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ROV teleoperation via human body motion mapping: Design and experiment

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ABSTRACT

Remotely Operated Vehicles (ROV) are widely used in subsea engineering such as inspection, construction and maintenance of underwater facilities. Currently, ROV controls are primarily based on control kiosks with the camera display and joystick control devices on a surface vessel. It sets a high barrier for ROV teleoperation and results in prolonged personnel on board (POB) time. This paper proposes a human body motion and hand gesture control method in Virtual Reality (VR) for ROV teleoperation in navigation and stabilization tasks. Specifically, a whole-body haptic suit converts ROV sensor data of hydrodynamic forces into haptic feedback of different magnitudes, then body-carried sensors capture and model human body motions and map them into the gesture controls of a remote ROV. As a result, a simulated haptomotor loop is accomplished, facilitating automatic and spontaneous motor controls of ROV in an intuitive way. A human subject experiment (N = 30) was performed to test the effectiveness of the proposed ROV control method. The result shows that with the proposed method, the navigation and stabilization control precision is improved, along with reduced mental load and perceived benefits. The findings will inspire the design of novel ROV teleoperation systems that would lower the professional barrier and increase broader participation in the subsea engineering of tomorrow.

1. Introduction

Subsea engineering, which involves tasks such as inspecting, constructing, and maintaining natural and manmade systems, is crucial in the exploration of the ocean for various purposes, including offshore energy, aquaculture, sustainability, disaster preparedness, seafloor mining and cabling, and maritime transport (Casey, 2020; McNutt, 2002). Remotely operated vehicles (ROVs), which are teleoperated robotic systems used for underwater exploration and operations, have been effectively used for many years (Azis et al., 2012; Kennedy et al., 2019). The global ROV market is rapidly growing due to its agility, safety, and endurance, and the demand for ROV pilots is expected to increase annually (Li et al., 2018; WBOC, 2021). Despite the increasing demands for the subsea engineering workforce, there is a significant shortage of ROV operators. A recent survey shows that the need for ROV pilots is expected to increase by 130% on an annual basis (IDI, 2018). At the same time, the ROV operator remains a highly specialized profession with a high training barrier to broader participation. Subsea engineering is dominated by male workers due to its harsh working environment, tremendous training requirement and high cognitive load during operation. Most ROV-related jobs require strict professional preparation (ocean sciences, mechanical engineering, and diving knowledge) that takes many years of training. Even for well-trained ROV operators, subsea tasks require long-time focus on operations with a constantly high mental load.

Traditionally, researchers have paid more attention to enabling methods and algorithms for autonomous ROV controls, such as simultaneous localization and mapping (SLAM) for ROV navigation (Meireles et al., 2014; Vargas et al., 2021), and self-stabilization with adaptive nonlinear feedback controller (Tran et al., 2020). Nonetheless, operating ROVs precisely underwater is still extremely challenging to achieve for a fully autonomous system due to the inherent challenges associated with underwater environments (Antonelli and Antonelli, 2014). Close-range operations, especially those requiring manipulation, are still carried out by ROV systems that are fully controlled by a human pilot. In certain tasks, such as ROV docking (Trslić et al., 2020), human agility in perceiving the dynamic environment, knowledge in conducting complex tasks, and intelligence in dealing with uncertainties and unexpected situations are indispensable and must be integrated with robot autonomy in subsea workplaces. A workplace-ready and worker-friendly ROV

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interface that properly simplifies control and increases remote operation confidence is a pressing need for the wide adaptation of ROVs.

However, compared to the ROV automation methods, the technical solutions and requirements for human-in-the-loop ROV controls are less thought out. Established algorithms, methods, and systems for automation are not effective for supporting tasks with intensive human engagement, such as overwhelming information for underwater environmental understanding; the difficulty of remote robot controls, the missing sensations of human operators underwater (e.g., inability to directly sense water flow), and steering and navigation difficulties in unknown and less explored subsea regions and works (Cohan, 2008; IDI, 2018; Xia et al., 2022; Xia et al., 2023). Especially, the majority of existing ROV control systems are based on visual feedback (such as camera systems mounted to the ROV) and joysticks for ROV steering and navigation tasks (BlueRobotics, 2021; IDI, 2018; NOAA, 2021). The human operator needs to take rapid and important navigational actions based on a large amount of continuous information about ROV locations, kinematics, status and underwater environments. And these decisions are often affected by the varying mobility capabilities of different ROV systems. As a result, to qualify for ROV teleoperation operator jobs, excessive training and a long process certification are often needed. To democratize human presence in future subsea engineering works, a new design paradigm for ROV that accommodates human needs and limitations in remote ROV controls is needed to lower the entrance barrier.

To fill the gap of human-centered ROV teleoperation, especially for ROV steering and navigation controls, this paper proposes a haptomotor control system that converts the complex ROV navigation operations into a straightforward haptomotor coordination task, i.e., human spontaneous motor actions based on haptic feedback (Zhu et al., 2022a, 2022b). Evidence has shown that a haptomotor reflex exists among humans in automatic (spontaneous) object manipulation corrections of the contralateral hand, and motor actions based on haptomotor feedback are faster than those initiated by the well-known visuomotor reflex (Camponogara and Volcic, 2019). Based on the findings of human motor literature, a simulated haptomotor feedback process is leveraged to substantially simplify the ROV steering and navigation operations. First, a virtual reality (VR) system is used to build the digital twin model of the remote subsea workplaces and used as the main user interface (UI) for ROV information displays. Then, a whole-body sensory augmentation system is built based on our previous works to covert the hydrodynamic forces sensed by the remote ROV (such as waterflows) as the vibrotactile feedback on the upper body of the human operator (Xia et al., 2023). Finally, a separate whole-body motion tracking system is leveraged to capture the natural body motions of the human operation and transfer them to the key posture commands of the ROV including the yaw, roll, pitch, moving forward/backward, and moving upward/downward. The motion capture system also includes a sophisticated hand gesture mapping system to control key ROV operation parameters when body motions are not easily achievable. With the proposed system, the human operator can intuitively “feel” and react to the ROV kinematic status changes with their natural body motions, analogous to common motor activities such as dodging to avoid an obstacle in walking and running (Reynolds, 1999). The remainder of the manuscript introduces the technical details of the proposed system, and a human-subject experiment (N = 30) to test the effectiveness and applicability of the system. The collected data also includes personal preference distribution to the control sensitivity that fine-tunes the magnitude of mapping body motion ranges into ROV posture changes.

2. Literature review

2.1. ROVs for offshore operations

ROVs are underwater vehicles that are tethered and designed for tasks such as intervention, inspection, exploration, installation, and data collection. (Brun, 2012; NOAA, 2021; Patiris, 2015). They can be classified based on various factors such as dimensions, functionalities, and costs, etc. For example, existing ROVs can be categorized into education, inspection, and work class(Wang et al., 2019) based on their primary designed functionalities Depending on working depth and payloads, ROVs can also be classified into micro class (100 m, 5 kg), mini-class (300 m, 10 kg), light work class (2000 m, 100 kg) and heavy work class (3000 m, 300 kg). While ROVs differ in sensing and actuation capabilities, they typically possess basic capabilities such as maneuverability along multiple axes, state estimation, and communication through the umbilical cable or additional wireless means. This research focuses on enabling better controls of mini-class ROVs in near-shore and offshore inspection tasks, given their popularity and relevancy in the existing subsea service market. To be noted, the focused workplaces are challenged by unique environmental conditions including the presence of uncertain flow disturbances, low visibility due to light attenuation and turbidity, inaccessibility to most radio frequencies, large variations in temperature and pressure distribution, and biofouling risks to long-term infrastructures (Lachaud et al., 2018; Nitonye et al., 2021; Xia et al., 2022). Operation hazards include entanglement of umbilical cables, collisions, loss of power and/or communication, long control reaction time and communication delays, and interruptions or damages caused by marine lives, electrical hazards, and loss of the link (Walker et al., 2020; Yang et al., 2020). Other challenges include limited on-site accessibility, which makes the deployment and operation of the system more complicated, and significant scattering light diffusion and restricted field of view of cameras limit the systems’ operational distance. These workplaces are also often in isolation given the difficulty of teamwork in these places (Devrelis et al., 2020; Wu et al., 2020).

To tackle problems related to the harsh environment of ROV workplaces, most existing efforts are made to seek solutions in autonomous algorithms as similarly seen in other intelligent systems (Schjølberg and Utne, 2015). Roughly speaking, these efforts can be categorized into the enhancement of two types of ROV control precision, including navigation trajectory controls and stabilization. The main approaches for navigation trajectory control integrate all kinds of sensor data, e.g., doppler velocity log (DVL), inertial measurement unit (IMU) and short baseline acoustic system (SBL), for precisive trajectory estimation and prediction (Soylu et al., 2016). Further, some studies designed an extended state-based Kalman filter (ESKF)-based model predictive control (MPC) to incorporate external disturbances and measurement noises into navigation trajectory control (Long et al., 2022; Long et al., 2021). As for stabilization, studies attempted to develop autonomous systems based on different sources of ROV status, including the embedded markers and vision-based localization data (Zaman and Mardiyanto, 2021), dual-eye vision-based docking system (Lwin et al., 2019), and acoustic-based 3D space underwater positioning system (Pedersen et al., 2019). All these autonomous algorithms contributed to integrating multiple input sources in enhancing the control precision of ROV navigation and stabilization.

2.2. Mixed reality for human-in-the-loop ROV controls

Despite the advances of autonomous ROVs, there is a growing awareness of the indispensable role of human operators in ROV teleoperation. It is widely believed that human capabilities in dealing with uncertain and novel task contexts and environments are extremely useful for subsea operations, and thus a human-in-the-loop (HITL) would be more suited for difficult ROV tasks (Trslić et al., 2020). However, the complex and dynamic subsea environment, coupled with the limited human operator ability to process and react to these dynamics and the lack of user-friendly control methods for ROV teleoperation, can disrupt the critical feedback-control loop necessary for precise motor actions during ROV operations. This can lead to perceptual-motor malfunctions during ROV operations (Finney, 2015). Traditional ROV control methods are based on joystick-type of controllers and imagery data as the main feedback. Usually, operators work on the vessel for control with 2D live video captured by ROV-equipped cameras. Such a kind of control and feedback method cannot fully transit uncertainties of the subsea environment to humans. The low visibility in the subsea environment can undermine the human perception of the workspace (Chemisky et al., 2021; Li et al., 2019), and complex and high-turbidity currents can significantly influence ROV's self-stabilization, which might cause disorientation in subsea exploration (Lawrance and Hollinger, 2018). For example, a prevailing issue in ROV navigation is drifting, which can be several kilometers per hour sometimes (Chutia et al., 2017). Subsea currents can push the ROV away from its original route (Lu et al., 1997), and high-turbidity currents can also bring an extreme burden on subsea installations and maintenance (Gupta and Paul, 2018). Novel control systems that can help alleviate the transition from in-land teleoperation to subsea ROV teleoperation are under exploration.

Among all HITL systems for ROV teleoperation, mixed reality (VR) is receiving a growing interest. VR is a widely used interface that simulates realistic scenes and provides rich spatial information to users (Brooks, 1999; Zheng et al., 1998). By incorporating VR into robot teleoperation, the perception and control of human agents and robots can be closely coupled (Chakraborti et al., 2017; Concannon et al., 2019; Zhou et al., 2020). resulting in better motion planning and interaction during difficult tasks that require both human and robotic intelligence (Williams et al., 2019). Additionally, VR is the most suitable platform for integrating multiple senses, such as visuomotor and haptomotor integration (Dangxiao et al., 2019; Ye et al., 2023). Literature has shown the great success of integrating VR and haptic feedback in robot teleoperation, such as in snake robot control (Zhu et al., 2022a,2022b) and tower crane balance control (Zhu et al., 2022a,2022b). Several studies have tested the advantages of utilizing VR in ROV teleoperation in different tasks, such as underwater capture tasks (Elor et al., 2021) and deep ocean remote control (Martin et al., 2021). These preliminary studies verified the effectiveness and efficiency of integrating VR into the existing ROV control system. Especially, it is widely believed that the greatest benefits of VR pertain to providing semantically rich visual information in an immersive way (Khadhraoui et al., 2016). As such, spatial awareness can be better granted that is critical in ROV operations (Chellali and Baizid, 2011).

However, it is also recognized that the potential of VR has not been fully explored due to VR's technological constraints. Any intelligent system operation including ROV teleoperation requires complex, sequential motor actions for driving the basic functions. In many cases, it also requires an egocentric cognitive awareness related to motor planning, execution, situational and safety awareness in an operating system (Salek et al., 2011). Nevertheless, although most VR systems are featured in high-quality visual modeling and rendering, they are insufficient to simulate and replay the physical interactions of the remote workplace, or the haptic stimulation (Dangxiao et al., 2019). It is extremely difficult, if not impossible, to create a VR-based simulated control environment that allows human operators to feel and comprehend the motor requirements, such as feeling the torque and resistance of operating a remote robot, as well as beware of the surrounding spatial constraints. It is recognized as the lack of physical embodiment with the current VR technologies (Wainer et al., 2006). It has caused disconnections between the embodiment requirements of robot teleoperation (i.e., the feeling of being or presence along with the remote robotic systems) and the increasing complexity of robot teleoperation. As for ROV teleoperation applications, human operators are usually asked to maintain a sitting position and still use a joystick or other types of hand-held props for ROV teleoperation (Abdulov and Abramenkov, 2021). VR is considered as an immersive UI rather than a fully integrated, embodied tool for engaged ROV teleoperation. The gap between the lack of embodied systems for ROV controls and the natural haptomotor process of human operators can induce perceptual-motor malfunction problems, i.e., the inability to effectively integrate perceptual information with the execution of voluntary behaviors (Ayres, 1965; Finney, 2015; Wallen and Walker, 1995). To design a more ROV teleoperation method, a deeper understanding of the haptomotor process is needed, i.e., understanding the critical neuromotor process humans rely on in coordinating difficult motor tasks.

2.3. Haptomotor embodiment for robot teleoperation

Human sensorimotor control relies on multimodal sensory feedback, such as the visual, auditory, and somatosensory (tactile and proprioceptive) cues, to make sense of the consequence of the initiated action (Kirsch and Kunde, 2013; Shadlen and Newsome, 1996; Wood et al., 2013). When the perceptual ability is affected, such as the missing haptic stimulation in most existing VR-based systems, the motor planning and feedback loop is broken. It is why perceptual-motor malfunction is often seen in clinical populations with impaired perceptual functions (especially visual, spatial and tactile disorders), such as Asperger disorders, Parkinson's disease, and Developmental Coordination Disorders (DCD), etc. (Jongmans et al., 2003; Price, 2006; Stern et al., 1983). In ROV teleoperation, missing the haptic feedback and the corresponding motor reaction methods could create a similar mismatch in motor perception, and therefore, lead to comparable consequences of perceptual-motor dysfunction.

In recognition of the importance of creating haptic feedback coupled with VR systems, scholars began to explore novel haptic simulation methods. Haptic devices are used to generate haptotactile stimulation (e.g., vibrations and force feedback) in correspondence with the occurring events (Tian et al., 2017; Tian et al., 2021). As for haptic stimulation in ROV controls, haptotactile signals can be used to augment the human operator's situational awareness for a better understanding of the motion and status of ROV. Early efforts included using one-dimensional haptic simulation (such as pressure or torsion forces) to produce the illusional proprioception and kinesthetic perception of the ROVs (Amemiya and Maeda, 2009). Later, linear-oscillating actuators using asymmetric drivers are used to simulate hydrostatic pressure in remote ROV systems (Ciriello et al., 2013). Advanced status sensors, such as gyroscope sensors, are used to provide dynamic data to drive haptic actuators to simulate torque feedback (Shazali, 2018). Despite the benefits of these novel ways of haptic stimulation in ROV teleoperation, many solutions are focused on providing a single modality of haptic feedback partially due to the constraints of limited sensing bandwidth and physics simulation abilities. With the recent advances in physics engines, the latest efforts are made to augment sparse sensor data and simulate physics-accurate, high-resolution haptic feedback. This feedback can be manifested via the latest haptic equipment such as whole-body haptic suits to generate the feelings of hydrodynamic forces on the upper body of a human operator (Xia et al.; Xia et al., 2022; Xia et al., 2023). On the other hand, some studies began to utilize human body pose or hand gestures for robot teleoperation and better human-robot interaction (Fan et al., 2022; Gao et al., 2023; Gao et al., 2018; Gao et al., 2019). By combining haptic feedback with hand gestures and motion control, it might be possible to build a close feedback-control loop with a better understanding of the work environment and direction interaction with events, which further benefits in improving control precision and reducing learning barriers.

In addition, neuromotor literature has also recognized that haptomotor feedback plays a critical role in human's automatic manipulation ability, i.e., motor reactions to haptic cues in a spontaneous way. For example, Camponogara and Volcic (Camponogara and Volcic, 2019) found that humans relied more on haptic cues to correct the grasping motions than using visual cues. The so-called haptomotor reflex seems to have facilitated automatic actions in difficult tasks (Camponogara and Volcic, 2019). These recent findings suggest that a better ROV teleoperation performance could be achieved by carefully calibrating and mapping haptic feedback into spontaneous motor actions. An analog of this haptomotor feedback loop is the ability of humans to dodge to avoid obstacles in steering tasks or keep the optimal path (Feygin et al., 2002).

And such an ability is often spontaneous, meaning that it does not require high-level cognitive processing. Stimulating such a natural haptomotor loop via a simulated control environment could be a novel way for easing the ROV teleoperation. Therefore, this research proposes a haptomotor embodiment system for ROV teleoperation. The system includes a human body motion capture and mapping method to control the gesture of the ROV. Then the ROV sensor data about the hydrodynamic forces are simulated as the whole-body haptic feedback. In this way, the human operator can naturally react to the hydrodynamic changes with spontaneous body movement.

3. System design

3.1. System architecture

As demonstrated in Fig. 1, the proposed system consists of the ROV and environment sensing component, the digital twinning component and the human control and feedback component. According to the design, ROV-equipped sensors obtain environment data and send them to the digital twinning component for modeling. VR is used to create an immersive environment and as a server to integrate all data including the environment data and human operator's control data. Data from ROV sensors will be processed in Unity (Unity, 2022) and used to generate multisensory feedback, including augmented visual and haptic feedback. The feedback is played via body-carried devices, including a VR headset and the whole-body haptic suit. The system also includes body motion capture sensors to track and model the motions of the upper body. The system converts human body motions into control signals of the virtual ROV in the digital twin model and finally synchronizes the control status with the real ROV. In the remainder of this section, an implementation case of the system is introduced.

3.2. VR environment and device setup

We set up the system as follows for a human-subject experiment. The subsea virtual environment was developed in Unity 2020.4.25 f based on our previous systems (Du et al., 2016; Du et al., 2018a,2018b; Du et al., 2017; Du et al., 2018a,2018b; Shi et al., 2018; Xia et al., 2022; Zhou et al., 2020). The VR environment ensured a high-fidelity underwater hydrodynamic simulation, subsea light rendering as well as adjustable water texture and field of view (FOV) by applying the crest ocean system API (Harmonic, 2022). In our system, the FOV was set to the range of 0–10 m to simulate visibility conditions in most offshore subsea environments. Besides, a particle system was developed to simulate the physical interaction between the water flow and ROV and generate haptic feedback, and a vector field system was developed for rendering augmented visual cues to indicate flow speed and direction. We used an HTC VIVE head mounted display (HMD) (VIVE, 2022) and bHaptics suit (bbHaptics, 2022) as the main control device. The VR device rendered an immersive VR environment and provided visual feedback for the human operator, who could control the ROV motion and orientation with their body motions. Meanwhile, the haptic suit generated haptic feedback on the upper body of the human operator, which simulated the feeling of waterflows hitting the body. With the intuitive feedback and control system, the human operator could react with their natural body motion simultaneously when hydrodynamic conditions were changing.

3.3. Sensory augmentation system

To transfer subsea environment information, especially the subsea hydrodynamic forces, to the human operator, a multi-level feedback system was designed. As shown in Fig. 2a, a particle flow and virtual sensor system was designed to simulate the hydrodynamic forces and generate the corresponding haptic feedback via the haptic suit. Since data collected by sensors were always spatially and temporally, a data augmentation process was necessary for Unity to enhance the coverage and the refresh rate of haptic feedback. Therefore, a particle system was designed to generate dense particle flows and simulate the physical interactions with the ROV in a realistic way. A series of virtual sensors were distributed around the ROV model, and particle flows would collide with these sensors and then generate corresponding haptic feedback on the haptic suit as shown in Fig. 2b. In addition, this system also provided a vector field (Fig. 2c) as a visual augmentation to indicate the flow speed and directions in the far field. Each arrow in the vector field would point to the flow direction at that area, and the length of the arrow indicated the flow speed, i.e., a longer arrow represented a higher flow speed. The system received the data of hydrodynamic conditions and generated the local transform for each vector. After converting the local transform with the global transform of the ROV, all the vectors could be arrayed with the orientation and scale adjusted depending on the pose of the camera. Besides, the color of the arrows could be changed

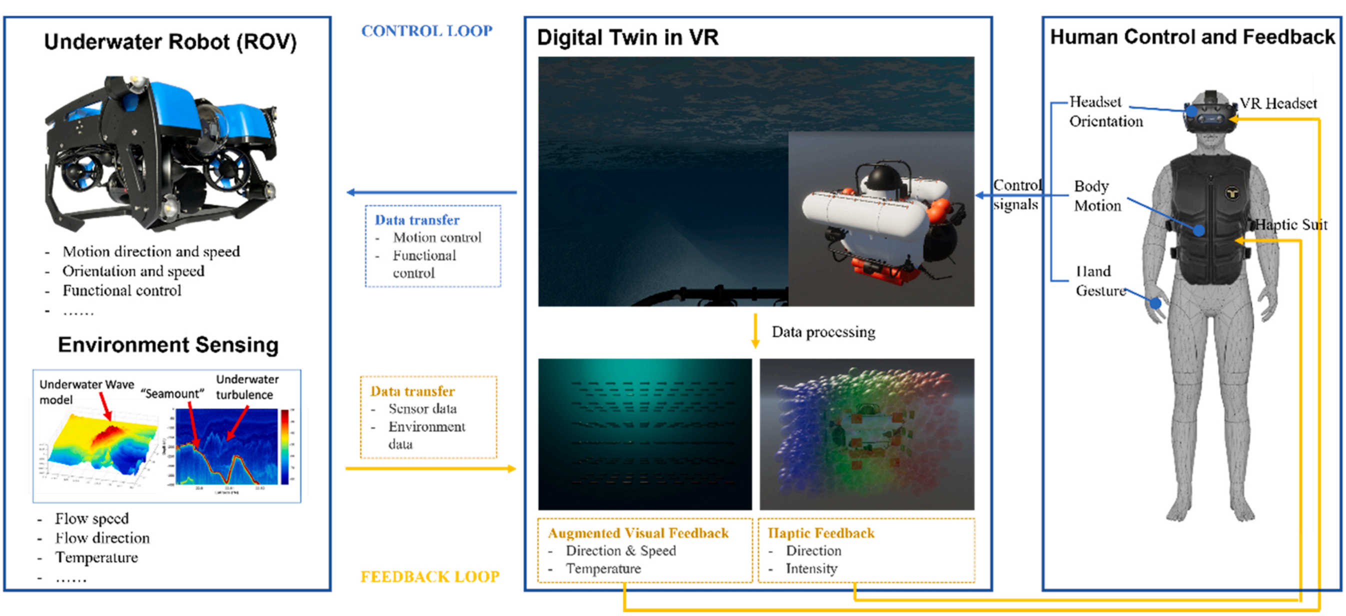

Fig. 1. System architecture of haptomotor embodiment control system.

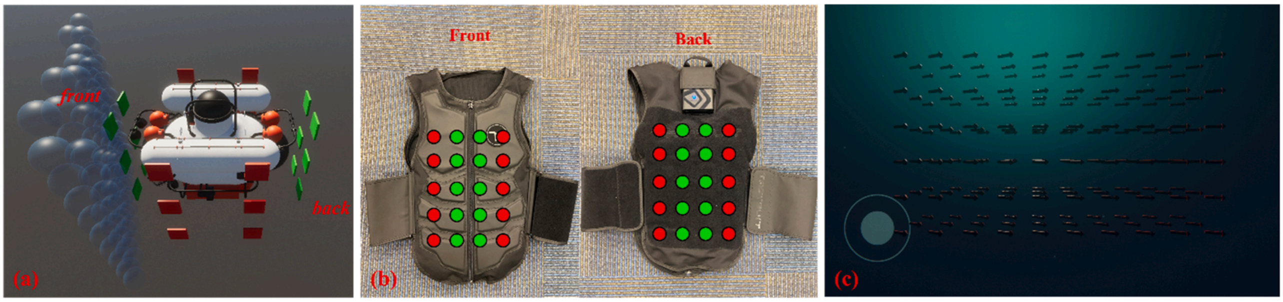

Fig. 2. Feedback function. (a) Particle flows and virtual sensors in VR. (b) Haptic sensor distribution and map on haptic suit. (c) Augmented vector field visual feedback.

to indicate the water temperature if needed. The effectiveness and efficiency of the feedback system in subsea tasks have been verified by our previous experiments (Xia et al., 2022; Xia et al., 2023; Zhu et al., 2022a, 2022b; Zhu et al., 2022a,2022b).

There were 24 virtual sensors in total distributed around the virtual ROV model to provide data to the 40 vibrators on the haptic suit. The emitter would shoot particle flows with the given speed and direction obtained from the ROV sensor data. Each virtual sensor would record its collision with particles per 0.5 s (2 FPS). The velocity of the collided particle was projected to the normal direction of the virtual sensor, the sum of which was finally converted to the haptic intensity on the haptic suit. Besides, human operators could adjust the sensitivity to the most appropriate level by themselves via the provided UI. As shown in Eq. 1 and Eq. 2, I is the haptic intensity, $\boldsymbol{n} \in [\boldsymbol{0}, \boldsymbol{1}]$ is adjustable haptic sensitivity, M is hydrodynamic data captured by virtual sensors, $\overrightarrow{\boldsymbol{v}}_{\boldsymbol{p}}$ is the particle velocity which collides with the virtual sensor, and $\overrightarrow{\boldsymbol{n}}_{\boldsymbol{sensor}}$ is the normal vector of the virtual sensor. The number and distribution of virtual sensors should be adjusted based on hardware and task needs. For example, the number of virtual sensors could be reduced for simple inspection-use ROVs, while for those heavy work class or large size ROVs, such dense distribution might be necessary to provide enough information.

$$I = \frac{e^{0.33*M} - 1}{e^{0.33*M} + 1} * n \tag{1}$$

$$M = \frac{\left|\overrightarrow{v}_p \bullet \overrightarrow{n}_{sensor}\right|}{\left|\overrightarrow{n}_{sensor}\right|} \tag{2}$$

3.4. Human body motion mapping

Fig. 3 illustrates the control mechanism of this system. All the ROV control parameters, such as rotation, pitch, roll and yaw, were driven by human body motions, including head rotation read from HTC VIVE headset, body postures and hand gestures. Specifically, the local rotation of the human body was read from the headset and sent to control the pitch, roll and yaw of the ROV. Besides, human body postures were designed to control the ROV horizontal motion, such as that the ROV would move forward when the human operator leaned forward. We recognized that most ROVs could accomplish certain actions beyond the capabilities of human body motions, such as raising up and sinking down vertically. Therefore, a hand gesture detection and recognition method was developed to enhance the vertical movement controls. The human operator could use their hand gestures, including thumb up and down to control the vertical ROV movements. Other functional control was designed based on hand gestures as well, including adjusting motion and feedback sensitivity and showing ON/OFF of the augmented visual cues. For the demonstration please refer to this video (https://youtu.be/8MismssRMpY).

To map human motion data into ROV control parameters properly, a series of conversion functions were developed. This system also provided adjustable parameters including feedback sensitivity and motion

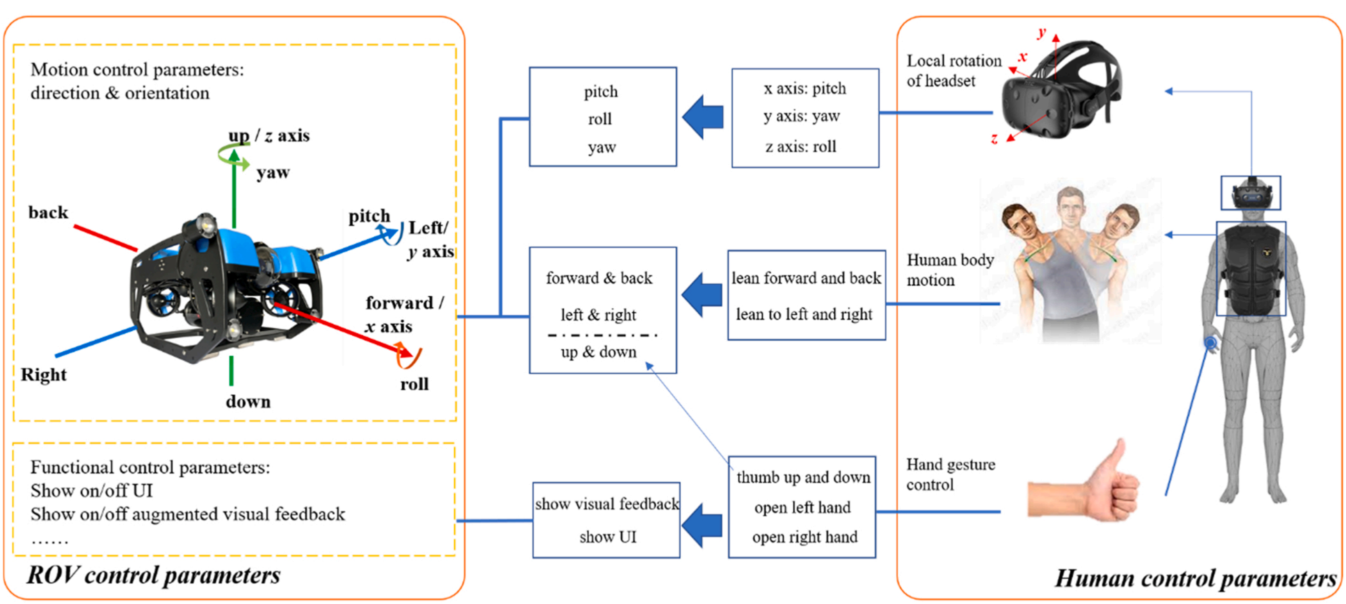

Fig. 3. Body motion and hand gesture mapping functions for ROV controls.

control sensitivity at the scale of 0–1 to accommodate the individual difference in motion preference. Specifically, human body motions were paired to control signals of the ROV in the x direction (left and right) and z direction (forward and back) in Unity. A hypothetical center was created when the system started, and any deviation of the human body from the hypothetical center was calculated to change the ROV moving speed proportionally. As a result, the human operator could control the speed by adjusting how much their own body leaned away from the hypothetical center. The mapping was realized by Eq. 3 and Eq. 4, where $\overrightarrow{\boldsymbol{v}}_{\boldsymbol{rov}}$ is the movement speed of the ROV, $\overrightarrow{\boldsymbol{d}}_{\boldsymbol{xz}}$ is human motion vector in x and z direction plane, $\boldsymbol{n} \in [\boldsymbol{0}, \boldsymbol{1}]$ is human adjustable motion sensitivity, $\overrightarrow{\boldsymbol{p}}_{\boldsymbol{1,xz}}$ and $\overrightarrow{\boldsymbol{p}}_{\boldsymbol{0,xz}}$ are current human headset position and control center position in the x and z direction plane respectively. In this system, human body motion was converted to thruster control signals within the range from -1.0–1.0. Meanwhile, human body rotation was sent to ROV for orientation control. Please refer to Section 3.4 for data transfer and conversion.

$$\overrightarrow{v}_{rov.xz} = \frac{\overrightarrow{d}_{xz}}{|\overrightarrow{d}_{xz}|} * \min\left(|\overrightarrow{d}_{xz}|, \frac{0.2}{n+0.1}\right) * 5.0(n+0.1) \tag{3}$$

$$\overrightarrow{d}_{xz} = \overrightarrow{p}_{1,xz} - \overrightarrow{p}_{0,xz} \tag{4}$$

Finally, a hand gesture detection and recognition method was developed based on the OpenXR function provided by HTC (VIVE, 2023). The hand tracking extension could capture hand motion from the dual front camera system on HTC VIVE headset. Then, the located hand model with 26 joints was reconstructed in Unity. The transform and rotation for each joint were collected and used for further detection and calculation. In total, four kinds of hand gesture functions were realized by the proposed system, as shown in Fig. 4. Specifically, a human operator could unfold their left hand in front of the cameras to indicate the ON/OFF of the augmented visual feedback, while a similar function was realized on the right hand to control the ON/OFF switch of the UI panel, which was used to adjust haptic sensitivity and body motion sensitivity. Meanwhile, the human operator could use their right index finger to adjust these two parameters to their most preferred values. Since it was impossible for the human operator to control the ROV upward and downward with their upper body motion, the function was realized by hand gestures as well. Operators could use their thumbs up and down for ROV floating and diving control. The motion speed was decided by Eq. 5, where $\overrightarrow{v}_{rov.y}$ is the ROV speed on y axis, $\boldsymbol{p}_{\boldsymbol{tip.y}}$ and $\boldsymbol{p}_{\boldsymbol{proximal.y}}$ are the position on y axis of thumb tip joint and proximal joint respectively, $\overrightarrow{\boldsymbol{p}}_{\boldsymbol{tip}}$ is the position of thumb tip joint and $\overrightarrow{\boldsymbol{p}}_{\boldsymbol{proximal}}$ is the position of thumb proximal joint.

$$\overrightarrow{v}_{rov.y} = \frac{p_{tip.y} - p_{proximal.y}}{|\overrightarrow{p}_{tip} - \overrightarrow{p}_{proximal}|} \tag{5}$$

3.5. VR-ROS data transfer and conversion

To feature the real-time data synchronization for ROV teleoperation, a network architecture, as illustrated in Fig. 5, was used to transfer sensor data, and convert human motions to control signals between ROS and VR (Zhou et al., 2020). This method built a WebSocket server to provide network communication based on TCP protocols. Specifically, on the ROS end, Rosbridge (Schultz, 2022) was used to provide JSON API for non-ROS programs to access ROS functions. The information from ROV, such as sensor data, was converted to JSON messages and published to the WebSocket. As well, Rosbridge could receive JSON data from the Internet and convert them to ROS messages. On the Unity end, ROS# (Bischoff, 2021) was applied to send and receive data via WebSocket with a specific IP address through the network. Unity subscribed sensor data to build the VR digital twin with hydrodynamic features and published human body motion data to WebSocket for ROV control.

Our system design was based on a mini-class ROV for inspection tasks, which was equipped with six degrees of freedom (DoF) thrusters (BlueRobotics, 2021). The ROV was directly managed by the ROS framework, which sends control signals to the thrusters. Fig. 6 illustrates the arrangement of thrusters on the selected model. The red arrows denote the positive direction of the thrusters. Six thrusters were installed to manage the 6-DoF ROV movements. Specifically, the ROS framework transmitted control signals to these six thrusters, commanding them to rotate either clockwise or counter-clockwise and adjusting their rotation speed to regulate the ROV's actual motion speed.

Specifically, the ROS system sent a 6-channel signal to the ROV corresponding to each thruster denoted as $\overrightarrow{\boldsymbol{con}} = [\boldsymbol{thru_1}, \boldsymbol{thru_2}, \boldsymbol{thru_3}, \boldsymbol{thru_4}, \boldsymbol{thru_5}, \boldsymbol{thru_6}]^{\boldsymbol{T}}$, where $\boldsymbol{thru_i} \in [-\boldsymbol{1}, \boldsymbol{1}]$ denoted the rotation direction and speed of the $\boldsymbol{i}$-th thruster. After subscribing to body motion control data from Unity, the system projected the control signal from Unity onto $\overrightarrow{\boldsymbol{con}}$. The data received included motion control signals $\boldsymbol{P_v} = [\boldsymbol{v_{rov.x}}, \boldsymbol{v_{rov.y}}, \boldsymbol{v_{rov.z}}]^{\boldsymbol{T}}$, where $\boldsymbol{v_{rov.x}}$, $\boldsymbol{v_{rov.y}}$, and $\boldsymbol{v_{rov.z}}$ are control signals in Unity coordinate, and rotation $\boldsymbol{P_\theta} = [\boldsymbol{\theta_{rov.x}}, \boldsymbol{\theta_{rov.y}}, \boldsymbol{\theta_{rov.z}}]^{\boldsymbol{T}}$, where $\boldsymbol{\theta_{rov.x}}$, $\boldsymbol{\theta_{rov.y}}$ and $\boldsymbol{\theta_{rov.z}}$ are human rotation in Unity coordinate.

$$\begin{bmatrix} P_{v.rov} \\ 1 \end{bmatrix} = ROSROVT \quad UnityROST \begin{bmatrix} P_v \\ 1 \end{bmatrix} \tag{6}$$

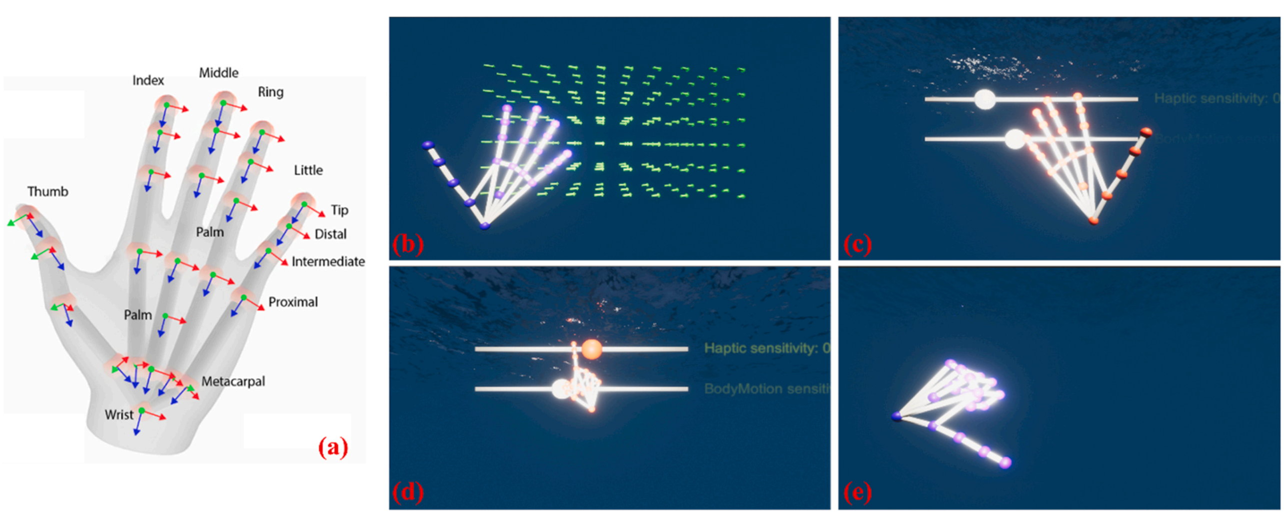

Fig. 4. Hand gesture recognition examples. (a) Hand joints' names; (b) Control of on/off switch of the augmented visual feedback; (c) Control of on/off switch of the sensitivity UI panel; (d) Adjusting sensitivities with scroll bars; (e) Upward/downward controls of ROV.

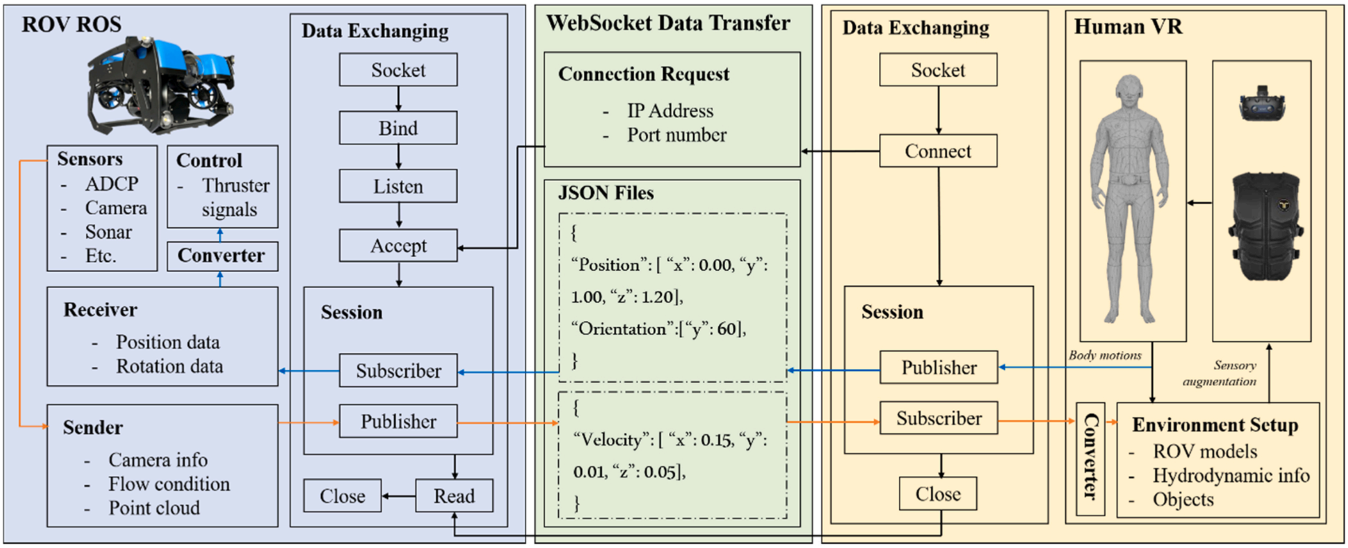

Fig. 5. ROS-VR connection and data transfer.

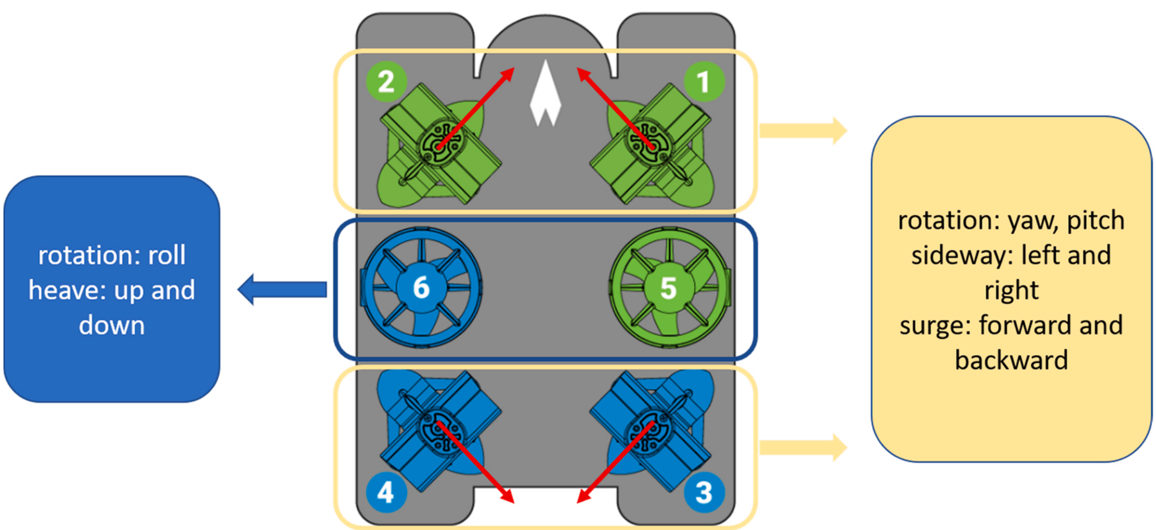

Fig. 6. The distribution of thrusters on ROV and the control of motion in 6-DoF.

$$UnityROST = \begin{bmatrix} 0 & 0 & 1 & 0 \\ -1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{7}$$

After receiving data, a transformation conversion was conducted to convert data from Unity coordinate to ROV coordinate, as demonstrated in Eq. 6 and Eq. 7, where $\boldsymbol{P_{v,rov}}$ is control signals for ROV, ***UnityROST*** is the transformation matrix from Unity to ROS, ***ROSROVT*** is the transformation matrix from ROS to ROV, and $\boldsymbol{P_v}$ is the control signal from the operator in Unity. Then, the control signals were finally converted to thruster control variables as shown in Eq. 8, where ***con*** is the thruster control matrix, and $\boldsymbol{P_{v,rov}}$ is the control signal matrix from the previous calculation.

$$con = \begin{bmatrix} -P_{v,rov}(1) + P_{v,rov}(2) \\ -P_{v,rov}(1) - P_{v,rov}(2) \\ P_{v,rov}(1) - P_{v,rov}(2) \\ P_{v,rov}(1) + P_{v,rov}(2) \\ P_{v,rov}(3) \\ P_{v,rov}(3) \end{bmatrix} \tag{8}$$

As for rotation control, similarly, the first step was to convert rotation data $\boldsymbol{P_\theta}$ in Unity coordinate to correct format $\boldsymbol{P_{\theta,rov}}$ in ROS coordinate with rotation matrix ***UnityROSR***, as shown in Eq. 9 and Eq. 10. Then, a PID controller was used to compare current ROV rotation with target rotation, and adjust ROV posture smoothly, separately on three axes. Specifically, parameters were set as $\boldsymbol{K_p} = \boldsymbol{2.463}$, $\boldsymbol{K_i} = \boldsymbol{1.812}$, and $\boldsymbol{K_d} = \boldsymbol{0.742}$. The PID parameters could be adjusted to optimized values by the particle swarm optimization (PSO) algorithm (Marini and Walczak, 2015) based on the real application needs.

$$\boldsymbol{P_{\theta,rov}} = \boldsymbol{UnityROSR} \quad \boldsymbol{P_\theta} \tag{9}$$

$$\boldsymbol{UnityROSR} = \begin{bmatrix} \mathbf{0} & \mathbf{0} & \mathbf{1} \\ \mathbf{-1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{-1} & \mathbf{0} \end{bmatrix} \tag{10}$$

4. Human subject experiment

4.1. Overview

To test the effectiveness of the proposed hapotomotor embodiment

ROV teleoperation system in comparison with the traditional joystick control method, a human subject experiment was performed in a VR simulation environment. Although the joystick control method has been widely applied in current ROV operations, it requires tremendous training and prolonged personnel on board (POB) time. Our proposed system is expected to provide an easier access and intuitive way for ROV teleoperation to reduce training barriers. As shown in Fig. 7, the experiment included two main tasks: 1) Task A: target following task. Participants needed to steer the ROV to follow a target (the ball in the view) while maintaining a trajectory as close as possible to the target movement trajectory (Fig. 7c); and 2) Task B: ROV stabilization control task. Participants needed to control the ROV to maintain in the same XYZ location on a given platform for one minute while random subsea waterflows with changing speeds and directions presented (Fig. 7d). Each participant was required to finish the two tasks with three conditions in a random order, including the joystick condition, the fixed control parameters condition and the self-adjustable parameters condition. Under the fixed control parameters condition, the control sensitivity settings, including the haptic sensitivity and body motion sensitivity, were set to a default value, which was n = 0.5. Under the self-adjustable parameters condition, the UI panel was provided and thus the participant could adjust sensitivity values with the scroll bars in VR prior to the tasks.

During the experiment, each participant began with a training session to familiarize themselves with the control and feedback system, the use of VR and haptic device, as well as the procedure of the experiment before each condition. After that, subjects were asked to finish the three experiment trials in random order. The system recorded the participant's body motion and rotation data as well as ROV's trajectories. For Task A, the average deviation to the target ball was calculated as the main performance measurement. Besides, Dynamic Time Warping (DTW) was applied to analyze the trajectory similarity (i.e., how close it was between a participant's movement trajectory and the desired trajectory), which was calculated based on the alignment between two given (time-dependent) sequences of time series data (Müller, 2007). A lower DTW value represents a higher similarity and thus a better performance. For Task B, the total moving distance and the absolute deviation from the center of the ROV platform were calculated as the ability to resist the drift effects caused by subsea currents. The standard deviation of the positional data was also used to analyze the stability of the ROV controls. Finally, the selected control sensitivities data was collected and fitted into a distribution, which was expected to set the basis for future control system designs.

After each experiment trial, participants were asked to finish two surveys, including a NASA-TLX survey (Index, 1990) for the workload level estimate, and a user experience survey to measure the perceived benefits of the control system. A demographic survey was also performed before the experiment, to collect information about gender, age, college majors, VR experience and ergonomic data such as body height, etc. At the end of the experiment, participants were asked to provide retrospective opinions about the proposed system, including the body motion control method and adjustable parameters designs. All results were analyzed with the Wilcoxon tests as preliminary analysis found that data did not satisfy the normality assumption (Cuzick, 1985), and figures were plotted with *ns* representing no difference and star symbol representing significant difference.

4.2. Participants

In total, 30 college students were recruited for the human subject experiment. As shown in Table 1, participants were aged from 18 years old to 42 years old (mean=26.3, std=4.38). In total, there were 19 males and 11 females respectively. As for college majors, 17 participants were from engineering majors (56.67%) such as Civil Engineering, Computer Science and Aerospace and Mechanical Engineering, and 13 participants (43.33%) were recruited from non-engineering majors such as Geography and Education. Despite the difference in educational background, all participants were trained carefully until they reported that they felt fully trained and were comfortable with using the provided system to finish the experiment.

Table 1
Background information of participants (n = 30).

Category	Item	Number	Percentage
Gender	Male	19	63.33%
	Female	11	36.67%
Age	Under 20	3	10.00%
	20–29	24	80.00%
	Above 30	3	10.00%
College Major	Engineering	17	56.67%
	Non-Engineering	13	43.33%

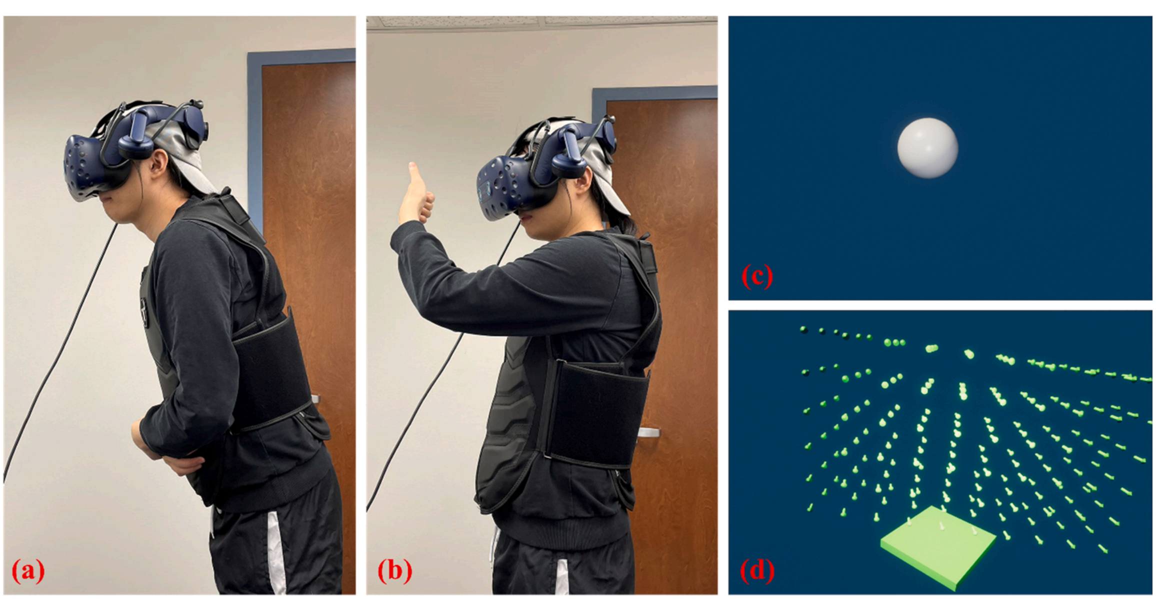

Fig. 7. Human subject experiment: (a) Body motion control; (b) Hand gesture control; (c) Task A: target following; (d) Task B: ROV stabilization control.

4.3. Task A performance

For Task A, we recorded the trajectory of the ROV operated by participants at 60 Hz and compared it with the target ball's trajectory. Three different trajectories were designed in three conditions to eliminate the learning effect in within-subject experiment design. The total trajectory length and the number of turns were designed as the same to ensure a similar difficulty level, therefor we can further compare the deviation and similarity to the target trajectories. As shown in Fig. 8, the solid line represents the target ball's movement trajectory and the point cloud indicates the distribution of participants' trajectories. The average deviation (m) per frame (0.01 s) under the joystick condition, fixed control parameters condition and self-adjustable condition were 7.426 m, 5.568 m and 3.926 m respectively, while the average DTW trajectory similarities for the three conditions were 472.736, 375.007 and 291.146. Although the joystick control method has been verified to be effective in ROV control, it was not easy enough for participants, especially for those who did not have much joystick control experience. In contrast, the haptomotor embodiment control method enabled participants to easily adapt to the ROV navigation tasks.

Specific results showed significant performance differences among the three conditions. Fig. 9a showed the Wilcoxon test in average deviation (m). Significant differences could be observed between the joystick condition and the fixed control parameters condition ($p = 0.001$), and between the fixed control parameters condition and the self-adjustable parameters condition ($p < 0.0001$). However, there was no significant difference between the joystick condition and the fixed control parameters condition ($p = 0.237$). Similarly, for the DTW similarities shown in Fig. 9b, significant differences could be observed between the joystick condition and the self-adjustable parameters condition ($p = 0.013$), and between the fixed control parameters condition and the self-adjustable parameters condition ($p = 0.0003$). There was no significant difference between the joystick condition and the fixed parameters condition ($p = 0.416$). The result showed that participants could perform better with natural body motions if they were allowed to adjust sensitivities by themselves. Fixed control parameters could not satisfy all participants' preference needs and may have influenced their performance. To better leverage the proposed haptomotor embodiment control method in ROV teleoperation, the most appropriate control and feedback sensitivity values were critical for performance.

4.4. Task B performance

Then we used three performance metrics to evaluate the performance of Task B, including the total moving distance (m), the average deviation from the target platform (m), and the standard deviation of position data. These measurements were used to indicate the capability of the participant in resisting the drift effect caused by subsea currents and the stability of the positioning actions. Fig. 10 showed the distribution of the ROV position data of all 30 participants. The total moving distance was 40.775 m, 14.752 m and 11.566 m, the average distance from the target platform was 2.065 m, 0.719 m and 0.618 m respectively, and the average standard deviation of the data was 1.635 m, 0.339 m and 0.234 m for the joystick condition, the fixed control parameters condition and the self-adjustable parameters condition. As shown, under the joystick condition, more than half of the participants could not maintain on the platform, showing as the points spreading away from the center.

Fig. 11 shows the statistical results of the Wilcoxon tests. A significant difference was observed in the total moving distance between the joystick condition and the fixed control parameters condition ($p < 0.0001$), between the fixed control parameters condition and the self-adjustable parameters condition ($p = 0.004$), and between the joystick condition and the self-adjustable parameters condition ($p < 0.0001$). There were no significant differences in the average deviation from the target platform (m) between the joystick condition and the fixed control parameters condition ($p = 0.952$), between the fixed control parameters condition and the self-adjustable parameters condition ($p = 0.271$), or between the joystick condition and the self-adjustable parameters condition ($p = 0.584$). Similarly, no significant difference was observed in standard deviation between the joystick condition and the fixed control parameters condition ($p = 0.318$), or between the joystick condition and the self-adjustable parameters condition ($p = 0.080$). But participants performed better in the self-adjustable parameters condition compared to the fixed control parameters condition ($p = 0.026$). In general, although participants could still maintain relatively similar stability and a low deviation from the target platform under all three conditions system, the total moving distance was significantly lower if the proposed haptomotor embodiment control method was provided. The reason might be that participants could better understand how much they should react to the haptic feedback that indicated the hydrodynamic forces imposed on the ROV. The intuitive control and feedback loop could help participants identify the optimal level of control inputs to resist the drift effect caused by subsea currents instead of repetitively trying with the joysticks.

4.5. Demographic impact

Mann-Whitney analysis (McKnight and Najab, 2010) was applied to test if demographic factors, including age, gender, college major (i.e., engineering versus non-engineering majors) and VR experience, influenced performance in the experiment. The result showed that only gender differences showed some impact. To be concise in reporting the findings, we only reported how gender influenced the performance differences among the three conditions.

As illustrated in Fig. 12, female participants seemed to be more

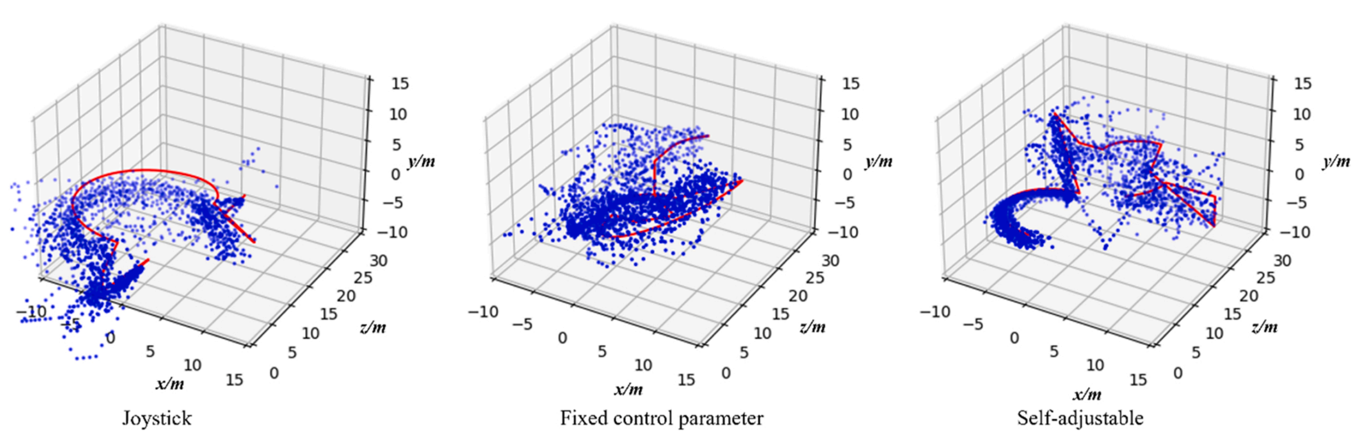

Fig. 8. Target ball's trajectory and distribution of human operators' control trajectories in Task A.

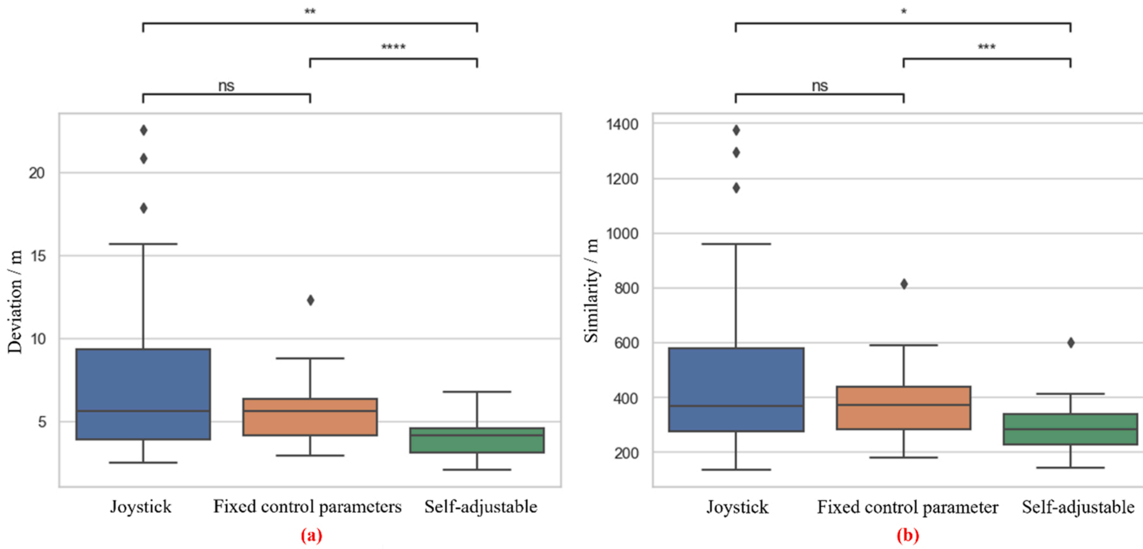

Fig. 9. Performance result in Task A: (a) Average deviation; (b) DTW trajectory similarities.

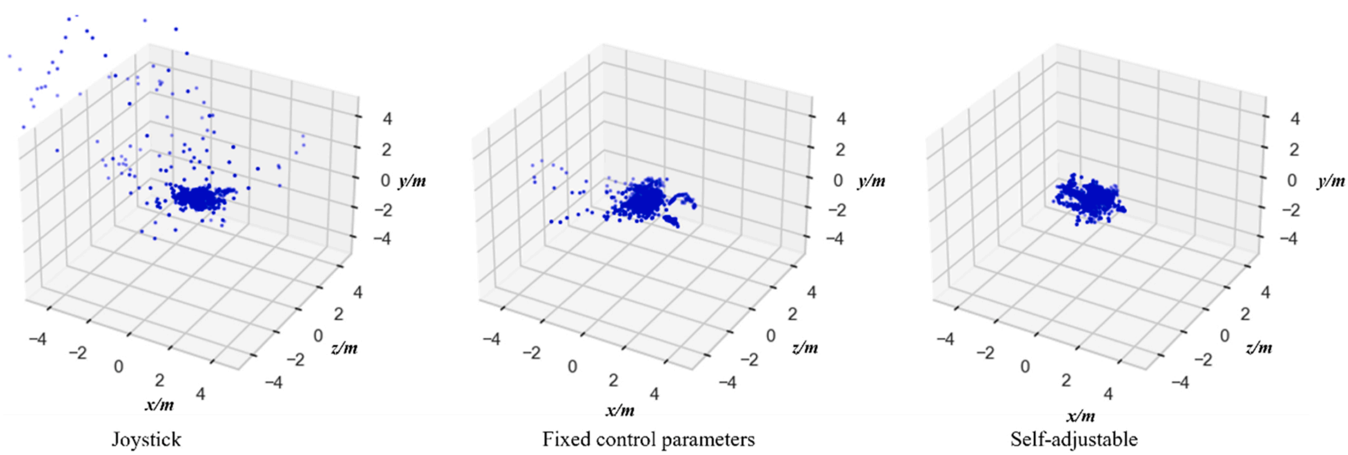

Fig. 10. Positions of ROV in Task B.

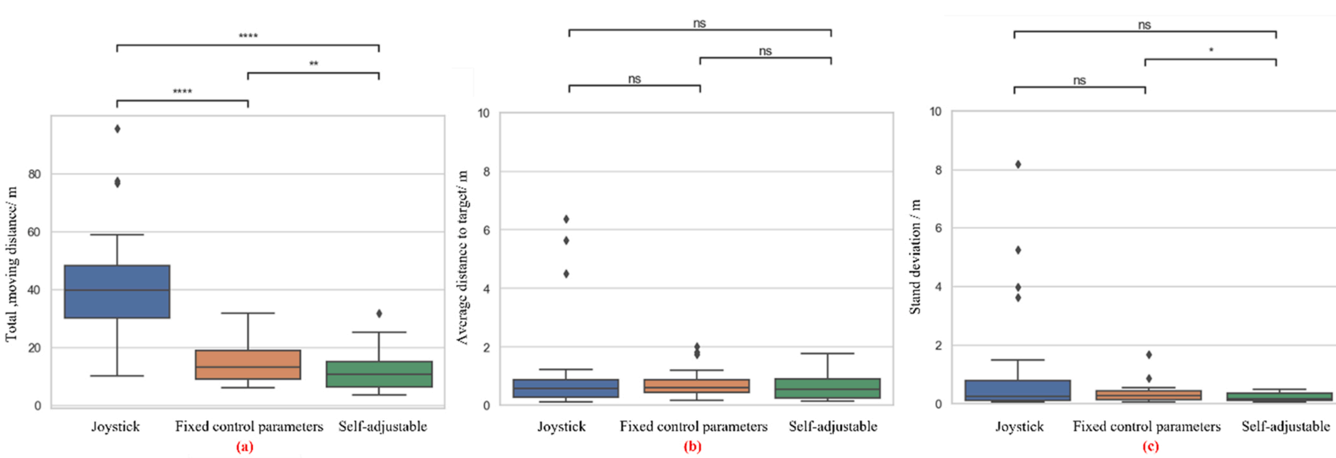

Fig. 11. Performance result in Task B: (a) Total moving distance; (b) Average deviation from the target platform; (c) Standard deviation of the position data.

benefited when changing from the joystick condition to the proposed haptomotor embodiment control condition. For example, as shown in Fig. 12a and b, the improvement in lowering deviation and increasing trajectory similarity in Task A was greater for female participants than male participants ($p = 0.015$). Similarly in Task B, greater improvements could be seen in female participants when switching from the traditional joystick control method to the proposed haptomotor embodiment control method (i.e., the fixed control parameters

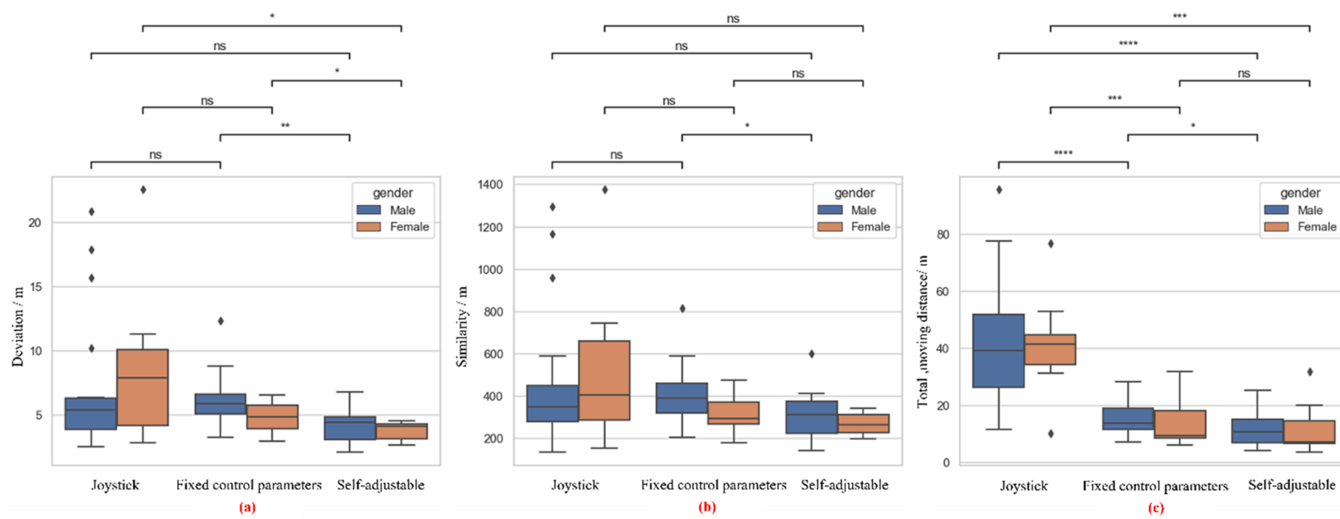

Fig. 12. Performance difference with gender groups: (a) Average deviation in Task A; (b) DTW trajectory similarities for the first task. (c) Total moving distance for the second task.

condition and the self-adjustable condition) (see Fig. 12c). In general, females could be benefited more from the proposed haptomotor embodiment control showing as better performance in both the first and second tasks, but whether they were allowed to adjust the sensitivity values (i.e., changing from the fixed control parameters condition to the self-adjustable condition) did not seem to be important. In contrast, male participants would perform much better if they could adjust sensitivities by themselves to their preferred values.

4.6. Survey results

After each experiment condition, participants were asked to finish a NASA TLX survey and answer user experience questions, including the perceived complexity of the control methods (complexity), self-evaluation of performance (self-evaluation), and perceived concentration on the tasks (concentration). Besides, they were also asked about their preference for different control methods, and evaluation of self-adjustable parameters after the experiment. As illustrated in Table 2, most participants (90.00%) commented that the proposed haptomotor embodiment control method was more intuitive and preferred to use it despite perceived performance in the experiment. On the other hand, most participants (90.00%) thought that the design of adjustable sensitivities was helpful in their control, and among them, 11 participants (36.67%) even though it was critical for their control performance.

Other survey results were shown in Fig. 13. Participants showed a higher overall workload in the NASA TLX survey in the joystick condition compared to the fixed control parameters condition ($p = 0.011$) and the self-adjustable parameters condition ($p = 0.0058$). For specific aspects in the NASA TLX survey, as shown in Fig. 13e, the joystick control method was reported to cause a higher mental load, which over-exhausted their efforts in the task, induced a sense of urgency during the experiment, and caused negative emotions such as frustration.

Table 2
Preference and evaluation of participants ($n = 30$).

Category	Item	Number	Percentage
Preference	Joystick control method	3	10.00%
	Body motion control method	27	90.00%
Evaluation of adjustable sensitivities	No help	3	10.00%
	Help a little	16	53.33%
	Help really much	11	36.67%

Besides, participant highly ranked their control precision in the self-adjustable parameters condition more than in the fixed control parameters condition ($p = 0.0018$) or in the joystick condition ($p = 0.0064$), but thought that the joystick control method was a less complex system compared to the other two methods ($p = 0.028$ and $p = 0.036$ respectively). As a maturely developed and widely applied control method (such as in gaming), most participants were no doubt more familiar with the joysticks and felt it was faster to adapt to. However, the high mental load and disconnection with the feedback loop resulted in worse performance in a complex ROV navigation task. In contrast, with the proposed haptomotor embodiment control method, although many participants thought it to be “too complex” at the beginning of the experiment, they could adapt to the use of the method rapidly, which help lower workload and achieve better performance later.

4.7. User-preference of control sensitivities

In order to start building a database about usability for the future design of hapotomotor embodiment control systems, we collected user preference data for haptic and body control sensitivities. The Shapiro-Wilk test (Hanusz et al., 2016) was used for the normal distribution test with a null hypothesis as that data is from the normal distribution. As shown in Fig. 14, the user-preferred haptic feedback intensity was tested as a normal distribution with $p = 0.398$, mean $= 0.391$ and std $= 0.248$. For body motion control sensitivity, a normal distribution could be fitted ($p = 0.064$) as well, with mean $= 0.593$ and std $= 0.183$. In addition, we previously assumed that the most appropriate body motion sensitives should be related to the user’s body height, since taller people might have a larger moving range for their bodies and thus prefer smaller sensitivities. However, the result did not show any relationship between body motion sensitivity and body height ($p = 0.209$). The fixed value that was close to the mean value seemed to be acceptable to most participants.

To further investigate how inappropriate parameters influenced performance in the experiment, we ran a multiple regression analysis (Maxwell, 2000) between the performance change (which was the percentage of similarity differences between the self-adjustable parameters condition and the fixed control parameters condition) and the deviation from the desired sensitivity values. The result (Fig. 14c&d) showed that there was a linear relationship between the performance change and the deviation from the desired sensitivity values. The multiple regression fitted these factors as Eq.11 with $p = 0.05$ for body motion sensitivity, $p = 0.014$ for haptic sensitivity, and $p = 0.343$ for

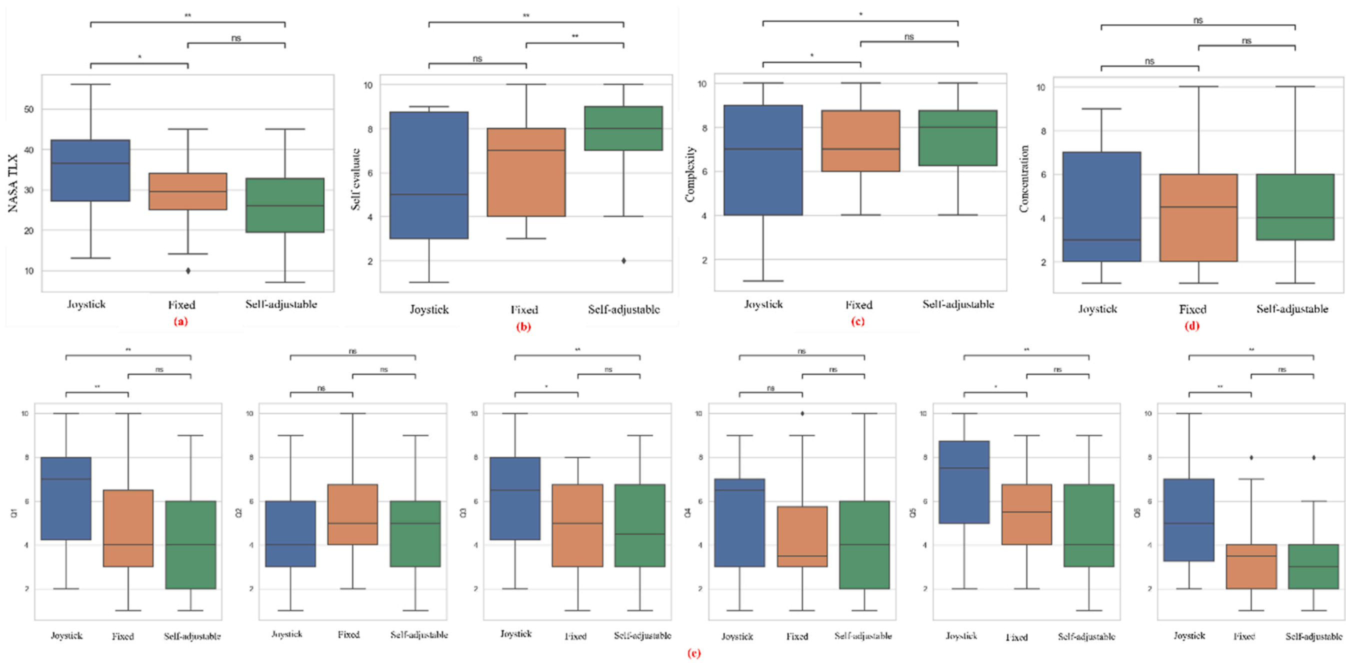

Fig. 13. Surveys results. (a) NASA TLX survey. (b) Self-evaluation for control. (c) Complexity of the control method. (d) Concentration during the experiment. (e) Specific results of each question in NASA TLX.

constant value, where P is the percentage of performance influenced, d_{motion} is the deviation from the desired motion sensitivity, and d_{haptic} is the deviation from the desired haptic sensitivity.

$$P = 0.6099d_{motion} + 0.7142d_{haptic} - 0.0701 \quad (11)$$

This result indicated that if the preset sensitivity value (provided in the fixed control parameters condition) was far away from the desired sensitivity (selected by the participants in the self-adjustable condition), their control performance would be negatively affected. For the proposed haptomotor embodiment control method, a UI that allows users to adjust the control sensitivity parameters seems to be helpful. And this is more obvious for male users as discussed earlier.

5. Discussion

In general, participants performed better in two tasks with the provided method than using the conventional joystick-based method. We don't intend to argue that joystick control methods are ineffective. Indeed, joystick control methods have been widely used and verified globally as effective methods for controlling intelligent systems. However, it takes time and excessive training to master when controlling complex systems. The increased mental load, as well as the uncomfortable working environment also increase the application barriers. Specifically in this research, participants can be viewed as novice ROV operators, working on simplified ROV tasks. Even so, participants still reported a higher mental load during the operations with the joystick and did not perform as well as they expected. In contrast, using our proposed new method, participants felt it was more complex to handle at the very beginning, but could easily adapt to the intuitive feedback-control loop and natural body motion interactions, which significantly reduced their mental load in the ROV operation tasks. Current subsea engineering remains a highly specialized area due to the high learning barrier, high mental load, and uncomfortable working environment. The proposed control method is expected to help solve the adaptation by simplifying the training requirements.

Several limitations need to be addressed in the future. Firstly, the collected dataset of control sensitivity is not sufficient to support the evidence-based design of the future ROV teleoperation systems based on the proposed haptomotor embodiment. Only limited factors were involved in this experiment and data size was not enough for efficient system design. Besides, it has remained unknown what factors influence human-preferred haptic and body motion sensitivity. More data and experiments are necessary to explore the reasons. Secondly, the proposed system utilized various sensory channel cues to convert complex information. These cues included 3D spatial information and augmented visual cues VR, direction and orientation synchronized with human body movements, and haptic feedback to convey flow conditions. This design aimed to reduce the amount of information displayed on the visual screen. However, in the context of real ROV teleoperation, additional instrument information might be necessary depending on task requirements. Therefore, an effective UI design becomes crucial for presenting complex information in VR (Zhou et al., 2023). Furthermore, some participants expressed difficulties in recognizing and operating the UI within the VR environment in the current system. To address this issue, future applications should prioritize the development of an improved UI design that enhances recognition and facilitates a smooth operation. Thirdly, it is important to consider that humans may experience sudden body changes that surpass the capabilities of the ROV. To address this issue, future developments could incorporate a smooth function that helps to mitigate abrupt variations in human body motion data. By implementing such a function, the system can ensure smoother and more consistent control of the ROV, compensating for any unexpected or irregular body movements exhibited by the operator.

Furthermore, there are three primary concerns regarding the future applications of this technology: user fatigue, the complexity of subsea environments, and data transfer delays. To address user fatigue, there are two potential solutions identified. Firstly, a sensitivity adjustment system was designed in the current study. Users could adjust to high sensitivity values, with minor body motion control for high moving speed. This is hoped to reduce human motion fatigue for long-time operations. Meanwhile, a certain level of autonomy could be involved to reduce human worktime with VR devices. For example, autonomous algorithms can be used for repetitive navigation tasks and human operators could be responsible for those complex tasks such as stabilization. On the other hand, it is important to note that real-world ocean conditions are often more intricate and diverse than what simulations

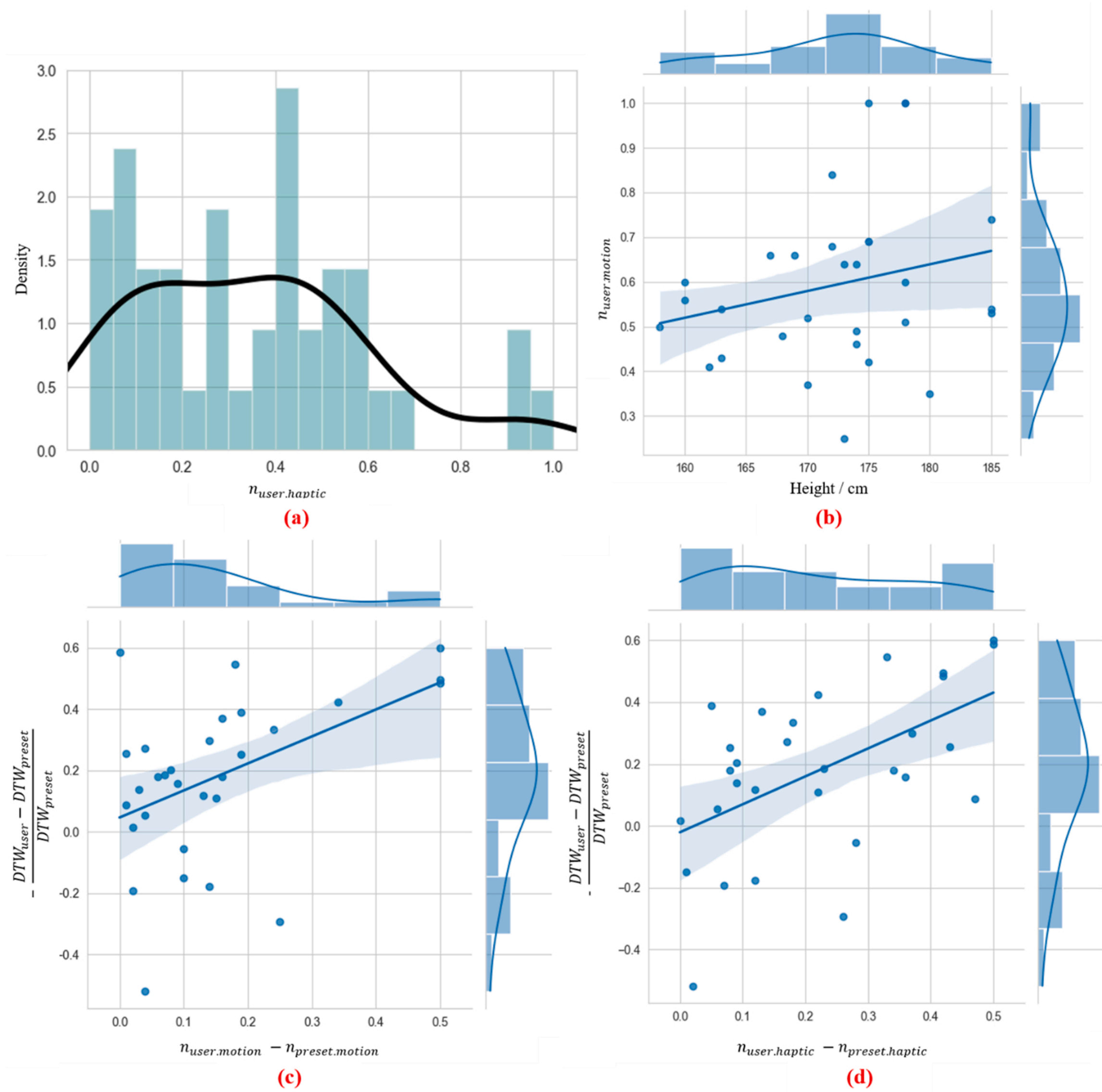

Fig. 14. Sensitivity data distribution and relationship. (a) Distribution of haptic sensitivity $n_{user.haptic}$. (b) Distribution of body motion sensitivity $n_{user.motion}$ and its relationship with height. (c) Relationship between the performance difference and motion sensitivity difference. (d) Relationship between the performance difference and haptic sensitivity difference.

can fully replicate. Moreover, data transfer delays may be encountered in practical applications. It is crucial to conduct further tests involving professional ROV operators in real ROV teleoperation scenarios using this system. While the current experiment has successfully verified the system's concept and frameworks, the next step involves teleoperating an actual ROV to evaluate its robustness in complex ocean conditions and assess the impact of data transfer delays. Additionally, it is worth mentioning that work-class ROVs typically incorporate manipulation arms for various tasks. However, our current study focuses solely on inspection-use ROVs without incorporating human body motion control for robotic arms. Future development will involve converting human hand motions into manipulation arm postures based on our previous research on human hand motion control for ground robotic arms (Zhou et al., 2021).

6. Conclusions

ROVs play an active role in the subsea engineering activities of today and tomorrow. At present, ROV control mainly relies on traditional control kiosks and feedback methods, such as using joysticks and camera displays equipped on a surface vessel. The high cognitive load, long training process, and uncomfortable working environment of the conventional methods have greatly increased the training barriers in the current subsea engineering market, causing the ROV operation job a highly specialized profession. This paper proposed a VR-haptics-based hapotomotor embodiment control method for future ROV teleoperation. Multisensory feedback, including augmented visual and haptic feedback, is provided to human operators for perceiving richer information about remote subsea workplaces and hydrodynamic features in an intuitive way. Then body-carried sensors are used to capture natural human body motions and hand gestures to control the steering and navigation of the ROV. By closing the loop of haptic feedback and motor actions, human operators could leverage the spontaneous haptomotor reflex in complex motor tasks of ROV teleoperation.

A human subject experiment was performed to verify the performance of using the proposed method in ROV navigation and steering (stabilization) tasks under three conditions, including the conventional joystick control condition, the fixed control parameter condition where preset control sensitivity values were provided, and the self-adjustable condition where participants were allowed to adjust the control sensitivities based on their own preference. The result showed that our proposed method was more intuitive and friendly to use.

In conclusion, with the urgent need for subsea engineering, a new teleoperation method is necessary to reduce career barriers. We expect that the proposed new method of ROV feedback and controls can help advance a booming subsea engineering industry, enable a much closer human-ROV collaboration for subsea inspection and survey, and reduce training barriers and workload for longer work life in subsea engineering. This method is also strongly positioned for better accessibility and inclusion because it aims to lower the career barrier for a traditionally highly professional area. The haptomotor embodiment method for ROV control may help mitigate the age requirement, promoting career longevity. The new technology may also help salvage the careers of experienced workers who have suffered from career injuries, such as diving diseases.

CRediT authorship contribution statement

Jing Du: Conceptualization, Methodology, Writing – review & editing. **Pengxiang Xia**: Investigation, Data analysis, Visualization, Writing – original draft. **Yang Ye**: Investigation, Visualization. **Hengxu You:** Investigation, Writing – review & editing.

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.

Data Availability

Data will be made available on request.

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