P, Q, R, and T (Figure 3). Participants performed three tasks in a fixed order:

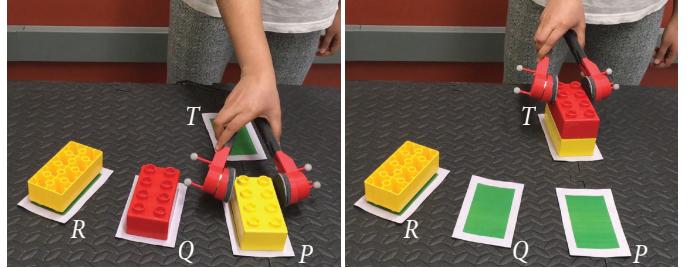


Fig. 3. Using *instrumented tongs* to demonstrate Lego block stacking.

**1) Training task:** For each trial, the experimenter places a foam block in one of the starting locations (P, Q, or R). The participant picks this block up and places it on the target (T). The task consists of eight trials.

**2) Foam block stacking:** Foam blocks are placed at positions P, Q, and R. The participant picks each one up and places them at position T, creating a stack. The third block is upside down and must be flipped before being placed.

**3) Lego block stacking:** This task is similar to *foam block stacking*, except that large LEGO blocks are used in place of foam blocks. These blocks must be snapped together, requiring precise alignment and appropriate forces.

The procedure was administered under a protocol reviewed and approved by the University of Wisconsin–Madison Education and Social/Behavioral Science Institutional Review Board (IRB). Following informed consent, participants watched a video outlining the experiment goals and then used each input method in the order assigned to them. For each method, participants first watched a training video, then performed the three tasks, and finally filled out two online questionnaires.

**Measurement and Analysis** — Here, we describe measures to assess support for our design goals. Interaction time, accuracy, path length, and jerk are captured for the block-stacking tasks, learning effect for the training task, and user preferences and workload at the end of all tasks.

**Interaction Time:** We measured the total amount of time taken to complete the foam and LEGO block-stacking tasks.

**Accuracy:** We measured the average accuracy of the final placement of the blocks at the targets by calculating the area of the target rectangle that remains exposed after the blocks were placed over it. Both position and rotation error were captured by this metric. If a block was not placed at the final position, the error was capped at the total area of the target position.

**Path length:** Total distance traveled by the hand, averaged across the two tasks, served as a measure of task efficiency.

**Jerk:** We used average jerk as a measure of extraneous movement. Jerk was calculated as the time derivative of the acceleration of the captured trajectory. Points missing from the data (e.g., from motion capture occlusions) were omitted.

**Learning effect:** Change in the time taken over multiple trials served as a measure of learning.

**User preferences:** We administered a questionnaire based on prior research on measuring user preferences [43]. The questionnaire included three scales, each with four items

measured on a seven-point rating scale (1 = strongly disagree; 7 = strongly agree), to measure ease of use of the input method (Cronbach's  $\alpha = 0.94$ ), enjoyment (Cronbach's  $\alpha = 0.89$ ), and confidence that the robot will be able to learn from the demonstration (Cronbach's  $\alpha = 0.94$ ).

**Workload:** We used the NASA Task Load Index (TLX) [44] to assess user's perceived workload. The total workload is divided into six subscales—mental demand, physical demand, temporal demand, performance, effort, and frustration—that are measured on a 100-point rating scale, where higher ratings indicate more workload. The scores are aggregated with equal weighting to calculate the TLX.

We analyzed data from all measures using one-way repeated-measures analyses of variance (ANOVA) to determine whether or not the input method had a significant effect. If the ANOVA test showed significant differences, we used Tukey's HSD test in order to determine where the differences lied while accounting for multiple comparisons.

## B. Results and Discussion

This section is organized according to the design goals set in Section IV-A. The descriptive and inferential statistics for the results described below are shown in Tables I and II.

**Quality** — Quantitative motion quality metrics are summarized in Figure 4.A–D. Across all metrics—accuracy, path length, smoothness, and interaction time—hand and tongs significantly outperformed teleoperation and kinesthetic demonstrations. More surprisingly, tongs were competitive with hand for all metrics. Differences were not significant, except a shorter average path length with tongs than with hand. Because the significance tests consider variance across the whole experiment, they smooth over the detail shown in Figure 4.D.2, which suggests that tongs are consistently slightly slower than hand. We discuss this observation under *plausibility* below. This analysis suggests that tongs meet the motion quality goals as they are competitive with the best of the prior methods. Although we did not directly assess its naturalness, its similarity to hand suggests tongs to be a natural input method.

**User Experience** — We found that the goals for a better experience for the demonstrator were met: the tongs allowed users to easily provide expressive demonstrations without prior experience. These results are shown in Figure 4.E–G. Tongs and hand provided significantly higher ease of use and enjoyment, and lower workload than teleoperation or kinesthetic guidance. However, there were no significant differences between hand and tongs. We found no significant differences among the methods in the participants' perceived confidence in the robot's ability to perform a similar task in the future.

Perceived workload, as measured by the TLX scores, followed the inverse trend as perceived ease of use, indicating an association between ease of use of the input method and demonstrator workload. Participants found kinesthetic guidance physically strenuous, consistent with the higher jerk and path length observed with this method. Participants found teleoperation control mentally demanding, perhaps because it

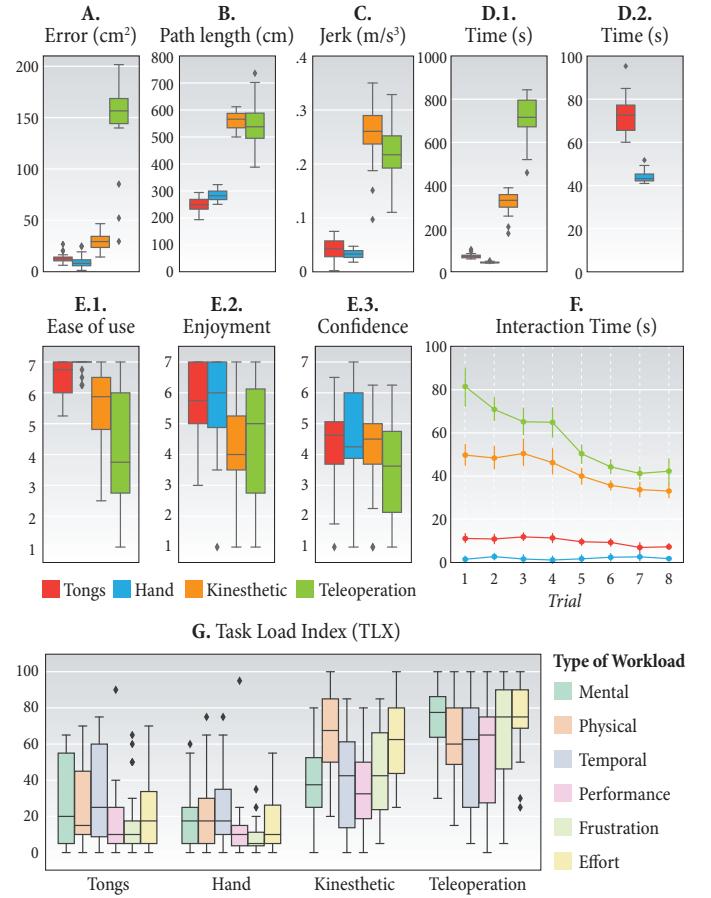


Fig. 4. Boxplots for (A) accuracy, (B) path length, (C) jerk, (D) interaction time, and (E) subjective measures of ease of use, enjoyment and confidence for the four methods of demonstration. (F) Point plot of interaction time during the training task. Vertical bars show standard deviation. (G) Boxplots of the perceived workload on each subscale of the NASA Task Load Index.

required them to constantly update their understanding of the correspondence between their movements and the robot.

Interaction time during the training task shows that participants were already adept at using their hands and tongs. However, they adapted and improved performance across multiple trials for other methods. In our experimental trials, we observed participants to rely on haptic feedback during demonstrations using hands or tongs. Often, participants fumbled during the assembly of blocks and depended additionally on visual feedback for better alignment.

**Correspondence** — Kinesthetic and teleoperation both provide demonstrations that have a direct correspondence with the robot. While mapping position and orientation of hands or tongs to a robot configuration requires complex optimization-based computational approaches (e.g., [31], [32]), demonstrations provide better *plausibility* with tongs. In our observations, while grasping the block with tongs, participants approached carefully from a direction that allowed a good grip, similar to what a robot would perform. In contrast, during free-hand demonstrations, participants grasped the block in a variety of ways from different directions. Participants also primarily flipped the block using an in-hand manipulation, although

some participants used a parallel grip after using other input methods. Using the tongs, the flipping action involved twisting the arm, as it would on the robot. We believe these plausibility differences account for the inefficiency of tongs relative to hand seen in Figure 4.D.2.

*Instrumentation* — As described in Section IV-B4, our tongs are instrumented to allow for precise measurement of position and orientation as well as force and torque at the contact surface. Tracking the robot during teleoperation or kinesthetic demonstrations also provides precise measurement of kinematic information (gripper position and orientation). The fingers of the robot gripper could have the same sensors installed as the tongs to capture forces and torques. On the other hand, our data collection lacked the instrumentation necessary to obtain good kinematic information from free-hand demonstrations. Because of the limitations of our sensing equipment, we were only able to measure the position and orientation of the hand as a rigid body. While these measurements were sufficient for comparing the amount of arm motion between different methods, most other scenarios would require capturing more information about the manipulations. Precisely measuring the positions of the fingertips, even in the relatively uncluttered environment of our experiment, would require sensors beyond what is readily available off the shelf.

*Summary* — Our evaluation showed that the use of tongs as an input method provides many of these features at levels comparable to the best existing input methods. No existing method provides the combination of good demonstration quality, good demonstrator experience, good correspondence with the robot, and good instrumentability, as provided by tongs. While kinesthetic demonstrations have been shown to be effective for

**TABLE I**  
DESCRIPTIVE STATISTICS FOR ALL MEASURES.

	Tongs		Hand		Kinesthetic		Teleoperation	
Measurement	M	SD	M	SD	M	SD	M	SD
Time (s)	73.2	10.6	44.2	2.7	319	53.9	715	99.3
Accuracy (cm <sup>2</sup> )	13.4	4.4	9.76	6.70	30.1	8.75	148	39.2
Path Length (cm)	247	25.5	284	20.2	561	35.1	547	82.7
Jerk (m/s <sup>3</sup> )	0.04	0.02	0.03	0.01	0.25	0.06	0.22	0.05
Ease of Use (1-7)	6.49	0.61	6.88	0.26	5.55	1.28	4.11	1.89
Enjoyment (1-7)	5.71	1.28	5.69	1.52	4.35	1.49	4.42	1.98
Confidence (1-7)	4.31	1.39	4.39	1.81	4.16	1.35	3.39	1.68
TLX (0-100)	24.0	17.6	17.4	10.7	47.5	15.8	64.2	16.5

TABLE II  
INFERENTIAL STATISTICS FOR ALL MEASURES.

Pairwise comparisons ( $\dagger p < 0.05$ , * $p < 0.001$ )								
		Hand	Kin.	Teleop.	Hand	Hand	Kin.	
Measurement	F(3, 69)	p	Tongs	Tongs	Tongs	Kin.	Teleop.	Teleop
Time	537	<.001	.295	.001*	.001*	.001*	.001*	.001*
Accuracy	185	<.001	.900	.030†	.001*	.005†	.001*	.001*
Path Length	70.1	<.001	.044†	.001*	.001*	.001*	.001*	.725
Jerk	151	<.001	.852	.001*	.001*	.001*	.001*	.024†
Ease of Use	19.8	<.001	.646	.033†	.001*	.001*	.001*	.001*
Enjoyment	4.09	.0097	.900	.021†	.030†	.023†	.033†	.900
Confidence	1.54	.2113				<i>Not Significant</i>		
TLX	35.4	<.001	.460	.001*	.001*	.001*	.001*	.002†

robotics applications, our study suggests that they have inferior motion quality and user experience compared to more natural input methods. Similarly, natural teleoperation interfaces that have been shown to be superior to other teleoperation schemes do not provide the advantages of direct natural interfaces.

## VI. GENERAL DISCUSSION

Our framework allows us to reason about the potential efficacy of different input methods, including the instrumented tongs. Because we cannot make claims regarding its comprehensiveness [45], how well it will generalize to new scenarios is unclear. Additionally, our selection of features is shaped by our focus within this paper on demonstrations of hand-scale manipulations to robot arms with two-finger grippers. Other features may emerge from considering more complex scenarios. For example, the consideration of more types of robot end-effectors would require us to add the ability to retarget the demonstration between end-effectors to the set of features. Expanding the framework to such scenarios is a promising direction for extension of this work.

Our study provides an example of an empirical evaluation, including measurement methods and tools, that can be used to understand input methods using this framework. However, it is limited by the specific tasks and device implementations that are considered. We are particularly interested in how our results extend to more complicated tasks in cluttered spaces. New techniques may provide better implementations, such as practical hand tracking in cluttered environments or better mechanisms to make kinesthetic control of robots easier, which may alter the relative merits of their respective methods. The findings from our study suggest that tongs provide a successful solution to a specific set of needs: capturing kinematic and force/torque demonstrations for hand-scale object manipulations. It is unclear how well its use generalizes to a broader range of scenarios. Our current design uses high-precision sensors that are costly and cumbersome and that require cables. The bulkiness of the device limits the tasks and environments in which it can be used. Variations in the design may allow the instrumented tongs to achieve the design goals with different trade-offs for other scenarios. For example, using smaller force sensors (that may be less precise) could provide a smaller device that can support finger-scale manipulations.

The framework introduced in our work provides a tool to characterize input methods for human-to-robot demonstrations. We believe that this approach can be extended to broaden the applicability of the framework. Our new input method, instrumented tongs, has already enabled the development of new techniques (e.g., [37], [46], [47]) through its combination of practicality, usability, and demonstration quality.

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