Communicating Physical Properties through Robot Object Manipulation

Xiang Pan
Kyoto University
Kyoto, Japan
pan.xiang.35w@st.kyoto-u.ac.jp

Malcolm Doering
Kyoto University
Kyoto, Japan
doering@i.kyoto-u.ac.jp

Stela Hanbyeol Seo
Kyoto University
Kyoto, Japan
stela.seo@i.kyoto-u.ac.jp

Takayuki Kanda
Kyoto University
Kyoto, Japan
kanda@i.kyoto-u.ac.jp

***Abstract*—When verbal communication is limited, robots passing objects to humans without providing additional information (e.g., temperature, weight) can result in potential poor handovers and disappointing user experiences. To address this issue, we introduced a method for conveying object properties through robot manipulation. We began by proposing four criteria for selecting properties from two widely recognized sets: one focusing on the semantic features of objects and the other on tactile sensations. These properties were clustered into eight physical categories: *hot*, *cold*, *heavy*, *light*, *slippery*, *sticky*, *fragile*, and *smelly*. Professional actors were then recruited to demonstrate these properties through object manipulation, from which we extracted a set of fundamental yet expressive manipulation behaviors, i.e., *key elements*, that help people recognize these properties. These elements were implemented on a dual-arm robot, followed by an evaluation of their *utility* through participant feedback. To generate time-constrained sequences of elements, we developed a property-based motion planner that balances time and utility in conveying object properties. Results from a within-subjects study involving 20 participants showed that individuals could accurately interpret the properties conveyed by robot object manipulation, validating the effectiveness of the proposed approach.**

***Index Terms*—non-verbal communication, object properties, robot object manipulation, property-based motion planner**

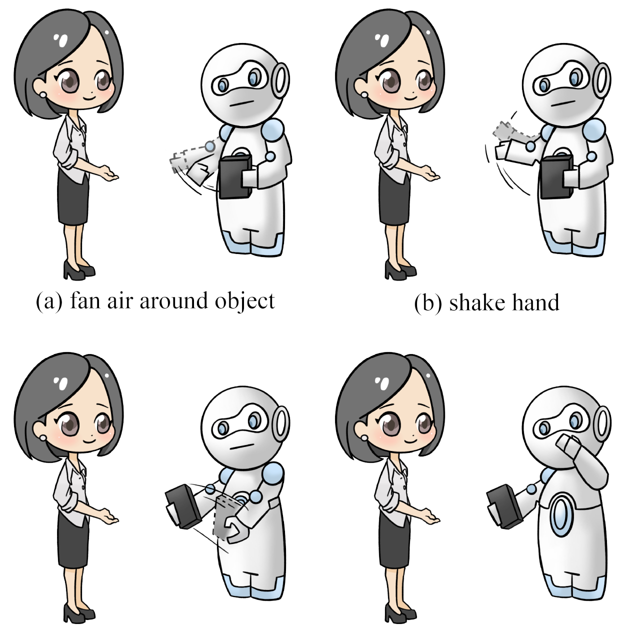


Fig. 1: Communication of object properties during handovers.

I. Introduction

Effective non-verbal communication between robots and humans is crucial in dynamic and unpredictable environments. Imagine a scenario in a noisy restaurant kitchen where a service robot needs to hand over a freshly prepared dish to a waiter. The plate is extremely hot, and while a verbal warning could suffice in a quiet setting, the loud clamor of the kitchen makes it difficult for the waiter to hear. Furthermore, the heat of the plate cannot be reliably perceived by simply observing its appearance. In such situations, a robot capable of conveying *hot* through intuitive hand motions—such as quickly fanning the air around the object (Fig. 1 (a)), rapidly shaking the hand (Fig. 1 (b)), or frequently switching the object between hands (Fig. 1 (c))—could effectively communicate the potential danger without relying on verbal cues.

Similarly, imagine a robot assisting with the curation and transport of delicate artifacts in a museum. If the robot encounters a biological specimen that emits a strong and unpleasant odor, it needs to alert the staff discreetly as speaking aloud is not appropriate in such a quiet and respectful environment. In this case, covering its nose with one hand while carefully holding the artifact with the other (Fig. 1 (d)) allows the robot to signal *smelly* to the nearby staff without disturbing visitors. These examples highlight the importance of non-verbal communication of object properties, especially when verbal communication is limited.

Extensive research has focused on using robot gestures for non-verbal communication, covering intentions [1], [2], emotions [3], [4], and personality [5], [6]. However, the communication of object properties, particularly through robot manipulation, remains significantly underexplored. To bridge this gap, our study makes three main contributions. First, we identify eight categories of object properties that are commonly communicated during handover interactions. Second, we propose a property-based motion planner capable of generating optimal hand action sequences to convey these properties. Third, we demonstrate the feasibility of our approach through human studies, showing that people can accurately infer object properties from robot object manipulation.

979-8-3503-7893-1/25/$31.00 ©2025 IEEE

II. Related Work

A. Gestures for Communications

Gestures play a crucial role in human communication by enhancing engagement, clarifying speech, and supporting cognitive processes such as learning and memory [7]–[10]. Beyond their role in human interaction, gestures are also critical for non-verbal communication between robots and humans. In human-robot interaction (HRI), robot gestures have been shown to improve the quality of interactions during narrations [11]. Additionally, robots use the support hand gesture to enhance perceptions of politeness and competence, particularly in service roles [12].

The existing literature offers substantial insights into how gestures facilitate communication. However, there is limited research on conveying object properties through robot gestures, particularly via robot manipulation. This gap motivates our investigation into leveraging robot object manipulation to effectively communicate a broader range of object properties.

B. Legibility

Legibility, i.e., the intuitive understanding of robots' intentions, is crucial for coordinating joint action and positive perception [13]. Numerous models and methods have been developed to enhance the legibility of arm motions [14], [15], ranging from gestures [1], [2] to handovers [16], [17]. Additionally, a viewpoint-based model was proposed to generate legible motions [18], and a method for synthesizing legible manipulation motions was developed to effectively communicate a robot's intent to human collaborators [19]. Legible motions have also been extensively applied in character animation, where animation techniques have been employed to express forethought, enhancing the legibility of robot behaviors and shaping human perceptions [20].

While prior research has primarily focused on enhancing legibility through direct robot motions to signal intent, our study shifts the focus to communicating object properties through robot object manipulation, distinguishing it from existing work.

C. Communication of Object Properties

Research has demonstrated that people can infer object properties by observing human behaviors. For instance, children can accurately judge an object's weight based on how others lift and transport it [21]. Similarly, individuals can deduce properties such as slipperiness and temperature from the way objects are handled [22].

This ability to infer object properties also applies to robot gestures and manipulations. Robots can use iconic gestures to convey the shape and size of objects [23]. Lifting behaviors have been employed to effectively communicate an object's weight [22], while teleoperated robots can convey weight through visuo-proprioceptive cues, where the robot's movements differ from those of the operator [24]. Furthermore, robots have been designed to express carefulness when handling full or empty cups, allowing observers to infer their contents [25].

While these studies focus on communicating specific object properties through robot gestures or manipulations, the communication of a broader range of object properties by robots remains underexplored.

III. How Do People Communicate Properties through Object Manipulation?

To investigate how people communicate object properties through manipulation, we selected specific object properties for this study. Subsequently, we recruited actors to convey these properties by their hand behaviors. From their role-plays, we extracted fundamental yet expressive hand behaviors, which we termed *key elements*.

A. Selection of Object Properties

To identify object properties commonly conveyed during interactions, we adopted two related sets of words and applied criteria for the selection. The selected properties were subsequently grouped based on their similarities.

We began by reviewing the literature on cognitive science, taxonomy, and materials, adopting a widely recognized set of semantic features for conceptual representation of objects [26]. From this set, we extracted 220 unique adjectives, as adjectives are directly relevant for describing object properties. In addition, recognizing the critical role of tactile properties in object handovers, we incorporated a list of 262 adjectives specifically designed to capture the nuances of tactile sensations [27]. Combining these two sets yielded a total of 342 distinct adjectives.

To select suitable object properties for this study, we established the following four key criteria:

- *Commonly communicated in handover contexts*. Knowing object properties in advance helps recipients avoid potential hazards, discomfort, or object damage during handovers.
- *Not directly audibly or visibly perceivable.* Properties that are easily perceived through hearing or sight do not require communication.
- *Descriptive adjectives for non-living objects.* While living beings possess properties, they are rarely manipulated during handovers. Therefore, we focused on non-living objects that are typically manipulable.
- *Associated with physical characteristics.* Properties related to functionality or emotions are often subjective. Hence, we prioritized physical ones that can be directly perceived during object interactions.

By applying these criteria, we identified 39 object properties and clustered them into eight categories based on their similar characteristics: *hot*, *cold*, *heavy*, *light*, *slippery*, *sticky*, *fragile*, *smelly*, as shown in Tab. I.

B. Observations of Human Hand Behaviors

To investigate how people communicate object properties through hand behaviors during handover interactions, we recruited two Japanese actors (male, 61; female, 48). Both actors have over 10 years of professional acting experience.

TABLE I: Eight categories of object properties

Hot	Cold	Heavy	Light	Slippery	Sticky	Fragile	Smelly
burning	cold	dense	light	damp	gelatinous	breakable	musty
hot	cool	heavy	lightweight	drenched	gooey	brittle	smelly
overheated	freezing			greasy	goopy	crumbly	strong-smelling
scalding	frigid			moist	gummy	delicate	
scorching	frosty			oily	icky	fragile	
warm	icy			slippery	slimy		
				wet	sticky		
					viscous		

(a) fan (b) rub (c) lift and lower while move (d) raise and lower (e) slip (f) open and close while move (g) support while move (h) cover while grasp

Fig. 2: Examples of human key elements for communicating object properties.

Neither had a background in robotics nor had they previously participated in robot-related experiments.

1) Procedures: Upon arrival, the actors were provided with a brief overview of the study and asked to sign a consent form. To familiarize them with the robot's capabilities, we demonstrated basic hand motions, including actions such as picking up an object from a table with one or both hands, switching an object between hands, and rotating an object.

Afterward, we instructed the actors to interact with a generic box in a manner that would communicate the eight specified object properties solely through hand behaviors. They were tasked with emulating the dual-armed robot within five different assigned time limits, beginning before picking up the object and ending with moving it to the goal position. For each time limit, the actors performed two trials. After each trial, they were asked to provide brief explanations of the behaviors they performed.

2) Identification of Human Key Elements: Key elements play a crucial role in helping people recognize object properties. To extract such elements from actors' role-plays, the first step was to define a resolution. What constitutes a good resolution? We propose that it should meet two criteria: (1) it should be minimal, avoiding unnecessary complexity, and (2) it should enable people to associate actions with a set of candidate object properties. For instance, the action of briefly touching an object and quickly withdrawing the hands did not individually convey *hot*; however, their combination evoked an association with the property and was thus regarded as a key element.

Applying this resolution, we analyzed video recordings of actors interacting with objects and identified a set of key elements, integrating the actors' explanations. These elements are listed in Tab. II, with examples corresponding to specific object properties illustrated in Fig. 2.

Finally, we divided these key elements into four sequential interaction stages:

- *Prepare*: actions performed before an object is successfully grasped.
- *Grasp*: actions performed during the successful grasping of an object.
- *Handle*: actions performed while holding an object, but before moving it towards the intended goal position.
- *Transport*: actions performed while moving an object towards the intended goal position.

We found that key elements from the *prepare* and *handle* stages were generally repeatable, whereas those from the *grasp* and *transport* stages were not. For example, actors raised and lowered an object repeatedly to indicate *light*, but supported an object from the bottom to the goal position only once to indicate *fragile*.

IV. Property-based Planner for Communicating Object Properties

This section proposes a property-based motion planner designed to enable robots to communicate object properties. To this end, we began by replicating human key elements on a robot. Subsequently, we conducted a user study to evaluate these robot hand motions (i.e., robot key elements). Finally, we designed and implemented the proposed planner on a robot.

A. Architecture

The architecture of the property-based motion planner is illustrated in Fig. 3. The proposed planner consists of two modules: the *action sequence generator* and the *motion planner*. The action sequence generator takes as input the object

TABLE II: Key elements for object properties

Properties	Key Elements	Stages	Descriptions	Utility
Default	grasp from middle	grasp	grasp an object from the middle with both hands	0
	move	transport	move an object to the goal with both hands	0
Hot	touch and withdraw	prepare	briefly touch an object, then quickly withdraw both hands	1.85; 2.1; 1.45; 1.1
	fan	prepare	fan away the air around an object with both hands	0.6; 1.1; 0.7; 0.65
	shake	prepare	shake with two hands	-0.1; 0.25; 0; 0.05
	wipe	prepare	wipe the sweat from the forehead with one hand	-0.1; -0.15; -0.45; -0.7
	grasp from top	grasp	grasp an object from the top with both hands	0.3
	fan while grasp	grasp	fan away the air around an object with one hand while grasping it with the other	-0.1
	shake while hold	handle	quickly shake with one hand while holding an object with the other	0; -0.2; -0.15; -0.4
	switch while move	transport	quickly switch an object between both hands while moving it to the goal	1.7
Cold	touch and withdraw with pause	prepare	touch an object for seconds, then withdraw both hands	0.7; 1.15; 0.6; 0.15
	rub	prepare	rub with two hands	0.75; 0.95; 0.5; 0.15
	grasp from top	grasp	grasp an object from the top with both hands	0.1
	rub while hold	handle	rub skins with one hand while holding an object with the other	-0.1; -0.05; -0.1; -0.2
	breathe while hold	handle	breathe one hand while holding an object with the other	0.35; 0.45; 0.2; -0.15
Heavy	fail	prepare	slightly lift an object from the top with both hands, then immediately place it down	2.5; 2.55; 2.05; 1.95
	grasp from bottom	grasp	lift an object from the bottom by extending both hands	0.1
	jitter while move	transport	jitter with both hands while moving the object to the goal	0.4
	lift and lower while move	transport	lift and lower an object with both hands while moving it to the goal	2.2
Light	grasp with one hand	grasp	grasp an object with one hand	1.3
	raise and lower	handle	raise and lower an object over the head with one hand	2.3; 2.75; 2.45; 2.35
	rotate	handle	rotate an object with one hand	0.95; 0.9; 0.75; 0.6
	raise and lower while rotate	handle	raise and lower an object over the head while rotating it with one hand	1.85; 1.9; 1.5; 1.3
Slippery	slip	prepare	slip along an object's surface with both hands	2.05; 2.55; 2.5; 2.3
	grasp from bottom	grasp	grasp an object from the bottom with both hands	0.1
	slip while hold	handle	slide along an object's surface with one hand while holding it with the other	0.1; 0.2; 0; -0.2
	slip while move	transport	slide along an object's surface with one hand while moving it to the goal	0.15
	support while move	transport	support an object from the bottom while moving it to the goal	-0.35
Sticky	touch and withdraw with pause	prepare	touch an object for seconds, then withdraw both hands	0.1; 0; -0.15; -0.4
	open and close	prepare	quickly open and slowly close both palms	1.85; 2.15; 1.5; 1.05
	grasp from top	grasp	grasp an object from the top with both hands	0.15
	open and close while hold	handle	quickly open and slowly close one palm while holding an object with the other	2.4; 2.3; 1.65; 1.45
	open and grasp while hold	handle	quickly open and slowly grasp an object with one hand while holding it with the other	1.05; 1.2; 0.5; 0.25
	open and close while move	transport	quickly open and slowly close one palm while moving an object to the goal	-0.3
Fragile	grasp from bottom	grasp	grasp an object from the bottom with both hands	0.35
	cradle	handle	slowly cradle an object to the chest with both hands	0.15; -0.4; -0.95; -0.95
	tap	handle	slightly tap an object with one hand while holding it with the other	-1.5; -1.75; -1.8; -1.85
	support while move	transport	support an object from the bottom while moving it to the goal	2.4
	turn over while move	transport	turn an object over while moving it to the goal	-1.5; -1.75; -1.8; -1.85
Smelly	fan	prepare	fan away the odor around an object with both hands	-0.1; -0.1; -0.15; -0.2
	fan while cover	prepare	fan away the odor around an object with one hand while covering nose with the other	2.5; 2.8; 2.9; 2.75
	touch and sniff	prepare	touch an object with both hands, then sniff the hands	-0.55; -0.7; -1.05; -1.1
	grasp with one hand	grasp	grasp an object with one hand	0.15
	cover while grasp	grasp	cover nose with one hand while grasping an object with the other	2.6
	fan while grasp	grasp	fan away the odor around an object while grasping it with the other	-0.45
	fan while move	transport	fan away the odor around an object with one hand while moving it to the goal	-0.4
	cover while move	transport	cover nose with one hand while moving an object to the goal	2.8

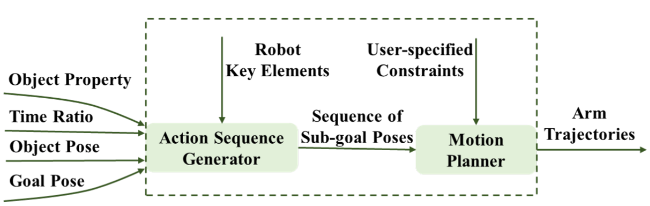


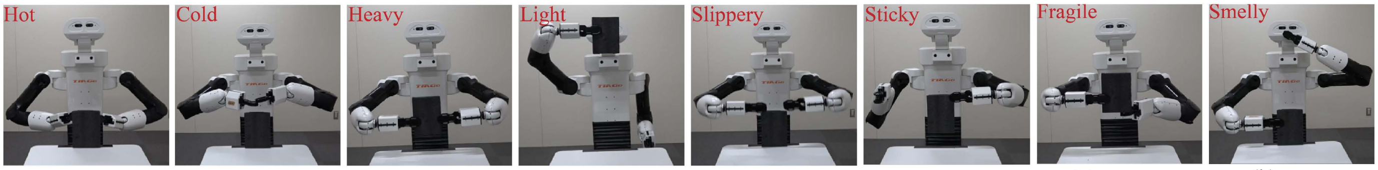
Fig. 3: The Diagram of proposed planner.

property, time ratio, initial pose of the object, and goal pose, along with the information about robot key elements, to generate a sequence of sub-goal poses. These sub-goal poses, combined with user-specified constraints, are then processed by the motion planner module to produce human-like arm trajectories that effectively communicate the specified object property.

B. Robot Key Elements

Human key elements are essential for conveying object properties. To evaluate their effectiveness, which we termed as *utility*, when implemented on robots, the first step was to represent the corresponding robot key elements. We identified three critical factors characterizing these robot key elements: *sub-goal poses*, *execution time*, and *utility*.

We selected a dual-arm robot for this study as it can closely mimic human behaviors, facilitating a better understanding of the robot's actions and intentions. Based on observations



(a) fan (b) rub (c) lift and lower while move (d) raise and lower (e) slip (f) open and close while move (g) support while move (h) cover while grasp

Fig. 4: Robot key elements corresponding to the human key elements illustrated in Fig. 2.

of human behaviors and the robot's physical capabilities, we manually defined sub-goal poses corresponding to all the human key elements in Table II. These elements were then implemented on the robot, with examples of robot key elements shown in Fig. 4.

C. Utility

To quantify the utility of robot key elements, we conducted a user study.

1) Procedures: We first developed multiple robot demonstrations showcasing all the human key elements in Tab. II, with the frequency of each key element varying depending on the stage. Specifically, we created one robot demonstration for the key elements of the *grasp* and *transport* stages. For the *prepare* and *handle* stages, four robot demonstrations were created for each key element, with the frequency of each element ranging from one to four. All demonstrations involved grasping an object from a table and moving it to the goal position.

Subsequently, we invited 20 participants (10f, 10m) to evaluate the utility of all the robot key elements for the corresponding object properties. To minimize potential order effects, we employed a partially Latin square design to determine the order in which participants viewed and evaluated the videos. Participants rated each video on a scale from -3 to 3, where a score of 3 indicated that the key element helped to recognize the object property, while a score of -3 indicated that the key element hindered recognition of the object property. A score of 0 represented neutrality, indicating that the key element neither helped nor hindered the recognition. The utility reflects the effectiveness of key elements in conveying object properties, with higher utility indicating greater expressiveness.

2) Results: We calculated the utility for all the robot key elements and their repetitions by averaging participants' ratings, as shown in the last column of *utility* in Tab. II.

The results revealed that the utility of repeatable key elements generally peaked at two repetitions when sufficient time was available. In contrast, the utility of unrepeatable ones was generally lower, except for those associated with the properties of *light* and *smelly*. Additionally, there were slight variations in utility on the grasping location (e.g., "grasp from bottom" versus "grasp from top").

D. Action Sequence Generator

Our observations of role-plays revealed that the allotted time significantly influences the variety and expressiveness of hand motions used to convey object properties. For instance, when given the shortest time, actors typically grasped the object with one hand and moved it to the goal position to represent *light*. However, with more time, they introduced additional actions (e.g., rotating an object) beyond these two basic actions.

To reproduce these adaptive behaviors, we introduced the concept of *time ratio*. The time ratio refers to a multiple of the time required to grasp the middle of an object and move it from the table to the goal position. A time ratio of one corresponds to the duration of these two default actions.

Building on this concept, we developed an action sequence generator. As shown in Fig. 3, this module takes two categories of inputs: (1) object property, time ratio, the object's initial pose, and goal pose; and (2) information about robot key elements including utility, execution time, and sub-goal poses. It then generates an optimal sequence of sub-goal poses corresponding to the action sequence of robot key elements with the highest utility for the given time ratio. Specifically, depth-first search is first employed to generate all possible action sequences with durations under the time limit dictated by the time ratio. Action sequence durations are calculated with pre-computed key element execution times obtained from tests on the robot. Finally, the action sequence with the highest utility is selected as optimal and mapped to the corresponding sequence of sub-goal poses associated with its key elements.

E. Motion Planner

Once the sequence of sub-goal poses is determined, the motion planner module computes the corresponding sequence of sub-goal arm trajectories.

F. Implementation

We implemented the property-based motion planner on a dual-arm robot system.

1) Robot Hardware: We used a dual-arm robot named TIAGo++ [1] from PAL Robotics. The robot features a mobile base, a lifting torso, a head, and two arms. Both arms have 7 degrees of freedom (DoF) ending in grippers, and the torso has a stroke of 35 cm so that the height of the robot can be adjusted between 110 and 145 cm. Its eyes are equipped with an RGB-D camera, and there are speakers inside the base.

2) Trajectory Execution: Our robot system is built on the MoveIt framework [2], which automatically takes the arm trajectories as input and executes them on the physical robot.

[1]https://pal-robotics.com/blog/tiago-bi-manual-robot-research/
[2]https://moveit.ros.org/

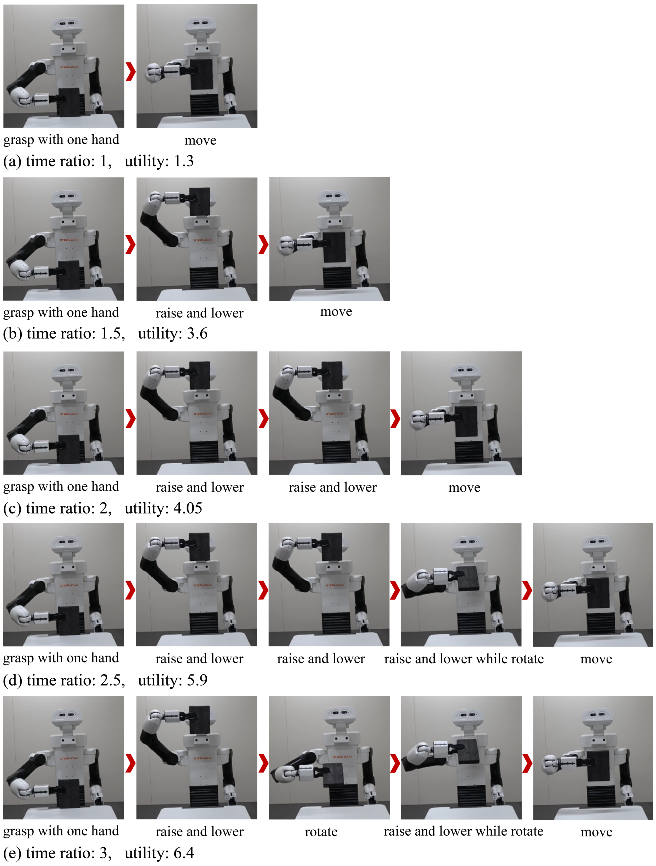


Fig. 5: The planning results for *light* at different time ratios.

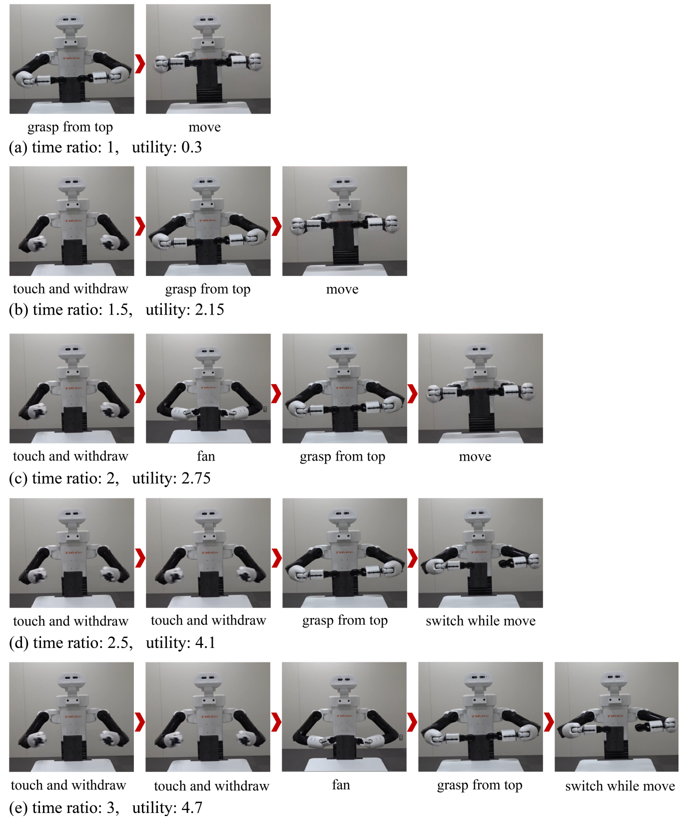


Fig. 6: The planning results for *hot* at different time ratios.

G. Examples of Planning Results

We evaluated the functionality of the proposed planner. As shown in Fig. 5, at the lowest time ratio (i.e., 1.0), the planner generates an action sequence consisting of two key elements, one from the *grasp* stage and the other from the *transport* stage, for *light*. As the time ratio increases, the planner incorporates additional key elements, such as "raise and lower" or "rotate," leading to higher utility. The results indicate a positive relationship between utility and time ratio: as the time ratio increases, utility also improves. Similarly, Fig. 6 illustrates the planning results for *hot*.

V. Evaluation

We designed and conducted an experiment to evaluate whether a robot could effectively communicate object properties by manipulating an object.

A. Participants

We recruited 20 participants through a part-time job recruitment website, ranging in age from 18 to 68 years (M = 36.6, SD = 15.48). Ten participants self-identified as male and ten as female, with a balanced distribution across age groups. Each participant received 3000 JPY as compensation for their participation in the experiment.

B. Conditions

The robot's performance was estimated under five conditions. Specifically, the participants needed to infer object properties under different time ratios (i.e., 1, 1.5, 2, 2.5, and 3). A within-subjects design was employed to allow participants to experience all conditions, as even in countries like Japan, where many robots are being deployed in public spaces, people remain unfamiliar with interpreting robots' behaviors and intentions. To minimize order effects, a partially Latin square design was used to determine the order of time ratios and object properties within each ratio.

C. Procedure

Participants were welcomed into a large room where the robot was situated, and the experimenter administered the experiment overview and consent form. To familiarize participants with the robot and to ease any potential discomfort, several demonstrations of the robot's hand motions were shown. To prevent visual identification of the properties of objects, a generic box that concealed its property was selected as the experimental prop.

Prior to the experiment, participants were informed that they could attribute any of the eight specified object properties to each robot hand motion, ensuring that each interaction remained independent. Additionally, they were asked to choose the most effective property for each robot demonstration. The

Fig. 7: Setup for experiments.

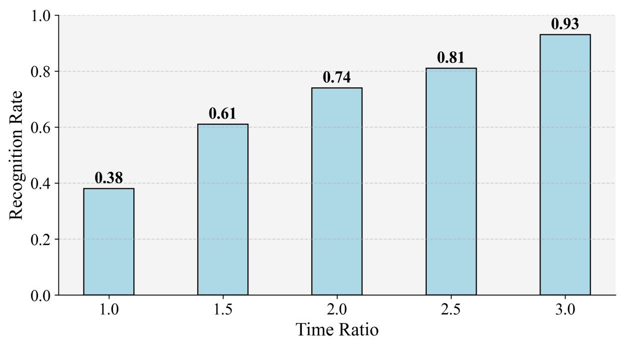


Fig. 8: Relationship between recognition rate and time ratio.

TABLE III: The recognition results for object properties at different time ratios

	Hot	Cold	Heavy	Light	Slippery	Sticky	Fragile	Smelly
Time Ratio: 1								
Hot	1	2	0	0	0	2	0	0
Cold	0	0	0	0	1	1	0	0
Heavy	1	1	17	0	6	0	2	0
Light	11	12	0	20	9	14	12	0
Slippery	2	2	1	0	1	0	4	0
Sticky	0	1	0	0	0	1	1	0
Fragile	5	1	2	0	2	2	1	0
Smelly	0	0	0	0	1	0	0	20
Time Ratio: 1.5								
Hot	15	0	1	0	0	1	0	0
Cold	1	1	1	0	0	3	0	0
Heavy	0	3	16	0	0	0	2	0
Light	2	14	0	20	2	16	5	0
Slippery	1	1	1	0	18	0	0	0
Sticky	1	1	0	0	0	0	5	0
Fragile	0	0	1	0	0	0	7	0
Smelly	0	0	0	0	0	0	1	20
Time Ratio: 2								
Hot	13	0	0	0	0	14	2	0
Cold	2	11	1	0	0	2	2	0
Heavy	0	2	19	0	0	0	0	0
Light	0	2	0	20	0	0	2	0
Slippery	2	2	0	0	20	0	1	0
Sticky	1	2	0	0	0	2	0	0
Fragile	2	1	0	0	0	2	13	0
Smelly	0	0	0	0	0	0	0	20
Time Ratio: 2.5								
Hot	14	3	0	0	0	7	0	0
Cold	3	12	0	0	1	4	1	0
Heavy	0	0	20	0	0	0	0	0
Light	0	0	0	20	0	1	0	0
Slippery	0	0	0	0	19	1	1	0
Sticky	3	5	0	0	0	7	0	0
Fragile	0	0	0	0	0	0	18	0
Smelly	0	0	0	0	0	0	0	20
Time Ratio: 3								
Hot	19	1	0	0	1	1	0	0
Cold	0	15	0	0	0	2	0	0
Heavy	0	0	20	0	0	0	0	0
Light	0	0	0	20	0	0	1	0
Slippery	0	0	0	0	19	0	1	0
Sticky	1	4	0	0	0	17	0	0
Fragile	0	0	0	0	0	0	18	0
Smelly	0	0	0	0	0	0	0	20

experimental setting is depicted in Fig. 7. Finally, we had semi-structured interviews with the participants. The experiment was approved as ethical by the Institutional Review Board. The experiments and interviews were conducted in Japanese.

VI. Results

A. Recognition Results

We evaluated the recognition accuracy for each object property at various time ratios, as illustrated in Fig. 8. The results indicate a positive relationship between the recognition rate and the time ratio: as the time ratio increases, the recognition rate improves, reaching a peak of 0.93 at the time ratio of 3. This suggests that longer interaction time helps participants accurately identify object properties.

To further explore participants' responses to action sequences of key elements across different time ratios, confusion matrices were employed and presented in Tab. III, where each column corresponds to a specific robot action sequence, while each row reflects participant ratings. The confusion matrices reveal not only the correct recognition patterns but also the types of misclassifications that occurred, showing how participants perceived and confused certain object properties.

Notably, some object properties achieved high recognition rates early on, particularly those with short but highly expressive key elements, such as "cover nose" for *smelly*, "jitter while move" for *heavy*, "raise and lower" for *light*, and "slip" for *slippery*. In contrast, others such as *hot* and *sticky* required more key elements presented over longer time ratios to reach similar levels of accuracy.

B. Interview Results

When asked about the ease of inferring properties from the robot manipulating objects, all participants found it straightforward to recognize *smelly*, *heavy*, *light*, and *slippery*, with *smelly* being the easiest to identify. Sixteen participants reported that it was relatively easier to infer *fragile*, as the support hand behaviors conveyed a sense of cautious handling, which aligns with the view in [12].

Seven participants mentioned that while they could infer *hot* from the element of "touch and withdraw", they still found it challenging to distinguish between *hot* and *cold*. Three participants suggested that rubbing hands could indicate either *hot* or *cold*. Similarly, two participants linked the element of "rub" with *sticky*, as it resembled behaviors used to remove stickiness. Furthermore, four participants associated the element of "open and close" either with both *hot* and *cold*, as it mimicked behaviors for cooling or warming hands. However, they noted that the element of "open and close while hold" was highly expressive and even humorous, as it simulated the robot's hands being stuck together, helping them confirm their judgments.

Interestingly, two participants expressed that adding more hand behaviors did not necessarily improve the clarity of conveyed properties. For example, they noted that additional behaviors, such as the element of "rotate" for *light*, caused confusion and made them hesitant in their judgments.

VII. Discussion

A. Generalizability

Humans naturally use a combination of cues (e.g., facial expressions, body movements, posture) to communicate information. However, not all robots are equipped to replicate such multimodal communication. For example, robots without legs might move on wheels, some may lack arms, and others may have only a head or a simple manipulator. To address this variability, we assume robots using our proposed technique must possess human-like qualities, focusing on hand motions as a primary means of communication. This minimal assumption ensures flexibility, making the approach applicable across different robot platforms. Although combining hand motions with other modalities (e.g., head or body movements) could enhance communication (e.g., a robot rotating its head or tilting its body while presenting a smelly object), our approach deliberately avoids multimodal dependencies to maximize adaptability.

To enhance generalizability across cultures, our study benefits from distinguishing between *motor-control motions* and *communicative motions*. Motor-control motions are universal, arising from innate responses to physical interaction (e.g., adjusting lifting speed for weight or withdrawing hand(s) quickly from a hot surface). In contrast, communicative motions are socially motivated and explicitly designed to convey information (e.g., rotating an object to indicate lightness or supporting an object to suggest fragility). These culturally influenced hand motions vary in interpretation, depending on shared conventions and experiences. By highlighting these distinctions, robots can be designed to interact naturally with diverse user groups, ensuring effective communication across different cultural contexts.

B. Optimization for System Performance

Enhancing system performance involves addressing multiple aspects, including adaptability to time-critical scenarios, personalization, and distinguishing similar key elements across object properties.

First, in time-critical scenarios, our system can be further improved by reducing the resolution of conveyed properties. For instance, similar properties such as *hot* and *cold* could be merged into a generalized cautionary category. Although users may not differentiate the exact property, they will still recognize the need for careful handling. This approach prioritizes safety and efficiency in environments where detailed communication is impractical.

Second, personalization can enhance performance by accounting for variability in individual and cultural preferences. Currently, utility metrics are derived from aggregated participant ratings, which may overlook nuanced differences. Incorporating personalization methods, such as tailoring utility scores for users with similar preferences or cultural contexts, could significantly improve effectiveness. Additionally, the system can benefit from co-designing gestures with end-users in specific environments, such as noisy or silent settings, to identify a set of hand motions that are intuitive, easily understood, and broadly applicable across diverse contexts.

Finally, distinguishing similar key elements across object properties is crucial for reducing ambiguity. Some properties, such as *cold* and *sticky*, share overlapping elements like "touch and withdraw with pause," while *hot* features a slight variation of "touch and withdraw." To address this challenge, the system can prioritize emphasizing unique key elements specific to each property, making the motions more distinct and easier to interpret.

C. Limitations

While our system demonstrates its effectiveness in generating expressive and property-specific hand motions, it presents a scalability limitation, particularly when integrating new object properties. Each new property requires the identification and extraction of key elements from actors' role-plays, the development of robot key elements, and the evaluation of utility for these elements. Although this approach ensures the generation of expressive and property-specific actions, it is inherently time-intensive and resource-demanding.

Despite this challenge, we believe our system design provides a strong foundation for designing robot hand motions that effectively communicate object properties, paving the way for further advancements in this area.

VIII. Conclusion

In this paper, we investigated how robots communicate properties through object manipulation. We first identified eight categories of object properties and extracted a set of key elements from role-plays. These elements were implemented on a dual-arm robot and evaluated for their utility based on participant feedback. To effectively convey object properties within time constraints, we developed a property-based motion planner that optimally balances utility and time ratio. Our within-subjects study with 20 participants demonstrated that individuals could accurately interpret these properties through robot object manipulation.

Acknowledgment

This work was supported in part by JST Moonshot R and D under Grant Number JPMJMS2011, Japan, and in part by JSPS KAKENHI under Grant Number 24H00722, Japan.

References

[1] M. J. Gielniak and A. L. Thomaz, "Generating anticipation in robot motion," in *2011 RO-MAN*. IEEE, 2011, pp. 449–454.

[2] R. M. Holladay, A. D. Dragan, and S. S. Srinivasa, "Legible robot pointing," in *The 23rd IEEE International Symposium on robot and human interactive communication*. IEEE, 2014, pp. 217–223.

[3] J. Li and M. Chignell, "Communication of emotion in social robots through simple head and arm movements," *International Journal of Social Robotics*, vol. 3, no. 2, pp. 125–142, 2011.

[4] Q. A. Le, S. Hanoune, and C. Pelachaud, "Design and implementation of an expressive gesture model for a humanoid robot," in *2011 11th IEEE-RAS International Conference on Humanoid Robots*. IEEE, 2011, pp. 134–140.

[5] A. Aly and A. Tapus, "A model for synthesizing a combined verbal and nonverbal behavior based on personality traits in human-robot interaction," in *2013 8th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. IEEE, 2013, pp. 325–332.

[6] H. Kim, S. S. Kwak, and M. Kim, "Personality design of sociable robots by control of gesture design factors," in *RO-MAN 2008-The 17th IEEE International Symposium on Robot and Human Interactive Communication*. IEEE, 2008, pp. 494–499.

[7] D. McNeill, *Hand and mind: What gestures reveal about thought*. University of Chicago press, 1992.

[8] A. Kendon, "Do gestures communicate? a review," *Research on language and social interaction*, vol. 27, no. 3, pp. 175–200, 1994.

[9] X. Dou, C.-F. Wu, K.-C. Lin, and T.-M. Tseng, "The effects of robot voice and gesture types on the perceived robot personalities," in *Human-Computer Interaction. Perspectives on Design: Thematic Area, HCI 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Orlando, FL, USA, July 26–31, 2019, Proceedings, Part I 21*. Springer, 2019, pp. 299–309.

[10] P. Feyereisen, "Further investigation on the mnemonic effect of gestures: Their meaning matters," *European Journal of Cognitive Psychology*, vol. 18, no. 2, pp. 185–205, 2006.

[11] C.-M. Huang and B. Mutlu, "Modeling and evaluating narrative gestures for humanlike robots." in *Robotics: Science and Systems*, vol. 2. Citeseer, 2013.

[12] X. Pan, M. Doering, and T. Kanda, "What is your other hand doing, robot? a model of behavior for shopkeeper robot's idle hand," in *Proceedings of the 2024 ACM/IEEE International Conference on Human-Robot Interaction*, 2024, pp. 552–560.

[13] C. Lichtenthäler and A. Kirsch, "Legibility of robot behavior: A literature review," 2016.

[14] A. D. Dragan, K. C. Lee, and S. S. Srinivasa, "Legibility and predictability of robot motion," in *2013 8th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. IEEE, 2013, pp. 301–308.

[15] A. D. Dragan, S. Bauman, J. Forlizzi, and S. S. Srinivasa, "Effects of robot motion on human-robot collaboration," in *Proceedings of the tenth annual ACM/IEEE international conference on human-robot interaction*, 2015, pp. 51–58.

[16] J. Mainprice, E. A. Sisbot, T. Siméon, and R. Alami, "Planning safe and legible hand-over motions for human-robot interaction," in *IARP workshop on technical challenges for dependable robots in human environments*, vol. 2, no. 6, 2010, p. 7.

[17] E. A. Sisbot and R. Alami, "A human-aware manipulation planner," *IEEE Transactions on Robotics*, vol. 28, no. 5, pp. 1045–1057, 2012.

[18] S. Nikolaidis, A. Dragan, and S. Srinivasa, "based legibility optimization," in *2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. IEEE, 2016, pp. 271–278.

[19] C. Bodden, D. Rakita, B. Mutlu, and M. Gleicher, "A flexible optimization-based method for synthesizing intent-expressive robot arm motion," *The International Journal of Robotics Research*, vol. 37, no. 11, pp. 1376–1394, 2018.

[20] L. Takayama, D. Dooley, and W. Ju, "Expressing thought: improving robot readability with animation principles," in *Proceedings of the 6th international conference on Human-robot interaction*, 2011, pp. 69–76.

[21] M. K. Kaiser and D. R. Proffitt, "The development of sensitivity to causally relevant dynamic information," *Child Development*, pp. 1614–1624, 1984.

[22] A. Sciutti, L. Patane, F. Nori, and G. Sandini, "Understanding object weight from human and humanoid lifting actions," *IEEE Transactions on Autonomous Mental Development*, vol. 6, no. 2, pp. 80–92, 2014.

[23] M. Salem, S. Kopp, I. Wachsmuth, K. Rohlfing, and F. Joublin, "Generation and evaluation of communicative robot gesture," *International Journal of Social Robotics*, vol. 4, pp. 201–217, 2012.

[24] P. Praveena, D. Rakita, B. Mutlu, and M. Gleicher, "Supporting perception of weight through motion-induced sensory conflicts in robot teleoperation," in *Proceedings of the 2020 ACM/IEEE International Conference on Human-robot Interaction*, 2020, pp. 509–517.

[25] L. Lastrico, N. F. Duarte, A. Carfí, F. Rea, A. Sciutti, F. Mastrogiovanni, and J. Santos-Victor, "Expressing and inferring action carefulness in human-to-robot handovers," in *2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2023, pp. 9824–9831.

[26] K. McRae, G. S. Cree, M. S. Seidenberg, and C. McNorgan, "Semantic feature production norms for a large set of living and nonliving things," *Behavior research methods*, vol. 37, no. 4, pp. 547–559, 2005.

[27] S. Guest, J. M. Dessirier, A. Mehrabyan, F. McGlone, G. Essick, G. Gescheider, A. Fontana, R. Xiong, R. Ackerley, and K. Blot, "The development and validation of sensory and emotional scales of touch perception," *Attention, Perception, & Psychophysics*, vol. 73, pp. 531–550, 2011.