

MODULE 3-P4: Intention detection of an assistive robotic arm during shared autonomy

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1 Introduction

- Robotic manipulators can assist those with low upper limb Manual Muscle Testing (MMT) scores perform activities of daily living, such as eating and grasping objects. However, the high degree of freedom (DoF) of robotic arms makes controlling them challenging, given low DoF control interfaces like joysticks.
- Shared autonomy can assist users by reducing the control burden of the user but relies on accurate intent prediction.
- State-of-the-art shared autonomy methods predict the human intention by **passively observing** the human's joystick inputs.
- However, in real-world scenarios, the goals are not well separated due to clutter and there are multiple valid ways to grasp each object, **making accurate intent prediction via passive observation of human joystick inputs very difficult**.
- To provide meaningful assistance in these scenarios, the shared autonomy system should be able to **actively gather information from the human when uncertainty is high** and move towards the goal when uncertainty is low.

2 Proposed framework

We formulate shared autonomy as a discrete action Partially Observable Markov Decision Process (POMDP), which offers a principled framework to balance exploration and exploitation.

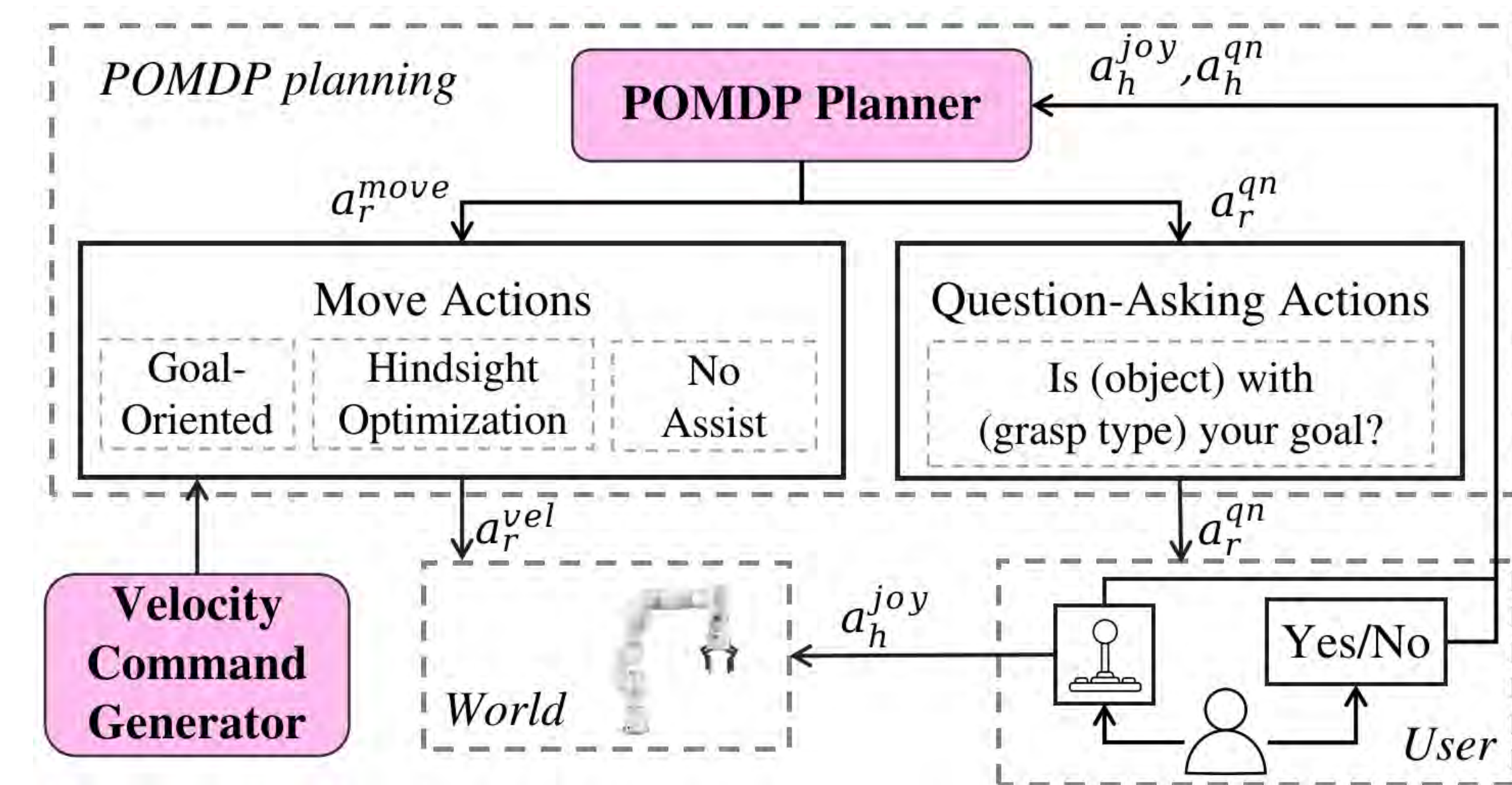


Figure 1: An active information-gathering shared autonomy framework using Partially Observable Markov Decision Processes (POMDPs). Instead of planning over low-level actions such as moving left or right, we plan over high-level actions, either moving towards a goal or asking questions about a goal. A velocity command generator is used to convert the high-level actions into low-level actions a_r^{vel} . The user action a_h^{joy} , which is the velocity command corresponding to the user's joystick input, is combined with the robot action a_r^{vel} during execution.

3 User study

- To evaluate our framework, we conducted a user study with 18 participants (15 healthy, 2 stroke, and 1 Duchenne muscular dystrophy).
- We compared our approach with the state-of-the-art passive information gathering method using hindsight optimization [1] and a manual teleoperation approach.

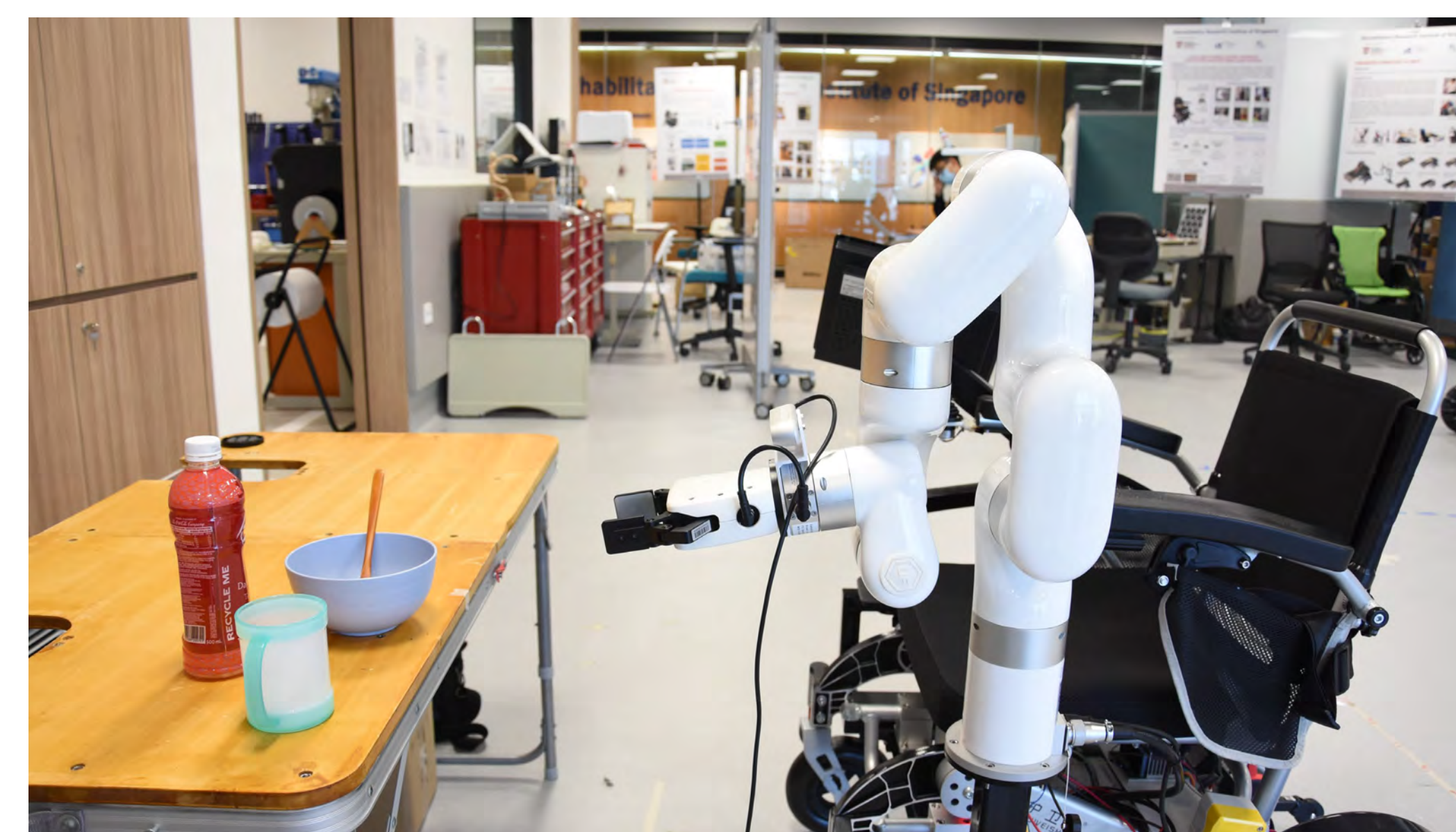


Figure 2: Experimental setup with four objects placed on the table. A 3-DoF joystick was used to control the arm. Participants had to complete three tasks by grasping the object with a particular grasp type in the following order - (a) bottle with side grasp, (b) spoon with top grasp, (c) cup with top grasp.

4 Results

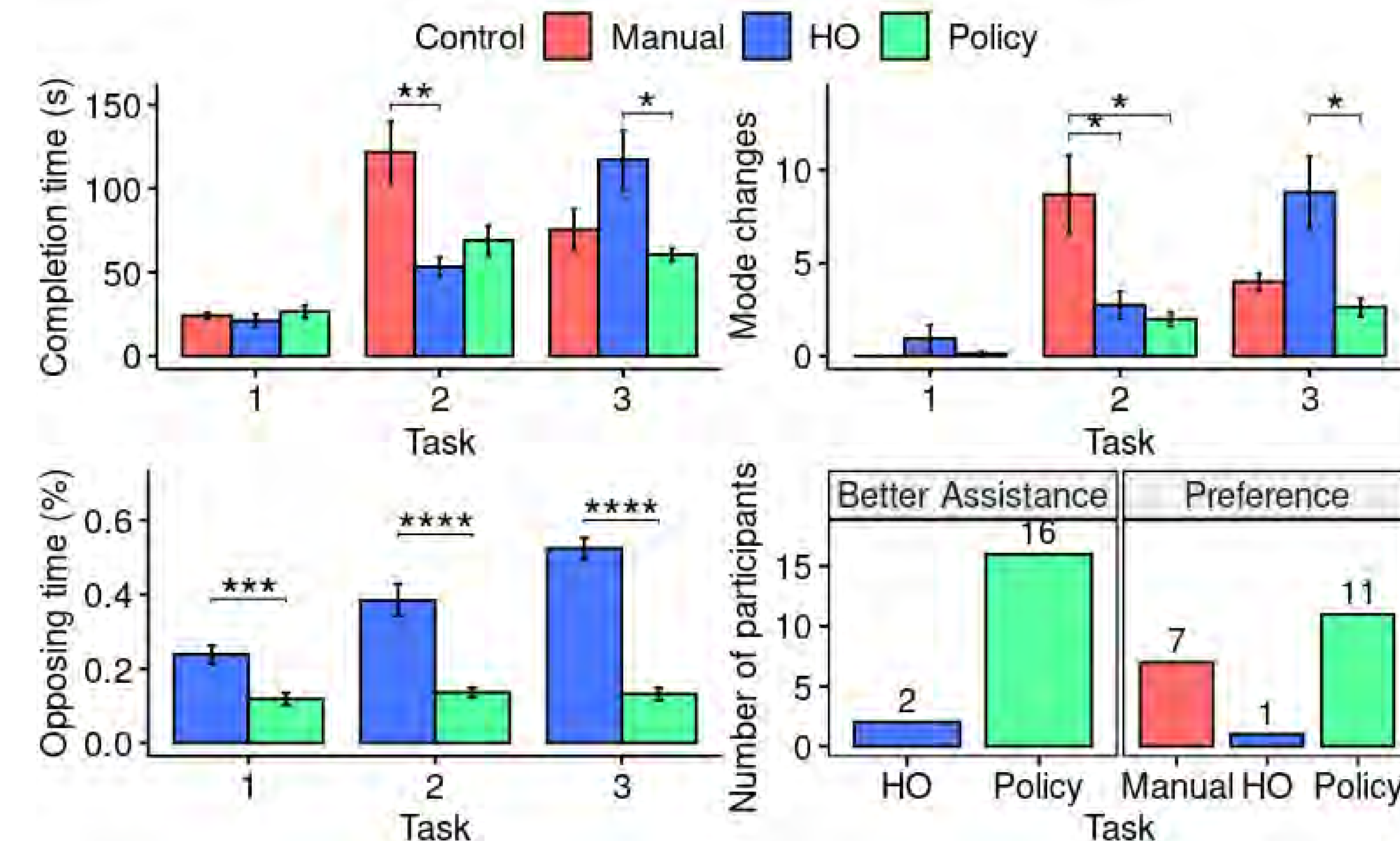


Figure 3: Experimental results show that our method can assist users towards their desired grasp pose at least as well as or better than [1], in terms of task completion time, number of mode changes and percentage opposing time. Most participants preferred our method over [1], but there is further room for improvement since many participants preferred manual as it provided the greatest control. Note that other subjective measures such as NASA-TLX, usefulness and ease-of-use measures were also collected, with our method outperforming [1].

5 Future work

We observe that users still provide joystick inputs to adjust the gripper pose even after the user intent is known (the user answered "yes" to a question). Future work aims to:

- Model human inputs as corrective feedback to understand human objectives and/or preferences.
- Explore an intuitive mode/interface for human-robot interaction to provide corrective feedback.

References:

[1] S. Javdani, H. Admoni, S. Pellegrinelli, S. S. Srinivasa, and J. A. Bagnell, "Shared autonomy via hindsight optimization for Teleoperation and teaming," The International Journal of Robotics Research, vol. 37, no. 7, pp. 717-742, 2018.

