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Sensation transfer for immersive exoskeleton motor training: Implications of haptics and viewpoints

Yang Ye [a], Yangming Shi [b], Divya Srinivasan [c], Jing Du [a,*]

[a] Informatics, Cobots and Intelligent Construction (ICIC) Laboratory, Department of Civil and Coastal Engineering, University of Florida, United States of America
[b] Department of Civil, Construction and Environmental Engineering, University of Alabama, United States of America
[c] Department of Industrial Engineering, Clemson University, United States of America

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ABSTRACT

Exoskeletons are promising physical augmentation tools that have shown potential to transform civil engineering operations, but the training is inherently challenging due to the diverse exoskeleton designs, functions, and guidelines across different occupational sectors. Traditional hands-on exoskeleton training is time-consuming and resource-extensive, while virtual training, such as video demonstrations, is ineffective for motor skill learning needed for the exoskeleton. It is unknown if an enhanced virtual environment can facilitate motor skill gaining for exoskeleton training. This paper proposes a haptic-based sensation transfer approach that migrates the egocentric motor experience of an expert exoskeleton user to another novice user, via a passive haptic system in virtual reality. The result of a human-subjects experiment ($n = 30$) showed that the proposed haptic-based sensation transfer approach significantly improved the motor learning rate in exoskeleton training, and validated the effectiveness of virtual training for even motor-intensive tasks. The proposed haptic-based sensation transfer approach can enrich the embodied motor learning experience and thus can benefit broader applications of motor training at work. It is worth exploring optimal haptic configurations in the future, to enhance embodiment whilst avoiding potential over-reliance on feedback.

1. Introduction

The labor-intensive nature of the construction industry makes construction practitioners more frequently exposed to work-related musculoskeletal disorders (WMSD) [1]. The construction industry's WMSDs rate was about 29% higher than all other industries combined in 2019 [2]. The back and the shoulder were the most impacted body regions, respectively accounting for 43% and 16% of all cases, with a median of 8 and 25 lost workdays [3]. This high burden of WMSDs is attributed to the high physical demands of construction work, involving overuse associated with frequent and repetitive exposures to well-documented risk factors such as lifting, bending, carrying, use of hand-held tools, or non-neutral/prolonged static postures [4]. To help reduce the occurrence of WMSD in the construction industry, there is an increasing interest in exploring the use of exoskeletons to augment users' physical capabilities and provide additional support [5]. Exoskeletons, defined as wearable, assistive devices, comprised of joints, links, and actuators to assist or support the physical capacity of the wearer [6,7] are emerging as innovative and promising solutions for reducing the physical demands on severely impacted body regions such as the shoulders and back [8,9]. For example, passive exoskeleton systems have been utilized to support construction workers in repetitive handling tasks, which can effectively reduce lumbar erector spinae muscle activities, improve comfort, and reduce perceived pressure [10]. Yet, despite several successful laboratory studies showing the effectiveness of exoskeleton technologies [11–13] and their rapid pace of commercialization, there are few successful examples of successful deployment. Broader adoption of exoskeleton technologies in construction operations can be potentially transformative for improving worker productivity and safety in construction.

In terms of practical applications, current evidence suggests that the effectiveness of the exoskeleton implementation in operations is largely driven by the specific task contexts and users' characteristics [8]. Certain types of exoskeletons are more appropriate for given industrial tasks than other tasks. Within a chosen exoskeleton, different configurations and motions (e.g., bending angle) trigger different torque outputs which further lead to varying restrictions on safe ranges of motion [14]. Correspondingly, the users may also have to engage in a variety of

* Corresponding author.
E-mail addresses: ye.yang@ufl.edu (Y. Ye), shiyangming@ua.edu (Y. Shi), sriniv5@clemson.edu (D. Srinivasan), eric.du@essie.ufl.edu (J. Du).

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different movement strategies to optimally derive the best benefits from an exoskeleton: for instance, the springs in a passive back-support exoskeleton would engage only when the trunk bent by more than a certain angle. So, if a user only squatted down to handle loads without any bending, they would not experience the beneficial physical effects of the exoskeleton while lifting the load (compared to some degree of bending the back to achieve the same motion). Misunderstanding of exoskeleton capacities and restrictions can also present users with a false sense of security, and when applied to tasks where their use is inappropriate, exoskeletons may also interfere with safety [15]. Exoskeletons also have a variety of torque profiles to choose from. From a sensory perspective, the enhancement of human physical capacity has the potential to make the user unaware of their contribution to the motion (versus the device contributions), and hence have difficulty in predicting the outcome of the human+exoskeleton system, thereby potentially losing balance or moving unintentionally beyond safety ranges of motion and torques [16]. Hence, it is critical to develop good training programs that allow a user to safely explore an exoskeleton's capacities and understand their benefits and risks, before extensively using them in safety-critical environments. This is all the more important as powered exoskeletons are now being developed, which have significantly greater augmentation potential, thereby accentuating the potential sensorimotor deficits described above: early evidence points to the need for training to utilize such devices safely and effectively [17]. A motor training system that enables users to experience various types of exoskeletons and various motion tasks to develop an understanding of exoskeleton properties and safety ranges, while developing necessary human motor skills for the safe and effective operation of the exoskeleton, would support such needs. Given the limited accessibility (from the user's side) and the high cost associated with physical prototype development and human subjects evaluations of exoskeleton systems (from the developer side), enabling a virtual and distributed learning experience to experience exoskeletons, would accelerate both exoskeleton development and use.

This paper proposes a distributed exoskeleton motor training system based on the so-called "sensation transfer" that migrates the human motor experience from a person wearing a real exoskeleton to another person who does not have the access to the exoskeleton. The sensation transfer is realized through a whole-body hapto-tactile system in an immersive virtual environment. The active motion data of the expert exoskeleton user is collected via motion tracking sensors. The tracked motion data can be then "displayed" and reproduced on the novice user's end via the media of haptics. A Virtual Reality (VR) headset, motion tracking devices, and haptic devices are used to digitalize the sensorimotor experience and transfer it to a prospective exoskeleton user via the haptic stimulation. A VR headset is used to create an immersive virtual environment that enables risk-free training for various scenarios and tasks. A whole-body tracking device (MVN Awinda, Xsens Technologies B.V., the Netherlands) captures an exoskeleton user's whole-body kinematics and streams them into the VR environment. Digitalized body motions of the exoskeleton user are reconstructed in VR to create an egocentric training experience, and data are also collected from the VR interaction logs to enable real-time assessment. As a novel measure, the haptic device generates haptic guidelines to transfer the sensation of wearing an exoskeleton including the feeling of touching and resistance in movement. Combining these systems, a virtual training environment can be simulated to transfer the human motor experience of wearing an exoskeleton with visual and haptic guidance in correspond to the real-time motor performance of the user. We conducted an experiment to assess the feasibility and effectiveness of this motor training system. We pre-recorded motions from an exoskeleton expert while he used a passive back-support exoskeleton to perform lifting tasks, and re-constructed the motions in VR. We recruited 30 novice users and instructed them to follow the motion and helped them recreate and learn the human motor experience in VR under different view perspectives and the novel hapto-tactile system. We implemented a within-subject experiment design with randomized condition orders to minimize the statistical intervention from cross-condition learning effect and individual differences. The rest of this paper addresses the point of departure, framework design, experiment pipeline, and findings.

2. Related work

2.1. Exoskeleton and exoskeleton motor training

Robotic exoskeletons can generally be classified according to the intended application domain [18]: rehabilitation robots that focus on lost motor function recovery, functional assistive robots like assisting grasping for disabled people, and occupational exoskeletons for enhancing/augmenting healthy industrial workers. Occupational exoskeletons have received increasing attention for augmenting human physical capacity and reducing bodily physical demands in a wide range of industries such as the military [19,20], medical [21,22], manufacturing [23–25], agriculture [26,27], and construction [5,8,10]. Specifically, previous studies [5] have suggested that exoskeletons show strong potential for reducing the occurrence of WMSD during construction operations that involve repetitive motion [28], kneeling or crawling [22], awkward position [29], and vibrations. For instance, back-support exoskeleton use (e.g., BackX [30], Laevo [31], SPEXOR [32]) produced reductions in trunk muscle activity and spinal compression force during bending and lifting tasks, which could have the potential for specific tasks in construction trades like brick masonry, concrete work, and roofing [5]; and shoulder-support exoskeletons (e.g., Eksovest [33], ShoulderX [34]) that could provide external joint torques and/or re-distribute the load and thereby reduce shoulder load during overhead work could be applicable to tasks in carpentry, electrical, and painting work [5]. Since many of these previous studies have utilized a variety of exoskeletons with different mechanical design features, and since different exoskeletons may hence need distinctly different strategies for ideal operation, universal training strategies are neither plausible nor likely to be successful. Hence, as an exploratory and novel paradigm, we attempted a new training protocol where instead of playing back videos or using voice instructions to a novice user, we captured an expert's use of a complex exoskeleton and transferred the motion patterns to a novice user through haptic sensations. As an expert can be considered to have already adapted to using an exoskeleton, the mechanical features of an exoskeleton can be considered to be reflected in the expert's motion patterns. With the advent of Industry 5.0, where the focus is on maintaining flexibility in production by combining humans and robots collaboratively, exoskeletons are thus promising tools for the future industrial workforce [35] to ease WMSD risks and increase productivity [5].

Exoskeleton control methods [18,36] generally involve a complex interaction between human and robotic exoskeletons [37]. Although the control and usage of exoskeletons are generally safe, training for using the exoskeleton is essential [38]. In addition, to acquaint new users with the operation methods, users should also be familiar with the triggering postures and safety ranges which are important knowledge and motor skills for ensuring safe operation [39]. For instance, the exoskeleton that Wang et al. [40] designed utilized the center of mass of the user to control the mechanical response. If users failed to move the center of mass in a defined pattern, the exoskeleton would not be actuated, and potential safety hazards could occur. Other than triggering exoskeletons, the user's motion could also impact the effectiveness of the exoskeleton. The experiment that Young et al. [41] performed on a pneumatically powered exoskeleton proved that the torque output profile and the user's rectified physical load were closely related to the user's motion. In worse cases, improper motion like misalignment between exoskeleton joints and user's joints can cause body injuries such as bone fracture [39]. Thus, it is critical to train the users on what's the correct motion in the exoskeleton and how to perform the motions [42].

Typical exoskeleton training adopted hands-on training with multiple sessions that spanned several weeks [42–44]. However, the broader implementation of such training methods not only faced challenges in financial feasibility and time efficiency [45] due to the expensive exoskeleton products but also exposed users to higher risks. In addition, exoskeleton designs varied with the use cases [8,46], which further reduced the availability and accessibility of hands-on exoskeleton motor training [8]. An accessible training method that can facilitate exoskeleton motor training by accelerating the convergence when real exoskeleton systems are not available remains a question to be answered.

2.2. VR and haptics for human motor learning

With the capability of providing immersive multimodalities experience [47,48], VR has been rapidly recognized and implemented for training [49,50]. Motor training is one of the emerging topics for VR implementation [51]. In motor training tasks, VR can provide multiple forms of supporting information including movement visualization, performance feedback, and contextual guidelines [51,52]. Among the different modalities, visual feedback is the most commonly adopted method for human motor learning in VR. Doniger et al. [53] conducted an experiment with the focus of studying the influence of VR visualizations on the lower extremities motor rehabilitation of Alzheimer's disease patients, and the result suggested the augmented visual information in VR played a key role in improving motor learning. Lee et al. [54] tested a VR motor training scheme for stroke patients' upper extremities rehabilitation and found that the visual information in VR was significantly effective.

A VR-based motor skill training paradigm also enables self-directed learning, with a virtual instructor and automated feedback, where trainees can practice motor skills as long and many as they wish without further costs, in a safe manner [55,56]. In addition, game-like exercises or activities and immersive interaction in VR may promote enjoyment and motivation for training, which may enhance engagement in training and thus promote efficient human motor learning [57]. VR-based human motor learning studies have also been pioneered in various domains, including rehabilitation [58], military [59], and industry [60], using game-like scenarios and different types of feedback modalities to promote human motor learning.

Other than VR, haptic guidance is widely used for motor training as well [61,62]. However, it is still not clear whether haptic guidelines are effective for the human motor learning process [61]. Some scholars implemented vibrotactile guidelines to instruct motion spatial pattern [63] and force amplitude [64], and reported that motor task performance was significantly improved. Bark et al. [65] tested arm motion learning with visual and vibrotactile feedback, and discovered that the vibrotactile group had significantly lower motion errors. In contrast, Sigrist et al. [66] reported that people performed worse during haptic feedback condition than visual feedback condition in a rowing-type task. On the one hand, a consensus conclusion on the effectiveness of haptic sensation in motor training has not been reached. On the other hand, the existing literature focused on partial bodily motions such as hand motion and arm motion. The body coordination function of whole-body motion has not been thoroughly discussed. In addition, VR and haptic guidance have great potential to be applied for exoskeleton-related motor training, which remains an area that is under-researched.

3. Methodology

3.1. System overview

As described in the introduction, although it is ideal to have new users trained with real exoskeleton systems, the financial cost (as well as any unintended risks) are current barriers for implementation. Thus, we would like to provide a scenario of training without real exoskeletons, as an intermediate step, to improve the safety and efficiency of further training when the user can access a real exoskeleton. We propose a whole-body haptic system for this purpose utilizing user sensation transfer as shown in Fig. 1. The system consists of an exoskeleton expert module, offline data processing, and an exoskeleton novice user module. The exoskeleton expert module collects and models the motion to be trained. The offline data processing module processes the collected motion data and configures the motion in VR, while instantiating visual and haptic guidelines to assemble the expert's motion dataset. Then the dataset is transferred to the exoskeleton user's module where novice users can follow the motion in VR with visual and haptic sensations.

This framework establishes a pipeline that transfers the visual and haptic effects of motions from an expert to exoskeleton novice users via the game engine processor.

3.2. Exoskeleton expert module

The exoskeleton expert module is used in the phase for the expert motion collection. Exoskeleton experts are instructed to perform a selected training task in a defined tracking space wearing exoskeleton. The training is defined by the type of motions and the model of the exoskeleton. Exoskeleton types and models are chosen according to the motion characteristics to fit the task context or can be customized according to the objective of training managers. A variety of motions can be collected and assembled. Whole-body motion kinematics was collected (MVN Awinda, Xsens Technologies B.V., the Netherlands [67]), with 17 sensors deployed at proper positions on the exoskeleton expert according to product specifications to track and document the whole-body motion at a frequency of 60 Hz. The collected data shows tracking positions and corresponding time series spatial position and rotation data, in addition to the logic correlation between components. Fig. 5 (a) shows an example in which a back-exoskeleton expert is wearing the XSENS sensors for motion capture.

3.3. Offline data processing

Expert motions are transferred to a game-engine-based offline data processing pipeline. This pipeline reconstructs visual and haptic characteristics from the raw motion data. The first step is re-constructing the expert's motion in VR through data formatting, body components registration, and configuring animation. The collected XSENS data can be transformed to film box (FBX) format which is accessible by Unity Engine in terms of hierarchy time-series datasets [68]. To establish the connection between FBX files and VR avatars, the FBX files are manually or automatically configured in Unity depending on the data collection mode. The two middle pictures in the Fig. 1 Motion Reconstruction in VR block show the key point registration process where the XSENS tracked points are mapped in a VR-supported virtual avatar. This configuration explicitly links the virtual avatar's whole-body motion to the real-life expert's motion. Then the configured files can be accessed as animation documents in Unity which are further attached to animation controllers to control the virtual avatar's motion. By configuring the animation controller with a virtual expert, the exoskeleton expert's motions in the physical world can be reconstructed in VR. The reconstructed animations are used as visual guides for the training.

The haptic guidance is configured based on the recorded motion in the form of hapto-tactile generated by bHaptics devices [69]. We designed a whole-body haptic stimulation system based on the bHaptics suit and the corresponding vibrators (Knoxlabs Inc., Los Angeles, CA). Fig. 2 (a) illustrates the configuration and deployment of the system. As shown, the upper body is equipped with a Tact-suit vest that includes 40 vibrotactile motors. Haptic sleeves with 12 motors each are placed at the left and right elbow. Two haptic gloves with 6 motors each are placed on the left and right hands respectively. The selection of body locations is based on the consideration of the key body parts in intensive human motor activities. Based on these principles, we placed the haptic

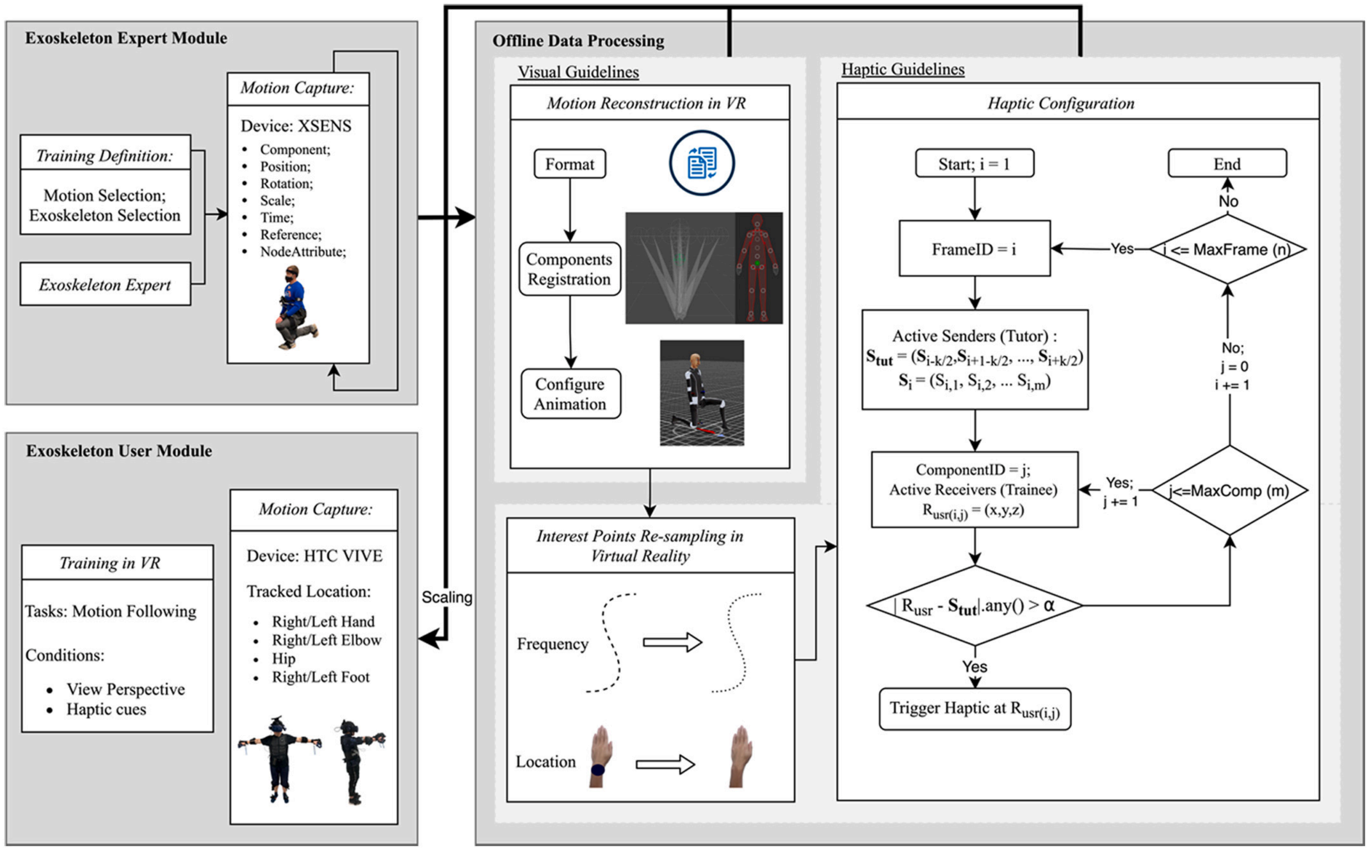

Fig. 1. System Framework of Exoskeleton Haptic Motor Training.

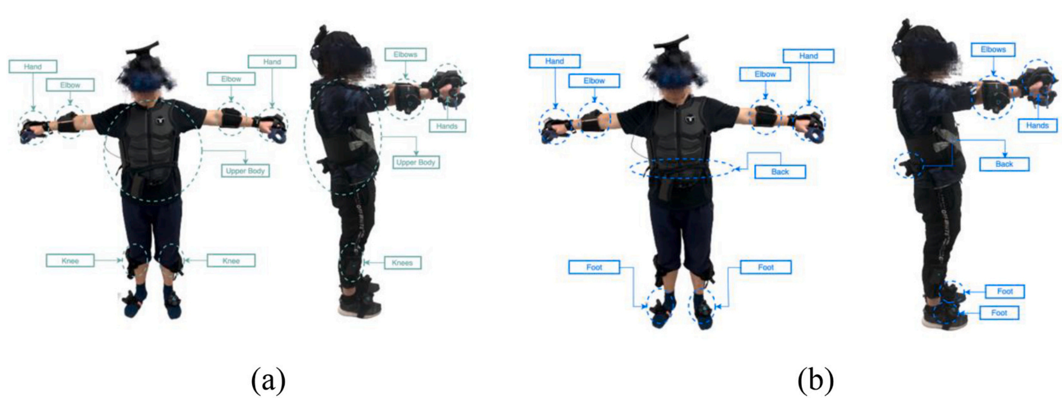

Fig. 2. (a) Haptic Simulation System Deployment; (b) Joint Layout for Whole-body Tracking and evaluating the performance.

vibrators on two knees instead of feet. The vibration magnitude is adjustable based on the manufacturing guidelines of bHaptics devices (120 Hz at 3 V input, with a strength of 5 g), depending on the degree of discrepancy between actual motion and target motion, such that closer the motion to the required target motion, the stronger the vibration experienced by the user.

It should be noted that the VR game engine is calculating and broadcasting data frame by frame instead of continuously. In VR, the hapto-tactile feedback is triggered at certain frames. The VR update frequency is typically not the same as the motion capture frequency of expert behaviors. In addition, the specific points in space tracked by the XSENS system may not be the same as the hapto-tactile points. For instance, SteamVR, a widely used VR platform, updates VR frames at 90 Hz by default; VR tracking devices (e.g., HTC VIVE [70]) track a hand using the position of the hand-held controller while the XSENS IMU system tracks a band worn at the wrist. This misalignment makes it infeasible to set up haptic feedback directly from the collected data. This problem can be solved by motion reconstruction. We tuned the VR frequency and selected new tracked points in VR to resample and log the spatial-temporal information. The resampled data thus contains the position of new body components with desired frequency. For example, the position of the right palm is computed at 90 Hz although the original XSENS data only had the position of the right wrist at 60 Hz. This resampled data, which specifies the location of the expert's desired body parts at desired time points, is then used as training data for the novice users.

After resampling the points of interest in VR, to create haptic guidance, the basic principle is to instantiate invisible haptic senders at the expert's position and haptic receivers at the novice user's body. Hapto-tactile feedback will be triggered once the sending and corresponding receivers collide with each other in space. The flowchart on the right side of Fig. 1 shows the logic behind haptic guidance. Once training is started, starting from the first frame of the whole-body motion of the expert, frames are refreshed in real-time. Each frame is subjected to a computational process to determine the haptic response according to the current novice user motion. In each frame, the program will activate the haptic senders that are within a certain period that covers k frames before and k frames after the current i^{th} frame. In other words, haptics will be triggered when haptic receivers (from the novice user) collide with any haptic senders (from the expert) that are no more than k frames before or after the current frame. Fig. 3 shows the time correspondence between the novice user's timeline and the expert's timeline. A novice user's timeline represents the online process that flows corresponding to real-time. The expert's timeline is the time-series data that we processed in previous steps and is stored offline. The value of k can be customized according to desired tolerance and computational resources. A lower k-value means a more accurate tracking and a larger k value results in a larger temporal tolerance, and the parameter k can be set according to both task needs (how accurate does the training need to be), and the availability of computational resources. The expert's effective frames are nonrecurrent in boundary conditions. Depending on the haptic pattern of bHaptics devices, a single vibration signal might last longer than one frame, which can result in a stacked haptic activation signal. To solve this problem, stacked haptic activation signals need to be cleared so the signals will not accumulate or cause residual effects. The activation of the expert's frames can be turned to be continuous as shown in Fig. 3 or can be discrete, for instance, activating once every t frames. According to how sparse the expert's frames are activated, discrete activation of the expert's frame might lead to an inaccurate haptic feeling due to some missing frames. The advantage of a discrete pattern is to save computational resources thus lowering the hardware burden.

Each frame of both novice user and expert contains a matrix of positional data of all interest points as expressed below:

$$A_i = \begin{vmatrix} \overrightarrow{P_1} \\ \overrightarrow{P_1} \\ \cdots \\ \overrightarrow{P_m} \end{vmatrix} = \begin{vmatrix} x_1 & y_1 & z_1 \\ x_2 & y_2 & z_2 \\ \cdots & \cdots & \cdots \\ x_m & y_m & z_m \end{vmatrix}, \text{m is the number of interest points}$$

The program will run through all body components (interest points) from $\overrightarrow{P_1}$ to $\overrightarrow{P_m}$ per user's frame. A body component at a certain frame has a 3-dimensional position $\overrightarrow{P}$, where a haptic receiver is activated. The algorithm checks whether the distance between $\overrightarrow{P}$ and any active haptic senders with the same body component ID are smaller than a threshold value α. If no effective sender is found, the program will continue to check the next body component until all components are finished. Otherwise, if any effective sender is within the threshold range, the algorithm will trigger the hapto-tactile feedback in the current frame at the corresponding body components and then continue to loop overall body components. Once a Bhaptics device is triggered, the embedded motors will vibrate with a pre-determined pattern. This algorithm runs in each frame until the training finishes.

This haptic configuration calculates the accuracy of motion in real-time and provides haptic feedback to reward correct motion. Haptic feedback functions as a positive feedback which denotes relatively accurate motion. When the exoskeleton novice user repeats the motions accurately, i.e., following the desired motion trajectories and velocities in the 3D body motion space, the haptic devices provide hapto-tactile feedback, creating an illusion of physical contact, or the feeling of wearing an exoskeleton. When the exoskeleton user veers off the track of more than a customized threshold value, the haptic-based sensation disappears completely, generating a feeling of having taken off the exoskeleton. Hapto-tactile is triggered once per activated haptic spot with an intensity of 50% of the maximum bHaptics device intensity. A demonstration video can be found here: https://youtu.be/S9bqf7fwaAQ

3.4. Exoskeleton user module

The visual guidance (reconstructed expert's motion) and haptic guidance are assembled to provide novice users with appropriate motion guidance in VR. While creating the data in VR, to tackle the differences in height between novice users and the expert, the expert dataset is scaled in space according to each novice user's height. VR motor training can be conducted under different virtual environments, mimicking various working conditions. Tuning the visual and haptic configurations can also provide different training conditions. Sensors from HTC VIVE are used to track the novice users' real-time whole-body motion [71]. The number of HTC VIVE sensors and their locations need to be carefully designed to track motions accurately while minimally interfering with the motion. The VIVE trackers are placed on the lateral sides of the right and left elbows, on the back, and on the right and left feet as shown in Fig. 2(b). The HTC VIVE controllers and headset also track the hands and head respectively. The captured data is instantaneously streamed into Unity engine to establish a connection between novice users' physical motions in the real world and their virtual bodies in VR. So, the novice user can see their body movement in VR which provides an immersive egocentric training scenario.

Visual guidance is delivered in the form of virtual experts demonstrating the performance of sample motions for the novice user to follow. Novice users can observe the motion from multiple view perspectives (i.e., the third-person view and the first-person view) and follow along. When activated, haptic receivers are activated on the novice user's body while haptic senders are activated and deactivated in space according to the time. Fig. 3 (a) and (b) demonstrate the VR visual and haptic guidelines for users at different stages of motion. The semi-transparent figure together with the two solid figures is the visual guidance that

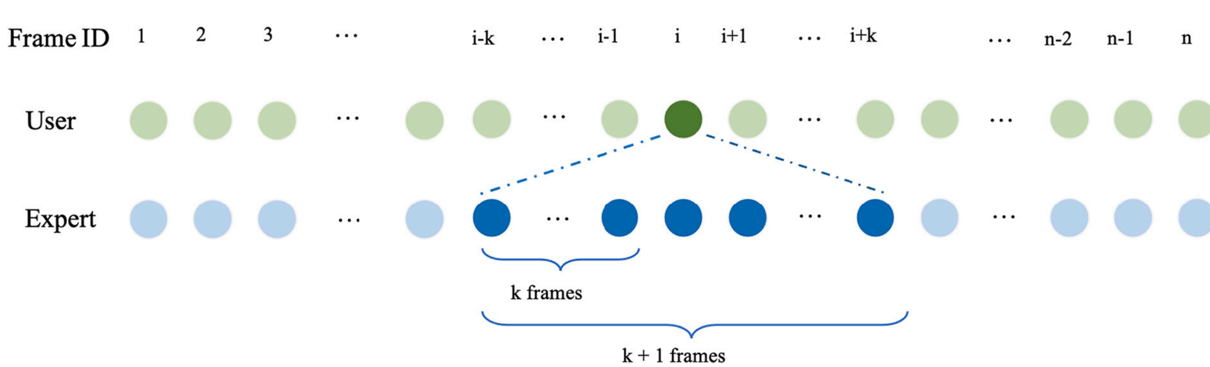

Fig. 3. Time Correspondence between novice user's and expert's timeline; Solid green circle denotes the current frame in which the novice user is being trained; Solid blue circles denote effective (active) frames that expert is performing the motion. When the novice user's motion in the current frame is the same as any effective expert frame, hapto-tactile will be triggered. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

users can observe and follow. A semi-transparent figure is a visual for an egocentric expert tutor, where users can align their body with the expert and observe the expert's motion from a first-person view. Solid figures are the virtual experts in the third-person view. The red spheres inside the semi-transparent figure demote the points at which users receive haptic guidance. The haptic senders are invisible when implemented, and are rendered with red color in Fig. 4 only for demonstration purposes.

4. Human subjects experiment

4.1. Overview

This haptic-based sensation transfer framework establishes a pipeline for transferring the motor skills of an exoskeleton expert to a novice user. Compared with traditional motion training methods that use 2D media (slides, documents, videos) or demonstration-and-follow methods, this framework enables an egocentric training experiment and haptic-based sensation transfer. We conducted a human-subject experiment using 30 healthy participants, to test the effectiveness of the proposed framework, as well as the marginal contributions of haptics-only against 3rd person view motor training method.

4.2. Experiment tasks

Since bending and lifting are common motions that result in WMSD in construction operations [1,72], we chose a standard Direct Ground Lift (DGL) motion [73] as the target motion for exoskeleton training. DGL started with half kneeling and then bending at the back to reach the object and lift it. After standing up with the object held, the DGL performer needed to walk to the destination and finally lay the object on a table.

A back exoskeleton was used to assist DGL motion. An exoskeleton expert was recruited to perform DGL motion wearing a back exoskeleton using standard approaches. Fig. 5 (a) shows the expert using a BackX exoskeleton system in the DGL task. XSENS trackers are used to track the expert's whole-body motion. The exoskeleton expert repeated the motion multiple times, and that each motion had small deviations in speed, timing, and amplitudes that characterize the natural variation in human movements. The recorded motions were processed through offline data processing to initiate visual and haptic guidance as shown in Fig. 5(b), which were used as the expert tutor motion for this experiment.

Recruited subjects were instructed to perform the exoskeleton tasks in the user module. View perspective as a variable that was proved to be impactful for the learning process, and hence we added it as a control variable in this experiment. To validate the effectiveness of haptic-based sensation transfer, we designed four conditions with variances in view perspective and haptic feedback: Third-person view (TPV), Third-person view with Haptic (TPVH), First-person view (FPV), and First-person view with Haptic (FPVH). TPV, in which novice users simply observed replayed motions in third-person view with no haptic cues, served as the baseline control condition to which all other experimental conditions were compared. The experiment procedure block in Fig. 6 showed some visuals of conditions. Human figures denote expert's motion. Yellow icons in space denote haptic senders and were invisible during the experiment.

In the TPV condition, two virtual experts performed correct motions in front of the subjects. One expert was facing the participant while the other had their back facing the participant. Participants were asked to observe the two virtual experts' motion whilst following the motion as accurately as possible, simulating a typical traditional demonstrate-and-follow method. In the TPVH condition, haptic feedback was added, i.e., novice users could feel vibrations on their body parts with the haptic system when the corresponding body components were moving accurately. In an egocentric visual condition, or "FPV", novice users could observe the motion from the first-person perspective. We set a virtual avatar semi-transparent (Fig. 4, Fig. 6) so the novice users could see through the expert while observing their motion. Instead of seeing the two experts that exhibited the motion in the third-person view, they observed a semi-transparent virtual expert performing target motions standing at the same location as the novice users. The novice users were instructed to align with the virtual expert before starting and follow the motion accurately. The novice users observed the virtual expert from an egocentric view, simulating the visual effect of doing the motion on their own. In addition to FPV, the FPVH condition activated positive haptic feedback when the novice user's motions were correct. In all conditions, novice users' tasks were to follow the experts' motions as accurately as possible. This controlled experiment design could distinguish the effectiveness of haptic-based sensation transfer by comparing TPV with TPVH, and FPV with FPVH, while providing implications on the role of view perspectives. Novice users were asked to perform the task for six continuous trials per condition to examine performance improvements and learning.

The hardware and parameter configurations used were the same across all conditions. The bHaptic devices were placed at points of interest as described earlier. The haptic senders (expert's frames) were continuously activated with a time window of 100 ms (90 Hz, k = 4). The haptic spatial tolerance α was 10 cm.

4.3. Experiment procedure

Fig. 6 shows the experiment procedure. Thirty healthy participants, with no recent (last 12 months) musculoskeletal or neurological disorders were recruited in this paper. Eligible participants were briefed on the experiment's purpose and procedure. We facilitated the participants to set up the VR headset, VIVE trackers, and the bHaptic devices. Then we demonstrated the use of the devices to the participants. This experiment adopted a within-subject design to minimize individual differences [74]. To rule out the initial adaptation process to our system from the final data, we demonstrated the experiment task (standard DGL motion) in great detail and allowed participants to practice an example task with the system for 3 min. This allowed enough time for the

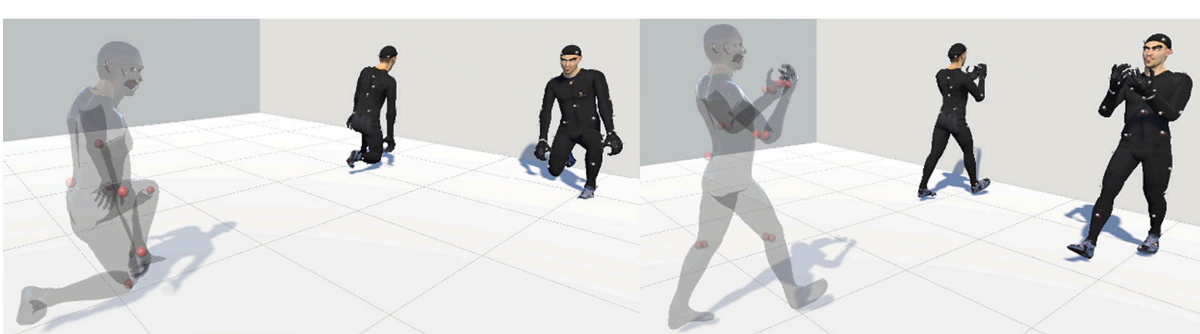

Fig. 4. Visual and Haptic Guidelines in Exoskeleton User Module.

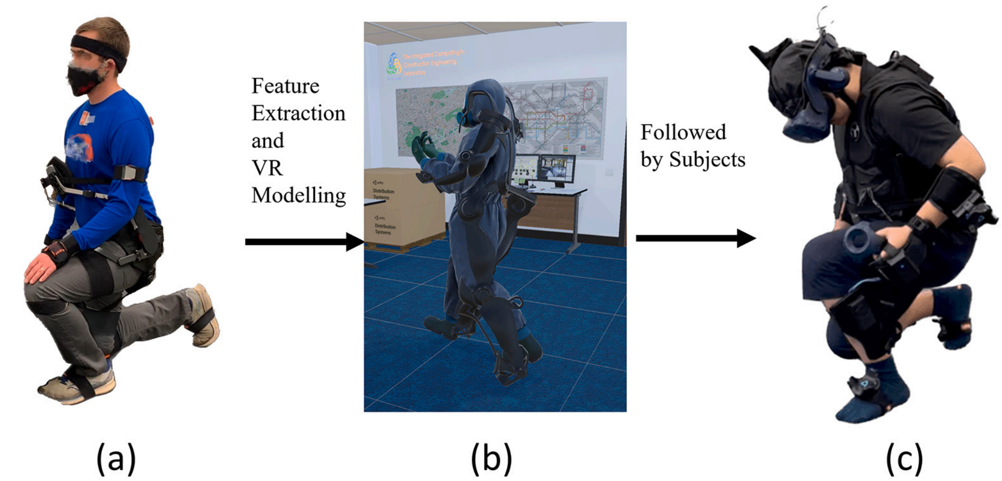

Fig. 5. (a): DGL by an experienced exoskeleton expert with a back exoskeleton. (b): *Re*-constructed VR expert according to the DGL motion by the experienced expert. (c): Training scenario where a system user (novice user) is following the DGL motion in VR.

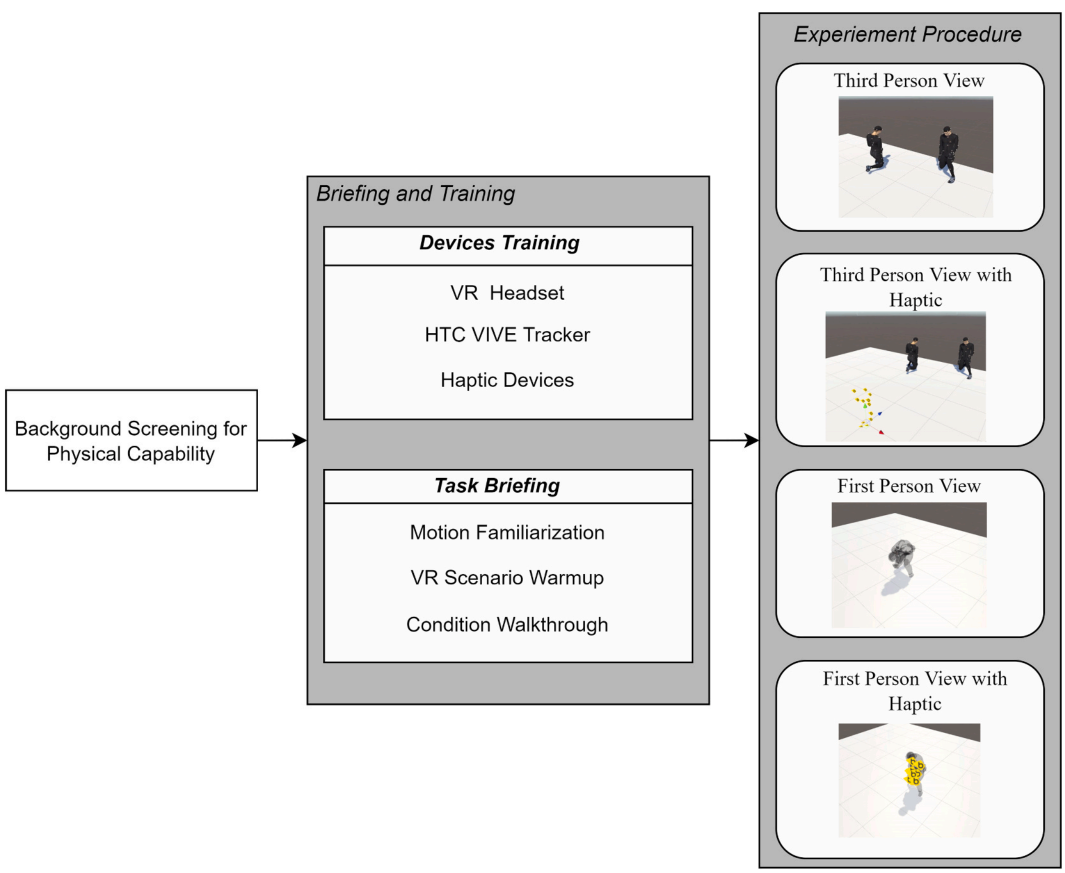

Fig. 6. Experiment Procedure.

participants to familiarize themselves with the system and the task.

After the pre-experiment briefing and training, we formally started the experiment. Each participant needed to go through all four conditions. The sequence of four conditions was randomly shuffled to further reduce the learning effect. A total of six training trials plus one retention trial were collected in each condition to reduce the significance of random error. In contrast to training trials, the retention trial was performed without visual cues or haptic guidance such that the participants needed to rely on their acquired muscular memory to repeat the motion. A NASA TLX questionnaire was conducted after finishing all 6 trials in each condition. Participants were allowed to take a short break between each condition. We collected the whole-body motion data during the experiment, which was further processed in data analysis. This study was approved by the Internal Review Board (IRB) at UF under IRB202100144.

4.4. Data collection

4.4.1. Data structure

Fig. 7 shows an example of a participant performing the task. After

Fig. 7. Example of a participant performing the task.

reconstructing the virtual whole-body motion, we sampled the time series of the 3-dimensional spatial data of both hands, both elbows, waist, and both feet. The seven sampled positions were used to evaluate motion performance. Fig. 8(a) shows a visualization of the trajectory of these sampled positions from a randomly selected trial. Each point in Fig. 8(a) represents the corresponding spatial position in one frame. Because the data were sampled with the same interval, the density of the data indicates the moving speed – with a faster movement leading to sparse data points. It shows that the data points were denser at some locations than others, suggesting that the participant's moving speed varied during the motion.

4.4.2. Motion performance evaluation methods

Expert's and novice user's motions were recorded in the same game engine environment with the same initial position. The explicit instruction provided to participants in this study was to copy the behavior of the experts to the greatest extent possible. If this were a naturalistic scenario where people were asked to accomplish a task, different individuals will show variability in "how" they accomplish the task. But given this experiment was designed for asking novices to mimic the expert motions, the performance measurement in this study focused on the motion trajectory alignment, i.e., how the motion trajectory of the participants varied from the desired one. This is the most relevant measure in the context of a motion task. We quantified human motor performance by comparing the cumulative spatial offset across the seven selected body components between the expert's motions and the participants' motions, with the idea that the greater the error in cumulative joint position difference (discrepancy) between expert's motion and the participants' motion, poorer the performance. Eq. (1) describes the how to evaluate the performance by measuring the motion discrepancy:

$$g(i) = \sum\nolimits_{n=1}^{m} (f(i,n)) \tag{1}$$

where $g(i)$ is the discrepancy for trial i, m is the number of selected body components (shown in Fig. 2(b)), $f(i,n)$ is the discrepancy between the participant and expert at trial i for component n. Fig. 8(b) compares a participant's spatial position (green scatter plot) against the expert's motion (red scatter plot). The criteria of selecting body location for analysis is whether the motion of such body location could be impacted by exoskeleton. In this study, we used BackX exoskeleton as a use case. BackX has passive springs at the hip joints on both sides, and these springs are producing additional torque at the hip joints and lower limb. Meanwhile, BackX imposes force on the chest to balance the overall mechanics [10]. The sum of the external torques, and any restrictions in joint range of motion produced by wearing the device are the main reasons to expect changes in movement strategies [11]. Changes in joint torques and muscle activities among hip, lower limb and chest could impact trunk and lower limbs motion. In addition, not only the chest is the positional base of shoulders and arms, but also the contraction of pectoral muscles could control the overall motion of arms in a higher level [12]. Thus, chest position and muscular activities are closely related to the motion of upper limbs. Although there is not sufficient

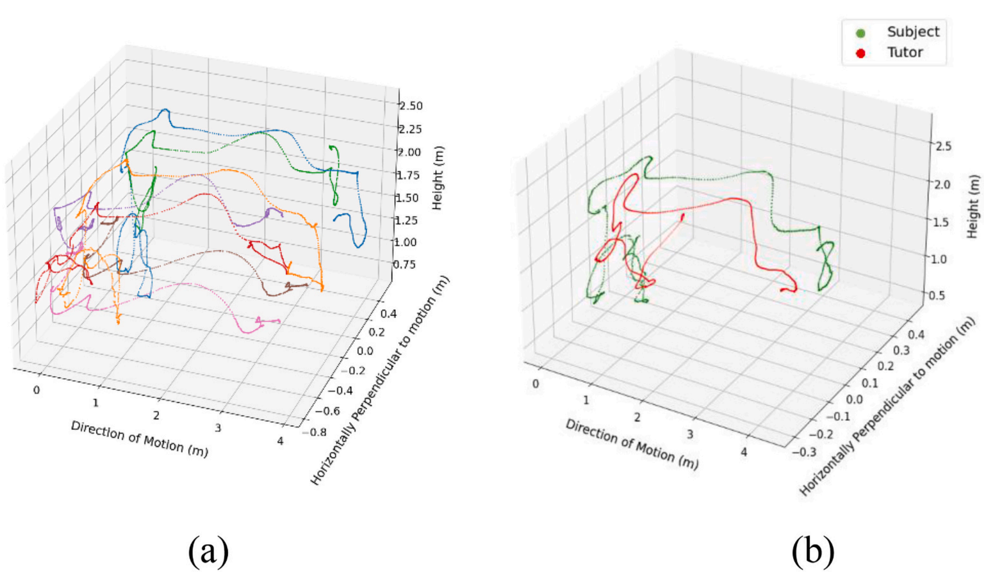

Fig. 8. Motion Trajectory: (a) spatial position of selected body components including right and left hand, right and left elbow, waist, right and left foot; (b) comparison of the trajectories between a participant and the expert's motion.

evidence showing how back-support exoskeleton impacts the motion of upper limbs, it is still necessary to include upper limbs in our analysis considering that back-support exoskeletons impact chest muscle activities, especially during bending and lifting tasks [10]. Thus, we sampled 7 body points (shown in Fig. 2(b)) across upper limbs, lower limbs, and trunk to evaluate users' motion in this study.

$f(i,n)$ is calculated in Pairwise Euclidean Distance (PED) and Interpolated Dynamic Time Wrapping (IDTW) to extract difference patterns. PED has been widely used for spatial similarity calculation [75] [76]. PED is indicated by the average Euclidean Distance between the participant's position and the expert's position for each frame and each component as shown in the equation:

$$f(i,n) = \frac{\sum_{k=1}^{t}\left(\boldsymbol{p}_{i,n,k} - \boldsymbol{p}'_{i,n,k}\right)}{t} = \frac{\sum_{k=1}^{t}\sqrt{\left(dx_k^2 + dy_k^2 + dz_k^2\right)}}{t} \tag{2}$$

where i and n are the trial ID and component ID respectively; t is the number of effective frames; $\boldsymbol{p}$ and $\boldsymbol{p}'$ are the spatial arrays of the participant and expert respectively; dx_k, dy_k, $dz_k$are the Euclidean distance between participant and expert at frame k in x, y, and z dimensions. PED took the temporal correlation into account. In other words, a mismatch between velocities is considered in PED, which calculates the spatial-temporal discrepancy as shown in Fig. 9(a).

On the other hand, IDTW emphasizes the spatial discrepancy only. The datasets are interpolated to smooth the curve such that the influence of velocity is decreased. Then DTW method is used to calculate the spatial discrepancy. DTW is commonly used to compare the spatial similarity between two temporal sequences which may have different speeds. As shown in Fig. 9(b), DTW warps non-linearly in the time dimension to find the optimal shape match between two spatial trajectories. Compared with PED, DTW weakens the influence of time (speed) and thus provides results prone to a shape comparison.

Both PED and IDTW are applied in this experiment to extract different features.

4.4.3. Learning stage and learning rate

We collected 6 trials in each condition for each participant. In order to examine if the human motor skill can be improved as the number of training trials increases, we categorized the experiment trails into different phases according to their sequence. The trials with clear instructions and guidance were considered as learning stages, while the trials without any additional guidance constituted the retention stage. To reduce random error, we grouped 2 trials into one learning stage, i.e., the early stage corresponded to trials 1 and 2, the middle stage corresponded to trials 3 and 4, late stage corresponded to trials 5 and 6. The task performance in each stage was evaluated by the average discrepancy of the corresponding two trials.

Learning Rate (LR) is one of the most important parameters for evaluating learning effectiveness. In this 3-stage learning task, we can approach LR by dividing the late stage by the early stage. Considering that the stage performances are measured by the discrepancy, we calculate the inverse of the division, thus the LR θ is calculated by:

$$\theta = \left(\frac{D_3}{D_1}\right)^{-1} = \frac{D_1}{D_3} \tag{3}$$

where D_1 and D_3 are the discrepancy in early-stage and late-stage respectively. If θ is larger than 1, it implies positive learning. The larger θ is, the higher LR is.

5. Results

5.1. Overview

The participants included 11 females and 19 males. Participants' age ranged from 19 to 32, with a median value of 25 years old. The participants on average did exercise 3.7 times per month with a median value of 4 times. 20 out of 30 participants had experienced VR previously. We also collected the participants' motor-control-related experiences, for instance, Yoga, Kung Fu, or gym training with specific muscular training goals. 18 out of 30 participants reported that they have had muscle-related training. Table 1 summarized the demographic factors.

5.2. Task performance

5.2.1. Whole body motion discrepancy

Fig. 10 shows the whole-body (all 7 tracked body components) discrepancy data across all trials, conditions, and participants. Each data point represents the average discrepancy in meters across 7 tracked positions for all frames in one trial. Due to the complexity of whole-body motion and cognitive burden, we observed random cases in which participants cannot follow motion accurately. The average spatial discrepancies varied from 5 to 35 cm, and sometimes higher. To eliminate individual differences and form a comparison baseline, each subject's data was normalized by its standard deviation of discrepancies before the statistical test. In a normality test (Anderson Darling Test), the normality assumption was rejected (with a confidence interval of 95% for both analysis methods).Left: spatial temporal result (PED); Right: Spatial result (IDTW).

Non-parametric repeated measures (Friedman test) showed that there were significant differences between conditions for both PED and IDTW outcomes ($p < 0.001$), which implied that conditions did impose a

Table 1
Demographic factors of recruited participants.

Demographic Factors	Response Range	Mean/ Percentage	Median
Gender	Male/Female	63% Male	–
Age	19–32	25.5	25
Exercise Frequency (Per Month)	0–12	3.7	4
Existing VR Experience	Yes/No	67% Yes	–
Experienced in motor control/ learning (e.g, Yoga)	Yes/No	60% Yes	–

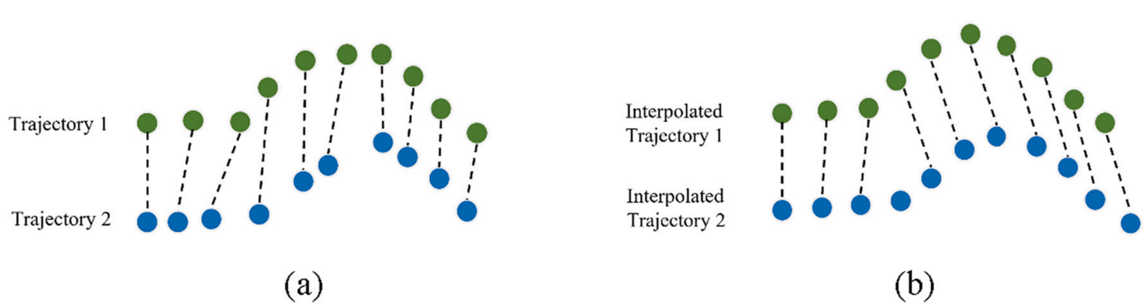

Fig. 9. Pairwise correlation between two trajectories by using (a) PED; (b) IDTW.

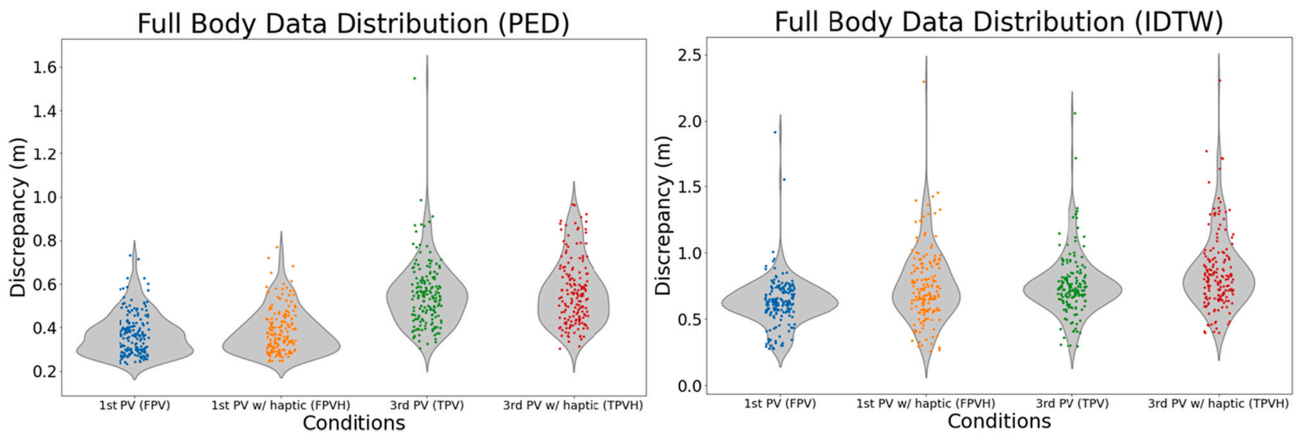

Fig. 10. Whole-body overall discrepancy distribution.

significant impact on the task performance. Then we sub-divided the dataset into learning stages. Fig. 11 shows the task performance broken down into early, middle and late stages.

We conducted a pairwise non-parametric posthoc test (Wilcoxon signed-rank test) to estimate the effects of haptic feedback, and to estimate the effect of view perspective, separately. The Wilcoxon pairwise test was used to compare performances in the early stage, middle stage, and late stage of learning, as well as the retention result and Learning Rate (LR). Table 2 summarizes the Wilcoxon test results. PED results were generally non-significant except between the early stage of FPV and FPVH condition, with a p-value of 0.021; with FPVH condition producing worse results than FPV in the beginning. This indicates that in the first-person view, haptic feedback led to a deteriorated performance in the beginning, and did not significantly influence performance in the later stages. This may be because our subjects were not used to the haptic feedback they received, or due to some extra cognitive burden that subjects may have experienced. IDTW whole-body results were significant in the overall performance between TPV and TPVH conditions ($p = 0.001$), FPV and FPVH conditions ($p < 0.001$). In addition, IDTW results showed a significant difference between the late stage of TPV and TPVH ($p = 0.030$), and both early and late stages of FPV and FPVH conditions (both with a p-value <0.001). Thus, haptic significantly impacted the motion trajectory shape throughout the motion. Meanwhile, all performances exhibited significant differences between first-person view training and third-person view training.

In general, the performance in the retention trial was worse than in the training trial, potentially due to the high spatial-temporal complexity of this task. PED results showed that the residual effect after training with FPVH was substantially different compared to after

Table 2
Significance by Wilcoxon Test (whole-body performance).

Analysis Method	Comparison	p-value: TPV V.S. TPVH	p-value: FPV V.S. FPVH	p-value: TPV V.S. FPV	p-value: TPVH V.S. FPVH
PED	All	0.256	0.090	<0.001*	<0.001*
	Early Stage	0.457	0.021*	<0.001*	<0.001*
	Late Stage	0.273	0.279	<0.001*	<0.001*
	Retention	0.633	0.098	0.893	0.063
	LR	0.877	0.192	0.517	0.039*
	LR Mean (Median)	1.078/ 1.088 (1.062/ 1.079)	1.109/ 1.181 (1.111/ 1.116)	1.078/ 1.109 (1.062/ 1.111)	1.088/ 1.181 (1.079/ 1.116)
IDTW	All	0.001*	<0.001*	<0.001*	<0.001*
	Early Stage	0.059	<0.001*	<0.001*	0.016*
	Late Stage	0.030*	<0.001*	<0.001*	0.003*
	Retention	0.191	0.705	0.345	0.874
	LR	0.530	0.766	0.033*	0.171
	LR Mean (Median)	1.010/ 1.007 (1.001/ 1.002)	1.129/ 1.182 (1.045/ 1.064)	1.010/ 1.129 (1.001/ 1.045)	1.007/ 1.182 (1.002/ 1.064)

FPV ($p = 0.098$) and after TPVH ($p = 0.063$). Average retention performance results showed that FPVH had the lowest discrepancy (best performance) among other conditions.

Learning rate results were not significant between the conditions with or without haptic. PED results' learning rate had average and median values of 1.078 and 1.062 in condition TPV, 1.088 and 1.079 in condition TPVH, 1.109 and 1.111 in condition FPV, and 1.181 and 1.116

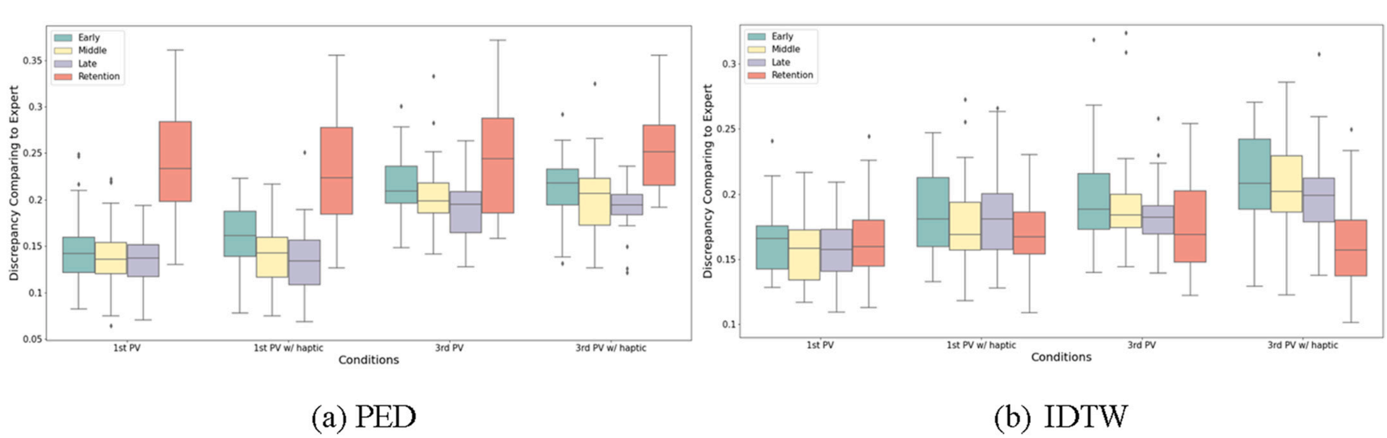

Fig. 11. Discrepancy in learning stages (whole-body).

in condition FPVH. IDTW results exhibited LR mean and median of 1.01 and 1.001 for condition TPV, 1.007 and 1.002 for condition TPVH, 1.129 and 1.045 for condition FPV, 1.182 and 1.064 for condition FPVH. However, from the perspective of the average learning rate, the addition of haptic accelerated the human motor learning process in general.

To further investigate the mismatch between PED and IDTW results, we compared the distribution patterns. Table 3 summarizes the distribution parameters of all conditions with different analysis methods. Compared to the spatial-temporal trajectory (PED), the addition of haptics in pure spatial trajectory (IDTW) increased the variances for both view perspectives, which indicates that participants tended to overcorrect their motion with haptic sensation.

5.2.2. Dominant hand

Haptics is an augmented sensation that may lead to cognitive overload in this relatively complex (full body) task [77]. The dominant hand has more accurate motor positional control and sensation capabilities [78] which might magnify the influences in motor training. In addition to whole-body results, we analyzed the dominant hand results to examine the role that haptics played in the body parts that people generally have the most human motor control capability on. Fig. 12 showed the overall result distribution with both PED and IDTW. The normality test failed for dominant hand data, so Wilcoxon signed-rank method was implemented. Fig. 13 visualizes the dominant hand discrepancy result.Left: spatial-temporal result (PED); Right: Spatial result (IDTW).

Friedman's test showed that the participants' dominant hands motion performances were significantly different in different conditions ($p < 0.001$ for both PED and IDTW). Table 4 summarized the Wilcoxon test results. PED method implicated that the spatial-temporal pattern between the first-person view with and without haptic was significantly different in the late stage ($p = 0.016$) and LR ($p = 0.037$). Mean and median values of LR were 1.093 and 1.032 for first-person view condition without haptic, 1.285 and 1.246 for the first-person view with haptic. Similar with whole-body retention results, dominant hand retention was substantially different between FPV and FPVH ($p = 0.092$) and between FPVH and TPVH ($p = 0.063$), and the residual effect after FPVH for dominant hand had the lowest average motion discrepancy.

Significantly different LR implied that haptic improved human motor learning. The pure shape comparison (IDTW) results showed that first-person view with or without haptic was significantly different in late-stage (p = 0.037) and overall performance ($p = 0.030$) which echoed the visual interpretation of Fig. 13.

6. Discussion

The experiment results indicated that our proposed haptic-based sensation transfer impacted the human motor learning process in a positive way. Participants seemed to be confused with the haptic guidance at the very beginning, but quickly adapted to it and started to leverage it in complex human motor learning tasks. In this study, PED results can be interpreted as a holistic performance measurement, i.e., a good learner shall follow the desired motions in terms of both temporal and spatial accuracy. PED results in this experiment implied that as for the whole-body motion, the addition of haptic sensation had a significant negative impact on task performances at the early training stage but not significant in the middle and late stages. Fig. 11 visualizes such a result in which the early stage of the FPVH condition had a higher discrepancy than the early stage of condition FPV while the middle and late stages between these conditions were similar. The significant negative impact became non-significant when the training reached the middle and last stages, suggesting that the negative impact was reduced as the training proceeded. The higher average learning rate in haptic conditions echoed such an observation. Under this controlled experiment, the only changing variable within a condition across different trials was time and experience. Thus, the initial difficulty of working with the haptic feedback at the whole-body level can be described as a cognitive challenge for adapting to a multi-channel sensorimotor process.

To better understand the haptic posed cognitive challenge, we analyzed the participant motion data in depth. We observed the mismatch between PED and IDTW, where PED mostly showed non-significance but IDTW showed significant differences between the first-person view with and without haptic. In contrast to PED, the IDTW result emphasized the pure spatial trajectory (shape) of motions. Haptic groups showed significantly higher discrepancies ($p < 0.001$) in the egocentric view of human motor learning. In the third-person view, haptic in early-stage, late-stage, and the overall result had p values of 0.059, 0.030, and 0.001 respectively, which also implied significant differences. Thus, this implied that the spatial misalignment was the main contributor to the spatial-temporal discrepancy. On the other hand, from the perspective of data distribution, we found that the haptic groups had higher variances in IDTW results which means the motions' spatial shapes under haptic guidelines were less stable. Considering that the addition of haptic did not impact visual perception, these pieces of evidence implied that haptic guidelines overburdened cognitive load at the early training stage. From the participants' perspective, the addition of haptic streamed too much information to proceed, which deteriorated the performance in the first few trials. After getting familiar with the motion and motion-specific haptic guidelines, participants were capable to proceed with the information and improve their performance. It was also an interesting observation that the discrepancy in the late stage of PED was low but the late stage discrepancy of IDTW was high, which means in the late stage, although the participants were making mistakes in motion shape, their overall motion accuracies were significantly improved. This finding implied that after mastering the general motion pattern, haptic-based sensation transfer encouraged novice users to move boldly to feel the motion in small granularity, resulting in a worse spatial trajectory but better spatial-temporal motion. This finding echoed with participants' subjective post-experiment feedback that they started to improve motion intentionally after the middle stage. This finding echoed the experiment by Säfström et al. [79] in which the sensorimotor learning process was found to have distinct stages, and the first stage was for familiarization and no learning effect was detected. Existing sensorimotor learning literature also observed a similar pattern [80,81].

Although the whole-body performance seems not to support the benefits of the additional haptic sensation, possibly due to the cognitive challenges required to adapt to this new experience, the dominant hand performance showed a different result. On the one hand, the dominant hand is the body component that people typically have the most motor control capability on and most mature neural interactivity [82]; On the other hand, the dominant hand is the end effector that is easier for motor adaptation. Under limited cognitive capability, dominant hand motion could imply the underlying influences more clearly. We found that the late stage in haptic condition was significantly better than non-haptic conditions. In addition, while the motor performance in the early stage was not significantly different, the FPVH condition had a significantly higher learning rate compared with the FPV condition. Pure spatial performance (IDTW) also proved that haptic sensation

Table 3
Overall Distribution Parameters.

Analysis Method	Conditions	Expected Value	Median	Variance (e^{-3})
PED	TPV	0.218	0.214	1.8
	TPVH	0.223	0.222	1.8
	FPV	0.148	0.144	1.5
	FPVH	0.154	0.152	1.3
IDTW	TPV	0.188	0.178	2.9
	TPVH	0.211	0.201	3.4
	FPV	0.157	0.149	2.9
	FPVH	0.185	0.179	4.1

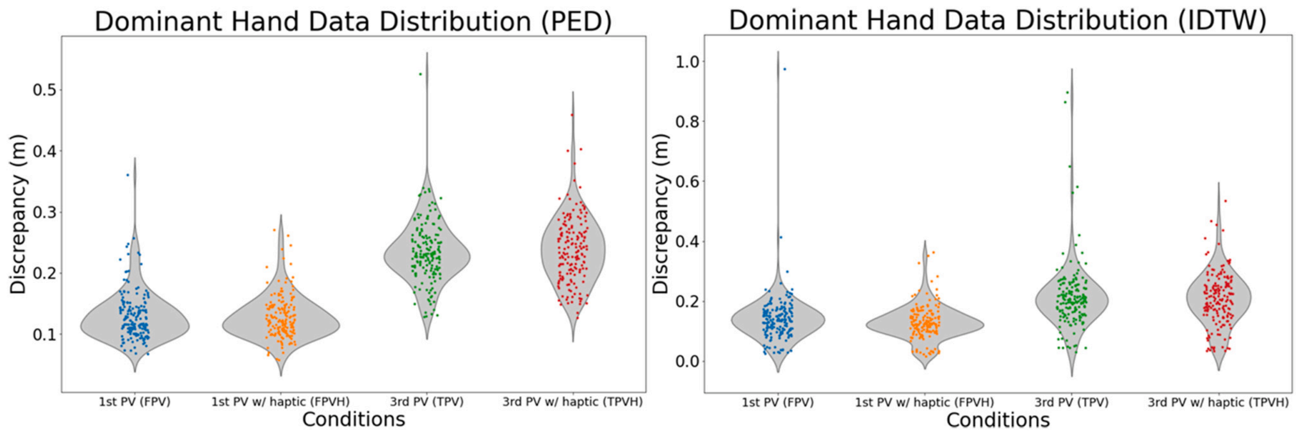

Fig. 12. Dominant Hand overall discrepancy distribution.

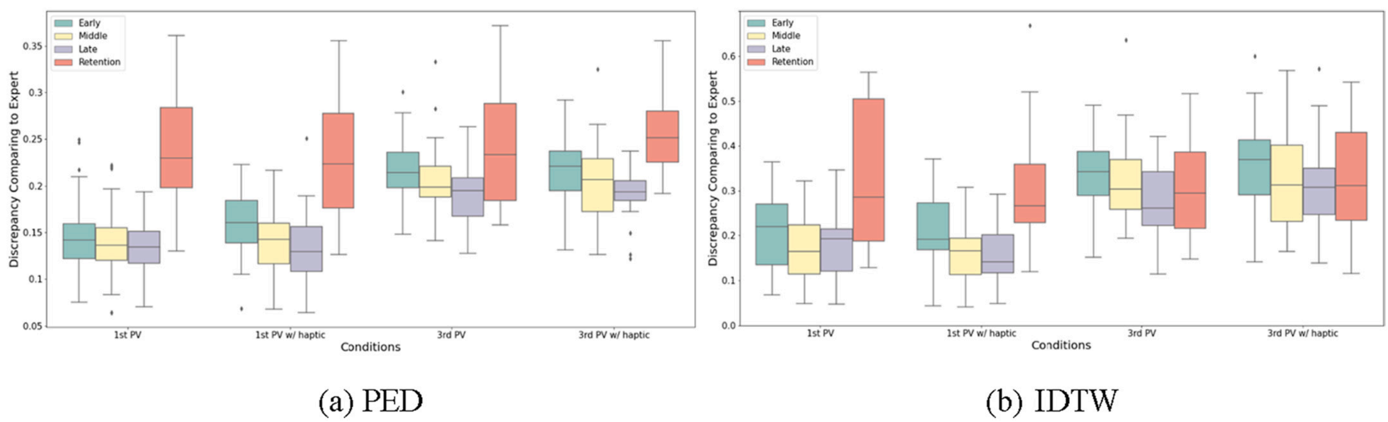

Fig. 13. Discrepancy in learning stages (dominant hand).

Table 4
Significance by Wilcoxon Test (dominant hand performance).

Analysis Method	Comparison	p-value: TPV V.S. TPVH	p-value: FPV V.S. FPVH	p-value: TPV V.S. FPV	p-value: TPVH V.S. FPVH
PED	All	0.530	0.444	<0.001*	<0.001*
	Early Stage	0.900	0.236	<0.001*	<0.001*
	Late Stage	0.457	0.016 *	<0.001*	<0.001*
	Retention	0.524	0.092	0.846	0.063
	LR	0.781	0.037*	0.910	0.008*
	LR Mean (Median)	1.074/ 1.073 (1.111/ 1.036)	1.093/ 1.285 (1.032/ 1.246)	1.074/ 1.093 (1.111/ 1.032)	1.073/ 1.285 (1.036/ 1.246)
IDTW	All	0.816	0.030*	<0.001*	<0.001*
	Early Stage	0. 257	0.393	<0.001*	<0.001*
	Late Stage	0.842	0.037*	<0.001*	<0.001*
	Retention	0.644	0.846	0.838	0.966
	LR	0.36	0.719	0.032*	0.254
	LR Mean (Median)	1.159/ 1.190 (1.016/ 1.133)	1.525/ 1.308 (1.194/ 1.176)	1.159/ 1.525 (1.016/ 1.308)	1.190/ 1.308 (1.133/ 1.176)

significantly improved DGL motor learning. These observations proved that haptic-based sensation transfer positively impacted the human motor learning process for the dominant hand. The significant improvement of haptic to dominant hand motor learning in contrast to the insignificant impact of haptic on whole-body implicated that haptic-based sensation transfer is a promising technique once cognitive overload issue is relieved. This experiment also echoed the findings that an egocentric view improves motor training.

We found that during the retention phase (i.e., after removing the visual and/or haptic guidance), performance was all worsened, no matter if haptics was used or not during the training sessions. It is understandable as participants had to go through a sudden change in the guidance environment. We also found several interesting patterns. First, under different conditions (with and without haptic cues), the residual effects were different. Specifically, there was a substantial difference in terms of retention performance after the "first person view with haptics" training versus after the "first person view without haptics" training ($p = 0.09$). The average accuracy of the former one was better than the latter one. To be noted, we recognize that the *p*-value was not smaller than 0.05, but it was still small enough to indicate a possible difference in the future. It means that as for the accuracy, it did show that the use of haptics had a possible residual effect at the end, even after it was removed. Second, we found that the residual effects of using haptics during training were affected by the view point as well. There was a substantial difference in terms of the retention phase performance after the "third person view with haptics" versus after the "first person view with haptics" ($p = 0.06$). It indicates that the first person view may have strengthened the residual benefits of haptic cues in the retention of the gained motor skill. Overall, it was found that the pattern of retention benefits given haptics was not as clear as in the training sessions, but it did show a possible benefit of using haptic method in retaining a gained motor skill. The use of haptics could possibly improve the retention performance, and such an improvement seemed to be strengthened by the viewpoint during the training phase.

This sensation transfer approach is a novel method that can be used for transferring learning from an expert/experienced worker to novices learning any new task, such as a new operation or a new tool. In our study, we focus on exoskeleton use as a particular use-case for studying the potential of the sensation transfer method. We believe that exoskeleton use is a relevant and good use-case because there are so many kinds of exoskeletons emerging in the industrial market with a variety of design features, and a key factor in industrial adoption of this technology will be how efficiently workers can be trained in the use of these devices. Hence, the potential for our haptic sensation transfer approach to function as a universal training paradigm is significant and impactful.

The gender difference was not considered in this paper. The musculoskeletal and cognitive differences between males and females might impact the effectiveness of haptic learning. In the future, we will expand our test with increased female participants to retrieve more solid evidence while adding gender difference as a cross-subject variable to the paper. In addition, the participants were mostly youngsters from the university. Senior age groups may have different musculoskeletal reactions toward haptic sensations that deserve further investigation. Moreover, we are aware that long term retention was not assessed in this paper. Both the doses of learning needed and its longer-term retention are important next steps to understand and verify whether the learning produced by the haptic sensation transfer method can be retained as part of an individual's motor-skill repertoire.

It is worth exploring in the future whether the sensation transfer method can improve whole-body motion by relieving the cognitive load, which may be accomplished by reducing haptic magnitude, reducing the number of haptic spots, changing haptic frequency, adopting negative haptic feedback, or any other methods. In addition, whether the effectiveness of the proposed sensation transfer method varies according to motions is a question that remains to be answered. We could also explore the cognitive impact of the sensation transfer method by using eye data or brain activities.

7. Conclusions

In this paper, we designed a haptic-based sensation transfer system for migrating the haptic and kinematic feeling of using an exoskeleton system from the expert to any new user who has no access to the real exoskeleton system. A whole-body haptic system is used to generate haptic feedback of different patterns depending on how the novice users follow the motion trajectories of the expert, which is captured and recorded with motion tracking techniques. To test the effectiveness of the proposed method, we conducted a human-subject experiment with 30 participants. The participants were asked to follow the motions of an expert exoskeleton user with the third-person view or first-person view, and with or without the whole-body haptic feedback. The performance was evaluated with the summed average of spatial discrepancies between the participant's motions and the expert's sample motions. The experiment result indicates that the first-person view motor training that visualized motion information from an egocentric perspective was significantly better than the third-person view. Haptic sensation originally induces a higher cognitive load at the whole-body scale but improves as the training proceeds. The general observation shows that haptics in VR may be an important approach for enhancing human motor learning, especially in complex motor tasks such as learning to use an exoskeleton system. In this paper, we also observed that not all body parts shared the same benefits from haptic feedback. To be more specific, body components with a higher sensorimotor capacity (such as the dominant hand) could benefit more from our created vibrotactile feedback, and thereby potentially reduce the required training time and cognitive load required for operation. It is worth exploring in future research how to tailor the configuration of haptic feedback to enhance motor learning while maintaining a reasonable cognitive load, based on the application of haptic feedback to different parts of the body and testing learning rates and cognitive load in more tasks. In addition, we found that the proposed egocentric haptic-based sensation transfer method could possibly improve learning retention, i.e., the residual effects even after the haptic feedback was removed. To validate it, more comprehensive retention tests with longer time intervals and more trials are needed.

In general, the proposed egocentric haptic-based sensation transfer method for exoskeleton motor training seems to be effective in DGL motion training with a back-exoskeleton. It inspires innovative learning frameworks for exoskeleton training in a cost-efficient, risk-free, scalable, and accessible way, and for the wider and further implementation of the exoskeleton in the future construction industry. Furthermore, the proposed method can be extended to a broader scope of human motor training in addition to exoskeleton training, for example, gym training, athlete training, musician training, rehabilitation, and construction operation training.

As for the future agenda, the retention effects of the proposed haptics-based sensation transfer should be further tested. Another experiment with more trials and longer retention periods can provide solid evidence about if the proposed method facilitates long-term motor skill gaining even in a virtual setting. The retention periods can be across multiple days based on the relevant literature. In addition, more modalities and sensor configurations of the haptic system should be tested. In this paper, a fixed configuration was used. It is worth investigating if personalized solutions are needed to meet individual perception and musculoskeletal features. Last, more task contexts should be tested in the future to examine the transferability of the proposed method. This paper focuses on a DGL task. Other tasks such as hand pickup, moving, and upper limb raising are also relevant for future exoskeleton applications in the context of construction operations. The finite difference in training outcomes across different tasks can be tested.

Data availability

All data used in this paper can be found at:
https://drive.google.com/drive/folders/1z8tXmoNubgDLOE3TT8lQRpmLCfYzpntN?usp=sharing

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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