LILA: Language-Informed Latent Actions

Anonymous Author(s)
Affiliation
Address
email

Abstract: We introduce Language-Informed Latent Actions (LILA), a framework for learning natural language interfaces in the context of human-robot collaboration. LILA falls under the shared autonomy paradigm: in addition to providing discrete language inputs, humans are given a low-dimensional controller – e.g., a 2 degree-of-freedom (DoF) joystick that moves left/right or up/down – for operating the robot. Crucially, LILA learns to use language to *modulate* this controller, providing users with a semantically meaningful control space that adapts based on the provided language: given an instruction like "place the cereal bowl on the tray," LILA might learn a 2-DoF control space where one dimension controls the distance from the robot's end-effector to the bowl, and the other dimension controls the robot's end-effector pose relative to the grasp point on the bowl. Similarly, given an instruction like "pour the milk into the cereal bowl," LILA might produce a control space where one dimension controls the height of the milk, with the other controlling the angle of the pour – realizing that the two degrees of the control space need to be mapped to different behaviors given these different instructions. We evaluate LILA with a series of real-world user studies pairing users with a 7-DoF Franka Emika Panda Arm, with the goal of completing a series of complex manipulation tasks with a lower dimensional control space conditioned on language. Our studies show that LILA models are not only more sample efficient and performant than imitation learning and end-effector control baselines, but also are qualitatively preferred by users.[1]

Keywords: Language for Shared Autonomy, Language & Robotics, Learned Latent Actions, Human-Robot Interaction

1 Introduction

Effective human-robot collaboration is rooted in the ability to strike the right balance between the nuanced capabilities of human users and the raw power of modern robotics. Finding this balance is becoming increasingly important; nearly a million American adults live with physical disabilities, requiring assistance for everyday tasks like taking a bite of food or pouring a glass of milk [1]. While robots are starting to be deployed in such collaborative applications [2, 3], we have yet to see widespread adoption and success. One path forward is with *shared autonomy* [4, 5, 6], a framework that couples user input with automated robot assistance. Unlike full autonomy approaches that enforce discrete boundaries between user intent and robot execution, shared autonomy approaches tap into the complementary strengths of both humans and robots; humans continuously provide inputs, while the robot deftly ingests a stream of rich and diverse observations, assisting the human in fulfilling their desired objective. Such approaches have boundless promise for interpretability, safety, and sample efficiency, amongst others. Despite their promise, though, approaches in shared autonomy are missing rich, intuitive ways of *specifying* and *disambiguating* tasks – a bridge that can be built by tapping into the potential of natural language.

Consider a kitchen or dining setting where a *high-dimensional* (high-DoF) robot (such as a wheelchair-mounted manipulator) aids a human user who may not be physically able to perform

[1] Additional visualizations, videos, and supplemental experiments can be found at the following webpage: https://sites.google.com/view/lila-corl21.

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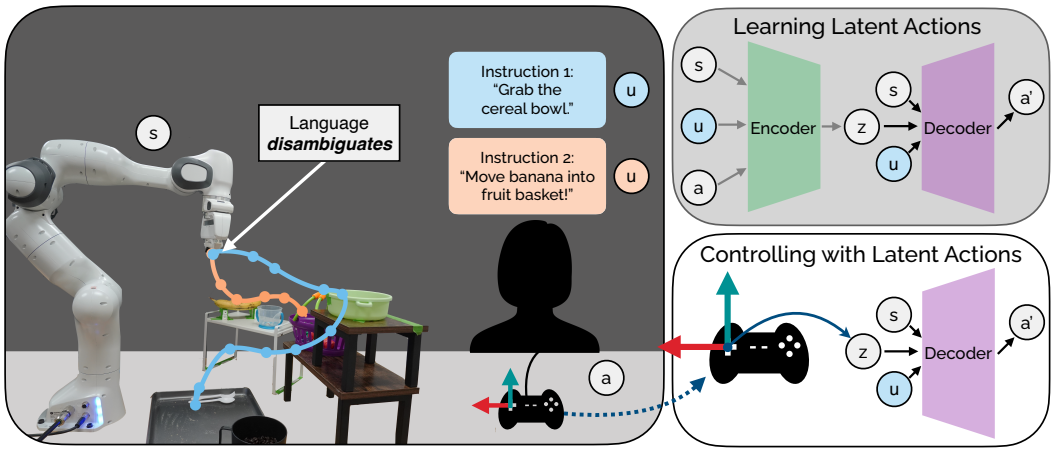

Figure 1: [**Left**] Our breakfast buffet environment with several diverse manipulation tasks. By providing both natural language input and low-dimensional joystick control [**Middle**], users *disambiguate* between different tasks while retaining the ability to maneuver through the environment. This is enabled by our language-informed latent actions (LILA) models [**Right**].

tasks requiring fine-grained manipulation. Eating a full meal, or even maneuvering around a kitchen, requires interacting with several different food items and utensils, with diverse motions. A user may wish to grab a cereal bowl and place it on a tray in front of them, grab a jug of milk, and pour enough to meet their preference – all requiring complex manipulation of the high-DoF robot arm. While one option for the human is to manually teleoperate the arm by controlling individual "modes" (separate degrees-of-freedom) of the robot's end-effector, past work has shown this to be unintuitive, slow, and frustrating [5, 7]. However, *learned latent actions* [8, 9] is a promising new paradigm that seeks to address the problem of building intuitive low-dimensional (low-DoF) controllers for high-DoF robot manipulators by learning *task-specific control spaces* via dimensionality reduction. While these approaches are reliable and sample efficient, they are limited by their single task nature. In dynamic environments where users wish to interact with multiple objects in different ways, latent action controllers fail to disambiguate user intent, proving unable to assist in realizing the goal a human wishes to achieve.

Language is an expressive way for humans to communicate intent. A user can easily express their desire to *"grab the cereal bowl"* or their preference to *"slowly pour the milk into the glass till it's half full"*. Prior work integrates language in robotics settings within the full-autonomy umbrella, most notably with work in instruction following [10, 11, 12, 13]. Unfortunately, these approaches are not silver bullets: they are often plagued with poor sample efficiency, inability to recover from failure, and poor generalization to novel states – many issues that shared autonomy methods (including learned latent actions) seek to address.

We propose Language-Informed Latent Actions (LILA), a framework for incorporating language utterances within the broader paradigm of learned latent actions. Key to LILA is the principle that language *modulates* a user's low-level controller based on their provided utterance; given the utterance *"grab the cereal bowl"*, our assistive robot exposes a semantically meaningful, low-dimensional (2-DoF) control space where one dimension (one joystick axis) may control the distance from the robot's end-effector to the cereal bowl, whereas the other might control the angle of the end-effector relative to the bowl such that the robot's gripper can obtain a solid grasp of the object. Future utterances modulate the controller in similar ways – "pour the milk into the cup" might result in one joystick dimension controlling the angle at which the milk jug is tilted, whilst the other controls the height of the jug relative to the cup. Language not only is a natural means for a human to communicate their intent to the robot, but it helps *disambiguate* across a wide variety of tasks as well: when LILA receives a user utterance as input, it collapses the robot's original, high-DoF action space onto a learned manifold – a manifold that defines a control subspace wherein the robot can assist the human in satisfying their original intent.

In addition to providing a formalism for integrating natural language within the learned latent actions framework, and a robust, sample-efficient model architecture that allows for reliable task execution, we perform a *comprehensive user study* across 10 users who use unprompted natural language and

our learned LILA controllers to complete a variety of diverse manipulation tasks in a simplified assistive "buffet" setting. Our results show that not only are LILA models more reliable, performant, and sample efficient than fully autonomous (imitation learning) and end-effector control baselines, but they are qualitatively preferred by users as well.

2 Related Work

We build LILA within a shared autonomy framework [4, 14], applied to assistive teleoperation [15, 16]. We additionally build off work at the intersection of language and robotics [17, 18, 19].

Shared Autonomy & Assistive Teleoperation. Shared autonomy casts robot control as a collaborative process between humans and robots [4, 6, 14, 20]. In this work, we focus on assistive teleoperation, where a user is provided a low-dimensional controller (e.g., a joystick, sip-and-puff device) to control a high-dimensional robot manipulator. Using these controllers to directly control the end-effector via inverse kinematics or operational space control [21] is incredibly difficult, requiring frequent mode-switching to control specific robot DoFs, failing to provide users with fine-grained control [5, 22]. Instead, we adopt *learned latent actions* [8, 9, 23, 24] a recent framework that uses conditional auto-encoders [25] to learn task-specific latent "action" spaces from demonstrations. These latent spaces match the dimensionality of the low-dimensional control interface, and provide intuitive, semantically meaningful control. However, existing models fail to differentiate between tasks when presented with similar states, hindering the ability to perform diverse behaviors in a workspace (e.g., manipulating a jug of milk in different ways – pouring, placing in the fridge, etc.). In this work, we use language for *disambiguation*; users naturally specify their intent with language, conditioning latent action models to produce intuitive control spaces that align with user objectives.

Language-Informed Robotics. A wealth of work looks at different ways to incorporate language for robotics, spanning approaches that map language to planning primitives [10, 26, 27, 28, 29], imitation learning from demonstrations paired with language instructions [12, 30, 31, 32], and reinforcement learning from language instructions paired with corresponding reward functions [13, 33, 34]. Other approaches use language in more nuanced ways, for example, to learn language-conditional reward functions directly [35, 36, 37], or within more adaptive frameworks, where language is used to correct or define new behavior [38, 39]. All of these approaches fall broadly under the category of full autonomy: after providing an instruction, human users cede control over to the robot policy, which then takes the actions necessary to perform a task.

While robots trained with these approaches can perform diverse tasks and generalize to new instructions, it is not without cost. Paramount is sample efficiency; imitation learning approaches often require hundreds to thousands of demonstrations to learn navigation tasks [31, 40], and reinforcement learning approaches can require millions of episodes of experience to learn robust policies [13, 41]. Whereas coarse behaviors are easy to learn, learning to recover from slight deviations from the training data, or to perform precise motions in a sequence is incredibly difficult. By casting our approach LILA within a shared autonomy framework instead, we intelligently offload these parts that are harder for robots – but easier and intuitive for humans – onto the user, who provides the necessary control inputs. The resulting LILA models are thus more sample efficient than existing approaches, whilst preserving the expressivity and naturalness of language.

3 Framing Language for Assistive Teleoperation

Consider our running example (Fig. 1): you – who may not be physically able to perform actions like reaching or lifting – are equipped with a high-dimensional robot manipulator and a low-dimensional controller (e.g., a 2-DoF joystick). You have simple tastes – breakfast consists of a bowl of cereal with milk. How do you achieve this goal?

With LILA, you lead with language – *"grab the cereal bowl"* – which is fed to a learned model that *modulates*, or restructures, your control interface. Pressing **`up`** on the joystick now moves the robot arm towards the cereal bowl, while pressing **`right`** aligns the end-effector angle to make the grasp. You press a button closing the gripper around the cereal bowl, then hold **`down`** on the joystick to bring it back to your tray (e.g. blue trajectory in Fig. 1). You speak – *"pour some milk into my cereal"* and your controls adapt; holding **`down`** has new meaning, bringing the robot closer to the cup of milk *and* angles the end-effector to grasp it. Tilting **`right`** begins to pour the milk, and so on.

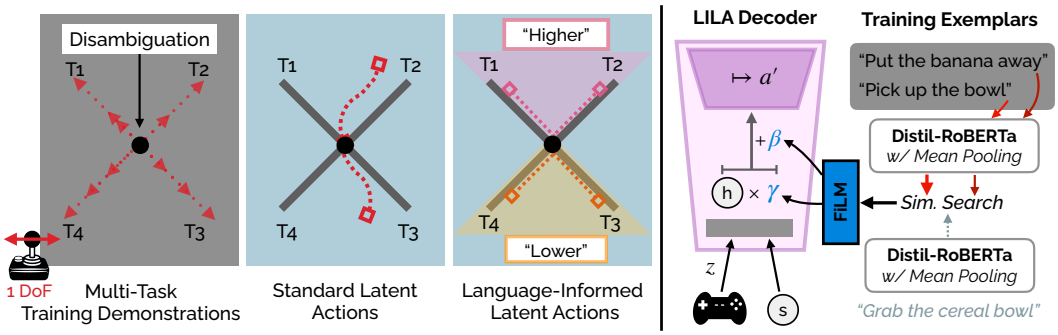

Figure 2: [**Left**] Navigating toward four points on a cross with a 1-DoF latent action, where there is a point of disambiguation. Standard LA fails at this task, while LILA accurately reaches the corners with the help of language. [**Right**] LILA decoder architecture. We embed a user utterance using a pretrained language model, then identify the closest exemplar in the training set via similarity search. We feed the embedding for this exemplar through a FiLM layer that injects linguistic information into the core of a standard latent action decoder.

Formalism. We formulate a user's task (on a *per-user basis*) as a fully-observable, language-augmented, Markov Decision Process (MDP) $\mathcal{M}$ defined by the tuple $(\mathcal{S}, \mathcal{U}, \mathcal{A}, T, R, \gamma)$ similar to prior work in language-conditional robotics [11, 30, 38]. Let $u \in \mathcal{U}$ denote a user's language utterance provided at the start of each task, where $\mathcal{U}$ is the full set of language utterances a user could provide to a robot. Let $s \in \mathcal{S} \subset \mathbb{R}^n$ be the robot's state, and $a \in \mathcal{A} \subset \mathbb{R}^m$ be the robot's action: taking action a in state s results in a next state s' according to the transition function $T(s, a)$. Given the language utterance u, the user implicitly defines a reward function $R(s, a, u) \in \mathbb{R}$; the human and robot collaboratively maximize this reward subject to discount factor $\gamma \in [0, 1]$.

In this work, we experiment exclusively with the Franka Emika Panda robot arm, a 7-DoF manipulator. States are taken to be the robot's joint states ($n = 7$) while actions are provided as continuous joint velocities ($m = 7$). Language utterances u are typed into a text console, but future work could easily extend this to use off-the-shelf speech recognition systems.

Problem Statement. This MDP forms the basis of a shared autonomy task wherein a human is equipped with a low-dimensional control interface for the robot. Let $z \in \mathcal{Z} \subset \mathbb{R}^d$ where $d << m$ be the human's control input to the robot, such as the $d = 1$ DoF controller in Fig. 2. Previous works on learning latent actions for assistive teleoperation [8, 9, 24] seek to learn a decoder $\phi(z, s) : \mathcal{Z} \times \mathcal{S} \rightarrow \mathcal{A}$ that maps user low-dimensional inputs $z \in \mathcal{Z}$ and current state $s \in \mathcal{S}$ to a high-dimensional action $a \in \mathcal{A}$. However, in situations such as the *disambiguation point* that may arise when desired task trajectories overlap and form a cross (Fig. 2), too low a control input dimension d may cause the learned latent actions to not aid in achieving *any* task in a multi-task setting.

Our goal is to use language to help specify which subspace of the continuous control space contains the latent actions that best match a user's desired task. We aim to learn a decoder $\phi(z, s, u) : \mathcal{Z} \times \mathcal{S} \times \mathcal{U} \rightarrow \mathcal{A}$ that incorporates the user's control input *and* initial language utterance u, and predicts the robot action a_u that maximizes reward. Thus, we propose using language as an expressive *conditioning* variable to enable prior work on latent actions to be useful in multi-task environments.

4 LILA – Language-Informed Latent Actions

LILA builds off the *learned latent actions* paradigm for assistive teleoperation, which essentially compress demonstrations to a low-dimensional space that distills the core components of the given task, akin to PCA. Specifically, we extend the original conditional auto-encoder models (CAE) from [8] to incorporate language and address the disambiguation problem discussed above. In addition to the general framing, we provide details on how we encode language in a way that generalizes effectively to diverse user utterances and integrate this method with the broader latent actions framework.

4.1 Extending Learned Latent Actions with Language

We assume a dataset of demonstrations associated with a corresponding language utterance. We split each demonstration into triples (s, u, a) and use these to learn a conditional auto-encoder, consisting

Task Name	Success	Example User Study Input	Mapped Training Data
Pick Banana	100%	*yellow in purple*	→ `pick up the yellow banana and place it into the purple basket`
Pick Fruit Basket	100%	*bring basket to center of pan*	→ `place the basket onto the tray`
Pick Cereal	100%	*go to the left side of the cream bowl, go down, grab the cereal bowl, and place it on the try*	→ `grab the cereal bowl and put it on the tray`
Pour Bowl	67%	*pick up the cup of marbles and pour them into the cereal bowl*	→ `pick and pour the cup of white balls into the bowl of cereal`
Pour Cup	100%	*pick up the clear cup with marbles in it and pour it in the black mug with the coffee beans in it*	→ `pick up the cup and pour the contents in the mug`

Table 1: Example utterances provided by user study participants paired with the retrieved exemplar per the method described in §4.2. As each participant only attempted 2 tasks, success rate can fluctuate significantly, as is the case with the **Pour Bowl** task.

of a language-conditional encoder $\psi : \mathcal{S} \times \mathcal{A} \times \mathcal{U} \rightarrow \mathcal{Z}$ that maps language and states to a latent "action" and a decoder $\phi : \mathcal{Z} \times \mathcal{S} \times \mathcal{U} \rightarrow \mathcal{A}$ that attempts to reconstruct the original action a. We minimize the mean-squared error between the predicted action and the original action:

$$L_{\phi,\psi} = \frac{1}{N} \sum_{i=1}^{N} (\phi(\psi(s_i, a_i, u_i), s_i, u_i) - a_i)^2 \tag{1}$$

Both the encoder ψ and decoder ϕ are neural networks optimized with stochastic gradient descent; we discuss how we integrate language (including the use of pretrained language models) in §4.2.

4.2 Integrating Language

Large-scale, pretrained language models such as BERT, T5, and GPT-3 [42, 43, 44] have revolutionized NLP, providing easy-to-obtain language representations that capture sentence-level semantics. Inspired by the success of using these models for encoding language in the context of robotics and reinforcement learning tasks [34, 45, 46], we opt to take a similar approach. For encoding language, we use a distilled variant of the RoBERTa-Base model [47], from `Sentence-Transformers` [48, 49]. Whereas traditional large-scale LMs are trained on a token-level objective, this model is fine-tuned on a large corpus of paraphrased sentences, allowing it to pick up on longer-term, sentence-level (utterance length) semantics. As these models output vector embeddings per-token, we generate sentence embeddings by performing mean-pooling over token embeddings for an utterance, as is done in prior work [34, 45]. We directly incorporate these embeddings into our latent actions models using feature-wise linear modulation (FiLM) layers [50], which inject linguistic information into learned features h by learning to map language to parameters (γ, β) of an affine transformation $h' = \gamma * h + \beta$ that is fed to later layers of the network Fig. 2. The Supplemental provides additional detail around the network architecture and implementation (with code).

Nearest-Neighbor Retrieval at Inference. A major concern for work in language-conditioned robotics is the ability to generalize to novel language inputs not seen at training. While it may be unreasonable to expect generalization to completely new tasks, for user-facing systems with clear task distribution (as in our work), there is an implicit expectation that any language-informed system is capable of handling moderate variations or paraphrases of utterances from the training set.

To do this, adding linguistically diverse data has been the gold standard [40, 46]; however, a new class of approaches have emerged that sidestep additional data requirements by tapping into the potential of pretrained language models [39, 45]. These approaches frame language interpretation at inference (when interfacing with real users) as a *retrieval* problem: each new user utterance u' is embedded (with the same pretrained model as above) and then used to query a nearest neighbors store containing all training exemplars; once the nearest neighbor u_i has been identified, it replaces u' as an input to the LILA decoder.

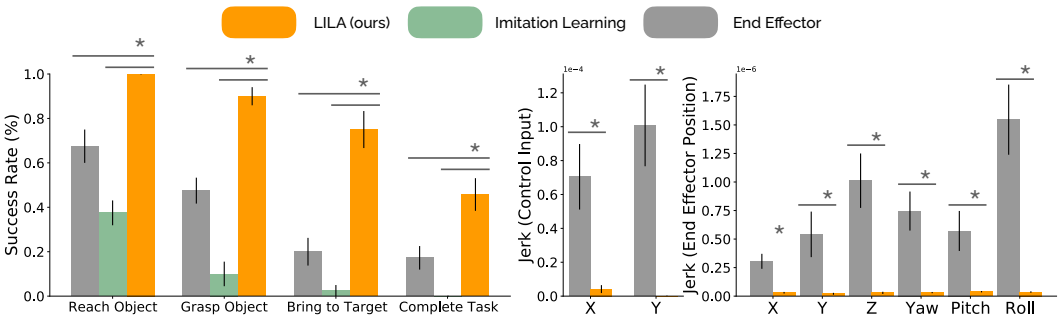

Figure 3: Quantitative Results. We average success rate [**Left**] across all sub-tasks for each control method, and find that LILA is significantly ($p > 0.05$) more performant. However, the steep drop in performance when completing the full task shows the difficulty of fine-grained control. We also calculate jerk as an indicator of controller smoothness, for both user control inputs [**Middle**] and end-effector position [**Right**]. Averaged across tasks and users, we find LILA leads to significantly smoother control for users than end-effector control.

The key benefit of such an approach is that there is no mismatch between train and test language inputs; all "test inputs" are drawn solely from the training set. This does mean, however, that user utterances that describe new tasks, or are otherwise unachievable also get mapped to language seen at training. While this limits generalization, it again highlights the benefits of operating within the shared autonomy paradigm (doubly so, considering the cost of a mistake in an assistive domain like the one we consider in this work): if, while providing control inputs to the robot, a user feels the robot is not acting in alignment with the user's desired objective, they can always stop execution.

5 User Study

We evaluate LILA with a real-world user study on a 7-DoF Franka Emika Panda Arm, on a series of complex manipulation tasks. Each user is provided a 2-DoF joystick for control. We compare against a non-learning, End-Effector (EE) control baseline where users "mode switch," controlling the velocity of 2 axes of the End-Effector pose at a given time – [(X, Y), (Z, Roll), (Pitch, Yaw)]. We also compare against a fully autonomous Imitation Learning (IL) strategy where users solely provide language inputs, and the robot attempts to perform a task without additional input.

Environment. Fig. 1 shows our "breakfast buffet" setting, a scaled down version of an assistive feeding domain. We perform a within-subjects study where each user is assigned 2 of the following 5 tasks to perform with each control method: 1) **`Place Banana`**: placing the banana in the purple fruit basket, 2) **`Place Basket`**: grasping the purple basket by the handles, and dropping it on the tray, 3) **`Place Bowl`**: grasping the green cereal bowl by its edge, and moving it to the tray, 4) **`Pour Bowl`**: pouring the blue cup of marbles (a proxy for actual milk) into the cereal bowl (positioned on the tray), and 5) **`Pour Cup`**: pouring the blue cup of marbles into the yellow coffee cup. Fig. 1 shows idealized example trajectories for the **`Place Bowl`** (blue) and **`Place Banana`** (orange) tasks.

These tasks vary in difficulty, with many requiring precise grasping and dexterous manipulation (e.g., pouring). Quantitatively, we evaluate partial success based on how many of the following 4 subtasks users are able to complete: 1) **`Reaching`**: touching the desired object, 2) **`Grasping`**: executing a successful grasp, 3) **`Bring to Target`**: successfully transporting the manipulated object to the target location, and 4) **`Task Completion`**: whether users are able to finish the given task (placing an object without excessive force, in an acceptable orientation, or pouring all marbles into the desired receptacle).

Demonstration Collection. Both LILA and IL models require learning from (language, demonstration) pairs for each of the 5 tasks. We collect task demonstrations kinesthetically, by manually backdriving the robot arm, as in prior work [8, 24]. We trace out the trajectory necessary and record joint states at a fixed frequency. We initially collected 15 demonstrations per task for each method. However, on manually testing the IL model, we found it incapable of performing even rudimentary reaching behaviors. To give IL the best chance, we collected twice the number of demonstrations (30 per task; 150 total), requiring an extra 2 hours of labor. Further details, including videos of our demonstration collection process for each method, are included in the Supplemental.

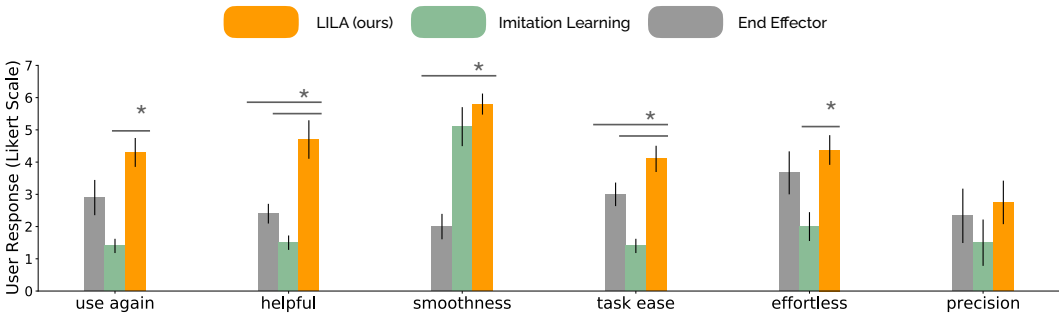

Figure 4: Qualitative Results. Using a 7-point Likert scale, we ask users to evaluate each of the 3 control methods for different properties. With high significance ($p > 0.05$), we find that LILA outperforms both Imitation Learning and End Effector Control baselines on several metrics, including degree of helpfulness the control method provided and ease in completing tasks.

Crowdsourcing Language Annotation. To realize our goal of building a *natural* language interface for human-robot collaboration, we collect language annotations for each task by crowdsourcing utterances. In order to capture the diverse ways users may refer to the objects and actions our tasks entail without any additional information (simulating a real user walking into our environment for the first time), we recruited 30 workers on Amazon Mechanical Turk and showed them a video of a recorded task demonstration, asking them to provide *"a short instruction that you would want to provide the robot to complete this task independently in the box below."*. After collecting annotations from our workers, we filter data to identify workers who provided "atypical" annotations. We defined "atypical" by measuring the cosine distance between the sentence embedding (per the pre-trained language model from §4.2) of an annotator's provided sentence, and the *average* sentence embedding aggregated over all annotators for the given task. Each annotator was then ranked by how "typical" their annotations were, and we used annotations only from the 15 "best" annotators under this metric as our ground-truth language utterances for training our models. Further details on our data collection and filtering procedure are in the Supplemental. Additionally, Table 1 provides examples of crowdworker utterances from our dataset (rightmost column).

Participants & Procedure. We conducted our study with a participant pool of 10 university students (5 female, age range 23.2 ± 1.87). Four subjects had prior experience teleoperation a robot arm.[2] We conduct a within-subjects study, where each participant completed 2 tasks, chosen randomly, with each of the three methods. Users were given 2 trials to complete each tasks, and an allotted 3 minutes per control strategy to practice. Users were also given a sheet describing controller inputs and details for each control method, which we include in the Supplemental. For Imitation Learning and LILA controllers, which require language inputs, participants provided a natural language utterance which was entered into the model – participants were allowed to verify the proctor entered their input accurately. In addition to tracking quantitative success rates (normalized, based on progress relative to each of the 4 defined subtasks), time taken per task, and detailed logs of the robot behavior, at the end of each study, users were asked to fill out a qualitative survey evaluating each control method. We present both quantitative and qualitative results in the following paragraphs.

Quantitative Results. Fig. 3 summarizes our objective results. We evaluate both full- and partial-task success rates for each task across all control methods, in addition to computing smoothness metrics directly on the logged user inputs and robot actions. Intuitively, smoothness is a measure for intuitiveness (when measured on user 2-DoF joystick inputs), and ease of use (when measured on the robot's end-effector pose). We measure smoothness by calculating jerk, the time-derivative of acceleration. Our results show that LILA significantly ($p > 0.05$) outperforms both methods across all sub-tasks, and is also smoother to use both in control input space (2 DoF input) and end-effector space (6 DoF). However, the relative drop in performance of LILA for the final sub-task "Complete Task" shows the room for improvement in fine-grained control, such as pouring motions.

Qualitative Results. Fig. 4 summarizes our subjective results. We administered a 7-point Likert scale survey after users finished performing tasks with each of the three different methods; this survey included questions such as the the perceived helpfulness of the controller in completing

[2]Due to the COVID-19 Pandemic and university restrictions, only those with pre-authorized access could participate in the study. See the COVID-19 considerations document in the Supplemental for more details.

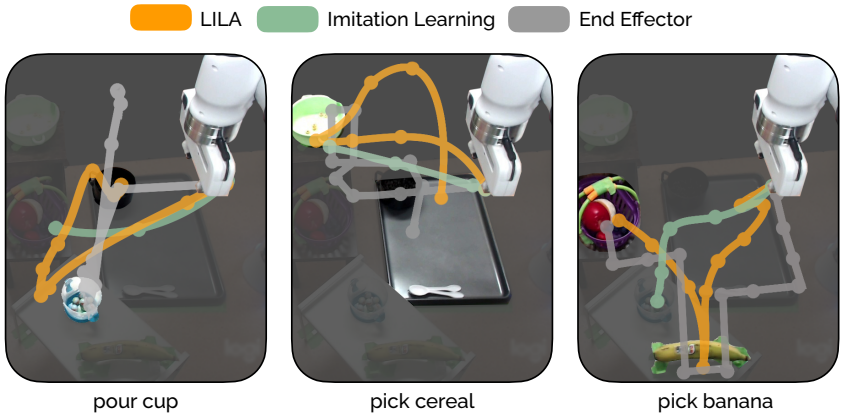

Figure 5: Trajectories from one user comparing three different control methods 3 out of our 5 tasks – **`Pour Cup`**, **`Pick Cereal`**, and **`Pick Banana`**. LILA provides smooth actions that immediately approach the target object for a task, while End-Effector control shows more rigid motions that result in users diverging from their intended paths. While imitation learning also enables smooth motions, it often fails shortly after reaching objects, hence the shortened trajectories.

the tasks (*helpful*) and whether the participant would use the control method again (*use again*). The survey results show that LILA outperforms both Imitation Learning and End Effector controls across most qualitative metrics, with statistically significant results ($p > 0.05$) marked with an $*$. We additionally visualize samples of the observed end-effector trajectories by individual users (collected during our study) for 3 of our 5 tasks in Fig. 5. We observe that across all tasks, LILA results in smoother end-effector trajectories than end-effector control, while Imitation Learning comes close to the target object but is unable to complete the entire trajectory for the task.

6 Discussion

Summary. We present Language-Informed Latent Actions (LILA) a framework that marks the first step in combining the expressiveness and naturalness of language for *specifying* and *disambiguating* tasks within the context of assistive teleoperation. Our user study results show that when compared to fully autonomous, imitation learning approaches, LILA is more sample-efficient and performant, training on half the number of task demonstrations, but obtaining significantly higher success rates. Compared with no-learning end-effector control methods, we again show LILA's effectiveness at obtaining high success rates, but also demonstrate its ability to produce intuitive low-dimensional control spaces from language input. Qualitatively, we find that users prefer LILA to alternative methods across the board, heralding a bright future for additional work on language & latent actions.

Limitations and Future Work. While users found LILA intuitive and natural, they found themselves wanting to further modulate the robot's behavior with language instructions *during the course of execution*. Many users, upon seeing the robot make slight deviations from a desired path would instinctively provide spoken corrections – *"a little to the right"*, *"no, grasp it by the handle!"* – indicating a desire for *multi-resolution* language control. Future work will not only look into this, and more adaptive approaches for incorporating language and latent actions, but will also investigate using natural language to its fullest potential, embracing compositionality and perhaps even commonsense knowledge for generalizing from limited data.

Shared Autonomy and LILA. LILA fits within the shared autonomy paradigm, where the role of language has been underexplored. With LILA (and shared autonomy approaches in general), humans retain *agency* – they are responsible for robot motion, and if the robot moves in a way that is not safe, or does not align with their objectives, they stop providing control (and possibly reset, give a new instruction, or drop into a more complex control mode). Behavior is *interpretable* – the latent actions model, *critically informed by language*, produces intuitive control spaces that humans can quickly grasp. Finally, language is *natural* – users specify their objectives as they would if speaking to another person, and the robot uses that language to shape their control space. These properties – preserving agency, maintaining interpretability, and leveraging the expressive and natural features of language for specifying objectives – are critical for widespread human-robot collaboration, and we hope this work is a first step towards achieving that goal.

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