Comparing BariFlex and UMI for Force-Sensitive Manipulation in Imitation Learning

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***Abstract*—This research investigates the performance of the BariFlex robotic gripper in comparison to the UMI gripper in force-sensitive manipulation tasks. While the UMI gripper lacks direct force sensors and relies on inferred force estimates, the BariFlex gripper incorporates direct force sensing capabilities, allowing for enhanced precision. Our objective is to determine whether the BariFlex's extra force-sensing capabilities allow for superior control in delicate deformation-based tasks. The primary experimental task involves squeezing a Gatorade bottle to dispense a precise amount of liquid, testing each gripper's ability to modulate force accurately. This experiment will also provide insights on the impact of different sensory modalities on imitation learning models. The study aims to provide insights into the effectiveness of direct vs. indirect force estimation in robotic manipulation and lay the foundation for future research in adaptive learning-based force control.**

I. Introduction

In recent years, imitation learning has become a powerful and prominent method of training machine learning models for robotic manipulation tasks. However, one of its most significant limitations is the lack of high-quality training data, which directly impacts generalization and robustness. To address this issue, new means of data collection like Universal Manipulation Interface (UMI) [1] have emerged, providing a more standardized and efficient pipeline for generating large-scale, high-quality demonstrations. These advancements in data collection are critical for improving policy learning and enabling robots to handle a broader range of real-world tasks effectively.

With the rapid progress in robotic manipulation, force-sensitive tasks have become a crucial area of focus, particularly in handling delicate and deformable objects. Despite this, many prior works, including the UMI, have traditionally ignored force feedback or relied on indirect estimations using visual and kinematic data. This limitation hinders the development of truly adaptive and precise robotic end effectors. Recent innovations in hardware, such as the BariFlex gripper [2], integrate force sensors directly into the gripper, enabling real-time force feedback. This capability allows models to dynamically adjust grip force, leading to more refined control in pressure-sensitive tasks like assembling fragile components, grasping soft materials, or performing nuanced human-robot interactions.

In this work, we aim to compare the force-control capabilities of UMI and BariFlex to evaluate how well each gripper can apply and regulate force across different manipulation tasks. A byproduct of our investigation allows us to compare the success rate of three separate experiments. Specifically, the UMI gripper, The BariFlex gripper without depth-based imaging, and finally the BariFlex gripper with depth-based imaging.

We want to evaluate two separate ideas:

1) How does the BariFlex gripper compare to the UMI gripper in force-sensitive manipulation tasks?
2) What impact do different sensory modalities (e.g., depth, color) have on the success rate of robotic manipulation using imitation learning?

II. Related Work

a) BariFlex: BariFlex was developed at the University of Texas at Austin as a hybrid rigid-flexible gripper designed for grasping. It features high back-drivability and direct force sensing, allowing it to effectively handle both rigid and deformable objects. We hypothesize that the BariFlex's ability to directly interact with force-based motor information removes a layer of estimation that IL models traditionally had to infer, thus improving accuracy when completing the task.

b) UMI: The UMI gripper, developed at Stanford, takes a different approach, relying on indirect force estimation by measuring changes in motor current and claw separation. While this method enables force-sensitive tasks to some extent, prior research suggests that indirect force estimation can introduce inconsistencies when dealing with objects that require precise pressure modulation.

c) Imitation Learning: Imitation learning allows robots to learn to complete tasks by observing human demonstrations. Frameworks such as Robomimic [3] and Diffusion Policy [4] have demonstrated effectiveness in training robots for complex manipulation tasks. Standard imitation learning approaches use multimodal sensory inputs such as RGB images, depth maps, and proprioceptive feedback. Prior research suggests that the inclusion of depth sensing improves manipulation accuracy by providing spatial awareness.

d) Diffusion Policy: Diffusion Policy is a recent approach to imitation learning that generates smooth and realistic actions for robotic tasks. Instead of predicting actions directly, it refines them over multiple steps, ensuring better precision and stability. This method has been shown to improve task performance by reducing errors in action execution, making it particularly useful for force-sensitive tasks like ours.

e) Robomimic: Robomimic is an imitation learning framework designed for learning from human demonstrations. It provides pre-collected datasets and tools for training robots to replicate human-like manipulation skills. By using Robomimic, we can leverage high-quality demonstrations to improve the learning process for our grippers, helping them achieve more accurate and controlled force application.

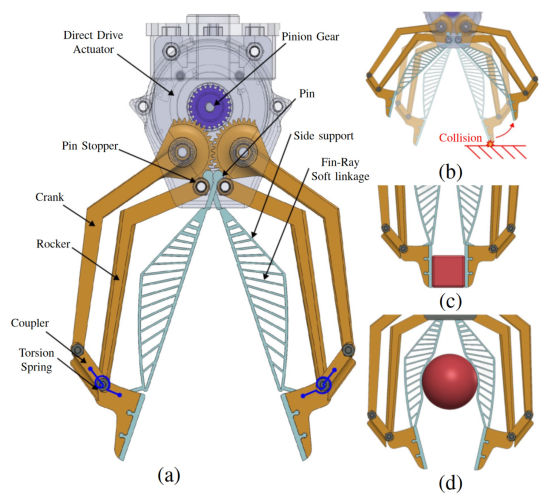

Fig. 1. BariFlex robotic arm CAD model.

III. Methodology and Experiment Design

Our experiment will involve collecting human demonstration data using both the UMI and BariFlex grippers to squeeze a Gatorade bottle and dispense a controlled amount of liquid. The methodology consists of the following steps:

1. **Data Collection:** Human demonstrators will perform the squeezing task using both grippers while sensors record grip force, finger displacement, and liquid volume dispensed. We aim to run multiple trials with both grippers, and reach a predefined water level.

2. **Force Variation:** Each trial will involve different force levels to assess the gripper's ability to regulate pressure dynamically.

3. **Hypothesis Testing:** UMI's indirect force estimation will result in inconsistent force application, leading to variable output. BariFlex's direct force sensing will allow more controlled force modulation, improving precision.

4. **Multi-Modal Comparisons:** BariFlex's direct force sensing will allow more controlled force modulation, improving precision.

5. **Model Training and Evaluation:** Data collected from human demonstrations will be used to train imitation learning models. Performance will be evaluated based on: success rate (accuracy in achieving the target liquid volume); precision (which is judged on water within the cup, and a proxy for Force control); adaptability across different bottle types.

IV. Experimental Task and Evaluation

Our benchmark task is designed to quantify the force control capabilities of each gripper:

- The robot must squeeze a full Gatorade water bottle to dispense a specified volume into a measuring cup.
- Success is defined as achieving the precise target volume within a margin of error, ϵ. We aim to consider two possible cases. A qualitative approach to consider how acceptable the margin of error is in the real world, and a quantitative approach, where we will determine if the difference between the performances of the two arms are statistically significant.

Evaluation criteria include:

- **Success rate:** Percentage of trials where the target liquid volume is achieved.
- **Force control accuracy:** Ability to modulate grip force without excessive squeezing.
- **Statistical Analysis:** We will conduct ANOVA tests to determine significant performance differences between the grippers. Pairwise t-tests will be performed to compare success rates and force accuracy across different experimental conditions.

V. Conclusion and Future Work

This research seeks to determine whether the direct force sensing of the BariFlex gripper offers a tangible advantage over the UMI gripper's indirect force estimation in force-sensitive manipulation. We hypothesize that BariFlex's ability to modulate force in real-time will lead to more precise and consistent outcomes.

Future research directions include:

- Extending the study to complex dexterous tasks beyond bottle squeezing, such as grasping fragile objects.
- Investigating additional sensory modalities, including tactile and thermal feedback, to improve robotic perception.
- More complex dynamic reasoning based on the deformation of complex materials; predicting deformation during tasks.

VI. Milestones

1) Model Creation: By April 8th
2) Data Collection: By April 14th
3) Model Training: By April 17th
4) Data Analysis: By April 22nd

VII. Acknowledgments

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