Robot-Assisted Immersive Kinematic Experience Transfer for Welding Training

Yang Ye, S.M.ASCE[1]; Tianyu Zhou, S.M.ASCE[2]; and Jing Du, Ph.D., M.ASCE[3]

Abstract: Human motor skills are critical for executing a variety range of tasks in construction. Traditional hands-on training is resource and labor intensive, whereas virtual training, such as video demonstrations, cannot provide trainees with egocentric kinesthetic or proprioceptive experience such as muscular engagement. It is important to develop remote training methods that can provide rich sensory feedback and leverage the trainee's proprioception. This paper proposes a novel remote motor skill training system that can transfer experts' kinematic and kinesthetic experience, including both positional and force experience, to novice trainees by using virtual reality (VR) and a robot arm without the physical presence of the experts. The system uses VR to simulate virtual operation scenarios and interactions to provide an immersive operation experience. The robotic system records experts' kinematic and kinesthetic patterns and trains novices with perceptual learning. The system design was demonstrated with a welding training task. A welding simulator was built with a Unity engine and a seven-degrees-of-freedom robot arm, which provided high-fidelity welding experience and could actively guide welding trainees. It was found that the welding simulator was resilient to external disturbance and provided accurate feedback and guidance. The proposed system contributes to the design of a more embodied remote motor skill training method. **DOI: 10.1061/JCCEE5.CPENG-5138.** © *2023 American Society of Civil Engineers.*

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Introduction

The advancement of remote learning technologies has sparked increasing discussions on transforming traditional in-person training into a more distributed and virtual learning experience (Mourtzis 2018). Distributed and remote training for knowledge-based tasks has been widely tested (Bond 2021; Wang et al. 2019), but human motor skill training in the context of remote learning remains relatively underexplored. Motor skills are foundational for the successful execution of tasks that require deliciated motion and force controls, particularly in the construction industry. Although descriptive knowledge, such as the task execution sequence order, is also important and can often contribute to good motor performance, motor skills are indispensable for forming and reinforcing proper motion coordination, which can hardly be acquired through verbal communications or written materials. As a result, effective motor skill training is still mostly based on traditional hands-on and face-to-face methods.

Traditional hands-on motor skill training typically relies on repetitive practices under the supervision and guidance of one or several experts at a specialized site (Reisdorph et al. 2013). The training can be resource intensive, risky, and inefficient under most circumstances. Take welder training as an example; except for lectures, conventional welding training typically needs to be conducted at welding schools with hands-on and interactive demonstrations (Rusli et al. 2019). The training process usually incurs substantial costs related to hardware platforms, consumables (materials, electrode sticks, gases), and equipment depreciation. It also results in intangible costs such as harmful gas emissions and potential health risks for both trainers and trainees (Papakostas et al. 2022). Given the increasing demand for remote training, new methods and systems are needed to transform conventional motor skill training from a face-to-face process into a more distributed, engaged virtual process.

Although recent studies have started exploring remote motor skill training methods (Gallegos-Nieto et al. 2014; Shankhwar et al. 2022; Wang et al. 2006; White et al. 2011; Wierinck et al. 2005), the sensory feedback provided by these methods is not sufficient to support the complete sensorimotor process needed for complex motor skill gain. In addition to visual guidance and feedback (e.g., visualizations in virtual reality to indicate desired motion trajectory), recent studies have ingeniously conceived and leveraged haptic devices to simulate contact and noncontact vibrotactile feedback, indicating status changes. However, to capture the motor coordination features in a complex motor task, such as welding, kinesthetic features (proprioception) are also needed, that is, nonvisual inputs that involve awareness of the spatial, mechanical, and force status of the musculoskeletal framework of the body (Stillman 2002). For example, in a typical welding task, seeing the target movement trajectory and desired pressing force as visual cues in virtual reality (VR) or through simple tactile feedback via handheld props would not be enough for a trainee to understand how to engage shoulder and forearm muscular groups for the proper force inputs. Although more advanced force feedback devices (e.g., TouchX) have

[1]Ph.D. Student, Informatics, Cobots and Intelligent Construction Lab, Dept. of Civil and Environmental Engineering, Univ. of Florida, Gainesville, FL 32611. ORCID: https://orcid.org/0000-0003-0101-5290. Email: ye.yang@ufl.edu

[2]Ph.D. Student, Informatics, Cobots and Intelligent Construction Lab, Dept. of Civil and Environmental Engineering, Univ. of Florida, Gainesville, FL 32611. Email: zhoutianyu@ufl.edu

[3]Associate Professor, Informatics, Cobots and Intelligent Construction Lab, Dept. of Civil and Environmental Engineering, Univ. of Florida, Gainesville, FL 32611 (corresponding author). ORCID: https://orcid.org/0000-0002-0481-4875. Email: eric.du@essie.ufl.edu

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been used to provide high-fidelity force cues including weight, torque, resistance, contact impact, and so on, these devices are limited by their applicable scales and force levels. In construction, there are cases when trainees desire to directly feel the extensive and intensive kinesthetic features of an expert's motion in a passive way, analogous to an expert holding the hands of a trainee in an over-the-shoulder exercise. A novel method that can record expert kinesthetic feature data and play it back in an immersive environment for the trainees is foundational for an embodied remote motor skilling training experience.

To fill the gap, this study designed and demonstrated a human motor training system that acquaints novice trainees with experts' kinematic and kinesthetic experience of not only positional control (trajectories) but also force control strategies. The system records kinematic (e.g., velocity, acceleration, and positional changes) and kinesthetic (e.g., initiated pressing force when punching a panel) features of an expert's motions and transfers this egocentric sensation to novice trainees in an immersive and embodied manner via robotic arms. We designed a VR system to establish immersive training scenarios and used a standby robotic assistant to provide encountered and recorded haptic feedback. This system, on the one hand, can record and digitalize the expert's motion patterns. On the other hand, it can proactively guide novice trainees through visual and force guidance, such that trainees can "feel" and comprehend the expert's motion features using their proprioception. The proposed system facilitates the motor skill training and transfer of a variety of motor tasks, such as surgery, welding, and instrument performance. These motor tasks share common features like operating certain tools to facilitate spatial motion and force exertion. Specifically, we chose keyhole welding training as a demonstration example because of the high demand for welders in the market (AWS 2022), as well as the resource-intensive nature of welding workshop training (Rusli et al. 2019). We implemented the proposed system for welding tasks and created a virtual training environment with interactive visual feedback and material properties. A seven-degrees-of-freedom Franka Emika robot arm (Franka Emika 2022) was repurposed as a haptic controller and robotic tutor. The robot arm provided haptic feedback when the electrode touched the welding surface following material properties. The expert welder's motion and force exertion were recorded to be replayed to a novice welder. We demonstrated the feasibility of the proposed system by implementing the system in keyhole welding training as well as testing the operability and accuracy. The rest of the paper further illustrates the point of departure, system design detail, and our findings.

Related Work

Proprioception for Motor Learning

This study used human proprioception or kinesthetics to assist motor skill acquisition. In motor tasks, a person often relies on nonvisual inputs to gain awareness of the spatial and mechanical status of the musculoskeletal framework and determine the spatial location and status of the body (Stillman 2002). Proprioceptive information is constituted of multiple channels, including muscle, tendon, and skin afferents (Yousif et al. 2015). It has been recognized that proprioception is critical to developing new motor skills (Adams et al. 1975; Rosenkranz and Rothwell 2012; Wong et al. 2012). While acquiring new motor skills, proprioception keeps the trainee aware of what is happening. The motor experience from participating body segments can be stored as a motion template in brains (Stillman 2002), which is confirmed by neurological evidence (Flament et al. 1996; Jenkins et al. 1994). The learning process in which proprioception mainly plays a role is so-called perceptual learning (Beets et al. 2012).

Previous studies have shown the feasibility and effectiveness of accelerating motor skill acquisition by proprioceptive stimulation (Adams et al. 1975; Wong et al. 2012). Representative methods leveraged linear slider motors (Sakamoto and Kondo 2015), powered exoskeletons (Chiyohara et al. 2020), robotic arms (Darainy et al. 2013; McGregor et al. 2018), or other customized apparatus (Beets et al. 2012) to manipulate participants' body parts, mostly arms, in active motor learning. Participants could feel and perceive the motion of their limbs and thus learn kinematic experience and develop relevant motor skills. Wong et al. (2012) compared motor training outcomes with proprioceptive feedback with those with active exploration. The result showed that the proprioception group showed improved time and positional accuracy. Those who actively explored the motion did not demonstrate the same benefit as pure proprioceptive learning. Similar results were provided by recent studies, in the sense that proprioception could help trainees better understand the motion pattern (McGregor et al. 2018), accelerate the learning speed, and improve motor task accuracy (Chiyohara et al. 2020). Although behavioral and neurological studies have indicated the effectiveness of perceptual learning in spatial motions, few studies discussed the perception of extensive force engagement during learning, such as passively feeling the simulated kinematic and kinesthetic features of another person, similar to the over-the-shoulder interactive experience in motor training. Most people have the ability to perceive force both in terms of direction (Long et al. 2021) and magnitude (Van Beek et al. 2013). It remains unclear whether individuals can make use of somatosensory capabilities to perceive force, contributing to comprehending and gaining new motor skills. We propose to create augmented sensory feedback pertaining to proprioception via virtual simulation for effective remote motor skilling training.

Augmented Experience for Motor Skill Training

Facing the increasing demand for remote work and remote training, researchers have been exploring the feasibility of using cut-edge technologies to transform the traditional centralized, in-person motor skill training methods into a more distributed, virtual approach (Mourtzis 2018). Owing to the ability to create an immersive virtual environment with augmented sensation (Ye et al. 2022a), VR has been considered a potential solution for remote motor skill training (Schüler et al. 2015). Among all modalities that VR can integrate, augmented visual cues are the most widely considered form of guidance for trainees (Clarke et al. 2018; Zhu et al. 2022b). In the context of motor training, visual information plays an important role to instruct (such as visualizing instructions) and alert (such as visual feedback on performance) trainees in knowledge-based components (Schüler et al. 2015). Ricca and colleagues found that the visual representation of hands and tools could facilitate motor performance during learning, potentially due to embodied feelings (Ricca et al. 2021). Wierinck et al. (2005) conducted motor skill training for dental students and found that augmented visual feedback in VR could significantly improve surgical task performance during training. In addition to the abundant training information in VR, VR can provide distributed and emancipated training experience such that trainees can initiate, pause, end, or repeat training according to their needs (Thielbar et al. 2014; Ye et al. 2022a). Meanwhile, motor training in VR can be designed as game-like exercises that promote enjoyment, motivation, and more attention to motor training tasks, ultimately leading to better training outcomes (Wenk et al. 2021). VR has become a widely implemented motor training tool in rehabilitation, manufacturing, and military applications (Faria et al. 2018; Gallegos-Nieto et al. 2014; Maxwell et al. 2018).

Haptic feedback can be integrated with VR (Levelé et al. 2020) or standalone (Hirano et al. 2020) to provide an important somatosensory experience, which is considered beneficial for motor skill training. In the context of training, haptic feedback can be generally categorized into vibrotactile feedback and force feedback. Vibrotactile feedback is typically imposed on individuals through vibration motors or electric pulses (Ye et al. 2022b; Yem et al. 2012) to instruct motion or convey hidden information like gravity and force (Lieberman and Breazeal 2007; Zhu et al. 2022b). Force feedback can be delivered through force feedback devices such as the Touch series (3DSystems 2022) and Falcon (anarkik3d 2022), creating a force interaction like push and resistance. Multiple studies have discussed the potential benefits of using haptic feedback in motor training, such as (Bark et al. 2015). However, as discussed earlier, the vibrotactile sensation is not a direct perception modality related to kinematic and kinesthetic experience and still needs a mental remapping process. Meanwhile, existing force feedback systems are typically designed to provide high fidelity for task simulation, such as creating like-real contact force when touching a virtual object (Zhu et al. 2021). Most existing off-the-shelf force feedback systems don't support playback of prerecorded force information and are limited by the scale for mostly hand-level dexterous tasks. Using haptic devices in motor training still heavily relies on the trial-and-error approach where a trainee uses the system to explore proper strategies for executing the task, instead of feeling the kinesthesia features of the expert. The abstraction of real-world physical processes and the lack of direct transfer of expert data might significantly deteriorate the learning processes (Eck et al. 2015). There is still a lack of haptic feedback methods that can instruct trainees on how to intuitively and properly conduct motor tasks, especially related to force learning.

There is a growing interest in the integrated use of VR and robotic systems for multiple applications in construction. These existing works have set a solid methodological foundation for the proposed work. For example, You et al. (2018) explored a VR system for safety perception in human–robot collaboration tasks. They found that VR systems provided an immersive environment for increasing the safety awareness of human workers in human–robot collaboration. Du and coworkers tested VR methods as an immersive training system for professional workers such as crane operators (Zhu et al. 2022a), firefighters (Ye et al. 2022c), and building inspectors (Xia et al. 2022b). In addition, VR has been actively explored as a testbed to understand workers' physiological and psychological status at work. Habibnezhad et al. (2021) created an unsafe virtual working scenario of standing at an elevated surface and found that VR could trigger significant changes in the subjects' gait pattern. In a simulated virtual environment, Kim et al. (2015) found workers' trust and team identification could be largely impacted by the presence of robotic coworkers. Recently the literature has also advanced robotic perception and control methods for specific construction operations. Asadi et al. (2021) proposed a vision-based system for instant scene understanding for object manipulation in complex construction tasks. The work of Chen and Cho (2022) promoted computer vision algorithms for scan-to-building information modeling (BIM) solutions, which set the basis for the semantic understanding of construction robotics applications. Liu and Jebelli (2021) tested natural body motion capture techniques for robotic bilateral controls. Liang et al. (2022) and Wang et al. (2021) explored digital twinning methods for robotic controls in construction tasks. Specifically, Zhou et al. (2020b) proposed and tested a workflow for exchanging data between Robot Operating System (ROS) and Unity, which was suited well for construction teleoperation applications. These methods have validated the efficacy of immersive simulated environments, such as VR, as a potential control system for robots. Inspired by these researchers, we found that integrating VR with a robotic haptic system could be a potential solution for difficult motor learning in construction.

System Design

System Architecture

The objective of this study was to design a motor skill training framework capable of transferring the kinematic and kinesthetic experience from an expert to novice trainees. Fig. 1 shows the overview of the proposed system architecture. The system consisted of hardware, software platform, supportive function, and algorithm layers. The hardware layer included the VR and robotic systems. The VR system provided the training scenarios, creating immersive training environments with coordinated visual–motor experience (Carlson et al. 2013). The robotic system was used to guide trainees in complex motor tasks actively, allowing them to perceive (feel) the motion kinematics and expert egocentric kinesthetic experiments through intuitive proprioception. The robotic system here is a collective term, referring to various mechanical devices such as exoskeletons (Chiyohara et al. 2020), sliding motors (Sakamoto and Kondo 2015), and robot arms that can sense force and exert torque. The robotic system consisted of one robotic device or several collaborative robotic devices, depending on the motor task specifications. For instance, arc welding can be trained with one robot arm; two-handed surgery training might involve several sliding motors that can move two hands; pianist training can be assisted by one to two powered exoskeleton arms. The hardware layer was enabled and supported by software platforms as well as the underlying functions and algorithms. A game engine platform, a Robot Operating System platform, and data exchange system were developed and integrated with the software platform layer (Zhou et al. 2020a). This layer not only presented an immersive virtual environment with haptic feedback but also synchronized and processed data in real time to create a digital twin of the robotic system. The functions layer broke down the control and simulation into individual problems, whereas the algorithm layer solved the problem. The following sections describe the platforms and the communications between them as well as the functions and algorithms.

ROS-VR Data Exchange

Per the proposed design, VR and robotic systems need to be seamlessly connected. Specifically, the mechanical response of the robotic system needs to be synchronized with the interaction events in VR in real time. When seeing an interaction in VR, a trainee expects to feel the corresponding force feedback with the assistance of the robotic system. In our proposed system, VR and robotic systems can be operated on two separate devices under a local network. Both VR and robotic systems had relatively independent functions while closely connected. ROS was used to facilitate the robot state calculation, control, and communication (Zhou et al. 2020b). On the one hand, the robot's current status, including joint positions, joint torques, and other abstractions of current robot status, could be published via ROS topics, allowing other processes to access the status data. On the other hand, robot control algorithms subscribed to ROS topics to fetch robot state features and complete calculations (Xia et al. 2022a). Calculated control commands, like the desired position and desired torque portfolio, were streamed to robotic devices for execution.

Meanwhile, bidirectional communication was established between the game engine and the robotic system: the robot state was

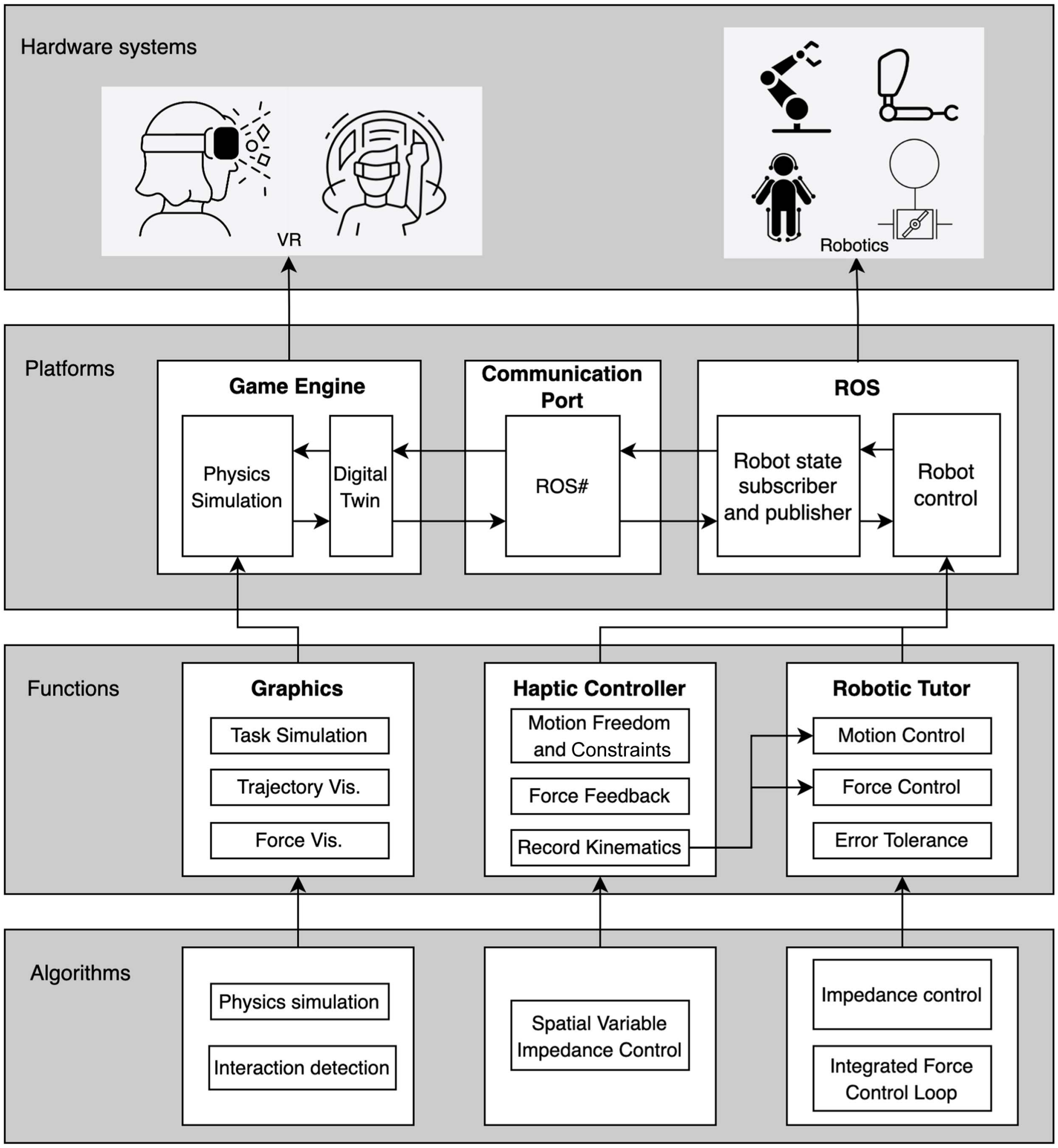


Fig. 1. Overall architecture of the proposed motor skill training system.

subscribed by a game engine such as Unity to construct a digital twin model of the robotic system (Hussein et al. 2018). The game engine also streamed data to ROS to trigger the robot control commands according to the current task context. The data exchange infrastructure for the game engine and ROS data synchronization is based on our previous works (Xia et al. 2022b; Zhou et al. 2020b). ROS# (Siemens 2019) facilitated the communication between the game engine and ROS. ROS# is a collection of open-source libraries in C# that provides compatible application programming interface (APIs) for both the game engine and ROS sides to facilitate bidirectional communication. ROS# has been applied in construction-related studies. In the proposed system, ROSbridge, one of the ROS# libraries, was used to stream data in JSON format via a public network between ROS and the game engine (Crick et al. 2017). The ROS server converted robot dynamics to and from JSON messages via ROSbridge and sent and received messages from the internet (Quigley et al. 2009). On the game engine side, ROS# established WebSocket nodes that could subscribe to the data from.Net applications (GitHub 2019), enabling the game engine to publish and receive data from ROS topics. The ROS server and game engine's WebSocket can be managed under the same IP address so that the data can be exchanged seamlessly.

The game engine platform received robot state data to synchronize a digital twin model and sent parameters as well as events to ROS to update the robot control methods. A digital model of a robotic system was built based on a Unified Robot Description Format (URDF) file (Whitney et al. 2018), which describes the structure and configuration of the real robotic system. The digital model was compatible to read robot status messages such as joint positions and orientations so that the digital model could follow the same robot behavior. Following this method, a digital twin model of the robotic system can be created in VR to realize the digital replica of the real robot, duplicating the properties, behavior, and status of the real robotic system. By using the digital twin model, users can see the actions of the robotic system and thus coordinate visual and perceptual information. In addition, the motion and torque matrices of the robotic system can be used to trigger interactions in VR such as collisions, pushing, and penetration. The VR interactions not only provide visual information to trainees for higher-fidelity visualization of the task and system but also trigger the physics simulations empowered by the game engine to facilitate complex physics calculations and further enhance the fidelity of robotic controls. The game engine is inherently powerful in simulating the interactions in three-dimensional (3D) space. For instance, in maxillofacial surgery training, instead of describing the 3D geometry of the face by complex tensors, the game engine could define the geometry using a graphical interface and capture the collision accurately (Ayoub and Pulijala 2019). When a virtual scalpel collided with virtual skin, the force from the haptic device or robotic systems could be used to determine whether the upcoming interaction would be a light touch or a deep cut. After physics rendering in the game engine, the data from the robotic system can be transformed into new commands and sent back to the robotic system.

Training Pipelines and Algorithms

Fig. 2 illustrates the training pipeline. The training consisted of two phases: the expert kinematics and kinesthetic recording and novice perceptual learning phases, whereas the novice perceptual learning phase can be further divided into force and trajectory perceptual learning. First, in the expert kinematics recording phase, the expert demonstrates how to properly conduct the motor task, assisted by VR and the robotic system haptic feedback. The robotic system functions as a haptic controller. The expert's motion kinematics and kinesthetics are recorded and decomposed into spatial trajectories and force patterns; In the perceptual learning phase, trainees can learn the expert's motion kinematics kinesthetics by VR visualization and robot-assisted perceptual learning. The robotic system functions as a virtual tutor. The proposed system used VR for three purposes: (1) creating high-fidelity graphical rendering for immersion, (2) simulating the physical processes of the interactions to enhance kinesthetics, and (3) providing visual feedback as an optional training modality. Depending on the specific task context, the physics simulation in the game engine needs to be customized and fine-tuned to create high-fidelity interactions.

The robot arm provides encountered and prerecorded haptic feedback (Mercado et al. 2021) for the trainees to physically experience. The purpose of using the robotic system varies depending on the training stage: the robotic system facilitates haptic feedback during the expert demonstration, creating like-real physical feeling to engage the experts in recreating their motor kinematic and kinesthetic experience; during the trajectory perceptual learning stage, the robotic system drags and moves trainee's limb through a trajectory tracking; during force perceptual learning, the robotic system aims to exert proper force to trainees for the enhanced kinesthetic experience. Finally, with the robotic system in haptic controller mode, trainees can test their gained skills.

Haptic Controller Mode: Using the Robotic System as an Impedance Controller

When an expert is using the robotic system and trying to record his or her motion and force data, the robotic system needs to function as a haptic controller, simulating the physical contact and interactions. To be more specific, the robot end effector can be moved freely in space with no resistance in all directions when no interaction with a virtual object is happening. When interaction happens, such as colliding with a metal panel, stiffness and damping need to be changed in a certain direction, creating a resisting or touching haptic feeling. The robot arm under haptic controller mode functions similarly to existing haptic devices such as Touch (3DSystems 2022): a virtual geometry is defined in space, and the interaction between the robot arm and the geometry is haptically enabled to create a like-real interaction experience. The fidelity of such interaction directly impacts whether experts can perform the motor task with their motor skill capability. Experts can hold the robot arm tip as if holding the operation tools (such as a lancet in surgery and electrode in welding) to conduct the motor task (see Fig. 3). The expert's motion can be recorded both in terms of how the expert moves and how much force the expert is applying to the operation surface.

Exploring the task with haptic force feedback can be considered a classical human–robot interaction problem. In general, it is expected that the user who holds the end effector feels resilience or damping resistance while pressing toward an object. From the robotic control perspective, the robotic system exerts force and torque on the human operator in response to spatial changes at the end effector due to environmental interaction (i.e., human motion). As a classic robot control algorithm, the impedance control algorithm can facilitate the robotic force and torque output in response to external environment-induced robot position changes. The impedance controller simulates a virtual spring–damper coupling system (Hogan 1984) between the environment and robot end effector, creating stiffness and damping resistance when the position of the robot end effector deviates from the desired position (Abu-Dakka and Saveriano 2020). The solid line part in Fig. 4 shows the impedance control method. The model can be described in Eq. (1)

$$\boldsymbol{\tau}_e = \mathbf{M}\ddot{\mathbf{x}}_t + \mathbf{D}\dot{\mathbf{x}}_t + \mathbf{K}(\mathbf{x}_t - \widetilde{\mathbf{x}}_t) \tag{1}$$

where $\boldsymbol{\tau}_e$ = external torque matrix; $\mathbf{x}_t$, $\dot{\mathbf{x}}_t$, $\ddot{\mathbf{x}}_t \in R^n$ refer to the position, velocity, and acceleration of all joints in the Cartesian space at time point t; $\widetilde{\mathbf{x}}_t$ = desired position in the Cartesian space at time t; and $\mathbf{M}$, $\mathbf{D}$, $\mathbf{K} \in R^{n^2}$ denote the desired inertia, damping, and stiffness in the joint space, respectively.

The impedance control maintains the robot through the desired trajectory. However, in the context of haptic exploration, the force and torque matrices are subject to the geometric relationship (i.e., normal vectors at contact points) and environmental features (i.e., stiffness and damping of the environment, mass change). The geometric relationship defines the direction of the robot's response torque, whereas environmental features define the derivative of torque amplitude to the positional changes. In addition, impedance control in Eq. (1) restores the robot position to a predefined desired position $\widetilde{\mathbf{x}}_t$, which is not the case in this study. In haptic controller mode, the desired position is defined by the interaction events as well: when a user pushes the end effector toward an object, the desired position should be the contact point position at the original space. As such, the impedance behavior needs to be calibrated with the virtual environment and contact events. A modified version of impedance control, spatial variable impedance control (SVIC), is deployed to facilitate these challenges, as shown in Fig. 4.

The SVIC model can be described as Eq. (2)

$$\boldsymbol{\tau}_e = \mathbf{M}_{(\mathbf{x}_e,t)}\ddot{\mathbf{x}}_t + \mathbf{D}_{\mathbf{x}_e}\dot{\mathbf{x}}_t + \mathbf{K}_{\mathbf{x}_e}(\mathbf{x}_t - \widetilde{\mathbf{x}}_t) \tag{2}$$

where $\mathbf{x}_e$ = end effector position; the inertia $\mathbf{M}_{(\mathbf{x}_e,t)}$, damping $\mathbf{D}_{\mathbf{x}_e}$, and stiffness $\mathbf{K}_{\mathbf{x}_e}$ matrices vary according to time and end effector position; inertia $\mathbf{M}_{(\mathbf{x}_e,t)}$ is a function of the current position and time, coping with mass change of virtual tools. Inertia matrix change is not significant in most cases. The values $\mathbf{D}_{\mathbf{x}_e}$ and $\mathbf{K}_{\mathbf{x}_e}$ are the damping and stiffness matrices distributed in Cartesian space. Because the game engine provides a convenient 3D graphical interface, it can perform geometry analysis to map the spatial position with damping and stiffness matrices. Eq. (3) describes the general form of such a mapping process

$$\mathbf{G}_{x_e} = \Lambda_{x_e} \cdot \boldsymbol{M}^{\boldsymbol{T}} \tag{3}$$

where $\mathbf{G}$ = material properties; $\mathbf{M} = [G_1, G_2, \ldots G_m]$ is a vector of all predefined material property; and $\Lambda = [0, 0, \ldots 1, \ldots 0, 0] \in R^m$

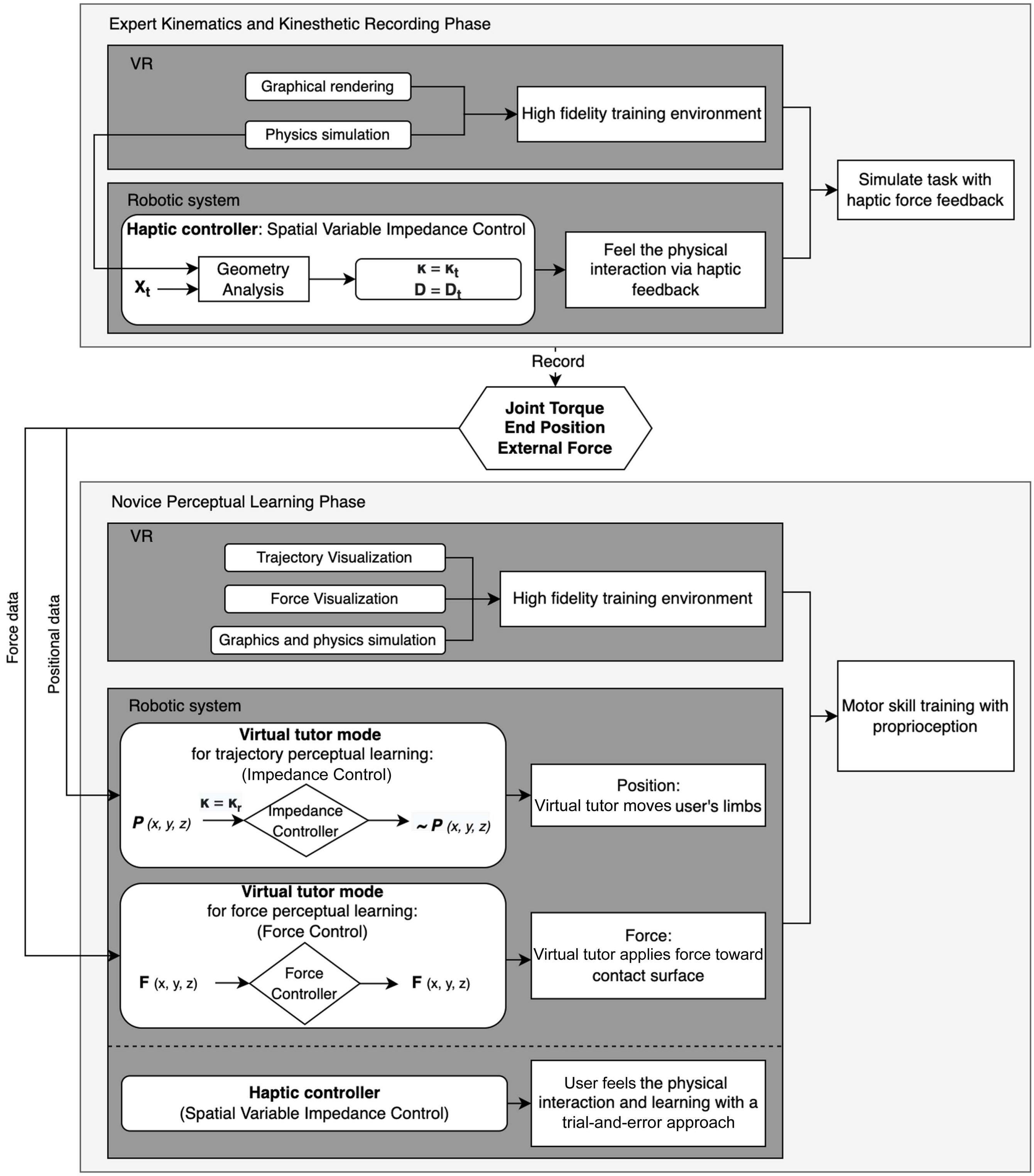
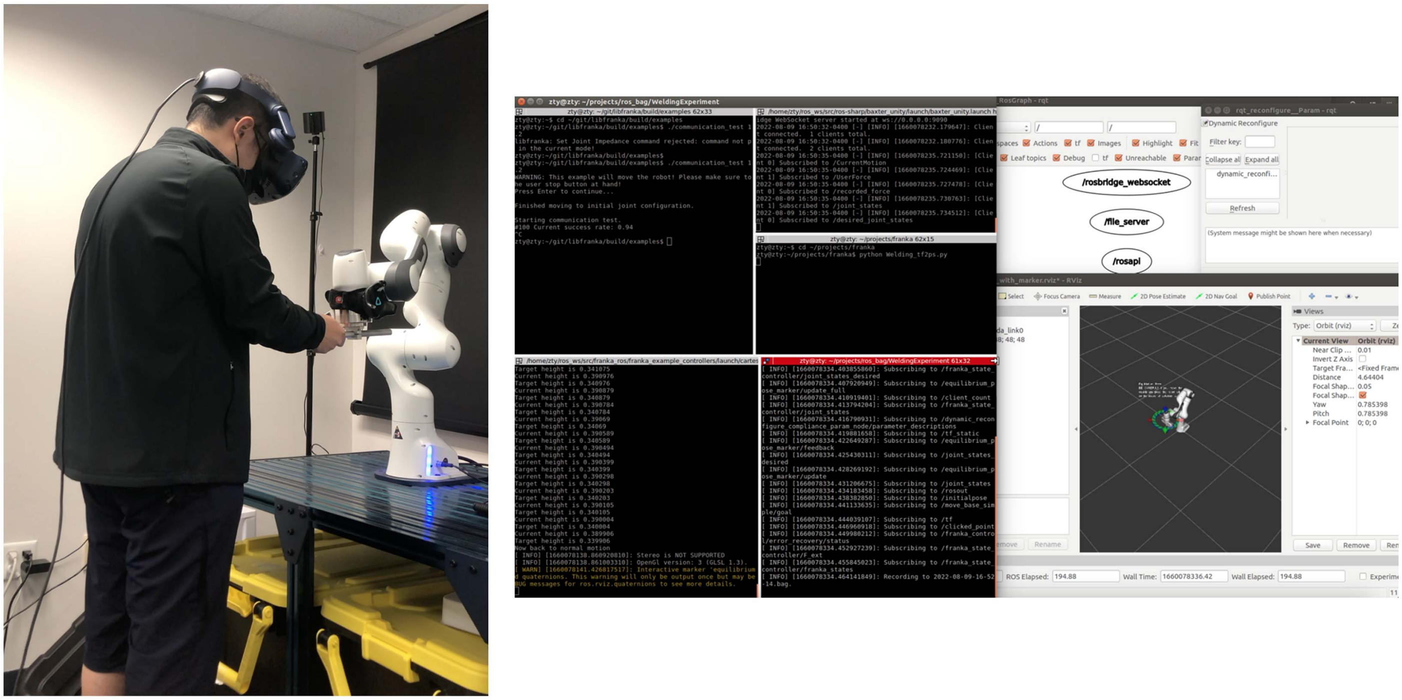


Fig. 2. Training pipeline of the proposed system.

is a vector indicating the spatial relationship between the robot end effector and m types of materials. Each type of material corresponds to a specific material property (i.e., stiffness and damping). The values of Λ are all zeros except at the index for which the robot end effector is colliding with the corresponding material, and Λ is calculated by the graphical processor in the game engine in real time. Depending on the material properties, the game engine can fine-tune the damping and stiffness of objects. For example, a rigid virtual surface in the game engine can be tagged with high damping and stiffness, which practically maps a Cartesian space with stiffness and damping matrices. The geometry analysis block returns the corresponding high-value $\mathbf{D}_{x_e}$ and $\mathbf{K}_{x_e}$ matrices when the robot end effector collides with the virtual rigid geometry, creating haptic feedback of rigid contact. The parameter $\widehat{\mathbf{x}}_t$ in Eq. (2) is updated by the geometry analysis at each time frame with inverse kinematics following Eq. (4)



(a) (b)

Fig. 3. Robotic system under expert kinematics recording phase. (a) Expert is holding the robot end effector to reproduce the motor task; and (b) ROS provides force feedback to the expert while it processes, transmits, and records the real-time kinematics.

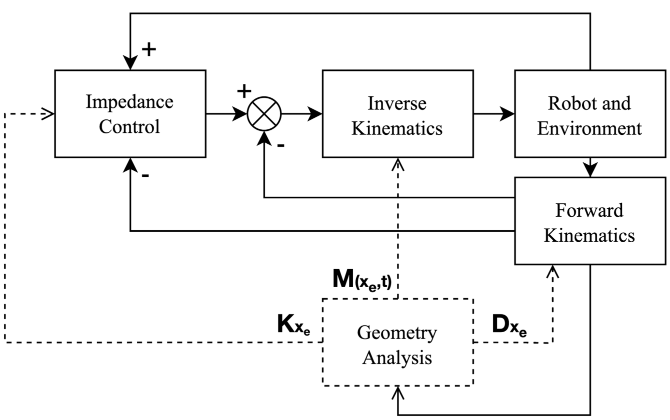


Fig. 4. SVIC block chart. Dashed lines and blocks show the modified sections based on the impedance control method.

$$\widetilde{\mathbf{x}}_t = \mathbf{J}^{-1}(\widetilde{\mathbf{x}}_e - \mathbf{x}_e) + \mathbf{x}_t \tag{4}$$

where $\mathbf{J}$ = Jacobian matrix (Aristidou et al. 2018; Buss 2004), defined by

$$\mathbf{J} = \left(\frac{\partial \mathbf{x}_t}{\partial \mathbf{x}_e}\right) \tag{5}$$

The value of $\widetilde{\mathbf{x}}_e$ is the position of the virtual contacting point at the original space without deformation. In practice, $\widetilde{\mathbf{x}}_e$ can be acquired by either the labeling or geometry normal vector method. The labeling method marks the position of initial contact as $\widetilde{\mathbf{x}}_e$, which is more straightforward but prone to being problematic, especially when the contact point is moving (e.g., scraping on the surface) or the contact geometry is complex (e.g., uneven surface).

The geometry normal vector method collects the mesh vertices around the contact area and generates a normal vector. The intersection point between the normal vector and the original geometry before deformation can be marked as $\widetilde{\mathbf{x}}_e$. Assuming constant stiffness and damping matrices, the normal vector $[(\widetilde{\mathbf{x}}_e - \mathbf{x}_e)/(|\widetilde{\mathbf{x}}_e - \mathbf{x}_e|)]$ and material deformation $(|\widetilde{\mathbf{x}}_e - \mathbf{x}_e|)$ determine the direction and amplitude of resilience, respectively. When no contact occurs, $\widetilde{\mathbf{x}}_e = \mathbf{x}_e$, making $\widetilde{\mathbf{x}}_t = \mathbf{x}_t$, in which the robot is considered to have no positional error and can be moved freely. Combining the adaptive virtual mass, damping, and stiffness matrices in Eq. (2) with the real-time evaluation of the desired position in Eq. (4), the robotic system can be repurposed as a haptic controller to interact with virtual objects.

The kinematic and kinesthetic data in haptic controller mode can be recorded in real-time and exported as bag files using rosbag, following previous studies (Jeong et al. 2017; Koo and Kim 2019; Lakshminarayana 2019). Rosbag is a ROS library widely used to record and play back ROS topics and messages. The recorded rosbag files need to be processed with offline data cleaning pipelines to trim the idling or noisy data at the beginning and end of recorded motion, depending on the task context. This general design and model can be fitted in multiple motor training tasks with customized adaptation in parameters, especially the geometry analysis block. For instance, welding training or simulation might involve more interaction with a rigid surface. Surgery operation training might have a more variable range of stiffness and damping to create the sense of scrabbing, cutting, and penetration.

Virtual Tutor Mode: Using the Robotic System as a Virtual Tutor

The expert's motion kinematics can be recorded under haptic controller mode and replayed to train novice trainees. Except for visual guidelines or feedback augmented by VR, trainees can learn from kinematic and kinesthetic experiences for both motion trajectory

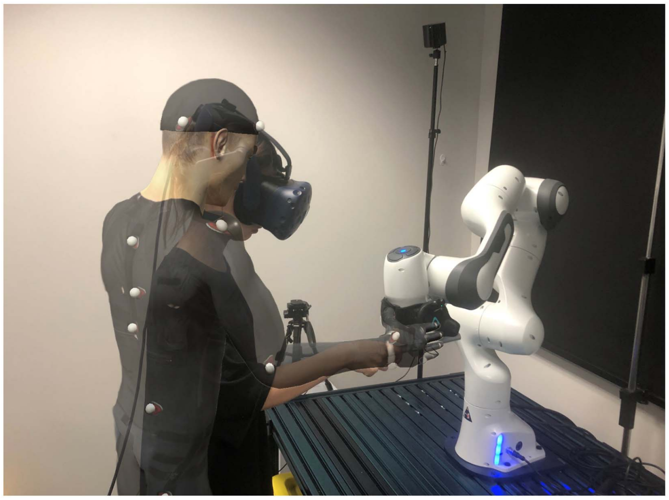


Fig. 5. Robotic system simulates a virtual tutor grabbing a trainee's hand/limb, creating an embodied training experience.

and force patterns with the assistance of a robotic system during the novice perceptual learning phase. The robotic system functions as a virtual tutor in the novice perceptual learning phase. Under virtual tutor mode, the robotic system actively moves through a spatial trajectory and applies forces to the environment (the trainee's hand). As shown in Fig. 5, the robotic system working under this mode simulates a virtual tutor holding a trainee's hand to show how to correctly perform the motor task. In other words, the trainee can feel how the expert moves and applies force and thus can comprehend the motor task from the expert's egocentric view in an embodied manner.

Virtual tutor mode can be decomposed into two components: spatial trajectory and force pattern learning. Spatial trajectory learning with perception has been studied in previous studies (e.g., Chiyohara et al. 2020) and is relatively straightforward. From the robotic control perspective, spatial trajectory learning is the process in which the robotic device maintains a predefined trajectory under external disturbance. The impedance control model in Eq. (1) can effectively facilitate such a process when stiffness ($\mathbf{K}$) and damping ($\mathbf{D}$) are configured as relatively high values. The high $\mathbf{D}$ and $\mathbf{K}$ matrices impose high counterforce in response to the minor positional mismatch between the desired trajectory and current trajectory, making $\mathbf{x}_t \rightarrow \widetilde{\mathbf{x}}_t$. Thus, the positional error can be eliminated promptly, creating a scenario in which the robot arm strictly follows a certain spatial trajectory. As such, impedance control can move the trainee's hand without the user initiating any motion.

However, although impedance control with high stiffness and damping can facilitate accurate motion replay in space, the underlying algorithm indeed uses force ($\boldsymbol{\tau}_e$) to compensate for the positional error. This becomes problematic if the force pattern learning is to be conducted at the same time: the desired force $\boldsymbol{\tau}_d$ and positional compensation force $\boldsymbol{\tau}_e$ are added together at the end effector. It is unrealistic to distinguish between $\boldsymbol{\tau}_e$ and $\boldsymbol{\tau}_d$ unless in an extreme condition that $\boldsymbol{\tau}_e$ and $\boldsymbol{\tau}_t$ at the end effector are perpendicular to each other ($\boldsymbol{\tau}_e * \boldsymbol{\tau}_d = 0$) in Cartesian space. This extreme condition is equivalent to $(\mathbf{x}_t - \widetilde{\mathbf{x}}_t) * \boldsymbol{\tau}_d = 0$, in which the direction of the positional error is always perpendicular to the desired force direction. It is merely possible to maintain such a condition constantly.

To solve this problem, the proposed system disentangles force perceptual training from trajectory perceptual training as a workaround. To be more specific, when training the force pattern of a specific motor task, the robotic system solely exerts desired force and does not follow the desired trajectory. No desired positional data are passed to the robot arm. Instead, the VR system can play a role here to visualize the desired trajectory and establish a mapping between the desired force and desired position. In other words, while learning the force pattern, the robot arm is not guiding the trainee's hand through a trajectory but applying force toward the trainee's hand to let the trainee perceive. The robotic control can be by a force control loop algorithm, in which the summed torque at the end effector of the robotic system maintains the same as desired force, imposing constant output to the external environment (in the current context, imposes a force on the trainee's hand). The control model is described in Eq. (6)

$$\boldsymbol{\tau}_o = \mathbf{J}^{-1}\boldsymbol{\tau}_{de} + \Delta(\boldsymbol{\tau}_m - \boldsymbol{\tau}_g) \tag{6}$$

where $\boldsymbol{\tau}_o \in R^n$ is the output torque of all joints; $\boldsymbol{\tau}_m \in R^n$ is the measured torque of the current robot state; $\boldsymbol{\tau}_g \in R^n$ is the torque matrix counting for gravity at joint space; and $\boldsymbol{\tau}_{de}$ = desired force at the end effector which is also the counterforce recorded when the expert applies force toward a virtual object. This equation yields the output torque profile of the robotic system, and trainees can feel the same force as the expert. For example, when an expert in the recording stage applied straight down force toward a horizontal rigid virtual plane, the robotic system (haptic controller) counterbalanced such a force by generating upward force with the same amplitude (assume the system is in a steady state with $\dot{\mathbf{x}}_t = 0$ and $\ddot{\mathbf{x}}_t = 0$). The counterbalancing force at the end effector was recorded as $\boldsymbol{\tau}_{de}$. During the force pattern learning stage, the robotic system under the force control algorithm could generate the same force $\boldsymbol{\tau}_{de}$ pushing upward to the external environment. Trainees need to push straight down to counterbalance such a robotic output and thus could feel the same muscular force as the expert.

Following this general system design, trainees can perceive the expert's kinematic and kinesthetic experience with the assistance of a robotic system. As mentioned in previous sections, the robotic system can be robotic arm(s), exoskeletons, or other customized devices. The algorithms described previously are suitable for motor tasks that focus on end effector interactions instead of linked kinematics. In other words, the algorithms focus on recording and replaying the kinematics at the experts' end effector (typically the hand). Although it is possible to extend the previously mentioned algorithms to multiple key points to restore the kinematics of the entire limb or even whole body, first hand-scale and arm-scale motor skill proficiency training is still the most common scenario. Second, this paper aimed to design this system to facilitate motor skill training; it is out of the scope to list the detailed algorithms and device setups for motor training tasks with all possible purposes and focuses. Instead, the following section describes the implementation of such a system architecture in welding skill training.

Safety Measures

The robot and human share the same working space in the proposed training system, which raises safety concerns. Safety measures should be developed in accordance with the ISO 15066:2016 standard. This session describes some key measures that need to be put in place in the context of the proposed system. For detailed requirements, please refer to BSI (2016).

All operation modes in the proposed system involve human–robot collaboration problems and need to be secured with safety-rated monitored functions such as speed and space in accordance with the ISO 10218-1:2011 standard (BSI 2011). These functions avoid overspeeding or moving beyond the safety range. In the context of this study, the robot's speed depends on the human operator's movement speed and typically will not lead to safety risks.

However, it is recommended to set a speed limit and instruct the operators not to move too quickly. The robot's range of motion should be limited to avoid collision with the environment or the robot itself. A stop switch needs to be used to allow emergent stops (BSI 2016).

The haptic controller mode is a hand-guiding collaboration type in which only the human operator initiates the motion. The position, speed, and force are controlled by the human operator, which involves minimum safety risks. The speed and space limit function described previously can further reduce the potential risks.

Compared with haptic controller mode, both trajectory and force perceptual learning modules involve a human–robot collaboration scenario in which the robot and human move simultaneously. Additional safety measures need to be put in place in accordance with the ISO 15066:2016 standard to ensure safe operation. It is recommended to enforce the strictest safety criteria. According to the ISO 15066:2016 standard, no transient contact with the skull, forehead, and face is allowed. In the proposed system, the robot's spatial position should be limited in height such that no collision with the operator's head could happen. Furthermore, the most critical area (except the skull, forehead, and face) is the operator's abdomen, for which the quasistatic contact force must not exceed 110 N, and the transient contact force must not exceed 220 N (BSI 2016). Quasistatic contact refers to the situation in which the human operator's body part is being clamped or entrapped. In the trajectory perceptual learning context, although the risk for quasistatic contact is minimum, it is also recommended to enforce a force limit strictly lower than 70 N, allowing around 60% redundancy in the most critical collision situation.

System Demonstration and Validation

We deployed the system with a keyhole welding training task. In manual keyhole welding, a welder needs to join two separate pieces of metal such as two pipes or two plates. These two pieces of metal, however, are apart from each other with a hollow gap (WeldGuru 2022). The welder should maneuver welding electrodes to fill the gap and create a binding. Specifically, the welder needs to push the welding tip toward the unfilled gap, stop the heat, exert a certain pressure toward the gap, and drag the electrode with appropriate velocity to fill the gap with the melted welding electrode. The pressing force should be neither too high, which might penetrate the material or weaken the binding, nor too weak, in which the temperature cannot be effectively brought down or the molten electrode cannot adhere well to the material (Weldtube 2019). As such, manual keyhole welding requires precise motor control for coordinated spatial trajectory motion and force exertion. A demonstration video can be found at Ye (2002). An expert welder and 15 novice participants who have no prior welding experience were recruited to validate the system.

Game Engine for Welding Visual and Physics Simulation

To create an immersive training experience, we created a welding training room with tools [see Fig. 6(a)] in a game engine (Unity engine) and used filmbox (FBX) renderings and computer graphics algorithms to simulate the welding process, including welding torch, surface deformation, and flames (Kim et al. 2018). Manual keyhole welding uses molten electrodes to fill the gap and create a binding. This process creates surface deformation such as the formation of welding beads and weld metal, which can provide important visual feedback to welders. As shown in Fig. 6(b), we simulated the surface geometry change using the marching cubes algorithm (Lorensen and Cline 1987). Any collision between the welding tip and surface would create new triangle vertices using linear interpolation, such that the welding surface geometry could be modified by the welding tip, simulating welding surface change. A new layer of

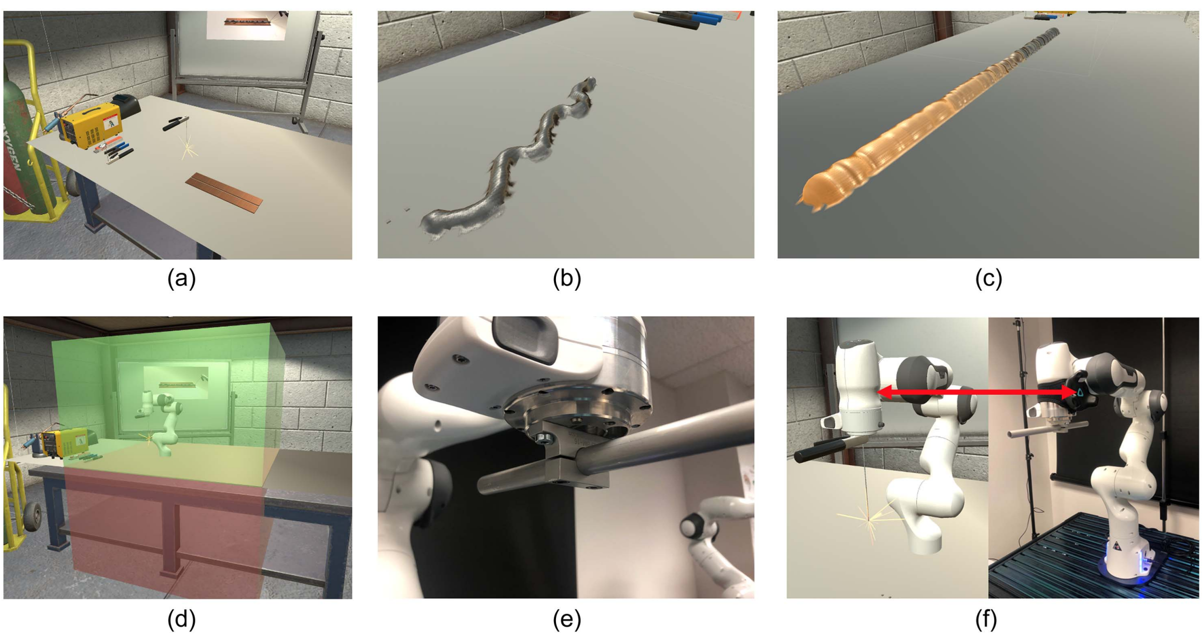


Fig. 6. VR welding simulation. (a) Welding training room; (b) the deformation of welding material was simulated by the marching cubes algorithm. The texture of the welded seam was created by triplanar projection; (c) the irradiance of molten metal was simulated by a customized shader that updated the material emission continuously; (d) spatial distribution of stiffness and damping. The shaded area shows the working area with material properties. The green block had zero stiffness and damping. The red block had high stiffness and damping, which corresponded to a rigid welding surface; (e) we used a robot end effector to simulate a real welding torch; and (f) the robot end effector and virtual welding scenario were well aligned for a coordinated visual–motor experience.

texture was then projected to the deformed surface using triplanar nodes (Unity 2022). The projected texture was configured according to the welded seam comparable with real-world applications. Bringing marching cubes and triplanar projection together, the formation of a weld joint was simulated. In addition to the geometry deformation, we also created an emission shader to render the weld seam material [see Fig. 6(c)], simulating the irradiance of molten metal. The shader calculated emission as a linear function of time since initialization to simulate a gradual-fading effect. This gradual fading effect corresponded to the molten metal cooling process. The VR simulation of the welding visual effect could provide a reference for welding expert to properly apply their welding motor skills. Apart from visual effects, we configured the material properties (stiffness and damping) in the Unity engine to provide high-fidelity interaction, as described in Eq. (2). Fig. 6(d) shows the spatial distribution of stiffness and damping matrices. The metal pieces were assumed to be rigid objects and thus to have high damping and stiffness.

We programmed a seven-degrees-of-freedom (7-DOF) Franka Emika robot arm to be our welding robotic assistant. A specialized end effector was acquired. As shown in Fig. 6(e), the end effector was installed on the robot arm, and an aluminum tube was fastened onto the end effector. This end effector set mimicked the handle of the welding torch. Meanwhile, we calibrated the position of the virtual welding torch in VR with the robot end effector [Fig. 6(f)]. The virtual welding torch and "real" torch were well aligned to coordinate users' visual-motor experience: as they were holding the robot end effector, they could see in VR that they were holding a virtual welding torch.

Robot Arm for Haptic Feedback

Whereas VR established visual feedback for welding training, the 7-DOF robot arm was programmed as a haptic controller and provided haptic feedback for the welding experts. While holding the robot arm end effector, the welding expert could move the virtual welding torch in space and perceive the resistance during the interaction. The robot arm was controlled by the SVIC algorithm. Constant mass was assumed. The robotic end effecter position was streamed to the Unity engine to synchronize the welding torch behavior. The Unity engine provided geometry analysis, as shown in Fig. 4. The Unity engine detected collisions between the welding tip and surface and streamed the corresponding desired position, stiffness matrix, and damping matrices to the robot arm. Specifically, when no collision was happening, the Unity engine streamed stiffness and damping matrices with all zeros to the robot arm, creating free motions. Although the desired position in this context was trivial, we streamed the desired position the same as the input current location ($\widetilde{\mathbf{x}}_t = \mathbf{x}_t$) for consistent data transmission. When the virtual welding tip collided with the virtual welding surface, the streamed stiffness and damping matrices became much higher. The desired position was calculated based on the contact geometry and streamed to ROS. The robotic system received the stiffness and damping matrices as well as the desired position as inputs and solved Eq. (2) to calculate the corresponding torque output. This process generated haptic feedback of touching a rigid surface. Thus, the expert could feel a similar haptic feeling as welding in real life.

Fig. 7 shows the haptic feedback in a simulated welding interaction and the change of robot torque summed at the end effector under different welding table stiffness. The positional change at the contacting point directly led to responsive haptic feedback for compensation. Higher stiffness corresponded with smaller positional error and thus higher surface rigidness. In this demonstration session, we configured the welding table stiffness as 3,000 N/m and damping at 0 referring to existing welding simulation studies (Brosque et al. 2021; Roozbahani and Handroos 2019; Wang et al. 2006). After some pilot tests, we found that the haptic feedback under this parameter configuration was stable and safe. Thus, we constructed a specialized spatial mapping function

$$\mathbf{G}_{x_e} = \Lambda_{x_e} \cdot \left[\begin{bmatrix} \mathbf{K}_1 & \\ & \mathbf{D}_1 \end{bmatrix}, \begin{bmatrix} \mathbf{K}_2 & \\ & \mathbf{D}_2 \end{bmatrix} \right]^T$$
$$= \Lambda_{x_e} \cdot \left[\begin{bmatrix} 0 \cdot \boldsymbol{I}_6 & \\ & 0 \cdot \boldsymbol{I}_6 \end{bmatrix}, \begin{bmatrix} \begin{bmatrix} 3000 \cdot \boldsymbol{I}_3 & \\ & 0 \cdot \boldsymbol{I}_3 \end{bmatrix} & \\ & 0 \cdot \boldsymbol{I}_6 \end{bmatrix} \right]^T \tag{7}$$

Because we only considered the end effector position here, $\mathbf{K}$ and $\mathbf{D}$ were the stiffness and damping matrices at the end effector in the Cartesian space counting for translation and rotation. The previous equation was used to map the spatial position and the robot control parameters. Only translational stiffness in the same direction was set to 3,000 N/m when touching the welding table.

Robot Arm for Perceptual Learning

After completing the expert kinematic and kinesthetic recording phase, the expert's motion data was replayed to novice trainees who have no prior welding knowledge. We leveraged the advantage of VR to visualize the desired motion including trajectory and force to acquaint trainees with the necessary knowledge. Other knowledge-based welding training methods (Ipsita et al. 2022; Shankhwar et al. 2022) can be conducted in this session as a supplementary. Before each training trial, the robot arm was initialized with the same beginning pose as it was in the expert recording stage. Trajectory perceptual learning was conducted by executing the impedance control algorithm with high damping and stiffness and then replaying the recorded rosbag file. Once played, the rosbag file wrote ROS topics and messages. Robotic control algorithms received the messages from corresponding topics and updated the desired values, such as $\boldsymbol{\tau}_{de}$ and $\widetilde{\mathbf{x}}_t$, and thus controlled and updated the robot status. When in trajectory perceptual learning, the robotic algorithm subscribed to rosbag topics containing positional data as the desired position $\widetilde{\mathbf{x}}_t$. Then, the robot arm could follow the same trajectory as the desired position (expert trajectory). The values of $\mathbf{K}$ and $\mathbf{D}$ determined the robustness toward the external disturbance. We tested the system stability and accuracy with two stiffness settings: 1,000 and 3,000 N/m. We found that higher stiffness for trajectory perceptual learning could reduce positional error tolerance, providing more accurate instruction. However, higher stiffness properties might lead to oversensitivity to positional error, leading to potential unstable mechanical jittering, as shown in the high stiffness condition in Fig. 8. With reference to previous studies (Roozbahani and Handroos 2019), we used $\mathbf{K} = (3{,}000 \times I_3)$ N/m to guide the trajectory perceptual learning during the system validation. For other tasks with specialized motion (speed and force), the control parameters need to be justified and tested under safety considerations.

Similar to trajectory perceptual learning, the initial position of the robot arm was reset before the force perceptual training. Under the robotic force control loop, ROS received the force data from the replayed rosbag file as the desired force ($\boldsymbol{\tau}_{de}$). Eq. (6) facilitated the torque output calculation at current robot states. In the learning process, the robot arm exerted force toward the trainee's hand. As shown in Fig. 9(a), the trainee could see the desired position of the welding tip at the time of force perceptual learning. It depended on the training protocol and trainee's preference whether the trainee observed the trajectory in place or followed the trajectory. The trainee stabilized the robot end effector, in either case, to counterbalance the

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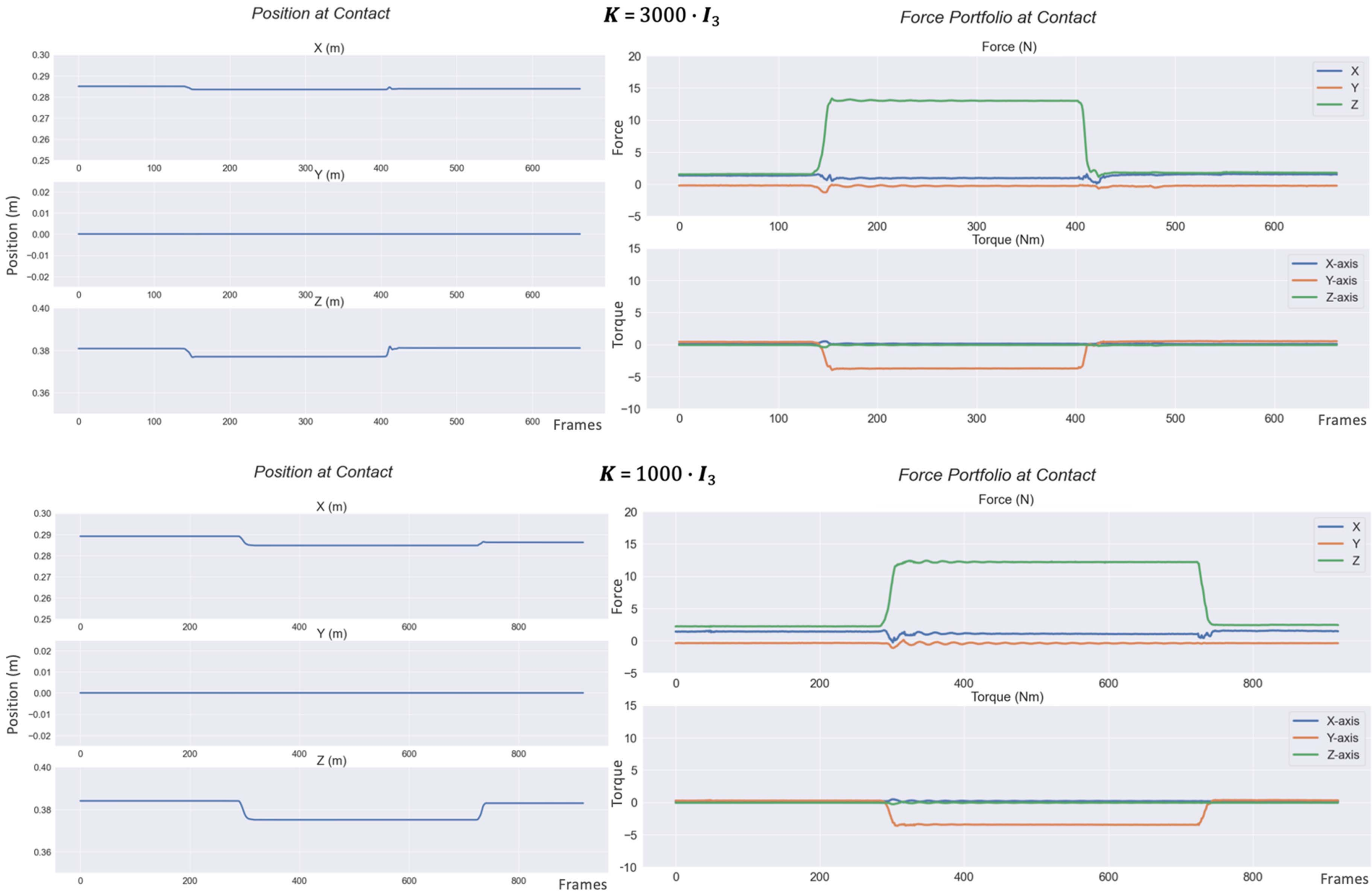

Fig. 7. Positional change and output force change when the virtual welding tip collided with the virtual welding table under the same external load.

force exerted by the robot arm and perceive the appropriate force levels. Fig. 9(c) shows the statistics during the force perception training.

In the demonstration test, it was seen that the desired force could be properly replayed to trainees regardless of the current pose of the robot arm. A delay between the robot output and trainee's response force can be observed in Fig. 9(c). This implies that trainees could compensate and adapt to sudden force field changes.

User Study

We recruited an expert welder to test the welding simulation and recorded the kinematics of him performing keyhole welding. The welder was asked to perform simulated welding, and we alternated the material to trigger different motions. The motions were all based on keyhole welding. Fig. 10(a) shows some trials of the expert motion. The recorded motions were used in the training session to validate the system design.

A total of 15 participants who had no prior knowledge of welding were recruited to learn the welding motion. We selected a within-subject design (Charness et al. 2012) to remove the impact of individual variations and improve the statistical power (Montoya 2022). In the within-subject design, participants were asked to learn the welding motion through all conditions: a control and perceptual learning condition. The objective was to learn the motion as close to the expert motion as possible. Both conditions were conducted in VR to ensure experiencing the same visual environment. In the control condition, participants were given a chance to understand the correlation between their muscular tensions and the force that they were applying: participants were asked to grab the robot end effector and press toward the welding table while the pressure was shown to them in real time. Then, participants were instructed to learn and practice the motion following the demonstration videos and force diagrams, simulating learning with traditional media. Afterward, a test trial was conducted to measure participants' understanding of such a motion, in which participants did the welding motion by themselves without the provision of any learning media. In the perceptual learning condition, participants went through the trajectory and force perceptual learning sequentially without the provision of any learning media. Then, participants' motor skills were measured by the same method as the test trial in the control condition. This learning–testing combination was repeated three times to enable potential learning in both conditions. To mitigate the potential learning effect of the within-subject experiment design, we randomly shuffled the sequence of control and perceptual learning condition. The motions were randomly assigned for each condition and each participant.

Because the task was a keyhole welding and the target motion was to weld the gap between two metal plates, the spatial trajectory was predetermined and fixed. Thus, we measured the spatial motion performance by comparing the welding completion time difference between the novice participant and expert welder. The force control accuracy was evaluated by the average pressing force. Fig. 10(b) shows the results. The data were not normally distributed [$p < 0.001$ for both spatial movement and force, according to D'Agostino and Pearson's normality test (1973)]. Wilcoxon (1992) tests showed that the control condition was significantly different from the perceptual learning condition, both in terms of spatial

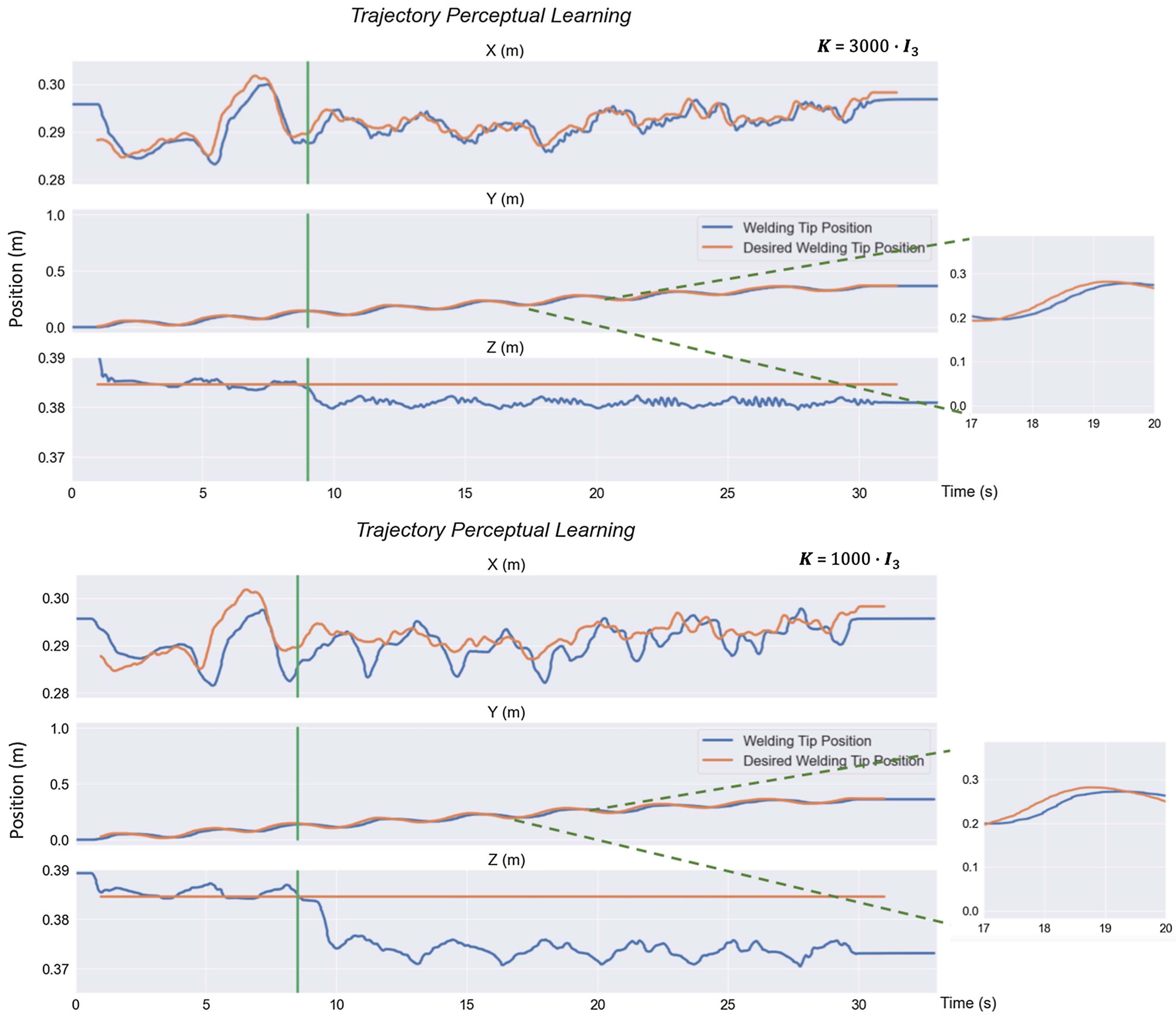

Fig. 8. Replayed trajectory. A consistent external disturbance (a weight) was applied at the time point indicated by the vertical line.

movement ($p = 0.018$) and force exertion ($p < 0.001$). From the average performance perspective, perceptual learning improved the welding motor skill training effectiveness by 10% in terms of spatial motion trajectory and 56% in terms of force control accuracy. We also performed a dynamic time wrapping analysis to compare the trajectory similarity; no significant difference was found between the control condition and perceptual learning condition, potentially due to the simplicity of the keyhole welding motion trajectory.

Discussion and Limitations

The proposed system was validated with welding training because welding is a particularly challenging scenario in terms of training skillful workers due to the high labor demand (AWS 2022; Miller 2022) and changing welding requirements (i.e., diversiform motion and force) (Nair 2022). We used rendering algorithms such as marching cube, triplanar, and fading shader to simulate the visual effect of the formation of welding metal and surface deformation. The visuals provided important references for welders. In the game engine, we assigned different objects different stiffness and damping properties. To be more specific, the metals to be welded were assumed to be rigid. In general, we essentially simulated and reproduced the over-the-shoulder welding experience as a virtual expert welder holding a trainee's hand. The simulated virtual tutor had more capability than an actual human tutor in terms of accuracy and customization and the ability to transfer force-using experience. In contrast, human tutors cannot directly teach or demonstrate force motor skills other than indirect measures such as verbal instructions and hand gripping tightness. We invited an experienced welder to record data via the system. We found that the expert recording stage in our system could effectively provide haptic feedback. The proposed SVIC method could facilitate haptic force feedback accurately and timely in response to the interactions in the simulated virtual environment. The stiffness configurations in the SVIC method could impact the haptic feedback patterns. We selected 3,000 $\mathrm{N/m}$ referring to existing studies, and the simulated haptic feedback was optimal according to the recruited welder.

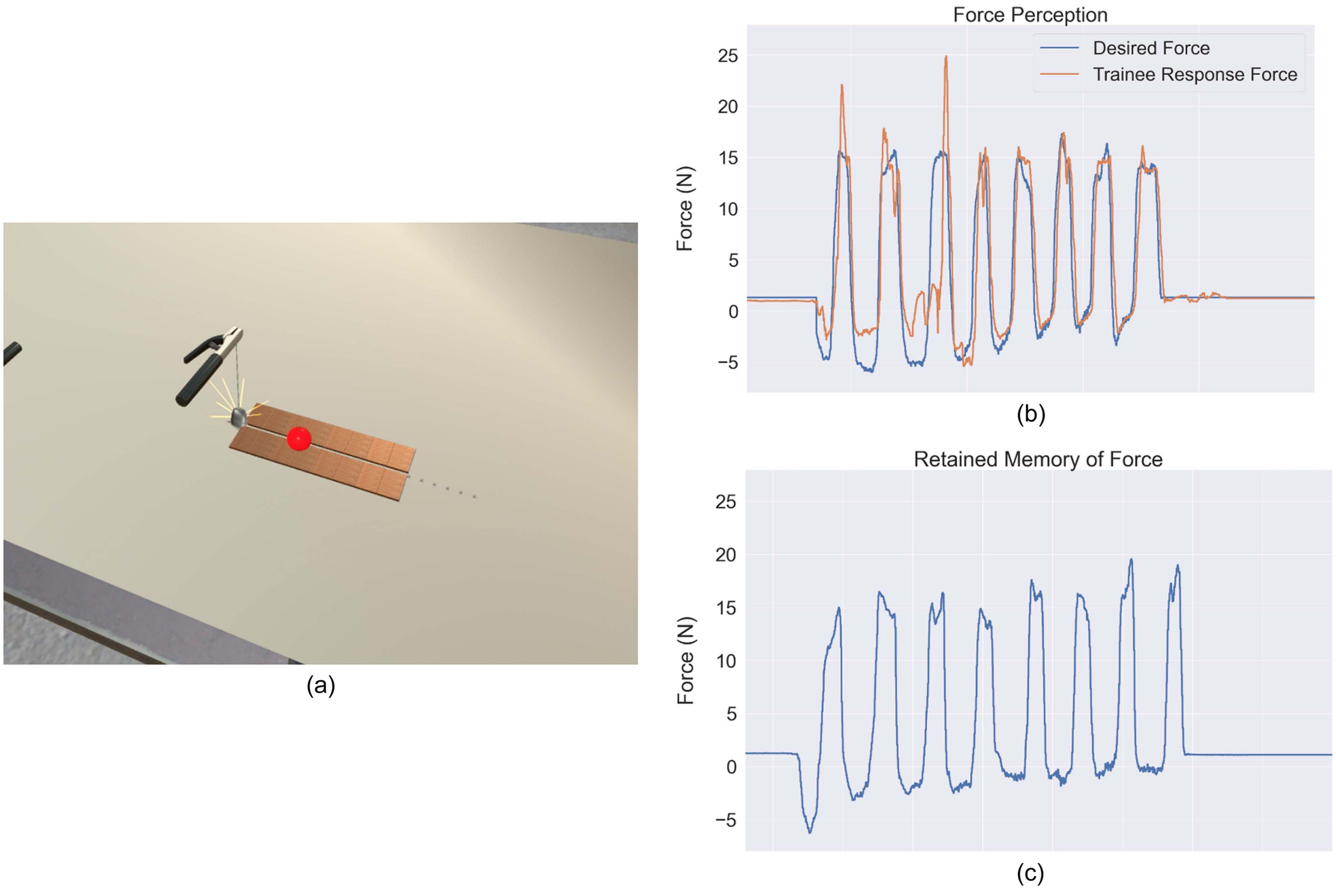

Fig. 9. Force perceptual learning. (a) While the robotic tutor exerted force for the trainee to perceive, VR visualized the desired welding tip position to create a mapping. To coordinate the trajectory and force pattern knowledge, the trainee can either observe the trajectory while holding the robot end effector in space or follow the trajectory; (b) robotic desired force as a function of time, compared with trainee's counterforce in response to the output force of the robotic tutor; and (c) trainee's perceived force level, visualized on the same scale as (b).

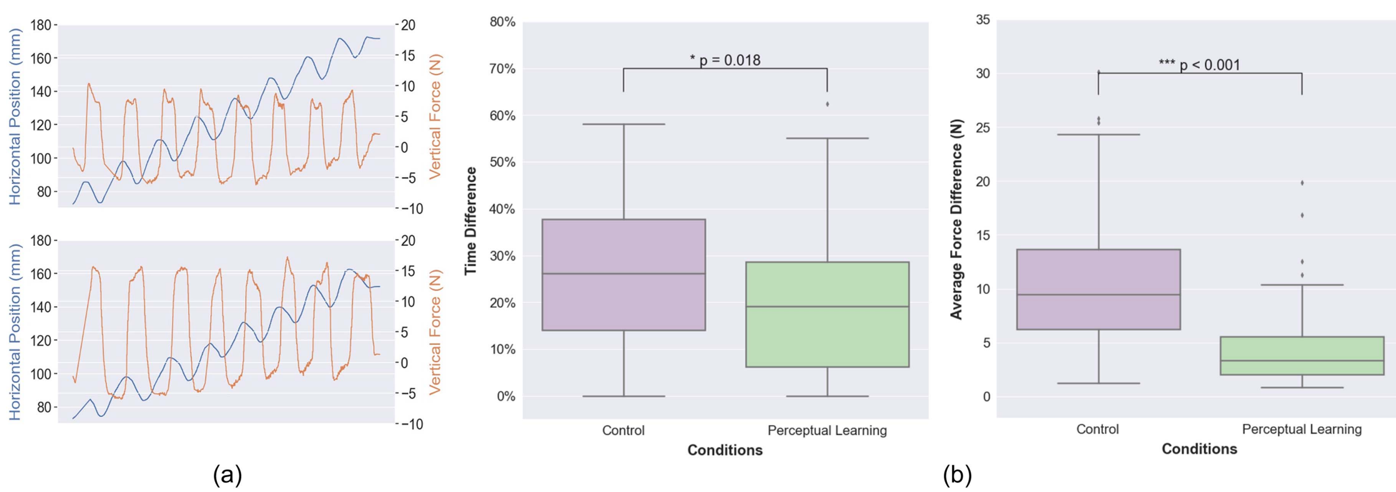

Fig. 10. (a) Example of expert motion with variations; and (b) user study results.

The perceptual training modules were evaluated by the system performance and user study. In terms of hardware performance, the recorded expert kinematics could be accurately replayed during perceptual training in general. The robot's resilience toward external disturbance was determined by the stiffness configurations in the trajectory perceptual learning module. Although a larger stiffness configuration induced a quicker mechanical response and a higher accuracy, we found that the safety risks increased along with the higher stiffness. Referring to Eq. (1), the trajectory perceptual training module considers the recorded expert motion the desired position $\widetilde{\boldsymbol{x}}_t$ and exerts a force ($\boldsymbol{\tau}_e$) to reduce such a spatial difference $(\boldsymbol{x}_t - \widetilde{\boldsymbol{x}}_t)$. The value of $\boldsymbol{x}_t - \widetilde{\boldsymbol{x}}_t$ can approach the value of $\widetilde{\boldsymbol{x}_{t-1}} - \widetilde{\boldsymbol{x}}_t$.

However, $\widetilde{x_t}$ is a set of discrete points, which means $\widetilde{x_{t-1}} - \widetilde{x_t}$ are not zero. Thus, large stiffness values amplified by the positional difference may lead to a larger exerted force ($\boldsymbol{\tau}_e$) and can potentially lead to a huge acceleration. It might overcorrect the spatial difference and even potentially hurt the operators. We visualized this effect by showing the minor jittering behavior in the high stiffness condition in Fig. 8, in which large $\boldsymbol{\tau}_e$ led to quick positional change, and then $\boldsymbol{\tau}_e$ reduced quickly, leading to unstable robotic reactions. Thus, high stiffness settings in the trajectory perceptual learning module can increase accuracy but lead to higher instability if the motion is quick. In this welding experiment demonstration, we explicitly instructed the expert not to move too quickly in order to reduce the $\widetilde{x_{t-1}} - \widetilde{x_t}$ values and thus increase system stability. For other training tasks, careful justification and tests need to be made to determine the control parameters under the consideration of safety and system performance.

We performed a user study with 15 participants who had no prior welding experience. By comparing the retained motor skills after training, the results indicated that the proposed perceptual learning method outperformed the traditional video and diagram demonstrations, both in terms of spatial motion ($p = 0.018$) and force exertion ($p < 0.001$) training. The results showed that it was effective to learn motor tasks through perceptual learning. Compared to remote learning through traditional media-based instructions, the proposed perceptual learning method provided trainees with embodied feelings of how to correctly conduct the motion, thus enhancing motor skill acquisition.

Although the proposed system was tested only for the context of welding, the system can be generally adapted to a much broader range of applications. For instance, bone sawing training (Maliha et al. 2018) requires deliciated force application and coordinated motion-force control skills. The proposed system can simulate the bone sawing process by creating multiple layers of materials with varying properties corresponding to the organism structures to create arm-scale haptic feedback. The kinematic experience of an expert physician can be recorded and transferred to a novice, creating embodied egocentric perceptual learning experience. In addition, this system can be extended to or integrated with more training protocols. Many existing studies discussed strategies to enhance complex motor skill learning in VR (Levac et al. 2019), such as reduced variability (Sternad 2015), magnifying variability (Ranganathan and Newell 2010), and error amplification (Liu et al. 2018). Our proposed system is versatile and flexible, with the potential to integrate various training theories. Meanwhile, another cluster of research explored the feasibility and effectiveness of new training protocols in VR such as virtual training courses (Ipsita et al. 2022). Our proposed system facilitates motor skill training and thus can be a complement to other knowledge-based training protocols, creating a complete knowledge-and-practice training closed loop. In short, our paper contributes to the development of the future education 4.0 era.

Several issues need to be addressed in future research. Although evidence has indicated that perceptual learning can be beneficial for motor skill acquisition as elaborated upon in the related works section, uncertainties still exist. Neurobehavioral and psychological studies generally consider motor task complexity (Donovan and Radosevich 1999; Levac et al. 2019) and individual differences (Anderson et al. 2021) important variables impacting the optimal motor skill training methods. The proposed system in this paper can capture the expert's kinematics and kinesthetics for trainees' perceptual learning, but the data captured can be inherently less consistent and subject to the expert's individual differences such as arm length and muscular performance (Chen et al. 2016; Yoshioka et al. 2015). Meanwhile, our proposed system requires the minimum participation of expert trainers, which on the one hand contributes to remote, distributed, and ecofriendly training but on the other hand lacks interpersonal interaction compared to traditional hands-on in-person training. Human trainers can provide irreplaceable help (Felix 2020) such as facial expression, body language, and emotion (O'Connor 2008). A hybrid type of training protocol that includes robot-assisted training and on-site training is recommended to leverage the benefit of human trainers as well as to transfer motor skills in practice. Furthermore, safety can also be an important concern, especially for dexterous tasks and tasks that involve high force, sudden force changes, large acceleration, or quick motion. If a trainee did not hold the robot arm tightly, a sudden desired motion or force change in the trajectory or force perception learning stage could disengage the robot arm, leading to a potential collision with the trainee's body. Although we have described some key safety measures with reference to BSI (2016), such as limitation functions on speed, spatial position, and force, safety measures still need to be customized according to the practical context. In addition, higher safety standards might on the other hand reduce the application scope of the training system because motor tasks with high speed, high force, and a large range of motion may exceed the safety limits.

Conclusion

The expertise of certain motor skills is important in many applications such as construction, manufacturing, and medical operations. Traditional on-site hands-on training is challenged due to resource-intensive and accessibility issues. A versatile motor skill training and practicing platform that is free of expensive training sites and training personnel would largely accelerate motor skill training. This paper proposed a generic robot-assisted motor skill training system and tested this system by implementing it in a keyhole welding training task. The proposed system is composed of two parts: expert kinematic and kinesthetic data recording and novice perceptual learning. VR and the robotic system work together to create seamless data sharing and interaction. VR facilitates visual feedback and synchronizes the robot status with a digital twin model to create a coordinated visual–motor experience. Meanwhile, the VR platform (game engine) uses its graphical processing capability to simulate physics and update contact-related parameters such as contact point position at the original space and stiffness to control robot operation. The robotic system uses SVIC to create haptic feedback, simulating a high-fidelity motor task experience. The expert can conduct their motion with the haptic feedback from the robotic system. The kinematic process of an expert's motor skill can be recorded and replayed to novice trainees through perceptual learning. The proposed system uses high stiffness impedance control to guide the trainee's hand through the expert's trajectory, enabling trainees to understand the motion pattern through proprioception. On the other hand, the robotic system exerts a certain force toward the trainee's hand to acquaint the trainee with the amplitude and direction of the force that the expert was applying. With this system, an expert's motor skill can be digitalized and used to instruct novice users with customized training experience: repeat, pause, or vary the speed of training as the novice trainee desires.

We demonstrated the system design with a welding training simulation. A system performance study and a user study on perceptual learning showed that the proposed system is feasible and effective. It is a future agenda to investigate whether there is a transition barrier between the motor skill learned through the proposed system and real-world operations.

Data Availability Statement

All data, models, or code generated or used during the study are available from the corresponding author by request, or the data can be accessed directly at: https://github.com/gilbert-yy/Robot-Assisted-Motor-Learning.git.

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