Embodied Robot Teleoperation Based on High-Fidelity Visual-Haptic Simulator: Pipe-Fitting Example

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Abstract: Robot teleoperation, a control method allowing human operators to manipulate robotic systems remotely, has become increasingly popular in construction applications. A significant challenge is the disconnection between the robot sensor data and the human operator's sensory processes, creating a sensorimotor mismatch in motor-intensive activities. This disconnection is particularly challenging in motor-intensive activities that require accurate perception and response. Researchers have started investigating haptic interactions to enhance the control feedback loop, including simulating contacts, motions, and tactile input. However, although current methodologies have advanced the field, they often focused on certain aspects and could be further expanded to provide a more comprehensive simulation of the physical interaction that occurs in typical construction operations. This study designs and tests a comprehensive high-fidelity embodied teleoperation method that simulates complete real-world physical processes via the physics engine. The proposed method captures all categories of physical interaction in typical motor-intensive construction tasks, including weight, texture, inertia, impact, balance, rotation, and spring. A human-subject experiment shows that the proposed method substantially improves performance and human functions in a teleoperated pipe-fitting task. The results indicate that the proposed multisensory augmentation method significantly enhances performance and user experience, offering valuable insights for designing innovative robot teleoperation systems for future construction applications. **DOI: 10.1061/JCEMD4.COENG-13916.**

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Introduction

In recent years, the exploration of human-robot collaboration (HRC) in various construction operations has surged, with a common belief that combining the strengths of robotic systems and human decision-making skills can address productivity and safety concerns in the industry (Davila Delgado et al. 2019; Liu and Wang 2018). One promising solution, robot teleoperation, has proven effective in reducing work-related injuries and enhancing labor utilization in various tasks (Hokayem and Spong 2006), including construction assembly (Brizzi et al. 2017), site inspections (Pouliot and Montambault 2008), and maintenance (Yew et al. 2017). Although the COVID-19 pandemic has greatly expedited the shift toward teleworking technologies, particularly in fields with labor-intensive tasks (Yang et al. 2020), it is important to note that this trend is also driven by several other factors. These include the increasing need for operational flexibility, reducing environmental impacts, and enhancing worker safety across various industries. As mentioned previously, one key area of such technologies is robot teleoperation, which holds great promise for a wide array of tasks in the construction industry. This includes motor-intensive activities such as lifting heavy materials, precision drilling, and tasks in hazardous environments. However, its effectiveness and applicability can vary, necessitating further research and development to fully realize its potential (Kazanzides et al. 2021; Weber et al. 2019). With these advancements, teleoperation can pave the way for the future of construction work and potentially other labor-intensive industries.

Although robot teleoperation is promising, the challenge is still overwhelming, particularly the design of human-robot interaction (HRI) that enables shared perception in between human agents and remote robotic systems in motor-intensive tasks (Lee Pazuchanics 2006; Pittman and LaViola 2014). Some HRI methods rely on visual feedback, suggesting that there is room for integrating additional sensory feedback for a more holistic approach (Lee Pazuchanics 2006; Pittman and LaViola 2014). This is not adequate in situations that require strong situational awareness (Görsch et al. 2020), sophisticated sensorimotor coordination in complex movements (Roja et al. 2016), and intensive motor activities (Paquet et al. 2005). These scenarios are commonly found in construction operations, including large-scale operations such as crane operations and small-scale tasks such as pipe maintenance. The pipe maintenance task required the participants to (1) correctly identify the materials and types of the pipes; (2) apply appropriate grabbing forces to pick up the pipe; (3) move the pipes along a path to avoid potential collisions; and (4) insert the pipe into another structure with the correct level of insertion force. This design of the task required the participants to possess a strong understanding and awareness of the space, to coordinate their motor actions in a safe and effective manner, and to sense the construction materials. In such scenarios, visual cues can hardly help

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restore a real sense of physical interaction between the robot and the remote environment, especially for complex construction scenes (open environment, changing targets, moving objects, and so on). The disconnection between the robotic perception and the human operator's sensory processes can cause a sensorimotor mismatch in motor-intensive activities (Kimura et al. 2018).

The exploration of haptic feedback as a solution to these challenges has proven to be arduous. Technical issues related to the accurate replication of force feedback or the lack of adequate simulation of complex physical processes are common (Liu et al. 2015). Additionally, there are knowledge gaps regarding how operators perceive and respond to different forms of haptic feedback in a construction teleoperation context (Gong et al. 2023). Furthermore, most existing haptic feedbacks are simplified for one specific operation, and given the diversity and variability of construction tasks, it is difficult to achieve a one-size-fits-all haptics-based solution for construction teleoperation (Bolopion et al. 2013; Talhan and Jeon 2017).

To address the identified gaps in the field, our research introduces an "embodied" robot teleoperation system, which uses a mixed reality (MR) simulator and a high-resolution haptic feedback system. This system aims to provide an accurate simulation of the interactions encountered during remote robot operations, fostering an immersive sense of telepresence. It combines visual and haptic feedback to simulate various physical interactions present in labor-intensive construction tasks.

The paper is structured as follows: the "Literature Review" section explores related work and identifies gaps; the "System Design" section describes the design of the embodied robot teleoperation system; the "Human-Subject Experiment and Test" section details the human-subject experiment conducted to test the system's efficacy; the "Results" section analyzes the experiment's data and present findings; the "Discussion" and "Conclusion" sections demonstrate the system's advantages, summarize the key findings, and propose the limitations and directions for future research.

Literature Review

Robot Teleoperation in Dexterous Tasks

Robot teleoperation, i.e., human workers manipulating remote robotic systems in complex tasks at a distance (Darvish et al. 2023), is a promising approach to converging advantages of both robotic systems and human agents in complex operations (Hokayem and Spong 2006). As for construction applications, robot teleoperation has received increasing interest in all kinds of human-robot collaboration methods. For example, it has been verified a great improvement in inspection task completion time for drone control by integrating augmented reality virtual surrogates with robot teleoperation (Walker et al. 2019). Nagano et al. (2020) examined utilizing tactile feedback to support the delicate teleoperation of construction robots by transmitting delivering contact information (collision vibrations) to human operators, which indicates an improvement in maneuverability. In order to avoid human physical interaction with dangerous or risky places, Caiza et al. (2020) generated an easily scalable teleoperation solution using distributed control schemes to remotely manipulate a KUKA mobile manipulator. Robot teleoperation has also shown potential in dexterous tasks that require sophisticated motor coordination, such as construction assembly, repair and replacement, and material handling (Hartmann et al. 2021; Riaz et al. 2020; Yin et al. 2021). These dexterous tasks are often framed as pick-and-place operations serving as the building blocks in robot manipulation to accomplish a variety of industrial applications (Tsai et al. 2014).

Performing dexterous tasks via robot teleoperation presents unique challenges that include maintaining precise control, understanding the task environment, and responding adaptively to dynamic conditions (Handa et al. 2020). These challenges become even more pronounced when such operations need to be carried out in complex environments, such as construction sites. A growing body of literature has focused on enabling robots to accomplish dexterous tasks effectively. For example, brain-computer interfaces (BCIs) have been explored to enable direct control of a robot using signals from the operator's brain (Liu et al. 2021); motion planning methods use algorithms to determine the optimal movement path for a robot, reducing the need for direct user control (Gao et al. 2022). Flexible robot teleoperation systems for intelligent oil fields inspection, assessment, and maintenance (Caiza et al. 2020). Robot-assisted glovebox teleoperation for nuclear industry material handling tasks (Tokatli et al. 2021), and augmented visual feedback systems for assisting manipulation and grasping in robot teleoperation (Arevalo Arboleda et al. 2021).

Without losing the generality, the presented methods can be generally categorized into geometry planning and sensor-based dynamic control methods (Braganza et al. 2006). The geometry planning method focuses on defining efficient, optimized paths for robot movement. These methods excel in static or controlled environments but may struggle when faced with unpredictability or changes in the task environment. Sensor-based dynamic control methods rely on real-time feedback from sensors to adapt the robot's actions to the current situation. This approach offers the advantage of being more adaptable to changes and more capable of handling dynamic or unpredictable conditions, characteristics that are highly beneficial in a construction setting (Braganza et al. 2006).

Despite the advances in the existing literature to add high-fidelity visual and physical feedback in human-robot interactions, many of the efforts have been providing evidence for specific modalities of feedback, such as tactless for system status changes, or visuals for main hazard identification. In our research, we concentrate on extending sensor-based dynamic control methods by integrating multisensory feedback, specifically both visual and a wide spectrum of haptic feedback, into a single teleoperation system of robots. This approach enhances the existing body of work by improving the generalizability and adaptability of robot teleoperation in executing dexterous tasks. The cruciality of integrating multiple sensory feedback mechanisms in robot teleoperation stems from the innate multisensory nature of human perception. Relying on visual feedback alone, as is often the case in current methods, might not fully exploit the human operator's ability to comprehend and interact with their surroundings.

Vision-based sensors are usually used to collect extensive visual information about the target object to cope with posture uncertainty (Zhang et al. 2009). These vision-based sensors rely on object-of-interest extraction (foreground/background segmentation), object detection, and object identification (Ayachi et al. 2021; Bozkir et al. 2021). Then, vision-based grasp planning is performed, which includes object position estimate, grasp point determination, and gripper motion planning (Ichnowski et al. 2020; Jiang et al. 2020; Kokic et al. 2019). There have also been efforts examining the vision-based pick-and-place control using visual servo control methods (Tsai et al. 2014).

However, the quality of visual feedback from vision-based sensors in robot teleoperation is restricted by factors such as faulty calibration and occlusions. Small inaccuracies in object posture are thus prevalent, even for well-known objects, and may result in gripping failures (Pinto and Gupta 2016). Typically, it is impossible to avoid these errors during the grip execution phase if the end

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effector of the robot arm is not equipped with sensors (Bekiroglu et al. 2011). The use of haptic and finger force sensors may resolve issues such as these inaccuracies and gripping failures by providing additional information about the object's position and the force being applied (Higashimori et al. 2005; Shimojo et al. 2010). Nevertheless, the current haptic feedback solutions remain limited in effectiveness due to the simplified and domain-specific designs, which are often incapable of reproducing high-resolution physical properties such as cutaneous and kinesthetic features (El Rassi and El Rassi 2020). More details of the state of the art of haptic control methods are discussed in the following section.

Haptic-Based Human-Robot Interaction

Robot teleoperation requires constant and effective communication between robots and humans, or HRI (Goodrich and Schultz 2008). HRI refers to the methods and systems concerning the feedback and control mechanisms that facilitate seamless integration between human intentions and robotic responsiveness (Al-Mouhamed et al. 2008; Burdea and Zhuang 1991; Hirche and Buss 2012). The successful robot teleoperation builds on the effective design of HRI methods perception, including the feedback stimulation and the control of remote systems (Al-Mouhamed et al. 2008; Burdea and Zhuang 1991; Hirche and Buss 2012). Specifically, human sensation and perception of robotic workspace highly rely on created sensations via HRI. As well, shared perception assists in robots' comprehension of human commands (Drury et al. 2003).

Recent advances in interfaces inspired the focus on enhanced HRI with trustworthy, safe, and efficient human-robot perception (Bonci et al. 2021). Advanced sensor technologies improved robot capabilities to perceive environment information, monitor human behaviors, and plan appropriate responses (Ishida et al. 2018; Peternel et al. 2017). Furthermore, the literature has identified that a variety of perceptual modalities of humans, such as visual, auditory, and haptic feedback, contribute to generating a proper perception of the workspace and eventually affect the teleoperated task performance (Boessenkool et al. 2013; Chen et al. 2007; Sallnäs et al. 2000). Especially, haptics plays an important role in shared perception due to its physical interactions with the environment and natural feedback to humans (Biswas and Visell 2021).

Haptic feedback for teleoperation refers to the sensory information derived from mechanoreceptors embedded in the skin (cutaneous input), muscles, tendons, and joints (kinesthetic inputs) provided to the human operator (Lederman and Klatzky 2009). Cutaneous stimuli enable humans to recognize the local properties of objects such as shapes, edges, and textures, which relies on measures of the location, intensity, direction, and timing of contact forces on the fingertips (Birznieks et al. 2001; Johnson 2001). Kinesthetic stimuli can provide the position, velocity, force, and torque of objects by means of receptors in muscles and joints (Edin and Johansson 1995; Hayward et al. 2004). Haptic feedback with both cutaneous and kinesthetic stimuli has been proven to play an important role in enhancing the performance of robot teleoperation including microassembly (Pacchierotti et al. 2017, 2016), palpation (Gwilliam et al. 2009; Pacchierotti et al. 2015b), and pipe inspection (Zhu et al. 2022b). The performance in terms of completion time, accuracy, and peak and mean exerted force (Bimbo et al. 2017; Moody et al. 2002; Pacchierotti et al. 2015a) can be improved based on the haptic feedback.

Recently, the literature has shown a great interest in testing the control of robotic arms through haptic feedback. For example, Fang et al. (2017) used 18 inertial measurement units (IMUs) to track the arm and finger movements of the operator to control the robot. However, the experiment requires the users to keep their bodies stationary, which can limit the freedom of the control of the robotic arm. Haptic gloves, such as the Robotics and Mechatronics Lab (RML) glove (Zhou and Ben-Tzvi 2014), ExoPhalanx (Fujimoto et al. 2013), and other haptic gloves (Li et al. 2019; Pacchierotti et al. 2015b) can control the robotic arm with a higher degree of freedom. Besides IMUs and gloves, force feedback systems have also been utilized in robot-assisted systems for medical (Pierrot et al. 1999), diseases (Kaminski et al. 2020), and robot cooperation (Qian et al. 2020). Haptic feedback is used to bridge the gap of physical sense between the operator and the remote robot for teleoperation tasks (Pinskier et al. 2016). Compared with other feedback modalities, haptics plays a more essential role because it allows the human operator to feel and interact with remote environments physically, rather than passively observe them (Biswas and Visell 2021).

Despite the well-recognized benefits of using haptic feedback in robot teleoperation, two major problems are still present. First, most existing haptic simulation methods are simplified in the sense that only one or a few specific physical interactions can be simulated. Most haptic feedback focuses on indicating binary changes of surface contact (Horie et al. 2021), pressure change (Li et al. 2019), and collision (Singh et al. 2020). Few efforts have been made to simulate the combined stimuli of cutaneous and kinesthetic as well as the physical properties of gravity, inertia, impact, friction, and so on. This limitation may be due to the complexity of reproducing complete physical processes given specially purposed devices, as well as the domain-specific focus (Sheridan 2016).

Second, although current systems have made significant progress, there still remains a challenge in accurately simulating the complex physical processes of a remote workplace and matching the variety and complexity of motor-intensive operations (Lelevé et al. 2020). The development of methods for effectively and efficiently simulating physical interactions in robot teleoperation remains an active area of research. Other limitations of existing haptic feedback systems may include the accessibility to smaller workspaces, restricted operator's mobility, and system stability and performance (Dangxiao et al. 2019; Ishida et al. 2018). In addition, although some successful works have been made in examining the integration of multisensory processes via visual and haptic simulators, there are further opportunities to enhance this integration, leading to more comprehensive and realistic teleoperation experiences. A combination of visuomotor and haptomotor has the potential to improve the situation awareness of the HRI (Camponogara and Volcic 2019).

System Design

System Architecture

The proposed embodied teleoperation system, named Haptobot, consists of four main modules, including digital twinning module (DT), simulation augmentation module (including visual and haptic augmentations) (SA), human interface (HI), and robotic control (RC). The DT module reproduces and simulates remote workplaces including both the geometries and the complete real-world physical processes via game engines. Based on the streaming data from the DT module, the SA module optimizes the feedback data and generates high-resolution renderings of the remote scene and stimuli of cutaneous and kinesthetic feedback via a haptic device. This is due to the fact that captured sensor data from remote robots may be subject to sparsity issues, meaning that the data can be incomplete or have gaps due to various reasons such as sensor limitations or environmental interference. The SA module helps to fill these gaps, enhancing the fidelity of the haptic feedback by providing a more complete and detailed representation of the remote environment.

Our HI module integrates a virtual reality (VR) headset with TouchX haptic devices (3D Systems, Rock Hill, South Carolina), advancing from the three-degrees-of-freedom Novint Falcon device (Novint Technologies, Albuquerque, New Mexico) used in the pioneering study by Martin and Hillier (2009). The TouchX device was adopted because the device allows six degrees of freedom tactile interaction including rotation, bringing us closer to simulating real physical interactions in robotic teleoperation, further increasing the intuitive of teleoperation methods in the construction industry. Based on the feedback information, human operators can use the haptic device to control the robot to finish the pick and place task. Fig. 1 shows the architecture of the system.

As illustrated in Fig. 1, for the DT module, the robotic specifications and unified robot description format (URDF) are used to build a virtual robot that replicates the same states of the real robot. The locomotion and manipulation of the grabber are controlled by the human operator. The poses of robot joints are calculated based on the inverse kinematics (IK) algorithm introduced by Aristidou et al. (2018), and the pressure force of the grabber can be adjusted by the pressure sensor. The physics interactions between the robot and the objects are monitored by collision detection and contact generation functions. All physics interactions are based on Newton's laws of motion. Newton's laws of motion are three basic laws of classical mechanics that describe the relationship between the motion of an object and the forces acting on it (White 1984).

The SA module provides both augmented visual feedback [mesh, texture, and three-dimensional (3D) modeling information of the object] and physical feedback (seven haptic feedbacks) to the HI module. The human operator can wear an HTC VR headset (HTC Corporation, New Taipei City, Taiwan) to display the first-person view (FPV) from the remote robot, feel haptic feedback based on the TouchX haptic device, and use controllers to send commands for the gripper's pressure force as well as the robotic end-effector's target pose to control the state of the robot, as shown in Fig. 2.

Augmented Haptic Simulation

In order to realistically simulate haptic feedback in the system in the embodied way, we designed seven physical force modes, including weight, texture, inertia, impact, balance, rotation, and spring. When the human operator controls the robot, basic properties of objects such as mass, velocity, and acceleration will be collected to calculate the force feedback. The realistic force feedback will be generated based on the Newton's laws of motion. However, these equations are not directly taken from Newton's laws. Instead, we have adapted these laws to suit our teleoperation system and haptic device. To accommodate the haptic device's force output, the input force will be converted to a range of zero to one based on the tanh function. This approach of customizing fundamental physical principles to our specific use case is commonly used in the field of haptic feedback and teleoperation system design. The details about how the seven modes are realized and modeled are described in the following subsections.

Weight

Weight models the gravity applied to the object, which should be generated in the system when an object is lifted and moved by the operator. The direction of this force feedback should always be toward the ground. In Unity version 2020.1.9f1, volume and material (with density) properties were set for each object, and the value of weight force will be calculated as Eq. (1)

$$F_{\text{weight}} = \frac{e^{\rho \cdot V/50} - 1}{e^{\rho \cdot V/50} + 1} \tag{1}$$

where ρ = density of the object; and V = volume of the object. A tanh function is applied in this equation to adapt the force output to a range of zero to one.

Texture

Texture models the force resisting the relative motion of solid surfaces, fluid layers, and material elements sliding against each other. In our design, texture forces are created when an operator contacts an object and causes relative motion on the contact surface.

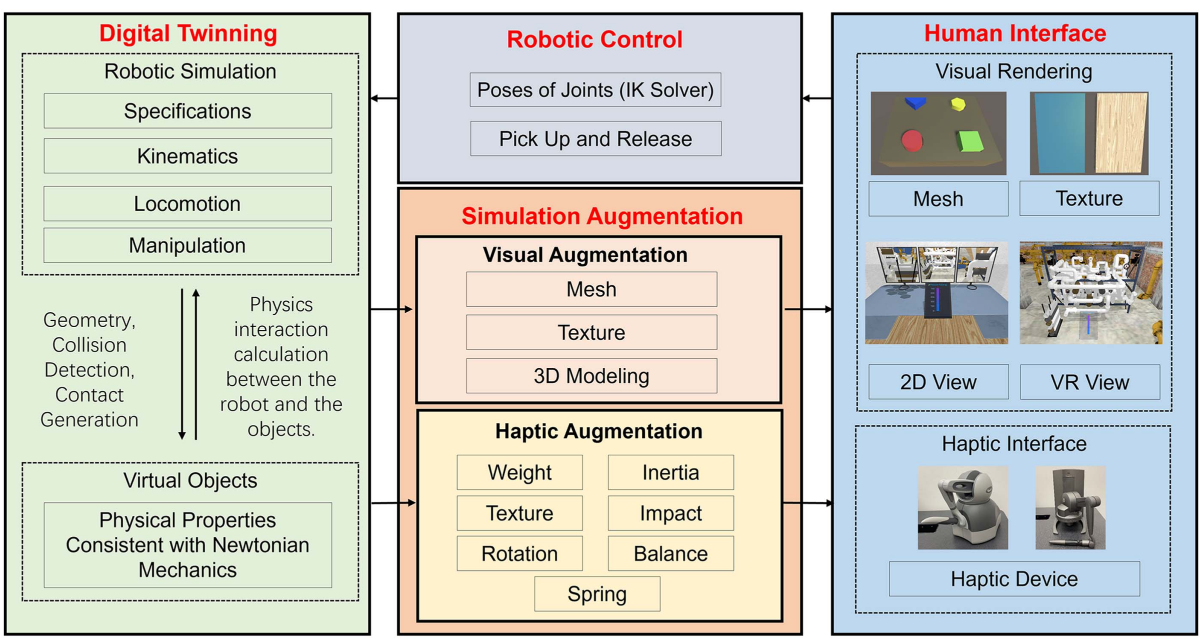


Fig. 1. Architecture of the embodied teleoperation system. (Images by authors.)

Fig. 2. Experiment field and device setup.

Essentially, it is a representation of kinetic friction, which is influenced by the contact surface properties and forces exerted on the surface. In Unity, we configured the kinetic friction coefficient as the object material property and reduced the applied force to a constant valve to emphasize the properties of the object. The force should be in the opposite direction of the motion, and its magnitude is determined by a mathematical formula Eq. (2)

$$F_{\text{texture}} = \frac{e^{2\cdot\mu_k} - 1}{e^{2\cdot\mu_k} + 1} \tag{2}$$

where μ_k = kinetic friction coefficient of the surface.

Inertia

Inertia models the inertial effect when the operator is moving an object, which is the resistance of any physical object to a change in its velocity. Therefore, the inertia force should always be opposite to the acceleration, and the value should be equal to the product of acceleration and mass of the body. In Unity, inertial forces are created when an operator grabs and moves an object. In our system, the inertial force was converted to a value between zero and one using Eq. (3)

$$F_{\text{inertia}} = \frac{e^{m\cdot a/50} - 1}{e^{m\cdot a/50} + 1} \tag{3}$$

where $m = \rho V$ is the mass of the object; and a = acceleration of the object.

Impact

Impact is a momentary force generated during a collision. It is essentially the impulse of force divided by the collision time, which indicates the momentum change within a limited time. It should be generated simultaneously and then disappears shortly. In Unity, impact forces are created when an operator grabs an object and impacts it with another object, or when the operator collides with an object. In our system, we set the collision time $\Delta t = 0.1$ s for all the collisions. The impulse of force for the object being collided is calculated as the impact force according to Newton's third law of motion, as illustrated in Eq. (4)

$$F_{\text{impact}} = \frac{e^{m\cdot\frac{\Delta v}{\Delta t}/500} - 1}{e^{m\cdot\frac{\Delta v}{\Delta t}/500} + 1} \tag{4}$$

where m = mass of the object being collided; Δv = velocity change of the object during the collision; and $\Delta t (= 0.1 \text{ s})$ = collision time.

Balance

Balance models how far an object deviates from the balance point. It is a force type specially designed for tasks with balance requirements, such as tower crane antisway control developed by Zhu et al. (2022a). We used the moment as the measurement of the deviation, which is the product of mass and distance. In our design, two haptic devices are connected with a 3D-printed bar. The operator can hold the center and sense the deviation of the center of gravity. In Unity, the operator can control two haptic devices to grab two sides of an object, and the force feedback from the two devices indicates the balance state of the object. The balance force is calculated as per Eq. (5)

$$F_{\text{balance}} = \frac{e^{m\cdot L/25} - 1}{e^{m\cdot L/25} + 1} \tag{5}$$

where m = mass of the content objects; and L = distance from the center of gravity to the balance point.

Rotation

Rotation models another force type specially designed for specific tasks, such as valve operation. To rotate a valve, operators should apply sufficient force tangential to the valve until a necessary torque M is reached. There should be less force needed to rotate the valve when the operator applies the force further away from the axis of rotation. We realistically reproduced this process in the system by the function indicated in Eq. (6)

$$F_{\text{rotation}} = \frac{e^{(M/L)/25} - 1}{e^{(M/L)/25} + 1} \tag{6}$$

where M = torque required to rotate a valve; and L = distance from the operator force point to the valve's axis of rotation.

Spring Force

Finally, spring force models the force needed to extend or compress a spring by some distance scales linearly with respect to that distance. In Unity, the spring force will only take effect when the operator interacts with the object with the spring component.

In this system, the spring force was converted to a value between zero and one using Eq. (7)

$$F_{\text{spring}} = \frac{e^{k \cdot x/25} - 1}{e^{k \cdot x/25} + 1} \tag{7}$$

where k = constant factor characteristic of the spring; and x = deformation of the spring.

In our system, we directly implemented the mentioned equations to program the force feedback in the haptic device using the Robot Operating System (ROS) version 1and Unity software. ROS, a flexible framework for writing robot software, provided crucial services such as hardware abstraction, low-level device control, and implementation of commonly used functionality, allowing for smooth communications between our high-level control software in Unity and the physical robot hardware. Unity, on the other hand, is a powerful and commonly used platform equipped with a robust physics engine. In our study, it managed the physics simulations, created the 3D virtual environment, and controlled the interaction logic for the robot teleoperation system. This integration ensured the haptic device provides the operator with realistic tactile feedback corresponding to the different physical forces being simulated.

Moreover, the motion of the haptic device is used to control the end-effector of the robot. This control is rooted in inverse kinematics, enabling the translation of the haptic device's movement into appropriate movements of the robot's end-effector. As such, the operator can intuitively use the haptic device to control the robot while simultaneously receiving accurate force feedback, ensuring the immersive and realistic user experience that is pivotal to the success of our research.

Robotic Control

To finish the pick and place task, the operator needs to simultaneously control the pose of the robot end-effector and the switch state of the robot grabber, which are controlled separately by the pose of the haptic device and the pressure force of the human finger. Due to the varying densities and coefficients of friction of objects made of different materials, the grabbing pressure varies accordingly. Operators need to respond differently based on the visual and haptic feedback they receive.

However, existing haptic devices have greatly enhanced our ability to interact with virtual environments. However, a device capable of simultaneously receiving force feedback and transmitting pose as well as pressure data could further advance our interaction capabilities, creating new opportunities for more immersive and effective teleoperation. In order to create this two-way communication device, we combined the Touch X haptic device (Martin and Hillier 2009) and the Arduino pressure sensor (Arduino LLC, Ivrea, Italy) as shown in Fig. 3. The Touch X haptic device was utilized to reproduce the sensed force (weight, texture, inertia, impact, balance, rotation, and spring) from the real robot, and control the joint poses of the remote robot. The Arduino pressure sensor was used to sense the human operator's grasping force to control the gripper of the robot. Fig. 3(b) shows the connection of the wires, and Fig. 3(a) illustrates the component of the pressure sensor. In order for the pressure sensor to work effectively and reliably, we first used moldable silicone to fix a flat platform on the TouchX haptic device. Second, we added a hard plastic board for the force surface of the pressure sensor. Then, we used the FSR402 (Interlink Electronics, Camarillo, California) as the pressure sensor. Finally, due to the fact that each individual's finger shape and force application technique are unique, we added two layers of mounting tape to filter the force on the pressure sensor and make our system stable.

Human-Subject Experiment and Test

Overview

To further test the effectiveness of the proposed embodied teleoperation system in construction robot teleoperation, we performed a human-subject experiment using the proposed system. We selected a pipe skid facility replacement and repair (R&R) task as the test case. The objective of this task was to control a remote industrial robot to pick up the target pipes and install them in the target positions. The pipe skid was chosen because of its high appearance in particularly confined workspaces. During the process, the operator was required to apply the appropriate amount of pressure force to grab the object without deforming it. When installing pipes, the operator needed to avoid collision with other pipes and maximize the installation accuracy (error from the center of target pipes) as well as insertion depth accuracy (error from the target depth). We modeled a 7-degrees of freedom (DOF) Emika Panda robot (Franka Emika, Munich, Germany) mounted on a base for maintenance tasks and recorded the occurrence of all 3D regions containing collisions in an immersive virtual environment.

Fig. 4 illustrates the scenario for the human-subject experiment. A total of six pipes needed to be installed in the target pipes of the same color, with the top three pipes installed in the top row and the bottom three pipes installed in the bottom row. The pressure indicator displays the operator's applied pressure force to the pipes in real-time. To pick up the pipe, the operator needed to control the robot end-effector to touch the pipe and apply sufficient force; insufficient forces would not be enough to grab the pipes, and bigger grabbing forces would cause deformation of the pipes. To put the pipes down, the operator needed to release the pressure. Then the operator would move the pipes to the target pipe and insert them. The desired insertion depth is three-quarters of the pipe (i.e., three-quarters are inserted and one-quarter stays outside the pipe), and the

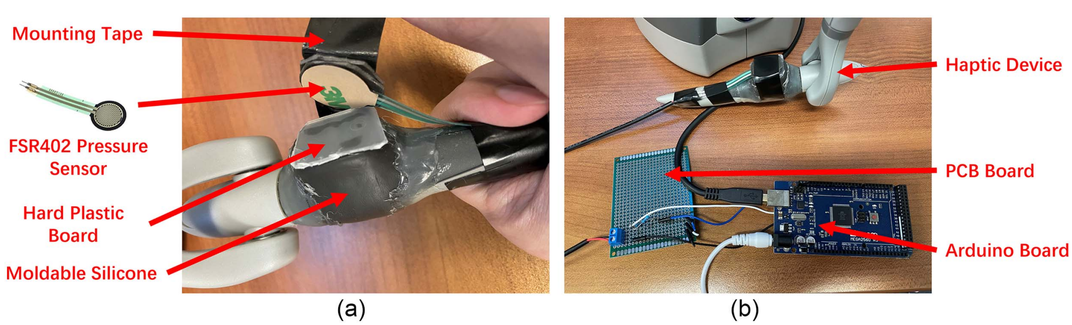


Fig. 3. Arduino pressure sensor mounted on the Touch X haptic device: (a) component of pressure sensor; and (b) wires connection.

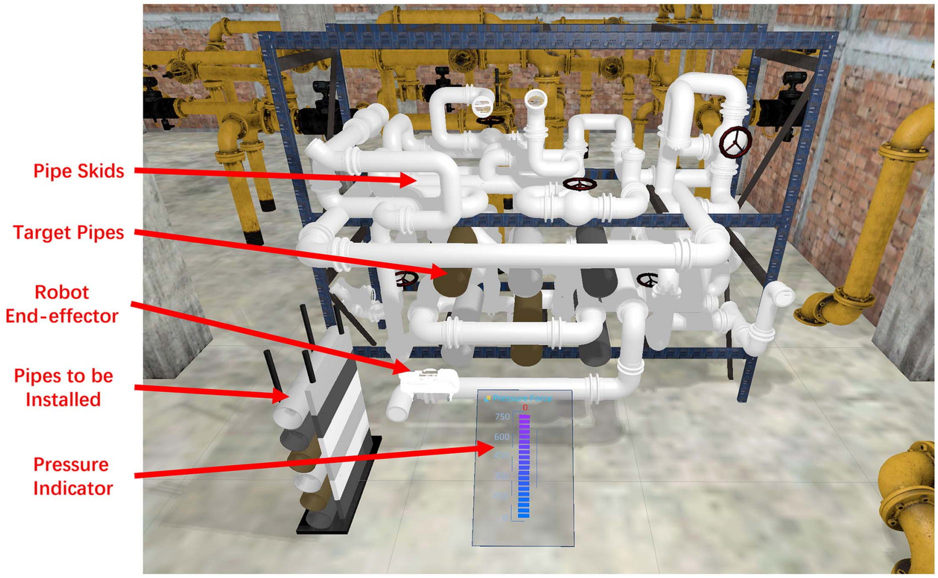


Fig. 4. Pipe skid and robot for the human-subject experiment.

target installation position is the center of the target pipe. During the insertion operation, the operator could feel the collision (via the impact feedback) and friction (via the texture feedback).

To evaluate the performance of the participants, unwanted collision events between the robot and the pipe needed to be recorded. We recognized and agreed that the control mechanism, once established, would require validation of real-world data before it could be deployed in real-world circumstances. However, a collision between a real robot and a real pipe can be hazardous and potentially cause robot damage. Therefore, a simulated environment with an immersive virtual robot and pipes was built to replicate the real-world task. To ensure identical poses between the simulated and real robots, we utilized URDF to construct a virtual robot and transferred the *joint_states* data to VR. The VR environment was designed to elicit similar behavioral responses to those observed in real-world work contexts, and hence was suitable for pipe skid maintenance tasks. Given the ease of data collection and experiment manipulation, the use of VR for human behavioral data gathering has gained favor in the literature (Kinateder et al. 2014).

Participants

To ensure the validity of our study, a power analysis was conducted. A power analysis is a statistical method used to determine the minimum sample size required for the study. It helps researchers ascertain the smallest sample size that would be sufficient to detect an effect of a given size at a desired level of confidence, hence helping to prevent Type II errors (failing to reject the null hypothesis when it is false). Given the within-subjects design of our experiment, each participant served as their own control. In our power analysis, we used a significance level (p-value) of 0.05. We also considered factors such as the expected effect size and the desired statistical power. The result of the power analysis suggested a sample size of 24 participants. To ensure the robustness of our results, we decided to recruit a few additional participants, which resulted in a final sample size of 31.

We recruited a total of 31 subjects for this experiment. The demographic information includes the gender, age group, and major of participants are illustrated in Table 1. The selection of participants for this study was deliberately made to be multidisciplinary,

Table 1. Demographic information of the participants

Category	Number	Percentage
Gender		
Male	19	61.29
Female	12	38.70
Age group		
18–24	8	25.80
25–30	22	70.97
31 and older	1	3.23
Major		
Engineering (civil, coastal, construction, and related)	16	51.61
Computer science	10	32.26
Biology	5	16.13

encompassing students majoring in engineering, computer science, and biology. This selection was designed to assess the system's usability across a spectrum of users with varying degrees of familiarity with technology and robotics. Engineering students, often familiar with mechanical and robotic systems, were included to evaluate the system's intuitiveness for users with direct domain knowledge. Computer science students, generally comfortable with technology interfaces, provided insights into the system's usability for tech-savvy individuals lacking specific domain knowledge. Biology students, who may have little prior experience with similar technologies, offered a perspective on the system's approachability for users without a strong technical background. This diverse participant pool aimed to create a comprehensive understanding of the system's user-friendliness across different user profiles.

Most of the participants had few experiences with VR and 3D gaming, as well as insufficient prior experience with pipe inserting tasks. All participants reported that they were right-handed and did not have any known motor disorders or a history of neurological abnormalities.

Demographic data such as age and gender were collected as standard practice in human-subject experiments. Although the main focus of this study did not hinge on differences based on age or gender, we collected this information to enable potential exploratory analyses in future. For instance, different age groups or genders might display varied performance in the task due to factors like physical strength, cognitive abilities, or previous experience with similar tasks. Thus, this data could provide valuable insight for subgroup analyses and offer a broader understanding of the applicability of our results to different populations.

The study was approved by the ethical approval of the ethics committee at the University of Florida (IRB202202606). All subjects were required to give their written informed consent before attending the experiment.

Experiment

To comprehensively evaluate the performance of the integration of the proposed system, we set up a robotic pick-and-place task for evaluation. The experiment followed a within-subject experimental design (Charness et al. 2012) with four conditions, which were two-dimensional (2D) perspective, three-dimensional (3D) perspective, 2D perspective with haptics, and 3D perspective with haptics. These conditions can be described as follows:

- 2D perspective condition: the entire trial was conducted with only real-time red green blue (RGB) camera (2D image) views and no further haptic or visual assistance.
- 3D perspective condition: participants received visual feedback in the form of 3D virtual modeling (VR).
- 2D perspective with haptics condition: the entire trial was conducted utilizing the proposed embodied haptic simulation system and 2D camera view.
- 3D perspective with haptics condition: both haptic and augmented visual guidance were provided.

The experiment consisted of nine sessions, as detailed in Table 2.

Table 2. Procedure of nine sessions

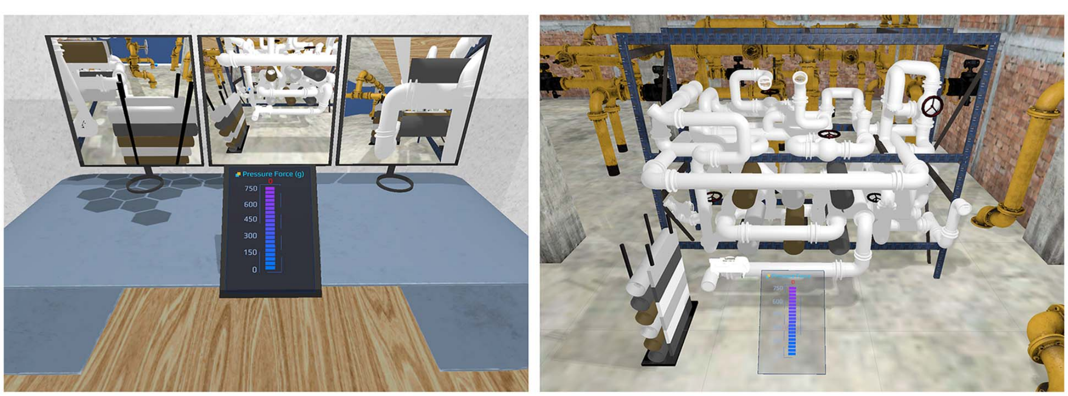
Session	Activity
1	Training
2	Pick and place task under Shuffled condition 1
3	Questionnaires about Shuffled condition 1
4	Pick and place task under Shuffled condition 2
5	Questionnaires about Shuffled condition 2
6	Pick and place task under Shuffled condition 3
7	Questionnaires about Shuffled condition 3
8	Pick and place task under Shuffled condition 4
9	Questionnaires about Shuffled condition 4

In the beginning, participants were asked to sign an informed consent form and fill out a background questionnaire about their age, gender, and VR experience. The experimental scene and content of each trial were the same. The sequence of tasks under different conditions was shuffled to eliminate the learning effects. A training session was provided in a virtual scenario. The training session was designed to familiarize participants with the VR system and interactions within the virtual environment. Each participant was instructed to be acquainted with the devices (VR headset and haptic controller) and the virtual environment. Then, participants were given instructions about how to use the haptic controller and pressure sensor to pick up and place the objects. After the training session, participants were asked to perform the pick up and place task based on one model in the virtual pipe skid system.

After completing each session, participants were given questionnaires to provide comments and feedback. Then participants were asked to perform the task based on the remaining three user interface (UI) models out of the four conditions (2D perspective, 3D perspective, 2D perspective with haptics, and 3D perspective with haptics) and provide feedback based on questionnaires. In order to further eliminate the learning effect, we shuffled the sequence order of the conditions in all sessions. The entire experiment took approximately 30 min for each participant. Participants were incentivized with a $15.00 gift card to finish the experiment.

Fig. 5 shows the 2D perspective and 3D perspective of the experiment. For the 2D perspective condition, the subjects could only control the robot through three 2D displays mounted on the wall of a virtual control room to complete the task. In the 3D condition, the subjects were able to control the robot through the embodied VR perspective.

In the experiment, before the subjects picked up a pipe, they were able to experience the sensation of the pipe's friction and texture through the haptic feedback system, simulating the tactile feedback as if they were touching the surface of a real pipe. The sensation of texture and friction was not conveyed through the use of haptic gloves. Instead, these sensations were simulated through the handheld haptic device that the participants were controlling. Specifically, when the virtual robot in our system interacted with an object—for instance, touching the surface of a pipe—the haptic device simulated the corresponding resistance. When the user moved over the surface of the virtual object, the friction was manifested as the resistance of the haptic device. Moving on a surface of smooth objects (such as aluminum), it would be felt more slippery, and moving on a rougher surface (such as cast-iron), the feeling was rougher.



(a) (b)

Fig. 5. (a) 2D perspective condition; and (b) 3D perspective condition of the experiment.

The device was programmed to provide force feedback to the user, thereby allowing the user to feel the texture and friction of the pipe, despite the interaction happening within a virtual environment. The subjects could also feel the weight of the pipe when they picked it up, as well as the inertia as they were moving the pipe. The heavier pipes and greater accelerations would result in a stronger inertial feeling. For impact, if a pipe collided with another object, the subject could feel the impact force (sudden halt and bouncing back of the haptic controller).

There were three types of pipes in the task that needed to be picked and placed, including a PVC pipe (1.4 g/cm^3, white rigid plastic), a cast-iron pipe (7.3 g/cm^3, dull black with a rough texture), and an aluminum pipe (2.7 g/cm^3, silver-gray). Each pipe type had distinctive properties in terms of mass and friction. The cast-iron pipes were the heaviest, followed by the aluminum pipes, and the PVC pipes were the lightest. The friction on the surface of the cast-iron pipes was the greatest, followed by PVC pipes, and the aluminum pipes exhibited the least friction.

Additionally, different pipes had different responses to applied pressure, as shown in Fig. 6. For example, the PVC pipe, due to its lower mass, could be grasped with less pressure. However, if excessive pressure was applied, the PVC pipe could deform. The cast-iron pipe, on the other hand, was able to withstand a significant amount of pressure without deforming, but required more force to pick up. The current study focuses primarily on a teleoperation system that displays the motion and force control signals from a human operator. The amount of pressure needed to lift the pipe was determined and exerted by the human operator depending on the material and mass. In our experiments, we designed the pipes with certain masses that could be lifted with a specific amount of pressure. During the teleoperation process, the participants needed to regulate the pressure within the suitable range for each material to avoid dropping or deforming the objects, and to prevent collisions as they transported the pipe to the designated location.

Fig. 7 illustrates the events happening during the experiment. Figs. 7(a and b) show the pick-up for different pipes, where the

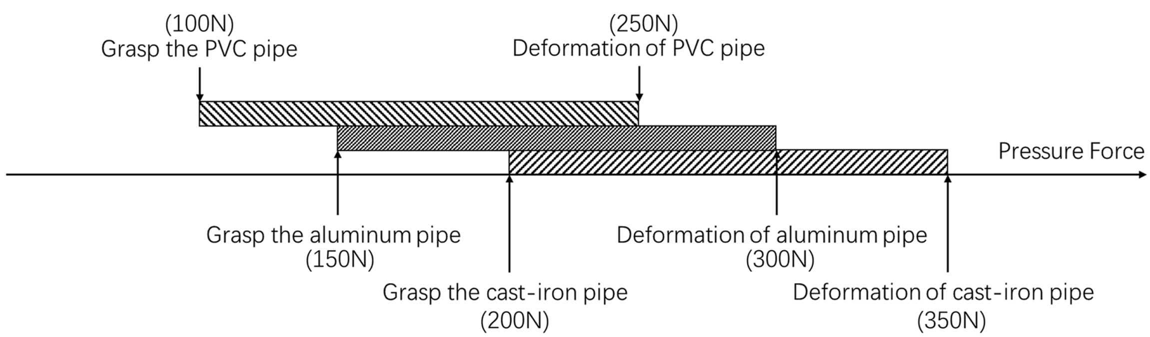


Fig. 6. Response of different objects to pressure levels.

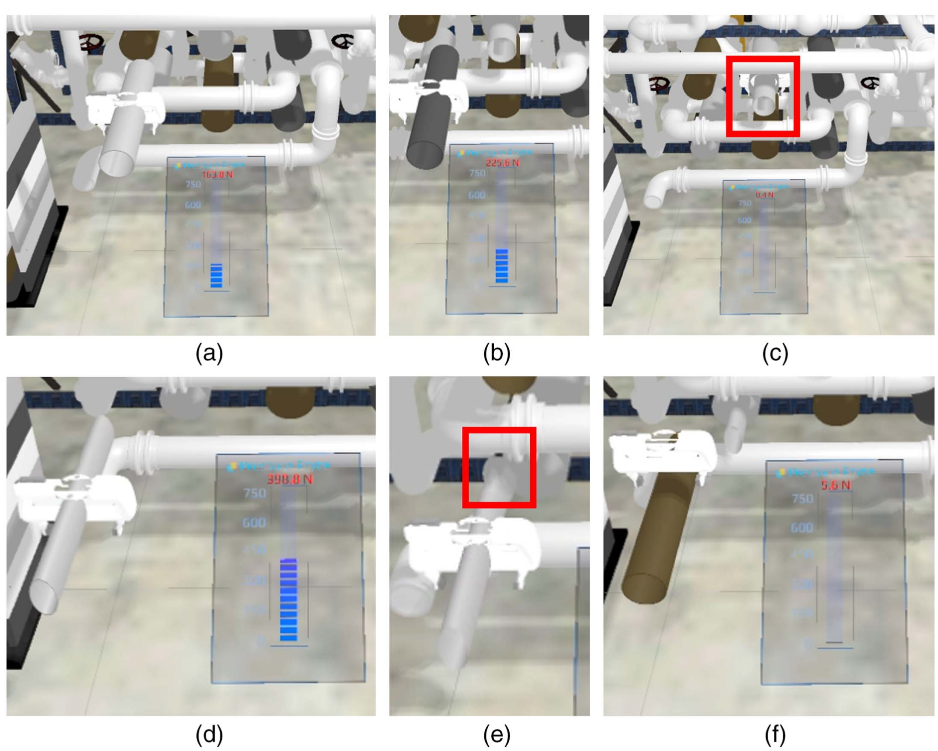


Fig. 7. Pipe skid maintenance task: (a) pick up PVC pipe; (b) cast-iron pipe; (c) successful installation; (d) pipe deformation; (e) pipe collision; and (f) pipe falling.

pressure force of the PVC pipe was smaller than that of the cast-iron pipe. Fig. 7(c) demonstrates the successful installation of the PVC pipe. Fig. 7(d) depicts the situation in which excessive pressure produces pipe deformation. Fig. 7(e) shows the case where the pipe is deformed by the collision. Fig. 7(f) depicts the fall of the pipe due to insufficient pressure.

Performance and Function Measures

The haptic controllers and VR devices were used to track eye-tracking data, the locomotion of the robot, the real-time position of the pipes, and task completion time. Task performance and human function were evaluated by six metrics: time on task, installation accuracy (error from the center of target pipes), insertion depth accuracy (error from the target depth), cognitive load, number of collisions, and number of deformations. In addition, we used three questionnaires [NASA task load index (NASA TLX) questionnaire developed by Hart and Staveland (1988), the Situational Awareness Rating Technique (SART) survey developed by Taylor (2017), and Trust Scale questionnaire developed by Merritt (2011)] to evaluate participants' self-reported cognitive load and situational awareness (details of the questionnaires can be found in the Supplemental Materials).

Collisions were also tracked as part of the performance metrics, although the experimental setup was designed to minimize the possibility of these events. The robot arm and surrounding objects were arranged to reduce the likelihood of contact, and the tasks were formulated such that the robot arm's proximity to other objects was limited. Nonetheless, in the rare instances where a collision did occur, we chose not to include these in our data analysis, considering them as nonrepresentative of the system's performance under typical conditions.

For data collection, we employed a VR system that capitalizes on real-time data synchronization between ROS and Unity based on a previous study (Zhou et al. 2020). This integration not only enables a more realistic and synchronized teleoperation experience in virtual reality systems but also ensures a seamless and synchronized interaction between the robotics middleware (ROS) and the Unity physics engine. Such integration is important for delivering accurate and responsive physical feedback to the operators, improving their situational awareness. This system architecture ensures comprehensive physical feedback, which is critical in our study.

In the experiment, participants were asked to control the robot to pick up six pipes and install them into the target pipes. Once the system detected that the drop position of the pipe that needs to be installed was in the target pipe, the pipe was marked as successfully installed and the task status was recorded as completed. In cases where a pipe was deformed during the pick-up action, we did not ask participants to redo the action. Instead, we instructed them to continue with the task. We recorded any instances of pipe deformation and included them in our data analysis. This allowed us to capture a comprehensive picture of the task execution, including both successful and unsuccessful interactions. These data will be particularly useful for identifying areas of difficulty and potential improvements for future iterations of our system. When all pipes were successfully installed (i.e., the task is complete), the system automatically stopped data recording and ended the task trial.

Subsequently, we employed the Mann-Whitney U-test, a nonparametric statistical measure, to compare two independent samples. It is especially useful when data do not follow a normal distribution, which is often the case in real-world data. The test essentially assesses whether one of the samples is stochastically larger than the other, and provides a p-value that we can use to test our hypothesis (Nachar 2008).

The p-values we report, which range from zero to one, are instrumental in establishing the statistical significance of our findings. This range represents a probability: a $p\text{-value} = 0$ would imply that the observed data absolutely contradict the null hypothesis, whereas a $p\text{-value} = 1$ would mean the data perfectly align with the null hypothesis. In the realm of statistical hypothesis testing, p-values help determine whether the null hypothesis should be rejected. They represent the likelihood of obtaining results as extreme or more extreme than those observed, under the assumption that the null hypothesis is true. Lower p-values (closer to zero) indicate more convincing evidence against the null hypothesis, thereby supporting our research hypothesis. Essentially, smaller p-values suggest that the results are less likely to have occurred by chance, thus pointing toward the credibility of the alternative hypothesis (Goodman 2008) Therefore, our reported p-values serve as evidence for the statistical significance of our findings, enhancing the reliability of our results.

To achieve the motion tracking and documentation functions in the VR, several C# scripts were developed based on Tobii Pro Software Development Kit version 1.11 (SDK) and the application programming interface (API) in Unity. After each VR experiment, the developed VR system automatically recorded the raw data and streamed it into a .csv file.

Results

Task Performance Analysis

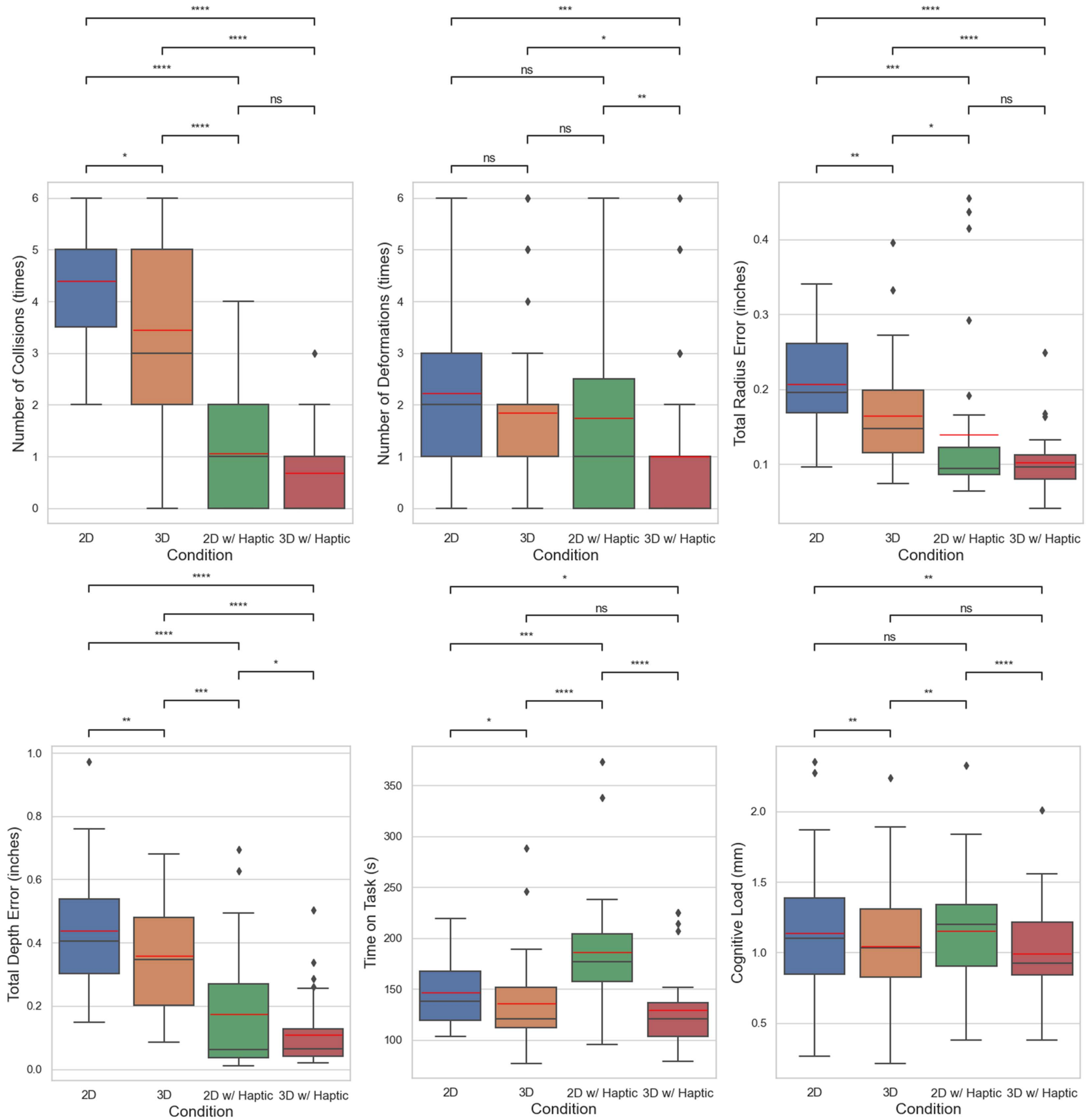
To capture human operator performance differences under the four conditions in the simulated pick up and place task, we used the aforementioned task performance metrics. We tracked performance data from each trial of all subjects and performed a Mann-Whitney U-test across the four conditions. One horizontal line in the box plots represents the median of the data and the other line represents the mean of the data. To be noted, in Fig. 8, the metrics are quantities where a smaller value indicates better performance. In contrast, some metrics in Fig. 9 (SART score and Trust Level) are such that a greater value indicates better performance.

As shown in Fig. 8, the 3D perspective with haptics condition outperformed the other conditions in most metrics, and the 2D perspective with haptics condition outperformed the 3D perspective condition. The 3D perspective condition outperformed the 2D perspective condition. Specifically, the 3D perspective with haptics condition significantly reduced the number of collisions and deformations and had better installation and insertion depth accuracy than the other conditions. In terms of time on task and cognitive load, the 3D perspective with haptics condition also outperformed the other conditions. The 3D perspective condition was significantly better than the 2D perspective with haptic condition. Table 3 illustrates the results of statistical analysis.

These findings suggest that adding haptic feedback to 2D displays or simply changing to 3D perspectives can improve teleoperation performance, and that the 3D perspective with haptics condition is particularly effective.

Human Operator Subjective Assessments

In addition to task performance, we also analyzed human operators' reported perception on task workload, situational awareness, and trust level of the control methods via different questionnaires. Three surveys were taken when the subject finished the task of each condition. In this way, they could report an overall evaluation of all trials related to the corresponding control method.



Comparison analysis results among four conditions: 2D (2D Perspective condition), 3D (3D Perspective condition), 2D w/ Haptic (2D Perspective with Haptics), and 3D w/ Haptic (3D Perspective with Haptics). Error bars indicate confidence intervals (CI = 95%). * indicates statistically significant change (* p<0.05, ** p<0.01, *** p<0.001, **** p<0.0001).

Fig. 8. Mann-Whitney U-test result of the performance metrics.

The Mann-Whitney U-test was performed to test whether there were any significant differences across the four conditions.

As illustrated in Fig. 9, the six subscale NASA TLX questionnaire (Hart and Staveland 1988), the SART survey (Taylor 2017), and six-item Trust Scale questionnaire (Merritt 2011) were used to evaluate the workload levels, situational awareness levels, and time in attention (TiA) behaviors (Kohn et al. 2021) from different perspectives.

The results show that the 3D perspective with haptics condition yielded the best performance in comparison with the other conditions. Moreover, the 2D perspective with haptics condition and the

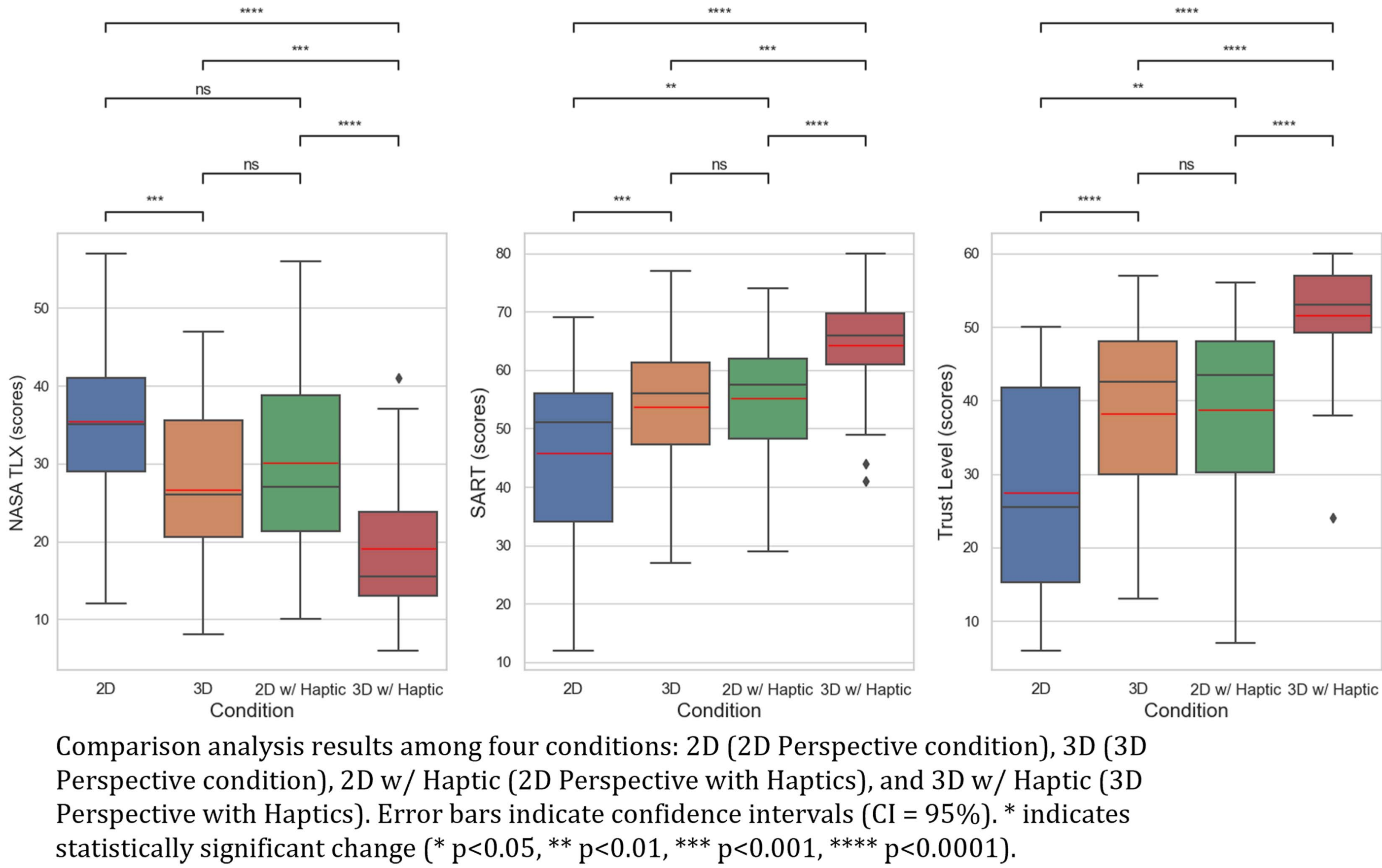


Fig. 9. Mann-Whitney U-test of NASA TLX, SART, and Trust questionnaires.

3D perspective condition exhibited better performance compared with the 2D perspective condition. However, there was no statistically significant difference between the 2D perspective with haptic condition and the 3D perspective condition. Table 4 illustrates the results of statistical analysis.

These findings show that the proposed 3D perspective with haptics method can improve the operator's perception of the remote environment, reduce the workload during the operation, and improve the operator's confidence in the robot teleoperation system.

Table 5 presents the result compared with the 2D perspective condition. A negative percentage indicates a reduction or decrease compared with the 2D perspective condition, whereas a positive percentage indicates an increase or improvement.

Discussion

The results of the human-subject experiment demonstrate the advantages of the proposed 3D perspective with haptics feedback method. Notably, the study finds that the haptic augmentation significantly enhanced the performance of pick up and place tasks compared with methods with visual augmentation only. Specifically, the proposed visual and haptic augmentation method (3D perspective with haptics) exhibited superior performance to all other methods in all performance metrics, including the number of collisions, number of deformations, installation accuracy, and insertion accuracy. Furthermore, methods with haptic augmentation but no visual augmentation (2D perspective with haptics) performed better than visual augmentation alone (3D perspective condition) and the conventional method (2D perspective condition). Moreover, the visual augmentation method (3D perspective condition) was better than the conventional method (2D perspective condition) in terms of the four performance metrics. Therefore, the findings indicate that haptic augmentation and visual augmentation can both improve task performance, with haptic augmentation presenting a greater benefit. The combination of haptic and visual augmentation proved to be the most successful method in enhancing task performance.

Our findings also provide valuable insights on how the combination of various conditions might be differentially advantageous based on specific requirements or constraints. Although it is not surprising that the condition of 3D perspective with haptics outperformed others in most metrics, it is not straightforward to tell if the benefits come from the use of 3D visual cues or more from the use of haptics. In other words, if the resource only allows one upgrade to the system, namely, either moving from 2D to 3D visual cues or adding haptic cues, one can hardly tell which sensory channel (visual versus haptic) plays a more important role for what performance metrics. Our experiment designed mix conditions of both visual and haptic cues to answer this question.

In tasks where accuracy and collision avoidance are crucial performance metrics, our results suggest that augmenting haptic feedback (2D perspective with haptics) can be more advantageous compared with solely enhancing visual feedback. On the other hand, in tasks where reducing cognitive load is of utmost importance, enhancing visual feedback (3D perspective) may be more effective than enhancing haptic feedback. These findings emphasize the significance of tailoring feedback augmentation in robot teleoperation to the specific requirements of each task. Rather than a simple hierarchy of conditions, it is this context-dependent understanding that we believe constitutes the primary contribution of our study. This information is essential for designers of teleoperation systems because it enables them to make informed decisions regarding the prioritization of feedback types based on the particular tasks at hand.

For practical implications, first, our findings have the potential to simplify future robot controls for construction. By improving the understanding of haptic feedback in robot teleoperation, we can design more intuitive control interfaces that will ease the operation process. This could drastically decrease the amount of time and resources invested in training, thereby reducing overall operational costs. Second, by providing a more immersive and responsive control environment, we can lower the learning curve associated with the teleoperation of construction robots. With our proposed system, operators could quickly familiarize themselves with the control scheme, thus minimizing the time spent on training and accelerating the adoption of this technology in the field.

Third, our research can positively impact workplace safety. By enhancing the operators' perception of the remote environment, we reduced the risk of accidents caused by misjudgment or lack of situational awareness. This could lead to safer work conditions, especially in hazardous environments where construction robots are often employed. Fourth, our work could result in increased productivity in construction operations. More efficient and accurate robot controls mean tasks can be completed faster and with fewer mistakes. The reduction in task completion time and error rates could lead to significant improvements in overall productivity.

Fifth, it is important to highlight the adaptability of our research to real-world conditions. The parameters used in our experiments are based on the known properties of the materials we worked with, enabling us to provide accurate haptic feedback under controlled conditions. However, in a real-world construction environment, it is likely that we may encounter materials with properties that differ from these predefined parameters or that change due to environmental conditions. A potential solution to this challenge is equipping the teleoperation system with additional sensors that can detect and measure the properties of the materials in real-time. This would enable the system to adjust the haptic feedback parameters dynamically, ensuring accurate feedback even when the material properties deviate from expected values. This adaptability highlights the robustness and potential of our system in diverse construction scenarios.

Regarding the user interface design and control mechanisms in robot teleoperation, reflecting on the findings of our experiment and feedback from our participants, we identified several key aspects that should be considered in the design of user interfaces and control mechanisms for robot teleoperation systems that incorporate haptic feedback. The first aspect is realism versus practicality in haptic feedback. Our study underscores the importance of haptic feedback in improving the efficacy of robot teleoperation. However, a critical challenge we observed is the need to balance the realism of haptic feedback with practical considerations. In particular, it is vital to prevent potential damage due to the application of excessive pressure or force when manipulating objects. Designing teleoperation systems with safeguards that limit the maximum force or provide real-time feedback to the operator when the force exceeds a safe threshold could be one way to address this issue.

The second aspect is user-centered interface design. The user interface plays a crucial role in the effective operation of teleoperated robots. Our research suggests that the design of the interface should be intuitive, clear, and tailored to the specific task at hand. In the context of our experiment, the interface was optimized for the manipulation of pipes in a simulated construction scenario. The third aspect is adaptive control mechanisms. Our study also

Table 3. Statistical results of the performance metrics

Condition	Collisions	Deformations	Installation accuracy (error from the center of target pipes)	Insertion depth accuracy (error from the target depth)	Time on task	Cognitive load
3D perspective with haptics versus 2D perspective	Smaller ($p < 0.001$)	Smaller ($p < 0.001$)	Smaller ($p < 0.001$)	Smaller ($p < 0.001$)	Smaller ($p = 0.015$)	Smaller ($p = 0.003$)
3D perspective with haptics versus 3D perspective	Smaller ($p < 0.001$)	Smaller ($p = 0.012$)	Smaller ($p < 0.001$)	Smaller ($p < 0.001$)	No difference ($p = 0.411$)	No difference ($p = 0.196$)
3D perspective with haptics versus 2D perspective with haptics	No difference ($p = 0.082$)	Smaller ($p = 0.009$)	No difference ($p = 0.100$)	Smaller ($p = 0.043$)	Smaller ($p < 0.001$)	Smaller ($p < 0.001$)
2D perspective with haptics versus 2D perspective	Smaller ($p < 0.001$)	No difference ($p = 0.181$)	Smaller ($p < 0.001$)	Smaller ($p < 0.001$)	Larger ($p < 0.001$)	No difference ($p = 0.176$)
2D perspective with haptics versus 3D perspective	Smaller ($p < 0.001$)	No difference ($p = 0.860$)	Smaller ($p = 0.018$)	Smaller ($p < 0.001$)	Larger ($p < 0.001$)	Larger ($p = 0.001$)
3D perspective versus 2D perspective	Smaller ($p = 0.011$)	No difference ($p = 0.201$)	Smaller ($p = 0.004$)	Smaller ($p = 0.007$)	Smaller ($p = 0.011$)	Smaller ($p = 0.005$)

Table 4. Statistical results of the NASA TLX, SART, and Trust questionnaires

Condition	NASA TLX	SART	Trust level
3D perspective with haptics versus 2D perspective	Smaller ($p < 0.001$)	Larger ($p < 0.001$)	Larger ($p < 0.001$)
3D perspective with haptics versus 3D perspective	Smaller ($p < 0.001$)	Larger ($p < 0.001$)	Larger ($p < 0.001$)
3D perspective with haptics versus 2D perspective with haptics	Smaller ($p < 0.001$)	Larger ($p < 0.001$)	Larger ($p < 0.001$)
2D perspective with haptics versus 2D perspective	No difference ($p = 0.367$)	No difference ($p = 0.543$)	No difference ($p = 0.845$)
2D perspective with haptics versus 3D perspective	No difference ($p = 0.094$)	Larger ($p = 0.005$)	Larger ($p < 0.001$)
3D perspective versus 2D perspective	Smaller ($p < 0.001$)	Larger ($p < 0.001$)	Larger ($p < 0.001$)

Table 5. Numerical results compared with 2D perspective condition

Condition	3D perspective with haptics	2D perspective with haptics	3D perspective
Collisions (%)	−84.6	−75.7	−21.3
Deformations (%)	−55.1	−21.7	−17.4
Installation error (%)	−50.8	−32.5	−20.3
Insertion depth error (%)	−75.4	−60.4	−18.3
Time on task (%)	−11.9	+10.8	−7.3
Cognitive load (%)	−12.8	+1.3	−8.1
Mental load (NASA TLX) (%)	−46.2	−15.1	−24.7
Situational awareness (SART) (%)	+40.6	+20.7	+17.3
Trust level (%)	+88.1	+41.2	+39.5

highlights the importance of adaptive control mechanisms in teleoperation systems. Depending on the operator's skill level, the system might need to offer more automated adjustments and guidance for novice users, but allow more freedom and flexibility for experienced operators.

Conclusions

This study presented an innovative embodied robot teleoperation system for construction tasks, offering an enriched perception of remote workspaces. Our system leverages physics engines to simulate physical interactions realistically and provide comprehensive physical feedback to the human operator, making it a more immersive and embodied experience. This high-resolution force feedback simulator not only outperformed the common tactile feedback systems but also captured a variety of physical interactions common in motor-intensive construction tasks, thus offering a scalable solution. Furthermore, our system provides synchronized visual and haptic feedback, allowing a more coordinated and immersive transfer of remote workspace perception to the human operator. In a simulated task involving the manipulation of a pipe skid, our 3D perspective with haptic feedback method was compared with conventional 2D perspective and single feedback augmented methods, demonstrating promising results.

Although this study introduces promising advancements in embodied robot teleoperation systems, it also opens up several exciting avenues for future research and development. First, our tests, conducted in a simulated environment, serve as a solid foundation upon which real-world application can be further examined, offering a prospect for validating the behavior similarity in more practical settings. Second, our research provides a basis for exploring how additional types of haptic feedback might enhance the performance of our system because our study evaluated only four types. Third, because our current system does not limit or adjust user-applied excessive force, future versions could innovate safety and effectiveness measures for force control.

Fourth, our experiment's focus on straight pipes represents a starting point, and future studies could enrich the system's utility by incorporating the complexities of handling pipes with different shapes. Fifth, although our haptic feedback currently relies on predefined material properties, there lies an opportunity to develop adaptive algorithms that respond to variable material properties in real-world settings. Sixth, our participant group, which primarily consisted of university students, offered a glimpse into the system's potential; future studies could extend the evaluation to seasoned construction practitioners, thereby assessing the system's effectiveness in broader professional contexts. Lastly, because our research is in an early phase, forthcoming work could focus on addressing deployment challenges in real-world conditions, including environmental uncertainties, system reliability, and human adaptability. These opportunities for continued research underscore the significant potential of our work in contributing to more sophisticated and practical solutions for robot teleoperation.

Despite these limitations, our prototype represents a promising step forward. It provides a platform for improving upon existing systems and models real-world complexity more accurately than previous attempts. It also opens up avenues for future research and development to address the identified problems. Thus, even as we recognize our limitations, we also highlight the potential of our work in paving the way for more sophisticated and practical solutions for robot teleoperation.

Data Availability Statement

All data, models, or code generated or used during the study are available from the corresponding author by request.

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Supplemental Materials

The questionnaires used for this work are available online in the ASCE Library (www.ascelibrary.org).

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