

Learning Contact Tasks Skills based on DMP and Affordance Templates

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Abstract—Learning from demonstration (LfD) enables robots to learn experts’ skills by human demonstration. Recently, LfD has been developed for learning and performing skills in contact-rich tasks. However, task performance has not been generalized to unknown poses in contact-rich tasks. In this paper, we propose a teleoperation-based learning from demonstration (LfD) framework for performing contact-rich tasks in unknown poses. Expert demonstrations are collected via a bilateral teleoperation system, with an orientation synchronization algorithm aiding intuitive manipulation. From demonstrations, position and wrench profiles are recorded. Task trajectories are learned using dynamic movement primitives (DMP), while strategy learning allocates input and compliance spaces based on affordance templates to adapt motion during contact. By combining trajectory and strategy learning, the framework successfully reproduces manipulation behaviors in novel configurations. Experiments on turning-valve and peg-in-hole insertion validate the method, showing improved success rates and robustness to pose variations.

I. INTRODUCTION

Learning from Demonstration is a method for acquiring skills by learning demonstrations data of human experts. Generally, humans acquire various skills and knowledge by observing and imitating others. Applying this natural learning process to artificial intelligence(AI) allows researchers to develop AI systems with the ability to learn on their own. This opens opportunities for efficiently training AI in complex environments and applying it to a broader range of tasks.

However, LfD still faces several challenges. High-quality demonstration data are essential for accurate and effective learning. In addition, developing models that sufficiently reflect the complexity of real-world environments remains a crucial research topic, such as contact tasks. To overcome these challenges, researchers continue to explore new algorithms and techniques to improve the efficiency of data collection and enhance the generalization capabilities of models in various environments.

In this paper, we propose a teleoperation-based LfD framework for executing contacto-rich tasks in unknown poses. Our proposed method utilizes a bilateral teleoperation system to perform demonstration and acquire position and wrench

*This research was supported by the MOTIE(Ministry of Trade, Industry & Energy)(No. 00416440, Development of the AI based autonomous task planning and robot teaching solution for highly complex manufacturing assembly process) supervised by the KEIT.

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data. The proposed method utilizes the dynamic movement primitives(DMP) for learning trajectories and affordance templates for learning strategies of contact tasks. The strategy learning part defines which direction robot should move to perform a task on the task object, and for which direction it should generate stiff or compliant motion in contact situations. We verified the effectiveness of our proposed method with a rotating-valve task, a challenging scenario for robots.

II. METHODOLOGY

A. Teaching Method

The purpose of the demonstration is to successfully demonstrate the task and acquires position trajectories and force profile of contact tasks. There are three main methods for demonstrating tasks, kinesthetic teaching, passive observation and teleoperation. Each of these methods has its advantages and disadvantages. We used a teleoperation method that enables precise motion control during contact tasks through the use of haptic feedback.

Teleoperation is the easiest method among three methods to perform complex contact tasks because of the haptic feedback. However, lack of work proficiency and the lack of information make it difficult to manipulate the robot. Therefore, we used a bilateral teleoperation system to intuitively know the information of the working environment.

The implemented teleoperation system is shown as Figure 1. The system includes sigma. 7 (Force Dimension) which can generate 6DoF force/torque as the leader and KUKA LBR 14 r820 manipulator as the follower. The Gamma ATI force/torque sensor is attached at the end of the manipulator to measure the contact wrench. The manipulator is equipped with a 2F-85 Robotiq gripper for grasping object.

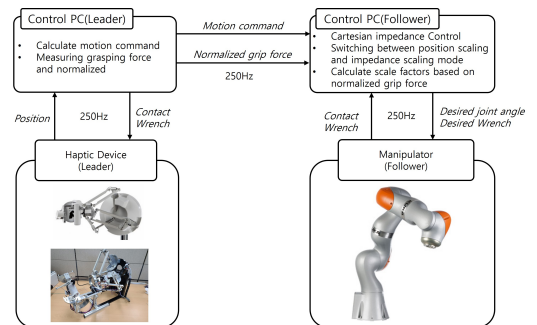


Fig. 1. Implemented teleoperation system for teaching contact tasks

B. Learning Method

In this paper, we configure two parts to learn human’s contact skills, trajectory learning and strategy learning. Figure n. shows the block diagram of our paper’s learning method.

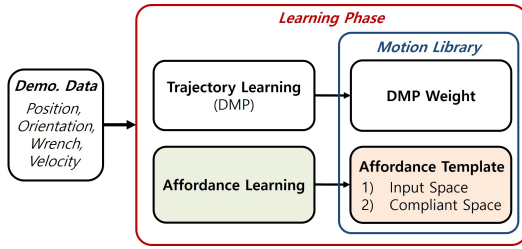


Fig. 2. Learning architecture including trajectory learning and strategy learning

The primary role of trajectory learning part is how to move in order to execute tasks based on position and orientation profiles. We used DMP to learn trajectories. To reduce noise in input trajectories while retaining essential features, we used spline interpolation and Gaussian Mixture Models(GMM) to average multiple trajectories.

The strategy learning part learns which direction to move and how to react to contact wrench to perform contact tasks. These concepts are derived from task affordance and are represented as affordance templates. In our study, we defined two affordance templates as the strategy for contact tasks, input space and compliant space.

III. EXPERIMENTS AND RESULTS

The proposed method was validated through two contact-rich tasks, turning-valve and peg-in-hole insertion. These tasks are both fundamental operations commonly performed in industrial fields.

A. Turning-valve

First, ten demonstration datasets for valve rotation were collected using the teleoperation-based teaching system, and the proposed method was used to learn the trajectory and affordance template for performing the unit task. Subsequently, experiments were conducted ten times for each of three different poses, and the results are shown in the table below.

TABLE I

STABILITY AND SUCCESS RATE OF MOTION DURING ROTATING-VALVE EXPERIMENTS IN THREE DIFFERENT POSES

Pose	Metric	Baseline	Proposed
Pos 1	Force (N)	13.671 (10.634)	5.751 (4.154)
	Torque (Nm)	0.695 (0.518)	0.403 (0.280)
	Success rate (%)	90	100
Pos 2	Force (N)	16.656 (12.680)	5.041 (4.560)
	Torque (Nm)	4.223 (0.416)	1.191 (0.298)
	Success rate (%)	80	100
Pos 3	Force (N)	13.280 (10.032)	5.334 (4.040)
	Torque (Nm)	0.622 (0.476)	0.370 (0.275)
	Success rate (%)	0	90

Note: Force and torque values are reported as RMS (STD).

TABLE II

SUCCESS RATE OF PROPOSED METHOD DURING PEG-IN-HOLE

Hole’s pose	Success Rate (%)
Pos 1	80
Pos 2	60
Pos 3	80

B. Precision Peg-in-hole

The second experiment involved performing a precision peg-in-hole task with a clearance of 40 μm . Similarly, demonstration data were collected and used to train the model with the proposed method. Subsequently, experiments were conducted five times for each of three different poses, and the results are presented below.

IV. CONCLUSION

This paper proposes a teleoperation-based LfD framework for contact-rich tasks, integrating bilateral control with an orientation synchronization algorithm to enable intuitive manipulation. The framework learns both trajectories (via DMP) and task strategies using affordance templates derived from force and velocity data. Experiments on valve turning and peg-in-hole tasks demonstrate robust performance across varying poses and successful high-precision assembly. However, the method is limited to trained object shapes, and future work aims to generalize to diverse objects for tasks such as rotation.