Safe Robot Learning in Contact-Rich Manipulation via A Low-Cost Soft Gripper and Haptic Feedback Teleoperation

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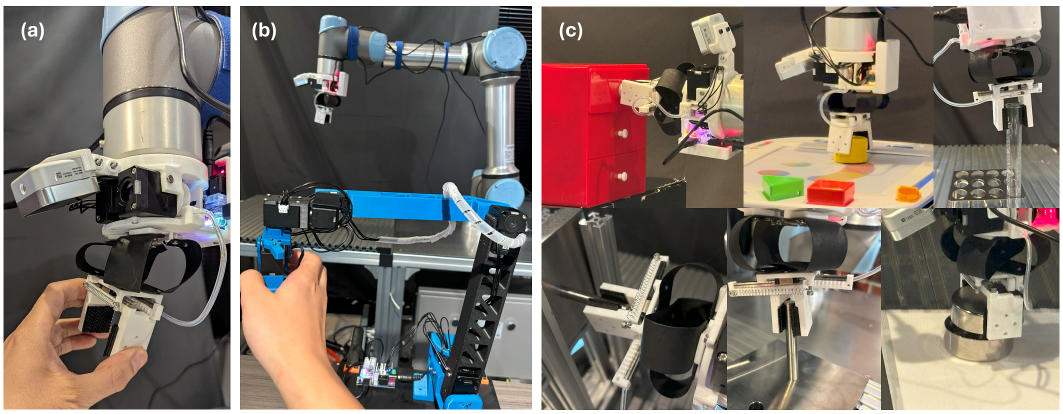

Figure 1: **Safe robot learning system in contact-rich tasks:** The proposed system integrates (a) a novel soft end-effector and (b) a haptic-feedback teleoperation interface for position-controlled robots. Using an imitation-learning approach, we demonstrate (c) a variety of contact-rich tasks.

Abstract: Safety is a critical challenge in robot learning for contact-rich manipulation tasks, where unexpected collisions can cause damage and hinder learning. Human demonstrations can improve safety by allowing robots to learn safe behaviors directly from expert guidance. However, existing systems struggle to provide both fail-soft capabilities—enabling robots to safely withstand or recover from collisions—and fault-avoidance features, which reduce operator errors by providing haptic feedback. This study introduces a low-cost robot learning system that combines a novel soft end-effector, CLAW (Compliant Leaf-spring in Anisotropic soft Wrist), with a haptic teleoperation interface for position-controlled robots. CLAW addresses key limitations of existing soft end-effectors by providing large 6-degree-of-freedom deformation, adjustable anisotropic stiffness, and lightweight (330g) at a low cost (∼$550). In this study, we show that our system achieves higher learning performance and enhanced safety compared to off-the-shelf end effectors.

1 Introduction

Ensuring safety during data collection and policy execution in real-world scenarios remains a critical challenge in robot learning. Leveraging human demonstrations is promising for enhancing safety and has driven recent achievements, including foundation models [1, 2] and advances in imitation learning [3, 4]. Nonetheless, special care is required when providing demonstrations for contact-rich tasks, such as assembly, and others [5]. This study introduces a safe and cost-effective robot learning

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system that combines a novel soft end-effector with an intuitive teleoperation interface to provide fail-soft and fault-avoidance capabilities to robot learning.

First, we develop a new soft end-effector: **C**ompliant **L**eaf-spring in **A**nisotropic soft **W**rist (**CLAW**) (Fig. 1 (a)). CLAW features a two-finger gripper and a soft wrist composed of a simple structure, utilizing only two leaf springs and two servo motors. It has large 6-DoF deformations and anisotropic stiffness and can switch between three compliance profiles. Its total cost is approximately $550, and the weight is 330 g. Second, we developed a haptic feedback teleoperation system (Fig. 1 (b)). This teleoperation system is inspired by GELLO [6] and its extensions [7][8] which incorporate haptic feedback. While the prior study utilized it for a torque control-based robot [7][8], we developed it for a position-control robot by incorporating a force-torque sensor mounted on the follower robot. We employed the Action Chunking Transformer (ACT) [3] imitation learning method and compared CLAW with a widely used Fin Ray gripper [9] and an off-the-shelf rigid gripper in a benchmark of contact-rich manipulation tasks [10]. The results show that CLAW outperforms Fin Ray and rigid grippers in peg-in-hole benchmark tasks. Furthermore, our system performed robustly in high-precision, delicate, and contact-rich manipulation (Fig. 1 (c)). More detailed information about CLAW, teleoperation device, and additional evaluation is introduced in the Appendix.

2 Main results

Our goal is to answer the following question via real robot experiments: Does our system complete contact-rich tasks more **successfully** and **safely** than other off-the-shelf end-effectors?

In our experiments, we compared CLAW with two baselines—a rigid parallel gripper (2F-85, Robotiq, Canada) and a TPU-printed Fin Ray gripper. After characterizing CLAW's compliance in deformation tests (Appendix C.1), we evaluated its task performance and safety in manipulation experiments.

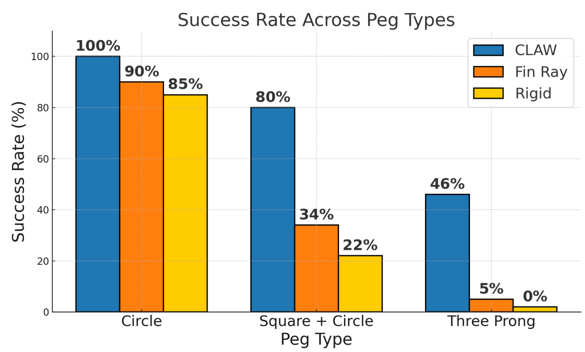

Figure 2: Learning success rate across end effectors in FMB insertion task.

Learning performance. Using the assembly board from FMB (a Functional Manipulation Benchmark for Generalizable Robotic Learning) [10], we evaluated CLAW against baselines in three different peg-in-hole geometries using ACT (experimental method described in Appendix B). Fig. 2 shows that rollout with CLAW has significantly higher success on every peg type. CLAW's failures were primarily due to slight misalignment, whereas the Fin-ray and rigid grippers most often failed by applying excessive lateral (X–Y) forces, leading to jamming and triggering emergency stops.

Table 1: User Study Results: Average Force and Number of Emergency Stop

	CLAW (haptic)	CLAW (no haptic)	Fin Ray (haptic)	Rigid (haptic)
Avg. Force [N]	**2.673**$\downarrow$ **± 1.479**	3.446 ± 1.941	3.815 ± 1.422	6.311 ± 2.444
Emergency stops	**0**$\downarrow$	0$\downarrow$	5	9

Safety. We conducted a pilot user study on the FMB Square+Circle insertion task with three participants (one expert and two novices) to teleoperate under the same conditions as the FMB benchmark experiment. We found task completion times to be comparable across all grippers; however, CLAW produced lower overall contact forces than both the Fin Ray and rigid grippers (see Tabl. 1). In addition, haptic feedback further reduced the forces required to complete tasks, and notably, only CLAW avoided triggering the robot's protective stop.

3 Conclusion

This study introduced a low-cost robot-learning system that integrates a novel soft end-effector, CLAW, with an intuitive haptic teleoperation interface for position-controlled robots, thereby enabling safe and effective teaching and learning of contact-rich manipulation skills.

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