Visualizing Hand Force with Wearable Muscle Sensing for Enhanced Mixed Reality Remote Collaboration

Hyung-il Kim, Boram Yoon, Seo Young Oh, and Woontack Woo

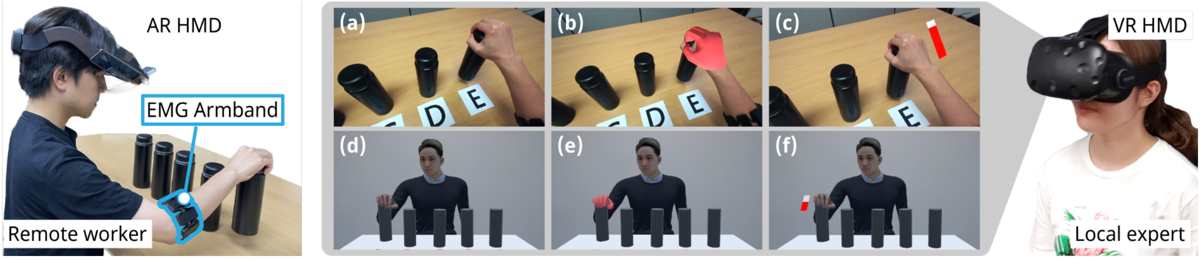

Fig. 1: Prototype system overview for remote collaboration between a worker and an expert. A remote worker's hand force is measured using an sEMG armband, and can be augmented by (b,e) changing the color of hand mesh or (c,f) augmenting gauge beside local worker's hand. A local expert monitors remote worker's behavior through (a-c) first person view or (d-f) third person view.

Abstract—In this paper, we present a prototype system for sharing a user's hand force in mixed reality (MR) remote collaboration on physical tasks, where hand force is estimated using wearable surface electromyography (sEMG) sensor. In a remote collaboration between a worker and an expert, hand activity plays a crucial role. However, the force exerted by the worker's hand has not been extensively investigated. Our sEMG-based system reliably captures the worker's hand force during physical tasks and conveys this information to the expert through hand force visualization, overlaid on the worker's view or on the worker's avatar. A user study was conducted to evaluate the impact of visualizing a worker's hand force on collaboration, employing three distinct visualization methods across two view modes. Our findings demonstrate that sensing and sharing hand force in MR remote collaboration improves the expert's awareness of the worker's task, significantly enhances the expert's perception of the collaborator's hand force and the weight of the interacting object, and promotes a heightened sense of social presence for the expert. Based on the findings, we provide design implications for future mixed reality remote collaboration systems that incorporate hand force sensing and visualization.

Index Terms—Remote collaboration, mixed reality, sensing, visualization, remote assistance

1 Introduction

Mixed reality (MR) technology, including augmented reality (AR) and virtual reality (VR), has the potential to revolutionize the way we work and collaborate by seamlessly integrating digital and physical elements into our daily lives. One application of MR technology is the remote collaboration system, which enables people to collaborate and share information in real-time, regardless of their physical location. Unlike traditional 2D video-based remote communication systems, an MR remote collaboration system allows users to interact with each other in a more natural and immersive way.

One of the main use cases of MR collaboration is *remote expert* scenario, where a remote knowledgeable person guides a local worker performing a physical task [11]. In this scenario, a remote expert monitors a worker's task by watching a worker in first-person view [24, 42] or in third-person view [2, 43] to understand the worker's task and workspace. Prior research has investigated various remote communication cues, such as gestures, gaze, movements, and physiological data, for enhanced collaboration. However, an area that remains underexplored is the incorporation of hand force data, which can enhance the understanding of hand activity for more effective collaboration.

In current remote collaboration scenarios without hand force information, challenges may arise. For example, estimating the weight of objects becomes difficult, potentially leading to errors or miscommunication. Additionally, when a worker must exert minimal force with delicate materials, the lack of hand force data hinders effective guidance. Without this crucial information, the expert may struggle to provide accurate instructions, resulting in damage or accidents. Incorporating hand force information into MR remote collaboration systems can mitigate these issues and improve collaboration experiences.

In this paper, we propose a mixed reality remote collaboration system that incorporates the measurement and visualization of a worker's hand force to improve the flow of information and enable more effective collaboration. By using surface electromyography (sEMG) sensors to measure the force of a user's hand and displaying this information visually to the expert, our system provides a more detailed understanding of the worker's actions and intentions. This allows the expert to more easily understand and respond to the worker's actions, leading to more effective collaboration.

To evaluate the effectiveness of measuring and visualizing a worker's hand force in an MR remote collaboration system, we conducted a user study to compare the impact of this feature on various aspects of collaboration performance from the expert's perspective. Specifically, the study measured the effect of visualizing hand force information on an expert's awareness of the worker's task, social presence, weight perception, force perception, and mental effort. The results of the study indicated that shared hand force information significantly improved the expert's awareness of the worker's task, as well as the expert's perception of the weight and force of objects being manipulated by the worker. It also led to a higher level of social presence and reduced mental effort for the expert. These findings suggest that measuring and sharing hand force can be a valuable addition to MR remote collaboration systems.

In summary, the main contributions of this paper include:

- Developing a novel MR remote collaboration system that shares

- *Hyung-il Kim is with KAIST UVR Lab. E-mail: hyungil@kaist.ac.kr.*
- *Boram Yoon is with KAIST UVR Lab. E-mail: boram.yoon1206@kaist.ac.kr.*
- *Seo Young Oh is with KAIST UVR Lab. E-mail: seoyoung.oh@kaist.ac.kr.*
- *Woontack Woo is with KAIST UVR Lab and KAIST KI-ITC ARRC. Corresponding Author. E-mail: wwoo@kaist.ac.kr.*

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the user's hand force, utilizing an off-the-shelf sEMG sensor for simple calibration and hand force estimation

- Reporting on a user study conducted for evaluating the proposed concept of sharing hand force in MR remote collaboration
- Providing implications and design guidelines for incorporating hand force data into MR remote collaboration systems

2 Related Work

2.1 Remote Communication Cues

To assist mixed reality remote collaboration, various uses of awareness cues are investigated to enhance collaborative performance and social presence. Awareness cues are used in MR remote collaboration to enhance collaborative performance and social presence by providing visual indicators of the other person's activity, attention, or physiological signals. In asymmetric remote collaboration between a worker and an expert, remote communication cues can be classified into two types: expert-to-worker cues and worker-to-expert cues.

The expert-to-worker cues, including hand gestures, hand pointers, or sketch cues, are employed by the expert to guide and instruct the worker remotely. Hand gestures and hand pointers can be used by the expert to indicate the location, orientation, and movement of objects or tools to the worker [21, 22, 35]. Sketch cues, such as drawing annotations on a video feed, can be used by the expert to provide visual instructions and annotations to the worker, indicating the desired movement or action [21,22]. Shared gaze has also been explored as a remote communication cue in order to improve the alignment and understanding of the task between the remote users by highlighting where each of them is looking [2, 12, 35].

On the other hand, worker-to-expert cues are utilized to enhance the expert's understanding of the worker's state and actions, thus helping the expert to provide more accurate feedback and guidance. Prior research in this area has focused on sharing various information such as worker's movement, gaze tracking, first-person view (FPV) video, and physiological signals to provide the expert with more information about the worker's actions and the task environment. The use of FPV video [21, 22, 24, 42] has been widely used to provide the expert with a live video feed of the worker's task environment, which can improve the expert's understanding of the worker's actions and progress in real-time. Sharing the movement of the worker and the surroundings by sharing the real-time pointcloud [2, 43] provides the expert with real-time information about the workspace and the worker's actions.

Moreover, researchers also have explored on sharing physiological data to enhance remote collaboration in terms of presence and immersion. Previous research has demonstrated that visualizing physiological cues, such as galvanic skin response (GSR), blood pressure, and respiration rate of a local worker in traditional video-mediated collaboration scenarios can aid remote experts in interpreting the real-time emotional behaviors of the local worker [40]. Empathy Glasses [27] explored the use of gaze data, facial expressions, and physiological signals such as heart rate and galvanic skin response as the remote communication cue in AR scenarios. More studies have been conducted on sharing physiological signals in social VR [26] or collaborative VR gameplay scenarios [9, 10]. In MR scenarios, Jing et al. [17] explored the use of heart rate in MR remote collaboration.

However, these remote communication cues alone may not provide sufficient information to accurately determine the intensity of the task being performed by the worker. For example, important information such as the amount of force being applied by the worker or the weight of the object being lifted may not be conveyed. Sharing the worker's hand force information can enable the expert to better understand the actions and intentions of the worker, providing the expert with a more complete picture of the worker's task. This can improve the accuracy and precision of the expert's guidance, leading to more effective and efficient collaboration.

2.2 Sensing and Visualizing Hand Force

In order to share the amount of force the worker is exerting on their hand with a remote expert, the system needs to measure and visualize the hand force in real-time. This can be accomplished using a force sensor placed on the worker's hand, which measures the amount of force being applied. This reading can then be transmitted to the expert, who can view it on their own device using a graphical display. This allows the expert to see the amount of force the worker is using in real-time, which can be helpful in providing guidance and feedback to the worker. By providing this information, the expert can help the worker to use the appropriate amount of force for the task at hand, ensuring that the work is completed safely and effectively.

Different techniques have been developed to measure hand force, such as sensors placed on the hand, handheld devices [1, 25], gloves [30, 41], or other wearable devices. These techniques allow for the measurement of hand force in a variety of scenarios. However, on-hand instrumentation can be problematic because it can hinder the worker's hand movements or tactile sense. This can make it difficult for the worker to perform tasks with precision and dexterity, reducing their overall effectiveness and productivity. Therefore, a force-sensing method that does not require on-hand instrumentation is necessary.

One approach to non-instrumented hand force sensing is using vision-based techniques [33,34]. These systems use a camera to capture images of the hand and objects, analyze the images, and estimate the amount of force being applied. Although this approach has the advantage of not requiring any instrumentation, it can be limited in terms of accuracy and precision. Moreover, it is not applicable to unknown types of objects or objects with the same shape and different weights.

Another approach is using wearable devices on the user's wrist or arm to measure the amount of force exerted on the hand or arm. As this approach does not require on-hand instrumentation, the user's hands are free to move, and tasks can be performed without any hindrance. There have been several studies that have investigated the use of wearable devices to measure hand force, including the use of surface electromyography (sEMG) [3, 4, 14, 28, 38], force myography (FMG) [44], photoplethysmography (PPG) [6], acoustic sensors [16], and wrist topography [39]. These studies have demonstrated that these wearable devices can provide data on hand force, allowing researchers to track changes in hand and arm strength over time.

However, one issue with using wearable devices to measure hand force is that they often need to be re-calibrated each time the user puts them on. This is because factors such as the position of the device on the user's body, changes in skin conductance, and other sources of noise can affect the sensor measurements. To ensure that the data collected is reliable, regular re-calibration is necessary. Therefore, a simple calibration process is necessary to make the system easy to use.

In terms of visualizing hand force in remote collaboration scenarios, not much has been investigated so far. Although, some research has been done on visualizing hand forces or grasping feedback [7, 36] in AR or VR systems. One way to visualize hand force is to use a *gauge* display to show the level of force [20, 44, 47]. Gauge visualization provides a quantitative representation of the value, allowing the user to more easily monitor the current level. Another method is to change the *color* of the hand to indicate the magnitude of the force. Virtual Mitten [1] showed changing the color of the virtual hand model to visualize the amount of force exerted on the user's hand, and SoftAR [37] investigated body appearance effect that changes the surface color of the user's hand according to pushing force in spatial AR scenario. Finally, there is arrow-based visualization method that visualizes the direction and the amount of force from the contact point [33, 34].

Compared to prior works, our research investigates sensing and visualizing worker's hand force to enhance mixed reality remote collaboration. In this paper, we describe the system design and implementation details of our MR remote collaboration system that senses, shares, and visualizes worker's hand force to expert. We also describe the report on a user study that investigates how sharing and visualizing remote worker's hand force can enhance remote collaboration.

3 System design

To investigate the use of the hand force cue in MR remote collaboration, we developed a prototype MR remote collaboration system that shares

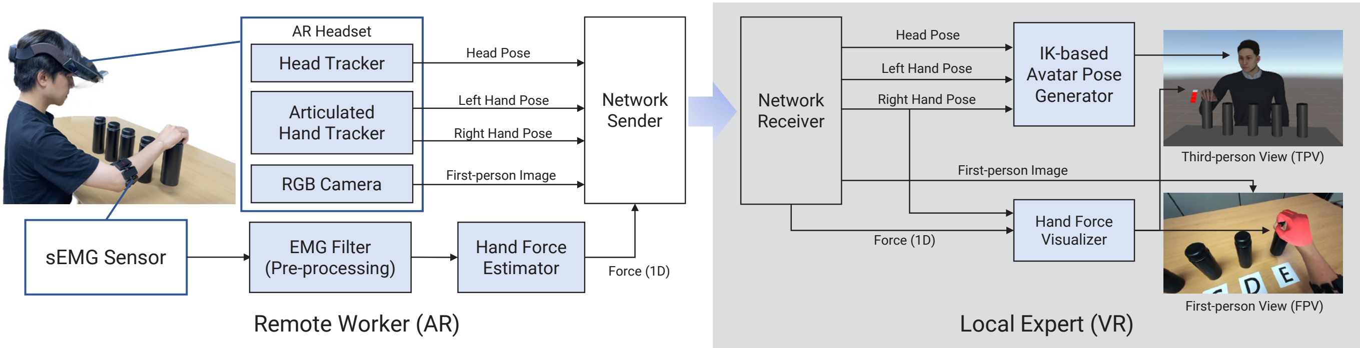


Fig. 2: System diagram of the prototype system.

the remote worker's hand force with the local expert. Figure 1 shows an overview of our system. A remote worker wears an AR head-mounted display (HMD) with a 3D hand tracker and an sEMG armband on the forearm. Our system senses a worker's hand force with a forearm sEMG armband, and allows a local expert to monitor a remote worker's view with augmented hand force. Our MR remote collaboration system supports two view modes (first-person view - *FPV*, third-person view - *TPV*) and two hand force visualizations (*Mesh*, *Gauge*). This section describes the design and implementation details of our proposed system.

3.1 Measuring Hand Force

To share the hand force exerted by the user, the hand force is necessary to be measured first. One method of measuring the hand force involves installing a load cell to each object the user interacts with and measuring the applied force. However, it needs modifications for the workspace environment and is not applicable to various scenarios. To be applied to various environments without modifying the workspace, the user's hand force must be measured using wearable devices. A simple wearable solution could be using a glove with pressure sensors, but wearing a glove is obtrusive and hinders tactile sensations of the hand. We wanted to design a system that can measure hand force while the user is using bare hands, without instrumentation.

As the forearm muscles are directly involved in the movement and force exertion of the hand, we opted for a forearm-worn sEMG sensor to measure hand force. Previous studies have employed forearm electromyography to determine finger touch pressure [3, 4], or the weight of handheld objects [28]. The use of a forearm-worn sEMG sensor offers a non-intrusive solution, allowing users to perform tasks with their bare hands while still accurately capturing hand force data.

3.1.1 Calibration

To measure the force the remote worker exerts on one's hand, we used a multi-channel sEMG armband worn on the worker's forearm. Since there are substantial variations of sEMG signal between people due to different anatomical properties (e.g., the position of muscle and bones) or different skin conductance, user-dependent calibration is needed. Also, as electrode placement changes with each armband usage, calibration is needed every time the user wears the sensor.

We describe the signal processing and propose a simple calibration method for measuring hand force exertion for a specific hand posture. From our empirical observation with the sEMG armband, we observed that taking a hand posture produces certain levels of EMG signals, and exerting force on that posture produces additional levels of EMG signals. From this observation, we define the *total muscle exertion* as the sum of *posture exertion*, which is the muscle exertion to make a certain hand pose and *force exertion*, which is the additional amount of muscle exertion. We define *total muscle exertion* as E_i, *posture exertion* for sEMG channel i $E_{p,i}$ and *force exertion* for sEMG channel i $E_{f,i}$.

To measure the muscle exertion, we measured the mean absolute value for each channel for noise reduction and a more stable muscle activation signal for each sEMG channel. The mean absolute value for channel i is defined as $\text{MAV}_i = \frac{1}{n}\sum_{j=1}^{n}|\text{emg}_{ij}|$. To solely measure *posture exertion*, we additionally measured the amount of muscle exertion required to make certain hand posture. Then we measured *total muscle exertion*, while exerting force on the hand. By subtracting *posture exertion* from *total muscle exertion*, we can get *force exertion*, which is the additional amount of the muscle exertion to exert force.

3.2 Viewing Modes

Our target remote collaboration scenario is asymmetric collaboration, where an expert observes the worker's behavior and provides instruction. To share a remote worker's hand force in MR remote collaboration, we designed the system to support two types of perspective modes for the expert: first-person view (*FPV*) and third-person view (*TPV*).

For the first-person view (*FPV*) mode, the egocentric view of the remote worker is shared with the local expert [18, 21, 22]. The remote worker's hand force is augmented on the video of the remote worker's view, and the real-time video is streamed to the local expert's VR HMD.

For the third-person view (*TPV*) perspective, on the other hand, the local expert has a view independent of the remote worker. We assume that the remote worker is represented in a 3D virtual avatar using real-time pose tracking [31] or real-time 3D volumetric scan [32]. Also, we assume that the worker's workspace and individual objects have to be tracked or reconstructed [2, 8] in real-time. Then the local expert wearing VR HMD can see a remote worker manipulating real objects via a virtual avatar and virtual objects, where the remote worker's hand force is augmented on the avatar's hand.

3.3 Hand Force Visualizations

To visualize the amount of force exerted on the remote worker's hand, we designed two different hand force visualizations: a *Gauge* visualization and a *Mesh* visualization.

Gauge visualization augments linear gauge beside remote worker's hand, and is widely used to visualize the amount of certain values. *Gauge* visualization can provide a clear and concise representation of the amount of force being exerted. By augmenting a linear gauge next to the remote worker's hand, it allows the user to easily see the exact amount of force being applied. This type of visualization can be useful in situations where precise measurements of force are important.

For *Gauge* visualization, we augmented 3cm x 10cm linear gauge 8cm beside user's dominant hand. Measured hand force is represented as red bar ranging bottom to top of the linear gauge, where bottom is zero and top is the pre-defined maximum force. For better reading of the gauge, we adjusted the orientation of the linear gauge for each viewing modes to face the viewer (Figure 1(c,f)).

Mesh visualization visualizes hand force exertion by superimposing red mesh on the remote worker's hand, which represents the amount of hand force using the intensity of color [1, 37]. *Mesh* visualization provides a direct and intuitive representation of hand force exertion and does not occlude surroundings. This can be particularly useful in applications where the expert needs to focus on the worker's hand itself, or where the expert needs to maintain situational awareness of the surroundings while monitoring the worker's hand force exertion.

For *Mesh* visualization, we used a virtual hand model that fits the worker's hand to superimpose on the worker's hand (Figure 1(b,e)).

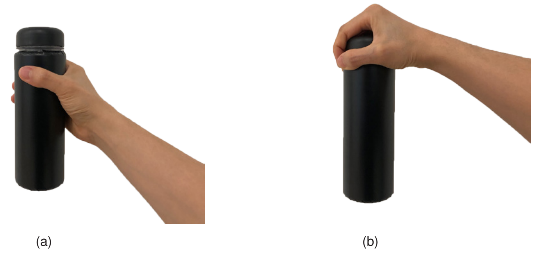


Fig. 3: Handheld object and grasping methods used in the validation study. (a) Cylindrical grasp and (b) Spherical grasp.

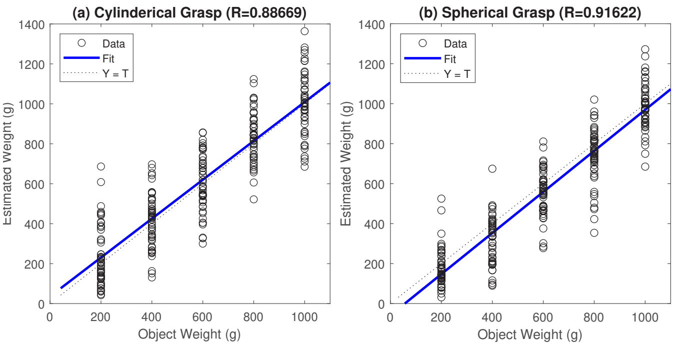


Fig. 4: The results of the validation study using (a) cylindrical grasp and (b) spherical grasp. The estimated weight is normalized for each participant using the average output with a 1000g object.

The color value of the mesh is adjusted from white to red, where white represents no exertion and red represents maximum force exertion.

3.4 Implementation

The prototype system was developed using the Unity (2019.4.4f1) game engine running on a Windows 10 PC (Intel Core i9-7920X CPU, 2.90GHz, 32GB RAM, NVIDIA GeForce RTX 2080Ti). For the AR HMD for the remote worker, we used Meta 2 optical see-through HMD with a Leap Motion sensor attached for hand-tracking. Meta 2 has a diagonal field of view of 90-degree, and supports 1,280 x 1,440 pixels resolution per eye with a refresh rate of 60Hz. For the VR local expert side, HTC Vive was used to display the remote worker's view or the remote worker's avatar with the augmented remote worker's hand force cue. HTC Vive supports 1,080 x 1,200 pixels resolution per eye with a refresh rate of 90Hz. Windows 10 Laptop (Intel Core i7-8750H CPU, 2.20GHz, 16GB RAM, NVIDIA GeForce GTX 1070) was used to drive the VR HMD on the local VR expert side.

We used the Myo armband for an sEMG sensor array. The Myo armband is a low-cost commodity sEMG device worn on the user's upper forearm, which has 8 dry electrodes. The Myo armband streams samples at a 200Hz rate from eight channels in an integer value ranging from -128 to 127.

4 Validation Study

Prior to the main study, we conducted a validation study to validate that our sEMG-based hand force estimation algorithm produces reliable output for different hand postures. The goal was to show that the estimated hand force shows a correlation with the user's hand force. Since grasping force is proportional to the grasped object's weight, we controlled the weight of the object the user is lifting. We prepared five cylindrical objects of identical shape and size (6.5cm in diameter, 19.5cm in height), weighing 200g, 400g, 600g, 800g, and 1000g.

The participants were wearing the Myo armband on the thickest part of their right forearm and sitting at a table during data collection. To measure hand *posture exertion*, participants were asked to set up a grasping posture and to relieve their strength. Then the EMG samples were collected for three seconds. In each lifting trial, participants were asked to lift the object for a duration of three seconds, and EMG data were collected during each lift. The whole data collection process consisted of five lifts per object, and the order of the lift was randomized.

Moreover, to ensure the system operates consistently across various grasping poses, two different grasping postures (cylindrical grasp, spherical grasp) were used to collect the data, and ten participants were recruited for each pose (Figure 3). Therefore, a total of 20 participants (10 participants x 2 grasping postures) were recruited for data collection and 15,000 samples were collected per participant (5 objects x 5 lifts x 3 seconds x 200 samples/s). The data collection procedure took around 5 minutes for each participant, and the participants could pause and have a break anytime during the study.

After collecting the data, *force exertion* was calculated using the methods described in Section 3.1, and then normalized to the mean value when lifting a 1000g object. A linear regression analysis was then performed on the relationship between the weight of the lifting object and the *force exertion*.

Figure 4 shows the results of the validation study. The linear regression analysis showed a high level of correlation for both grasping methods. The results for the cylindrical grasp method showed a correlation coefficient of $R = 0.89$, a mean error of $M = 115.36$g, and a standard deviation of $SD = 99.15$g. For the spherical grasp, the results showed a correlation coefficient of $R = 0.92$, a mean error of $M = 98.87$g, and a standard deviation of $SD = 90.61$g. These results suggest that the proposed method was able to accurately predict the weight of the objects for both grasping methods with a high degree of correlation.

5 User Study

We conducted a user study to verify the proposed system and investigate how shared hand force cue affects the local expert's collaborative experience while observing their remote partner's task completion. For the user study, we set the following research questions:

RQ1 **Does sensing and providing a remote worker's hand force cue help an expert to understand a remote worker's task?**

RQ2 How do the viewing modes affect the MR remote collaboration with shared hand force?

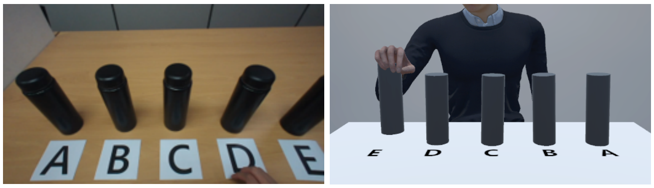
RQ3 How do hand force visualization methods affect the expert's perception on MR remote collaboration with a remote worker?

The main focus of this research is developing and verifying an MR remote collaboration system with shared hand force. Therefore, RQ1 is our primary research question asking whether the shared hand force actually improves MR remote collaboration. RQ2 and RQ3 are our additional research questions, asking how the different viewing modes and visualization methods influence user's experience.

5.1 Task

To evaluate the effectiveness of visualizing the worker's hand force to the expert under different viewing modes, we designed a user task that requires visualizing the worker's hand force information to the expert. The main task was ordering the weights of the cylindrical objects lifted by the worker from the expert's perspective. For the user study, we set up an MR-based remote collaboration application, and the participants experienced each view sharing mode (*FPV* and *TPV*) in VR. Because the collaborator's body movement and reaction should be consistent across all participants for the weight ordering task, the pre-recorded sequence in first-person and third-person view was prepared beforehand by the researcher.

For the first-person view, sequences were prepared in 2D video by placing the video in front of the participant in VR. The size of the displayed video was 60cm in width and 33.8cm in height, positioned in front of the participant at a distance of 50cm. And for the third-person view, the real-time pose of worker's head, hands, and objects were recorded for each sequence. For the playback, the motion of the objects are replayed, and the motion of the avatar was generated by applying inverse kinematics algorithm with the pre-recorded motion of



(a) (b)

Fig. 5: Placement of the cylinders for the user study. The cylinders were marked in alphabetical order. Left: First-person view (FPV), Right: Third-person view (TPV).

the head and hands. The worker's avatar was positioned 1m in front of the participant, facing toward the participant.

The objects to be ordered were the same as the ones used in the validation study - cylindrical objects weighing 200g, 400g, 600g, 800g, and 1000g. As illustrated in Figure 5, the IDs of the cylinders were marked in alphabetical order: The leftmost cylinder was marked as 'A' and the rightmost as 'E'. In each condition, the participant observed a sequence of the remote worker lifting each object in the left to right order. After observing the sequence, participants were asked to arrange the cylinders by weight from the lightest to heaviest, by pressing the alphabet-marked front button with the controller.

5.2 Experimental Conditions and Hypotheses

To answer the main research question (RQ1), we postulated the following hypotheses:

- H1. Users will require less time to order the weights when the collaborator's hand force cue is provided.
- H2. The discrimination accuracy will increase when the collaborator's hand force cue is provided.
- H3. Users will perceive higher social presence when the collaborator's hand force cue is provided.
- H4. Providing hand force cue will increase users' perception of the collaborator's hand force and the weight of the collaborator's interacting object.
- H5. Providing collaborator's hand force cue will decrease users' mental effort.

As the primary aim of the user study was not to compare performance between each viewing mode and visualization type, no hypotheses were formulated regarding these aspects.

5.3 Study Design

The experiment was a 2x3 within-subject design to observe how the user's task performance and experience differ among the hand force visualization types in each viewing mode. The independent variable *View* had two levels (First-person View (*FPV*) and Third-person View (*TPV*)), and the second variable *Vis* had three different levels (*None*, *Mesh*, and *Gauge*). All three visualization types were exposed to the participants under the two types of viewing modes, and a total of six experimental conditions were performed.

The experiment was conducted with recruited participants, and the researcher asked them to assume the following: The 3D human avatar in front of them (*TPV* condition) or the shared video (*FPV* condition) represents the worker's task, and they are remotely working together. The order of the two viewing modes was randomly assigned for each participant to avoid ordering effects, and the order of the three visualization types was also counter-balanced based on a Latin Square Method.

5.3.1 Measures

As dependent variables, we measured both objective and subjective factors. The objective task performance measures, including ordering time and ordering error, were collected during every trial of the user task logged by the application. The ordering time was calculated based on the time taken from the end of sequence playback to enter an answer. For the ordering error, we used the Kendall tau rank distance [19] between the correct answer and the participant's input. Kendall tau rank distance K_d can be defined as the total number of discordant pairs between two ranking lists τ_1 and τ_2:

$$K_d(\tau_1, \tau_2) = \sum_{\{i,j\} \in P, i<j} \bar{K}_{i,j}(\tau_1, \tau_2) \tag{1}$$

where P is the set of unordered pairs of distinct elements in τ_1 and τ_2, $\bar{K}_{i,j}(\tau_1, \tau_2) = 0$ if i and j are in the same order in τ_1 and τ_2, and $\bar{K}_{i,j}(\tau_1, \tau_2) = 1$ if i and j are in the opposite order in τ_1 and τ_2. Since user input is the ranking list of length 5, ordering error is an integer value from zero (correct input) to ten (completely opposite input).

As subjective measures, we measured social presence, force and weight perception, subjective mental effort, and likability after finishing each hand force visualization condition given as a post-task questionnaire (Figure 6). Social presence, which is defined as the 'sense of being together,' is an important indicator of assessing how the remote collaboration system sufficiently conveys the feeling of communicating with each other [5, 15]. To investigate the effectiveness of hand force visualization for remote collaboration, social presence was set as a dependent factor with utilization of a questionnaire based on the Networked Mind Measure of Social Presence proposed by Harms and Biocca [13]. Their social presence measurement includes an essential aspect of the mediated interaction, such as co-existence of the partner, mutual understanding, and attention. We eliminated immeasurable items asking about the perceived social presence of the interaction partner because the remote partner in the recorded video showed constant action across the participants. As a result, a total of nine items on a 7-point Likert scale for three sub-scales–Co-presence, Attentional Allocation, and Perceived Message Understanding–were evaluated.

To evaluate the participant's subjective perception of force and weight induced by each visualization type under the two perspective conditions, we utilized four customized 7-point Likert scale items (1 = strongly disagree; 7 = strongly agree). The four questions were designed to explore the participants' perception of whether they could feel the hand force of the collaborator and the weight of the object being lifted by the collaborator. The two out of four asked about force perception (Q1: *"I felt like the collaborator was exerting force on the hand."*; Q2: *"I felt like the collaborator exerted different force on each object."*), and the rest two items asked about weight perception (Q1: *"I felt the weight of the object that the collaborator lifted."*; Q2: *"I felt that the weight of each object (lifted by the collaborator) was different."*).

Other factors such as mental effort and likability were also assessed. A Subjective Mental Effort Questionnaire (SMEQ) [48] was used to observe differences in participants' mental load according to experimental conditions during the task, and it was rated between 0 to 150. The likability measurement, which was also utilized in previous studies related to the virtual hand representation [23, 29, 46], was evaluated with a single questionnaire item rated on a 7-point Likert scale. For further analysis, qualitative data was gathered from post-session and post-experiment interviews at the end of each *Vis* and *View* condition as illustrated in Figure 6. The questions asked about participants' subjective feelings, usability, overall experience, and more general feedback on each visualization type under each viewing mode.

5.4 Participants

We recruited a total of 24 participants through the university's online community board (16 males and 8 females, ages 20-31, $M = 25.83$, $SD = 3.64$). The participant's previous experience related to VR/AR and telepresence systems was asked based on the self-reported familiarity level within a 7-point rating scale (1 = novice, 7 = expert). The resulting average familiarity level was 3.71 ($SD = 1.76$) for VR/AR experience, 5.54 ($SD = .88$) for 2D videoconferencing systems, and 1.46 ($SD = .88$) for 3D social VR/AR systems. The study was conducted with Institutional Review Board (IRB) approval in advance, and followed COVID-19 safety protocols. The participants were compensated with $10.

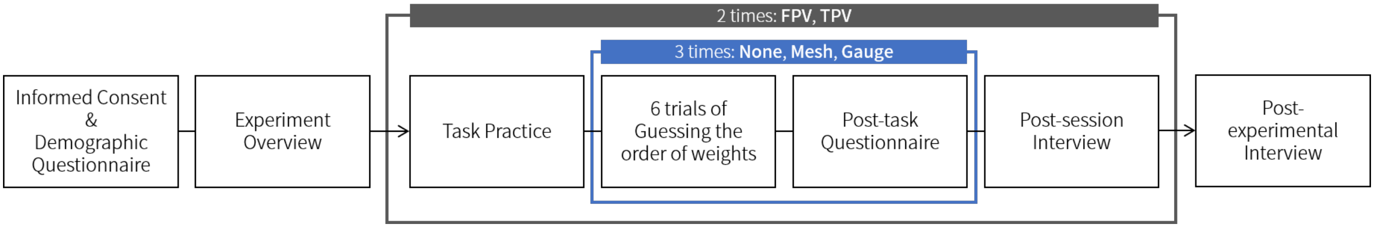


Fig. 6: Flow chart of overall study procedure

5.5 Procedure

In our within-subject study, participants underwent a total of 36 task trials divided into six trials for each of the two *View* conditions (*FPV* and *TPV*) and three *Vis* types. To ensure they were familiar with the process, two additional practice trials were provided for each *View* mode. Six ordering trials were conducted per *Vis* condition, with weights distributed in random order. To minimize potential effects from varying difficulties of trials, we balanced the frequency of each weight appearing in a specific order in the sequence as much as possible (Figure 6).

Initially, participants filled out an informed consent form and a demographic questionnaire about their age and experience with AR/VR and 2D/3D remote collaboration systems. They were then briefed about the study, and given enough time to understand the procedure and to practice with the provided sample trials (Figure 6).

During the experiment, participants evaluated both *View* conditions (*FPV* and *TPV*) in a randomized order. Each session comprised of practice, three *Vis* type evaluations (*None*, *Mesh*, and *Gauge*), and a post-session interview. After completing six trials, participants filled out a post-task questionnaire about the exposed condition, which assessed their subjective perception of the experience.

For the second *View* condition, the same procedure as the first session was followed with proper explanation and a different practice question. Participants repeated the process for all three *Vis* types, and a post-session interview was conducted after finishing all conditions. This interview consisted of open-ended questions asking about general experiences with each hand *Vis* type under the corresponding *View* condition. The entire process was performed twice to evaluate both *View* conditions in separate sessions.

Each session lasted approximately 20-30 minutes depending on the participants. Additionally, 10 minutes for the initial briefing and 10 minutes for the final post-experimental interview were allocated. During post-task, post-session, and experimental interviews, participants removed the VR HMD to avoid discomfort or headaches. On average, the entire user study took about an hour to complete.

6 User Study Results

In this section, we report the results of the user study. The quantitative and qualitative results gathered during the main user experiment are presented in Figures 7 to 11. For the quantitative results, we analyzed task performance and questionnaire items. For both the objective and subjective data analysis, we excluded outliers such as contaminated trials and system errors. The qualitative general feedback was also collected during the post-task interview, which asked about the overall experience for each condition.

6.1 Task Performance

The task performance data consists of ordering time (Figure 7(a)) and ordering error (Figure 7(b)). The data's normality and the variances' homogeneity were first tested through measures based on the Shapiro-Wilk test and Levene's test. The two-way repeated-measures ANOVA ($\alpha = .05$) for parametric analysis was used if the data passed both tests. For the post-hoc analysis, Bonferroni-adjusted Paired t-test was used for the pairwise comparison. On the other hand, we applied a two-way repeated-measures ANOVA ($\alpha = .05$) procedure with the Aligned Rank Transform (ART) for non-parametric factorial analysis among multiple factors [45]. Post-hoc pairwise comparison analysis was also conducted using the Aligned Rank Transform contrast tests with Bonferroni correction.

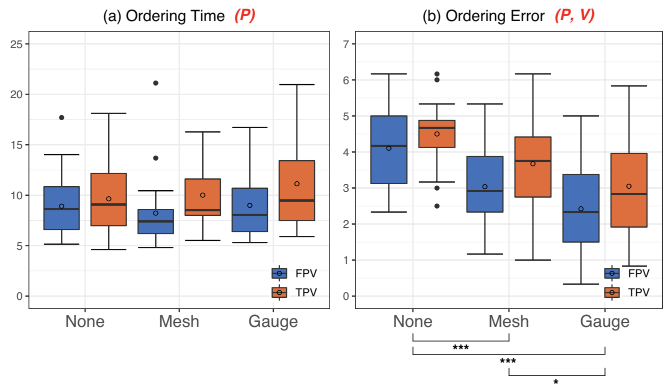


Fig. 7: Task performance results (P and V: a significant effect of *View* and *Vis*, respectively): (a) Ordering Time, (b) Ordering Error.

Ordering Time The results of the ordering time is summarized in Figure 7(a). A significant main effect of *View* was found for the user's ordering time (*FPV*<*TPV*, $F(1,115) = 9.997$, $p = .002$). However, we found no significant main effect of *Vis* on ordering time ($F(2,115) = .702$, $p = .500$). There was no significant effect of *Vis*×*View* interaction ($F(2,115) = .565$, $p = .560$).

Ordering Error The ordering error was derived based on the rank distance between the correct order and the order guessed by the participant (Figure 7(b)). We calculated the mean value of the Kendall tau distance measured through repeated trials. If the participants correctly guessed the order, the value is close to zero. A significant main effect was found for both *View* (*FPV*<*TPV*: $F(1,23) = 10.949$, $p = .003$) and *Vis* ($F(2,46) = 27.609$, $p = .001$), and the post-hoc analysis showed significant differences between every pair in *Vis* (*None*>*Mesh*: $p < .001$, *None*>*Gauge*: $p < .001$, *Mesh*>*Gauge*: $p = .037$). There was no significant interaction effect of *View*×*Vis* found for ordering error ($F(2,46) = .115$, $p = .866$).

6.2 Subjective Measure

We used the Aligned Rank Transform (ART) for non-parametric analysis ($\alpha = .05$) [45]. For the pairwise comparison for the post-hoc analysis, the Aligned Rank Transform contrast test corrected with Bonferroni adjustment was used. The internal consistency among test items of 7-point Likert scale questionnaires–Social Presence, Force Perception, and Weight Perception–was examined based on the reliability coefficient of Cronbach's alpha.

Social Presence The social presence questionnaire [13] included the following three sub-scales: Co-presence (*CP*), Attentional Allocation (*AA*), and Perceived Message Understanding (*PMU*). The aggregated social presence (*SP*) score, merging all three sub-scales, was used for analysis. The internal consistency of the participant's social presence scores showed an accepted level of Cronbach's alpha ($\alpha = .841$).

We found a significant main effect of both *View* (*FPV*>*TPV*: $F(1,115) = 10.799$, $p = .001$) and *Vis* ($F(2,115) = 3.360$, $p = .038$) on the aggregated Social Presence(*SP*). The post-hoc analysis showed significant differences between *None* and *Gauge* type (*None*<*Gauge*:$p = .032$), and other pairs showed no significant differences (all $p > .05$).

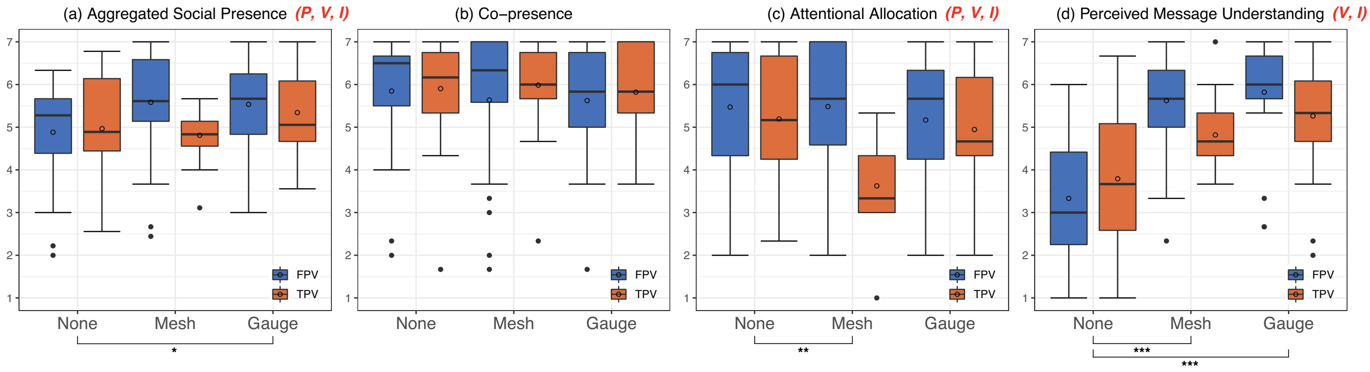


Fig. 8: Results of subjective measures on Social Presence (P and V: a significant effect of *View* and *Vis*, respectively; I: significant interaction effect between independent variables): (a) Aggregated Social Presence (*SP*), (b) Co-presence (*CP*), (c) Attentional Allocation (*AA*), (d) Perceived Message Understanding (*PMU*).

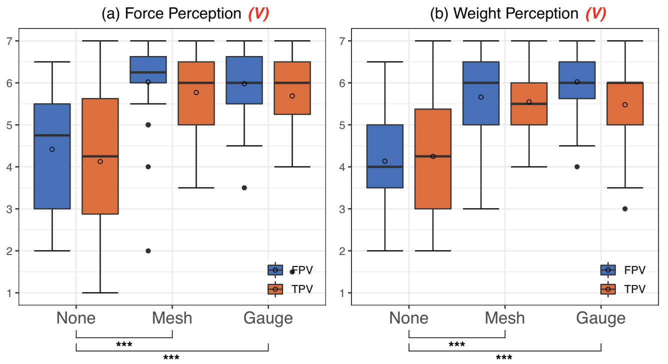


Fig. 9: Results of subjective measures on user's perception of force and weight (V: a significant effect of *Vis*): (a) Force Perception, (b) Weight Perception.

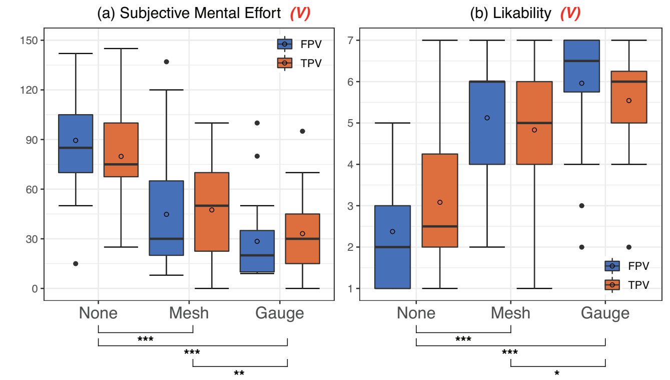


Fig. 10: Results of subjective measures on user's mental effort and likability (V: a significant effect of *Vis*): (a) Subjective Mental Effort, (b) Likability

The significant interaction effect was also found between two factors ($F(2,115) = 4.815$, $p = .01$): the cross-factor post-hoc comparison found the interactions of *View* and visualization types between *None* and *Mesh* ($p = .007$). In *FPV*, aggregated social presence was higher for *Mesh* visualization than *None* condition. However, presence was higher for *None* condition than *Mesh* condition in *TPV*.

We also analyzed the result for each sub-scale. Co-presence (*CP*) did not show any significant effect (*View*: $F(1,115) = .208$, $p = .649$; *Vis*: $F(2,115) = .925$, $p = .399$), nor significant interaction between *View* and *Vis* ($F(2,115) = .215$, $p = .807$). Attentional Allocation (*AA*) showed a significant effect of *View* (*FPV>TPV*: $F(1,115) = 18.720$, $p < .001$), and *Vis* ($F(2,115) = 6.167$, $p = .003$). The pairwise comparison revealed significant differences between *None* and *Mesh* visualization (*None>Mesh*: $p = .002$). The significant interaction effect between *View* and *Vis* was also found ($F(2,115) = 7.749$, $p = .001$): The post-hoc comparison found the differences between the two different view type and *None-Mesh* pair ($p = .002$), and also *Mesh-Gauge* pair ($p = .002$). *Mesh* showed higher Attentional Allocation than *None* condition and *Gauge* condition in *FPV*. However, Attentional Allocation was lower for *Mesh* condition than *None* and *Gauge* condition in *TPV*.

Perceived Message Understanding (*PMU*) showed a significant main effect of *Vis* ($F(2,115) = 38.936$, $p < .001$), but there was no significant effect found for *View* factor ($F(1,115) = 3.333$, $p = .071$). The pairwise post-hoc comparison showed significant differences on the following visualization pairs: *None<Mesh* ($p < .001$) and *None<Gauge* ($p < .001$). However, other *Vis* pairs were not significantly different (all $p > .05$). The significant interaction effect between *Vis* and *View* was found ($F(2,115) = 4.959$, $p = .009$), and the following post-hoc revealed significant interactions of *View* and *None-Mesh* visualization conditions ($p = .006$). *Mesh* showed higher Perceived Message Understanding than *None* in *FPV* condition, but lower Perceived Message Understanding was observed for *Mesh* than *None* in *TPV* condition.

Force and Weight Perception The questionnaire for user's force perception (*FP*) and weight perception (*WP*) consists of two items each, and scores obtained from the participants were aggregated to analyze the results. The internal consistency of the participant's force and weight perception showed an accepted level of Cronbach's alpha ($\alpha_{FP} = .799$, $\alpha_{WP} = .866$). Force perception (*FP*) showed a significant main effect of *Vis* ($F(2,115) = 30.453$, $p < .001$): The post-hoc pairwise comparison revealed significant differences between *None<Mesh* ($p < .001$) and *None<Gauge* ($p < .001$). We found no significant main effect of *View* ($F(1,115) = 1.539$, $p = .217$) nor significant interaction effect of *Vis* and *View* on *FP* ($F(2,115) = 0.019$, $p = .982$). Weight perception (*WP*) also showed a significant main effect of *Vis* ($F(2,105) = 23.968$, $p < .001$). The post-hoc analysis found significant differences between the following pairs: *None<Mesh* ($p <.001$) and *None<Gauge* ($p < .001$). However, we found no significant effect of *View* ($F(1,105) = 1.566$, $p = .214$) nor *Vis*×*View* interaction on *WP* ($F(2,105) = 0.698$, $p = .500$).

Subjective Mental Effort To compare the participant's mental load induced during the task, Subjective Mental Effort Questionnaire (*SMEQ*) results were analyzed (Figure 10(a)); A significant main effect of *Vis* was found for *SMEQ* ($F(2,110) = 57.942$, $p < .001$). The post-hoc pairwise comparison found significant differences in every pair of *Vis* (*None>Mesh*: $p < .001$; *None>Gauge*: $p < .001$; *Mesh>Gauge*: $p = .006$). There were no significant effects of *View* and interaction on *SMEQ* (*View*: $F(1,110) = .037$, $p = .847$; *Vis*×*View*: $F(2,110) = 1.550$, $p = .217$).

Likability The likability (*LIKE*) was analyzed based on the 7-point Likert scale question about the most preferred visualization (*Vis*) condition (Figure 10(b)). A significant main effect of *Vis* was found on *LIKE* ($F(2,115) = 52.847$, $p <.001$). The post-hoc analysis with pair-

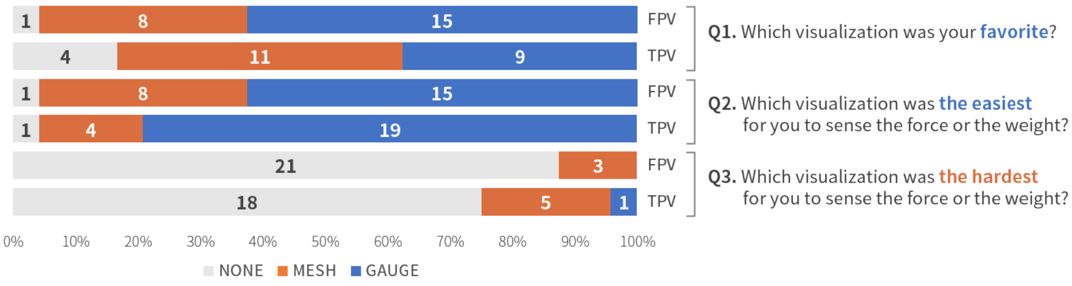


Fig. 11: User preference between hand force visualizations.

wise comparison showed significant differences in every pair of *Vis*: (*None<Mesh*: $p < .001$; *None<Gauge*: $p < .001$; *Mesh<Gauge*: $p = .015$). However, no significant effects on *LIKE* were found from the other factor as well as interaction (*View*: $F(1,115) = .001$, $p = .973$; *Vis*×*View*: $F(2,115) = 2.017$, $p = .138$).

6.3 Post-experiment Interview

The summary of participants' responses on their preferences among three *Vis* is shown in Figure 11. Participants favored different *Vis* for each of the two *View* conditions, coinciding with the result of likability in Figure 10(b).

In *FPV*, participants preferred *Gauge*, as it displayed both an accurate measure of force and the real hand. In *TPV*, preference shifted slightly from *Gauge* to *Mesh*, with participants appreciating various advantages of both options. *None* was least preferred in both views due to the lack of information and increased mental effort.

Participants said *Gauge* helped them most under both *View* conditions, attributing its usefulness to the clear digitization of force. *None* was the most difficult to perceive force and weight in both views due to the lack of information.

The lack of information with *None* made participants pay hard attention to small details of the hands or rely on their intuition, but the naturalness and familiarity helped them concentrate on the task and the partner. In contrast, *Gauge* made participants focus on the gauge rather than the partner, but helped them identify the weight order. *Mesh* received mixed opinions regarding concentration, naturalness, and problem-solving, with participants noting drawbacks under both *View* conditions.

7 Discussion

7.1 Analysis on the Results

Regarding Ordering Time (H1), there was no significant effect of *Vis* on the time taken to discriminate the order of the weights. Therefore, we reject H1, which assumed that the ordering time will be shorter when hand force visualization is provided. It is possible that participants were able to think of the answer while viewing the sequence and determining the order of weights, as most of the participants provided their answers immediately after the sequence ended.

Ordering error showed a significant effect of *Vis*, and post-hoc analysis showed significant differences between every pair (*None-Mesh*, *None-Gauge*, *Gauge-Mesh*) of *Vis* conditions. When hand force visualizations were provided, participants accurately ordered the objects' weights that the collaborator lifted compared to when no hand force cues were available. From this result, we accept H2, which hypothesized that lower ordering errors will be observed when hand force information is provided.

Regarding social presence, Aggregated Social Presence (*SP*) showed a significant effect of *Vis*, and post-hoc analysis revealed that the provision of Hand Force Cue had a significant difference between *None* and *Gauge* conditions. However, no significant difference in social presence was found between *None* and *Mesh* conditions. Therefore, we partially accept H3, which postulated that social presence would be enhanced when the hand force cue is provided.

Looking into the subscales of the social presence, the results of our study revealed that the provision of Hand Force Cue had an effect on certain sub-scales of the social presence measure, specifically on the attentional allocation and perceived message understanding. However, no significant effect was found on the Co-presence sub-scale. One possible explanation for this is that the provision of Hand Force Cue may have a greater impact on the cognitive and cognitive-affective aspects of Social Presence, such as attentional allocation and perceived message understanding, as opposed to the presence aspect, such as co-presence. This suggests that hand force cue can be used as an efficient way of aligning attention and collaboration between remote users.

Regarding the user's perception on the remote collaborator's hand force and the weight of the handheld object, a significant effect of *Vis* was found for both force perception and weight perception. They both also showed significant differences between each *None-Mesh* and *None-Gauge* pairs. Thus, we affirm H4, hypothesizing enhanced perception of collaborator's hand force and object weight with provided hand force cues. This result shows that providing visual cues of the worker's hand force significantly affects the expert's ability to accurately perceive the collaborator's hand force and the weight of the handheld object.

Lastly, the result of the user study showed that hand force visualization (*Vis*) had a significant effect on the participant's mental workload, and there were significant differences between each *None-Mesh* and *None-Gauge* pairs. We thus accept H5, which hypothesized that providing hand force information would reduce mental effort to understand collaborator's task. It is important to note that these results suggest that providing the worker's hand force visualizations can help reduce cognitive load of the expert in the remote collaboration on physical tasks.

7.2 Additional Discussions

Regarding the effect of the view type (RQ2), the result of the user study indicates that the type of view, whether it is a first-person view or a third-person view, has a significant impact on task performance and the perception on social presence in MR remote collaboration on physical tasks. Specifically, the results show that the use of a first-person view (FPV) led to faster ordering times and lower ordering error compared to the third-person view (TPV). These findings suggest that providing a first-person view of the worker's hand activity may be more beneficial in terms of task performance in MR remote collaboration on physical tasks with shared hand force cue. However, the variance in perceived object sizes and the scale of visualizations across different views may have also contributed to the results.

Moreover, the results also showed that the type of view has an impact on users' perception of social presence and attentional allocation. The use of FPV was found to increase the users' perception on social presence and attentional allocation, which may indicate that providing a first-person view allows for a more immersive and engaging experience for the expert. The results also suggest that when sharing hand force in MR remote collaboration, the type of view should be carefully considered. For example, in tasks that require fast and accurate performance, such as assembly and disassembly tasks, providing a first-person view may be more beneficial.

Also, we investigated the use of Gauge and Mesh hand force visualizations to visualize the worker's hand force to the expert (RQ3).

Regarding the difference between Gauge and Mesh visualizations, the results of the user study showed that the Gauge visualization was found to be the most effective in terms of ordering error and mental effort and to be the most likable. The post-experiment interview further confirmed the preference of participants for the Gauge visualization, particularly in FPV. Participants reported that the clear digitization of force in the Gauge visualization helped them to accurately identify the weight order of the objects. However, in third-person view (TPV), the preference slightly moved away from Gauge to Mesh, making the favorite less prominent. This change in preference might be attributed to the difference between the real hand of FPV and the avatar hand of TPV.

In addition, we discovered some interesting insights concerning the relative advantages of Gauge and Mesh visualizations. The Gauge visualization provided a more accurate and detailed representation of the worker's hand force, allowing the expert to make precise judgments about the order of weight of the objects being manipulated. On the other hand, the Mesh visualization, while less precise, was reported as offering a better holistic view of the hand and the object being manipulated, particularly in the third-person view (TPV). This suggests that while Gauge is preferred for tasks requiring precision and numerical understanding of force, Mesh could be beneficial for tasks needing a broader view and understanding of the manipulation.

7.3 Implications

Based on the analysis of our results, we propose design implications on MR remote collaboration on physical tasks:

Share worker's hand force cue in MR remote collaboration on physical task. Our study results suggest that sharing the worker's hand force in MR remote collaboration not only improves the expert's understanding of the worker's task, but also significantly enhances the expert's perception of the collaborator's hand force and the weight of the interacting object. Moreover, we found that sharing the hand force of the worker could improve the perception of social presence for the expert. Therefore, we suggest that sharing the worker's hand force cue in mixed reality remote collaboration on physical tasks can improve the user's perception and overall collaboration experience.

For tasks that require a fast and accurate understanding of the worker's task, sharing first-person view of the worker is recommended. The results of the user study indicate that the use of FPV led to better task performance including faster ordering time and lower ordering error. Moreover, FPV also led to a higher sense of social presence and attentional allocation, indicating that participants felt more connected to the worker, indicating that participants felt more connected to the worker and were better able to focus on the task at hand. Overall, these results suggest that for tasks that require fast and accurate understanding of the worker's task, sharing the first-person view of the worker can be beneficial for improving task performance and collaboration.

Gauge visualization is recommended for the accurate understanding of the worker's physical task. Another design implication that can be derived from the study results regarding the difference between gauge and mesh visualizations is that gauge visualization may be more effective in terms of providing an accurate understanding of the worker's physical task. This was evident in the ordering error measure and the mental effort measures, where the participants performed better with the Gauge visualization compared to the other visualization methods (None and Mesh). Additionally, the post-experiment interviews revealed that participants had a strong preference for the Gauge visualization, as it provided a clear digitization of force and helped them identify the weight order. These findings suggest that for tasks that require accurate understanding of the worker's physical task, the use of the Gauge visualization is recommended.

However, it may be beneficial to provide users with the option to switch between visualization types, depending on the task requirements. For example, for the tasks that do not require fast and accurate discrimination, the Mesh visualization may be less distracting to the expert, allowing them to focus more on the hand and the worker's movements rather than the visualization itself.

7.4 Possible Applications

There are various possible application scenarios for our proposed mixed reality remote collaboration system that incorporates the measurement and visualization of a worker's hand force. In these scenarios, the understanding of the remote collaborator's exerted hand force plays a crucial role.

Remote Maintenance and Repair Our proposed system could be beneficial for remote maintenance and repair tasks, such as PC repair or vehicle maintenance. In these scenarios, a remote expert can guide a local worker to apply the correct hand force when handling tools or parts. This would prevent damages caused by excessive force, ensuring the task is carried out safely and efficiently.

Personal Training In the context of personal training, our system could be used to guide individuals in performing physical exercises. The exerted hand force data would allow the remote trainer to better understand the individual's performance and provide personalized guidance. This would be especially beneficial in weight lifting or resistance training, where the trainer could monitor the individual's hand force to ensure exercises are performed correctly and safely.

7.5 Limitations

The results of this study provide insight into the effects of hand force visualization on collaborative tasks. However, there are several limitations to consider.

Firstly, the proposed sEMG-based hand force sensing method produces different outputs for various grasping gestures. To accurately capture hand force information in real-world scenarios involving a range of hand gestures, an adaptive calibration method for different hand gestures may be necessary.

Additionally, we selected and evaluated only two hand force visualization methods. The objective of the user study was to investigate the impact of sharing hand force information on user performance rather than comparing various visualization methods. Further research is needed to extensively explore the hand force visualization methods and determine the most effective way to display the shared content.

Lastly, the proposed MR remote collaboration system was evaluated only from the perspective of the expert side using pre-recorded data of the worker side. It is not clear how well it would perform in a real-time synchronous collaborative task between a worker and an expert. To better understand the system's potential, further research is needed for real-time collaboration and interaction, and we view our work as laying the groundwork for such future investigations.

8 Conclusion

In this paper, we proposed a system for sharing users' hand force in MR remote collaboration on physical task, and conducted a user study to understand the impact of sharing hand force on the user's perception. We proposed a simple calibration and estimation method of hand force with an off-the-shelf sEMG sensor that can be used for MR remote collaboration on physical tasks. The results of the user study indicated that providing the worker's hand force cues to remote collaborators can influence their collaboration in terms of task understanding and subjective measures such as social presence, perception on force and weight, and mental effort. We additionally explored the effect of the viewing modes and the visualization methods in MR remote collaboration with shared hand force cue. Overall, this study contributes to the advancement of MR remote collaboration by proposing the importance of hand force as a cue and providing insights on the design of mixed reality remote collaboration systems, which could help designers to develop effective MR remote collaboration systems on physical tasks.

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