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Is a Simulation better than Teleoperation for Acquiring Human Manipulation Skill Data?

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***Abstract*— This study explores the feasibility of using simulations as a better interface to collect human object manipulation skills for learning from demonstrations (LfD). Recently, numerous researchers have started introducing teleoperation systems to acquire human manipulation skills. However, capturing the subtle, force-involved interaction skills of humans in teleoperation is still challenging due to its inherent dynamic delays and feedback transparency. This research evaluates the effectiveness of demonstration data obtained through simulation versus teleoperation. To evaluate the efficacy of this approach, tasks such as plane cutting, tight peg-in-hole, and deformable pipe plugging were performed to assess the quality of demonstrations acquired. The experimental results highlight the effectiveness of demonstration through simulation in capturing the operator's force-involved interaction skills. Simulation creates an environment similar to performing tasks with bare hands by minimising dynamic delays due to the exclusion of physical robots and effectively rendering high stiffness. As a result, the demonstration through simulation method has proven effective in extracting interaction data and capturing physical task performance skills.**

I. Introduction

Recently, learning from demonstration (LfD) through teleoperation has attracted significant attention as it allows robots to acquire dexterous human manipulation skills or to learn the expertise of skilled operators [1]. This approach has been used in several research projects, such as teaching task operations to mobile robots in the Mobile ALOHA [2], learning large behavior models at Toyota Research Institute [3], and acquiring dexterous manipulation skills in humanoid robots like TESLA's Optimus and Sanctuary AI's Phoenix. These studies have utilized teleoperation to extract demonstration data from operators. Teleoperation offers the advantage of easy manipulation of multiple degree of freedom (DoF) bodies, such as fingers, and simultaneous sensing across multiple modalities [4]. Additionally, bilateral teleoperation can facilitate the acquisition of subtle, force-involved interaction skills by accurately replicating the robot's contact forces using actuators in haptic devices.

Therefore, capturing interaction force data is essential, particularly for demonstrating physical tasks such as assembly and contact manipulation. Associating with positional and visual information, interaction force data have been found to provide easy adaptation even in the presence of target parameter errors [5], [6], reduce reliance on visual feedback [7], and contribute to improved learning policy performance [8]. Several studies have shown that passive observation [9] and kinesthetic teaching [10] are not effective methods for learning force-involved interaction skills. The passive observation method faces difficulties in extracting physical contact data from visual information while kinesthetic teaching enables the acquisition of force skills [11]. However, kinesthetic teaching has been revealed to introduce significant distortions between the forces indirectly felt by the operator through the robot hardware and the actual forces involved in task [12].

Compared to passive observation and kinesthetic teaching, bilateral teleoperation enhances the data acquisition process by providing force feedback [4]. These force data have been shown to be useful for estimating variable stiffness parameters [13] and for adjusting the task phase in real-time [14]. However, these studies face challenges due to technical constraints such as time delay and inherent dynamic delay in teleoperation systems. These delays can easily lead to instability in bilateral systems, and the methods used to stabilize them often restrict the feedback, preventing the attainment of an immersive experience [15]. As a consequence, a teleoperator struggles to execute precise manipulation tasks due to the diminished sense of immersion. In turn, data obtained through teleoperation have limitations in fully capturing the operator's intentions and manipulation skills.

This study investigates a new demonstration method, namely demonstration through simulation, for the stable and effective acquisition of data reflecting the operator's intentions. Specifically, this method facilitates immersive demonstration experiences for tasks unattainable through bilateral teleoperation, experimentally proving the capability to acquire demonstration data that captures the subtle task intentions inherent in actual contact tasks. The use of simulation has already been used as a method for validating learning outcomes [16] and collecting data through integration with reinforcement learning [17]. This paper, however, offers a distinct evaluation of simulation's utility from the demonstration perspective, particularly their efficacy in collecting

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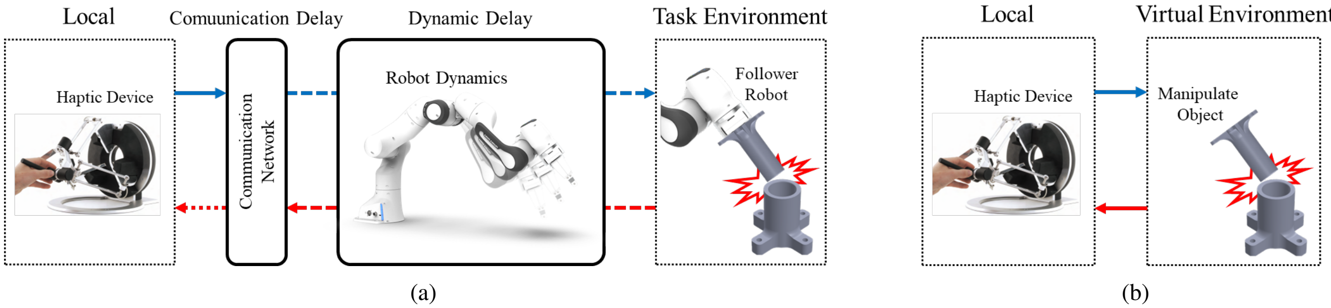


Fig. 1: Schematics diagram of each demonstration methods. (a) Learning from teleoperation. The operator's commands and feedback experience delays due to communication network and robot dynamics. The dashed line represents the delayed signals. (b) Demonstration through simulation. The operator can concentrate on the demonstration without experiencing either time-delay or dynamic-delay.

demonstration data for physical contact task skills, which have recently gained significant attention.

This paper is organized as follows: Section II introduces two paradigms of learning from teaching using a haptic device, including learning from teleoperation and learning from demonstration through simulation. Section III describes the experimental design, including the tasks and comparison evaluation metrics. Section IV presents the experimental results, including statistical observations of a human subject study. Finally, Section V concludes the research by summarizing the results and suggesting future research directions.

II. Learning from Demonstration using Haptic Feedback

A. Learning from Teleoperation

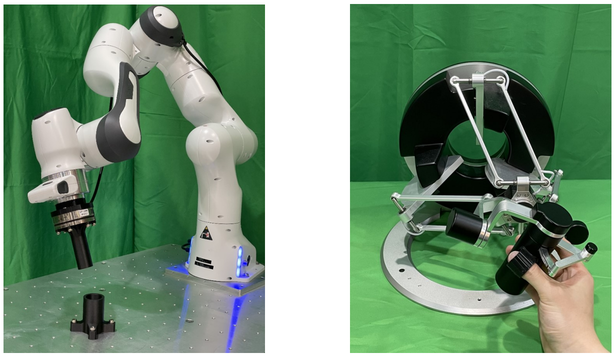
In the field of learning from teleoperation, bilateral teleoperation was utilized to acquire force-involved interaction skills of humans while having haptic feedback [18]. As shown in Fig. 1a, a haptic device is introduced into bilateral teleoperation to provide force feedback to the human operator. The human operator can be immersively engaged in manipulation tasks, experiencing high transparency when the haptic device renders proper and stable force feedback. On the other hand, delayed force feedback rendering results in diminished system stability and task performance. Two types of delay, time-delay and dynamic-delay, can lead to delayed force feedback rendering in a typical teleoperation system. Time-delay occurs when command and feedback signals are exchanged through the communication channel between the remote and local sides. Dynamic-delay arises from pose latency due to the lack of robot agility, and it is unavoidable feature as teleoperation involves a physical robot with heavy inertia. To address the issues caused by these delays, the time-domain passivity approach (TDPA) [19] and scaled teleoperation [20] have been proposed. TDPA aims to prevent system divergence by introducing additional damping based on an analysis of energy exchange between systems, while scaled teleoperation enhances stability by attenuating the overall level of force feedback.

While these solutions enhance task success rates by improving system stability, they have limitations in accurately acquiring force-involved interaction skills. Moreover, potential distortions in force feedback can lead to the recording of demonstration data that does not accurately reflect the operator's intentions, or it may introduce difficulties in task execution. TDPA may induce chattering phenomena in the force feedback. Additionally, the passivity observer, which monitors the energy flow of TDPA, has limitations in resolving system instability issues attributable to dynamic-delays because energy monitoring is primarily conducted at the communication network level. Scaled teleoperation leads to a decrease in displayed stiffness of force feedback, attributable to the scaling gain.

B. Learning from Demonstration through Simulation

Unlike teleoperation, employing simulation for the task demonstrations can mitigate the challenges associated with dynamic-delay in bilateral teleoperation. As illustrated in Fig. 1b, demonstrations through simulation do not require either a physical robot in the real world and a robot in the simulation during the demonstration phase. By eliminating the necessity of physical robot, operator can perform agile demonstrations by directly controlling manipulation object which is lightweight compared to the robot. Specifically, demonstration through simulation facilitates direct manipulation of the object, rather than controlling it via robot's motion in the actual workspace.

Meanwhile, learning from demonstration through simulation necessitates the development of a comprehensive simulation environment. This includes scanning task environments and the estimating their material properties, a process referred to as real-to-sim. Additionally, it is essential to execute generalization and robust learning processes using demonstration data within the virtual environment, a process termed sim-to-real. However, this study assumes that the CAD models and material properties of task environments are known a priori. Given the importance of accurately understanding the dimensional tolerances and material properties of objects, using materials with explicitly defined properties simplifies the challenge of obtaining these characteristics for unknown objects. This assumption allows us to focus on exploring the utility of demonstration through simulation for



(a) (b)

Fig. 2: Experimental setup for comparison study. (a) Franka Emika Panda manipulator as the follower robot in the teleoperation system. (b) Omega 7. haptic device to provide the demonstration.

data collection during the demonstration phase.

As previously mentioned, due to the inherent nature of dynamic delays in teleoperation, using teleoperation-based demonstrations may not be ideal for acquiring human interaction skills in contact-rich manipulation tasks. This research primarily aims to evaluate the effectiveness of demonstration through simulation in capturing an operator's force-involved interaction skills during contact-rich physical manipulation tasks, as compared to teleoperation-based demonstrations. Furthermore, this study will explore the potential benefits of utilizing data acquired through simulation on the learning and development of task-specific skills.

III. EXPERIMENTAL DESIGN

In this study, a comparative study between teleoperation-based demonstration and demonstration through simulation was conducted to explore the advantages and effectiveness of simulators.

A. Experimental Setup

In the case of teleoperation-based demonstration, a 7-DoF industrial manipulator, Panda by Franka Emika, and a six degrees of control input and translational force feedback haptic device, Omega.7 by Force Dimension, were used. Visual and force feedback were provided by an Intel RealSense D455 camera and an ATI Axia80-M8 force/torque sensor. The robot applied a cartesian impedance controller for interaction tasks, achieving tracking performance and stable operation within the hardware's limits by setting the gains at 2500 N/m and 250 Nm/rad. Both devices were operated on a single computer, running at 1 kHz for real-time control. The two devices communicate without any artificial time delay on the communication channel. Therefore, only the robot's inherent dynamic-delay was present in the bilateral teleoperation system as described in Fig. 1a.

In the case of demonstration through simulation, the choice of a suitable simulator is crucial. There are several critical requirements for the stable force feedback from physical simulators. Firstly, the physics engine must generate contact forces that are both continuous and realistic, similar to force data measured by sensors. Secondly, the computational speed of the contact solver is required to reach at least 1 kHz to ensure real-time performance and avoid the effects of time delays. The open-source physical simulator, Drake [21], satisfies these conditions. Drake accurately represents the behavior of objects than other commonly used simulator [22], [23] and provides continuous contact force results by employing the hydroelastic contact model which calculate contact forces based on distribution [24]. In addition, the fast computation of Drake's SAP solver [25] can achieve real-time operation of 1 kHz. This capability makes Drake suitable for providing stable force feedback and demonstrating physical interaction tasks. Therefore Drake and haptic device were used for demonstration. A cartesian impedance controller was applied for stable interaction of the physics engine and using the same gains of 2500 N/m and 250 Nm/rad for direct comparison with the bilateral teleoperation. The computing environment for this system was powered by a Ryzen Threadripper 5975WX and equipped with two NVIDIA A6000 GPUs.

Additionally, for stable force feedback, both demonstration methods applied a non-linear median filter [26] to capture outliers while minimizing the phase delay.

B. Task description

This study conducted a comparative analysis by selecting contact and assembly tasks as representative physical contact tasks. These tasks are widely required in industry and daily life; however, the low displayed stiffness of feedback and the dynamic-delay of robots hinder the delicate rendering of force feedback, increasing the difficulty of teleoperation and negatively affecting the result of tasks. Contact tasks include plane cutting (PC), while assembly tasks include peg-in-hole (PH) task requiring high-precision tolerances and deformable pipe plugging (PP) task. The PH task represents the assembly of a rigid object, while the PP task represents the assembly of a compliant object. In contact tasks such as cutting, plugging and polishing, constant force control is critical to successful task completion, along with manipulation. The success of assembly tasks depends on the recognition of the target object's shape or constraints through force feedback and the manipulation based on this recognition. For example, in insertion tasks, accurate recognition of the orientation of the hole and its wall constraints is essential.

The experiments were conducted in a mock-up environment using 3D printed materials, as illustrated in Fig. 3. In the PC task, the follower robot or manipulated object was controlled to mimic the process of cutting along an S-shaped curve. Here, contact was considered as successful execution of the cutting and maintaining a constant interaction force is key to the operation. The key objective of the tight PH task was the precise control of a peg for insertion into a tight hole through force feedback, while the deformable PP task aims to simulate contact tasks with flexible objects by controlling a deformable pipe for insertion into a adapter. For the PH task, the tolerance between peg and hole was set

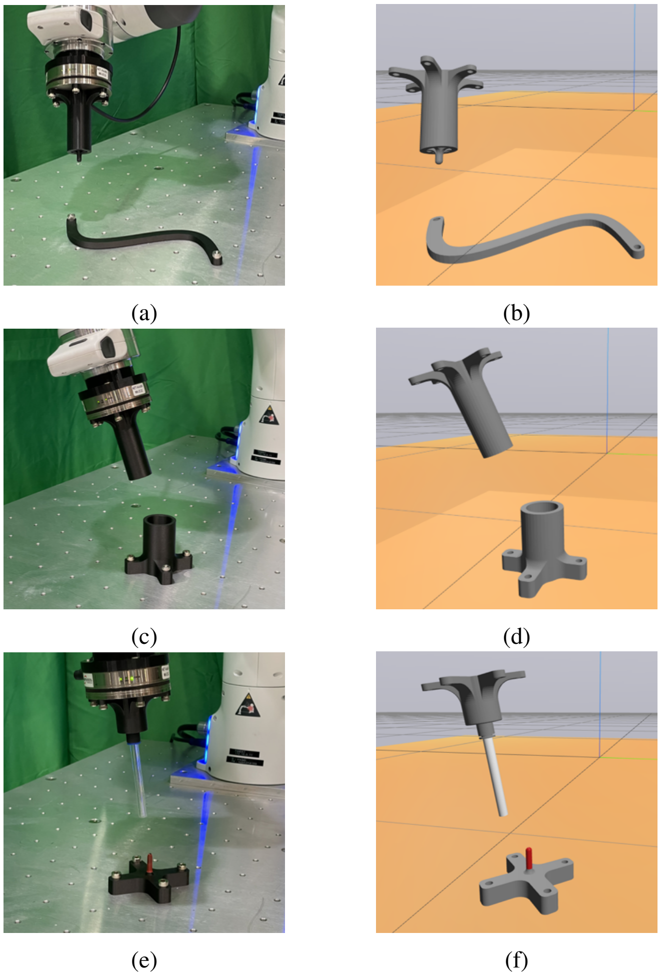


Fig. 3: Experimental tasks. (a) and (b) PC task. (c) and (d) Tight PH task. (e) and (f) Deformable PP task. (a), (c), and (e) were conducted using a bilateral teleoperation system. (b), (d), and (f) were performed using Drake.

at 0.5 %, and for the PP task, polyurethane hydraulic hoses were utilized. The CAD files used for 3D printing were also utilized in Drake, and the material properties of each object were reflected based on their specifications.

C. Experimental Protocol and Evaluation Metrics

The experiment was conducted with ten human subjects aged between 28 and 40, who performed the experimental trials until they were familiar with the task, before performing the actual test. The subjects consisted of five who were experienced with haptic devices and five who had limited experience. Also detailed instructions including the objectives of the each task, experimental conditions, criteria for failure, and fundamental ethical guidelines were provided to the subjects.

During the PC task, operators were instructed to aim to maintain a consistent force. The comparison and analysis aimed to use the force variance, which indicates force control performance, and the task duration to complete the demonstration, which indicates the overall performance. In teleoperation PC tasks, a scaling gain (η) of force feedback was set to 0.2 to ensure all operators can successfully complete the task while maintaining high displayed stiffness. For simulations, η was set to 1.0, without any scaling applied. To compare the variability between different groups, a dimensionless number, the coefficient of variation (CV), was introduced and can be calculated as follows:

$$CV = \frac{S}{\bar{F}} \cdot 100, \tag{1}$$

where $F = \{F_1, F_2, \ldots, F_n\}$ denotes the time-series of recorded force data during the task, $\bar{F}$ represents the average force, and S is the standard deviation. The standard deviation S is calculated using the following equation:

$$S = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(F_i - \bar{F})^2} \tag{2}$$

A lower CV of force value indicated more consistent force maintenance. The data utilized for this calculation were the interaction forces in the z-direction, aligning with the cutting direction, not the feedback forces.

In the assembly tasks, the operators were instructed to achieve successful completion, particularly in the tight PH and deformable PP tasks, which are challenged by the system instability due to the robot's dynamic-delay. The analysis was conducted by comparing the task success rates and the task durations according to the different η values, chosen as 0.1, 0.2, and 0.3 for the experiment. The definition of task success and failure was based on whether the system remains stable until the end of the tasks, with failure automatically detected when the system becomes unstable and exceeds the collision threshold set in the robot's internal controller. In addition, as force feedback is crucial to the perception of shape or constraints in assembly tasks, the quality of demonstration can also be compared using the CV for forces in the direction that recognize the object shape. A lower CV indicated that the operator is able to immediately perceive the shape and perform the task based on this perception.

For all three tasks, the duration from the start to the completion of the task was automatically measured using the robot operating system (ROS) clock. Subjects conducted the experiment for both bilateral teleoperation and simulation scenarios, and each experiment was randomized to prevent learning effects.

IV. Experimental Results

In this section, the results of PC task and assembly tasks are summarized. The experimental results are presented as error bar plots to show the statistical results, means and standard deviation of each human study result. A t-test was conducted for check the statistical difference. If there was a significant difference, bold brackets connect each bar and a star over the bracket is indicated.

A. Plane cutting task

The contact manipulation task was conducted to investigate the effect of displayed stiffness on the performance of demonstration. As mentioned in Section III, a uniform

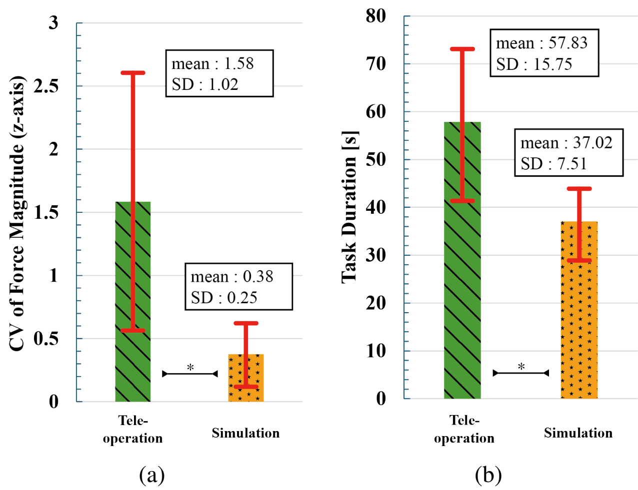


Fig. 4: Experimental results for the PC task in error bar plots. (a) CV of the interaction force magnitude in the z-axis. (b) Task duration. The green bar with the diagonal lines denotes teleoperation-based demonstration case, and the orange bar with dots represents demonstration through simulation case.

gain of 2500 N/m was applied to both the teleoperation and simulation systems and the η was set to 0.2 and 1.0 respectively. In other words, the maximum displayed stiffness in the teleoperation and simulation systems was limited to 500 N/m and 2500 N/m, respectively.

Fig. 4(a) presents the results of measuring CV of the contact force after the initial contact in the demonstration. The results indicated that the demonstration through simulation method yielded significantly better outcomes in terms of CV when compared to the teleoperation-based demonstration method. The average CV of the contact force in the simulation demonstrations was significantly lower at 0.38, whereas the average CV was recorded at 1.58 in the teleoperation case. Also, CV of the two methods exhibited statistically significant differences ($p = 0.004$). The demonstration through simulation method effectively maintained a constant contact force, a critical factor for success in contact manipulation tasks. The operator endeavored to maintain as constant a force as possible, resulting in a higher quality demonstration characterized by a reduced CV. Specifically, the demonstration through simulation method was found to be approximately four times more effective than the teleoperation-based demonstration. Furthermore, the simulation method facilitated more rapid task completion, as depicted in Fig. 4(b). On average, the task completion time using the teleoperation was 57.83 s, compared to 37.02 s with the simulation, revealing a statistically significant difference ($p = 0.003$). The higher displayed stiffness facilitated task performance, enabling more precise control of the interaction force with greater sensitivity. Furthermore, a comparison between the standard deviation (SD) of CV and task duration in Fig. 4 revealed that SD for tasks performed in simulation was significantly lower than that observed in teleoperation. Specifically, the SD for the CV was 1.02 in teleoperation, while simulation demonstrated a significantly lower value of 0.25, approximately four times lower. For the task duration, the SD was 15.75 in teleoperation compared to 7.51 in simulation. This result suggested that employing simulation for task demonstration offers additional advantages than utilizing teleoperation. This result is attributed to the reduced influence of the operator's level of proficiency in conducting demonstration tasks.

TABLE I: Success rate of the assembly tasks for each scaling gains (η)

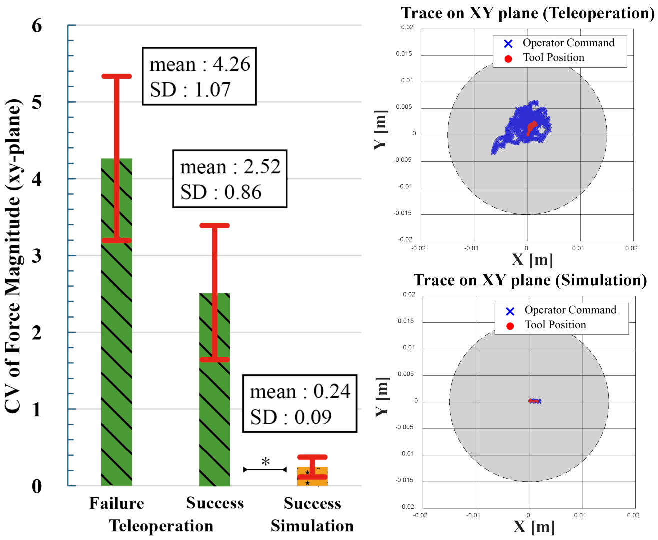
	Bilateral teleoperation			**Physical simulator**	
	Success subject / Total Subject				
Tight PH	10/10 (η=0.1)	6/10 (η=0.2)	0/10 (η=0.3)	10/10 (η=1.0)	
Deformable PP	10/10 (η=0.1)	8/10 (η=0.2)	1/10 (η=0.3)	10/10 (η=0.9)	6/10 (η=1.0)

B. Assembly tasks

The second experiment aimed to compare the effects of dynamic-delay on demonstration performance in assembly tasks focusing on tight PH and deformable PP tasks. TABLE I presents the results for the success rates of assembly task demonstration according to scaling gain (η). The success rate for teleoperation-based demonstration tasks peaked at $\eta = 0.1$, subsequently diminishing with increasing η. This result arises from employing high η in teleoperation, which may induce instability through intensified feedback forces, thereby elevating the risk of task failure. An additional factor contributing to failure in teleoperation case was the amplified instability resulting from substantial feedback forces with rigid objects, particularly in tasks subject to strict constraints. Consequently, in tight PH tasks, which were characterized by large feedback forces, an increase in feedback gain was observed to significantly reduce success rates. Conversely, in the deformable PP task, operators attempted to mitigate relatively low feedback forces, resulting in slightly elevated success rates compared to the tight PH task.

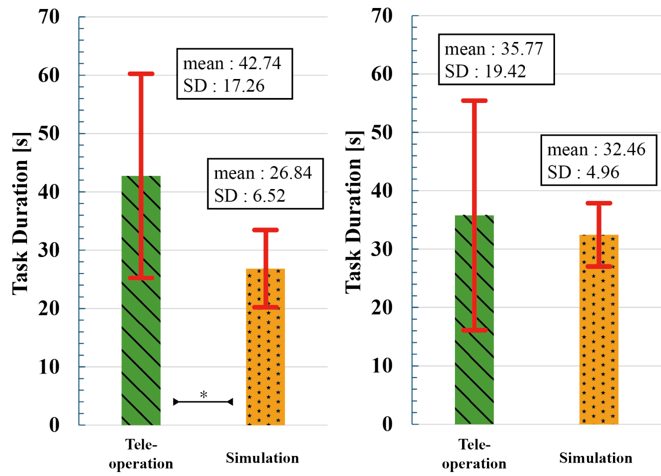
However, demonstration through simulation was found to achieve a high success rate even under the same intensity of actual feedback force ($\eta = 1.0$). On the other hand, unlike the tight PH, the success rate of the deformable PP task in simulation is not 100 %, which is attributed to frame drops during demonstrations caused by extended computation times for simulating deformable objects. These drops can cause system instability, leading to task failure. Although stable demonstrations were achieved at a gain of 0.9, demonstration through simulation still outperformed teleoperation by achieving higher success rates at elevated η, despite these challenges.

A success of demonstration did not always guarantee that the given demonstration is qualitatively good enough. To understand how well the operators perceived the target object and performed the assembly task stably based on this perception, the CV values for the force magnitudes relative to the cross-sectional area of the hole were also



(a) (b)

Fig. 5: Experimental result of CV and trace on xy-plane during tight PH task (a) CV of interaction force magnitude on the xy-plane. (b) Traces of the tool position and the operator's command. A significant discrepancy between the tool position and the command indicates an unstable demonstration, leading to large interaction forces on the xy-plane.



(a) (b)

Fig. 6: The error bar plots depicting task duration for demonstrations of assembly tasks. (a) Tight PH. (b) Deformable PP. The green bar with the diagonal lines denotes teleoperation-based demonstration case, and the orange bar with dots represents demonstration through simulation case.

compared. Fig. 5(a) presents a statistical graph of the CV data for force magnitude on the xy-plane for all subjects and Fig. 5(b) displays the position of the haptic device and the tool in randomly selected cases of teleoperation and simulation. A smaller difference between these two positions indicated that the operator has accurately perceived the shape of the hole or the constraints of its walls. Based on this, the simulation could be considered to perform the insertion tasks ideally, even when compared to successful cases of teleoperation. However, even when comparing successful cases of teleoperation with those of simulation, it is observed that the teleoperation case showed significantly higher CV values ($p = 0.000$). Moreover, a comparison of the average CV values between failed and successful cases in teleoperation revealed that the average CV is relatively higher in failure cases. This finding suggests challenges in accurately perceiving and responding to the task's physical constraints in these instances.

The data presented in Table I suggest that reducing η was imperative for increasing the success rate of teleoperation-based demonstrations in assembly tasks. However, lowering η compromised the operator's ability to accurately perceive the object's shape, resulting in unnecessary contacts to accomplish the task from the Fig. 5. Hence, to assess the overall quality of demonstrations, we compared task duration in scenarios where teleoperation and simulation methods demonstrated their peak success rates. Fig. 6 illustrates the comparative results of task completion duration. The mean duration for the tight PH task was recorded at 42.7 s for teleoperation and 26.8 s for simulation, revealing statistically significant difference ($p = 0.019$). In the case of the deformable PP task, the mean durations were 35.8 s for teleoperation and 32.5 s for simulation. Compared to teleoperation, the demonstration through simulation significantly reduced the task duration for both tight PH and deformable PP tasks, with average reductions of 15.69 s and 3.3 s, respectively. This reduction in task duration, consistent with findings from the PC task experiment, suggested that demonstrations conducted through simulation were more efficient. Furthermore, the simulation's lower SD indicated that stable demonstrations could be achieved independent of the operator's proficiency. This was attributed to the minimization of disruptive factors affecting feedback from interaction forces, notably the dynamic-delay inherent in teleoperation system. Operators of teleoperation had to account for both the task dynamics and the dynamic effects imposed by the robot manipulator. Conversely, simulation enabled operators to concentrate more fully on the demonstration itself, thereby enhancing the acquisition of human-like task skills.

V. Discussion and Conclusion

This study explored the effectiveness of demonstration through simulation in acquiring force-involved interaction skills of humans. Comparative experiments between demonstration through bilateral teleoperation and demonstration through simulation were conducted across tasks, including plane cutting, tight peg-in-hole, and deformable pipe plugging, to compare the efficacy of both methods.

The experimental results demonstrated that demonstration through simulation potentially facilitates capturing force-involved interaction skills by enabling humans to concentrate on given tasks, free from unwanted effects such as dynamic and communication delays from teleoperation. Notably, configuring virtual environments without physical robots minimized dynamic-delay and effectively rendered high stiffness. Consequently, simulation was able to precisely reflect and capture the operator's intention to control interaction forces during tasks. Moreover, the lack of distortion in force feedback and the accurate positional correspondence between the manipulated object and the haptic device during contact significantly enhanced task success rates and yielded optimal outcomes. This created an environment that closely resembles performing tasks with bare hands, simultaneously facilitating the acquisition of demonstration data. Ultimately, the demonstration through simulation efficiently extracted interaction data, proving its effectiveness in capturing physical task manipulation skills.

The elevated task success rates facilitated by simulation promote versatile learning applicable to a wide range of real-world tasks. The low variance in demonstration data across operators supports task classification and identification within data-driven learning methodologies, such as reinforcement learning. This potentially contributes to accelerating convergence and improving learning robustness. Additionally, demonstrations through simulation are more time-efficient, enabling comprehensive data collection and improving overall data acquisition efficiency. These results highlight the importance of demonstrations through simulation as a critical methodology that can significantly enhance the effectiveness of learning phases.

The comparative study in this research, despite considering material properties when designing virtual environments, was constrained by the gap between real-world and simulation conditions. As a result, direct comparisons of demonstration data, such as the magnitude and direction of contact forces, were not feasible. Future research will focus on reducing this gap to enable comparisons across a broader range of conditions. Additionally, enhancing the performance of demonstration environments is crucial. More complex contact geometries, beyond those explored in this study, may increase the computational load on simulators, causing delays in force feedback. Addressing these challenges, future efforts will concentrate on developing robust computational methods to maintain a real-time frame rate and ensure system stability.

Our research is not limited to simply proposing a new demonstration method. Despite advancements in physics engines that closely replicate real-world physical dynamics, the sim-to-real gap still remains. Although existing demonstration data from simulation can achieve a certain level of performance using foundational learning and reproduction methods such as dynamic movement primitives [27], [5], our ultimate goal is to leverage the advantages of demonstration data obtained from simulators, particularly in tasks where physical interaction is crucial. Instead of merely replicating the operator's manipulation data, our future work will focus on extracting the operator's intent and skill from this data and developing a learning and reproduction framework that can be actively applied to a variety of tasks.

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