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Sensory augmentation for subsea robot teleoperation

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ABSTRACT

Subsea construction operations heavily rely on remotely operated vehicles (ROV). Due to the dynamics of the subsea environment such as uncertain turbulences, affected visibility and interference with subsea ecosystems, control of subsea ROV is challenging for human operators, especially for construction professionals who have never been exposed to such an environment. The traditional visual feedback method can hardly provide direct and intuitive cues about workplace uncertainties, especially the flow conditions, which makes the ROV operation a work with a high mental load and high training barrier. To augment human sensation of the ROV and workplace status, this research proposes a hierarchical intuitive control method based on Virtual Reality (VR) and haptic simulators. A distributed sensor system that allows a flexible add-on sensor package for subsea environmental data collection is applied to the ROVs to collect hydrodynamic data of subsea workplaces. Then, a Digital Twins (DT) module receives and integrates all data to drive a simulation approach for data augmentation. Last, multi-level sensory feedback methods, including far-field augmented 3D visual feedback, near-field haptic suit tactile feedback, and micro-field haptic suit turbulence feedback are generated and sent to human operators through haptic devices. Compared to previous studies, this system reconstructs the realistic subsea environment with detailed hydrodynamic features in VR digital twin. Whole-body level haptic feedback is realized based on hydrodynamic information. This proposed system ensures an immersive awareness of the proximity conditions and predictions of potential damage and status changes during ROV operations. As a result, a less-trained operator can pilot the ROV based on intuition to maximize the performance and avoid potential mistakes.

1. Introduction

According to the National Oceanic and Atmospheric Administration (NOAA), about 95% of the world's oceans and 99% of the ocean floor are unexplored (Baird, 2005). Augmentation of human abilities in subsea engineering work, such as offshore construction and inspection (e.g., floating cities and offshore wind farms) and subsea exploration and operations (e.g., offshore mining, subsea cables, and energy harvesting), provides a historic opportunity for the new economic growth and scientific discoveries. There is an urgent need to seek versatile, high-efficiency, low-risk-cost subsea engineering solutions. In practice, remotely operated vehicles (ROVs) have been an effective tool for subsea exploration and operations for decades (Kennedy et al., 2019). The applications of ROVs have been increasing rapidly in recent years and are expected to continue growing in the future (Brun, 2012). Global Underwater ROV Market Size is projected to reach $124.6 million by 2026, from $76 million in 2020, at a compound annual growth rate of 8.5% during 2021–2026 (WBOC, 2021).

Subsea engineering operations benefit from ROVs because of their agility, safety, and endurance (Li et al., 2018), but the teleoperation of ROVs can still be challenging and risky due to the mismatch between the complexity of subsea workspace and the environmental perception of human operators. In general, a typical ROV system consists of a submersible vehicle, a surface control unit, and a tether management system (Salgado-Jimenez et al., 2010). Technicians from above sea level, usually working on a vessel, can take control of the whole system to accomplish complex tasks with the live video streaming captured by the cameras equipped on the ROVs (Zhang et al., 2017). The complexity of the subsea environment, such as the dynamic internal currents, low visibility, and unexpected contacts with marine life, may undermine the stability of the ROVs, or the stabilization control (Khadhraoui et al., 2016). Although many ROV studies are focusing on autonomous algorithms, such a certain level of self-stabilization and even self-navigation functions nowadays, human controls are still necessary for complex

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tasks that require precise operations (Fossen, 2011). Human sensorimotor control relies on multimodal sensory feedback, such as the visual and somatosensory cues, to make sense of the consequence of any initiated action (Wood et al., 2013). In ROV teleoperations, only visual feedback is provided in existing methods. The lack of ability to perceive various subsea environmental and spatial features, such as the inability to directly sense water flows and pressure changes, can break the critical feedback loop for accurate motor actions, resulting in an induced *perceptual-motor malfunction* (Finney, 2015). Especially in future ROV application scenarios, there will be complex and diverse tasks for ROVs, such as navigation in tight, cluttered, and unstructured environments; stabilization in highly dynamic flow conditions; repeated docking/undocking operations, etc., which all require varieties of environmental information and in-situ perception of the ROV workspace (Lachaud et al., 2018; Xia et al., 2022). In addition, the information about the ambient fluid environment at different spatiotemporal scales would also benefit ROV operations substantially (Lin and Yang, 2020). There is an urgent need to grant ROV operators the ability to "see, hear and feel" the subsea workplaces and ROV status with multisensory capacity in an intuitive way (Moniruzzaman et al., 2021; Xia et al., 2022).

This research proposes a virtual telepresence system based on VR and a sensory augmentation simulator to mitigate the perceptual-motor malfunction, and enhance human perception as well as operation accuracy in ROV teleoperation. In order to provide multi-level information to meet the versatility of future ROV teleoperation, a hierarchical haptic simulator is proposed to simulate the following subsea environmental features on the body of the human operator via haptotactile sensations: 1) near-field (<3 m) and small-scale hydrodynamics around the ROVs that could affect the vehicle stabilization and maneuverability; and 2) far-field (>3 m) mean hydrodynamic flows that are critical to the ROV navigation and motion planning. Besides, an augmented force rendering with a pair of high-fidelity haptic gloves for sensing micro-scale turbulence is provided as well to further extend human sensation. The multi-level environmental information is collected by ROV-equipped sensors, sent to the Digital Twin module for data fusion and reconstruction, and converted into different scales of visual and haptic feedback through different devices accordingly. Compared to previous VR and haptic teleoperation studies, this system reconstructs a realistic subsea environment with both visual objects and hydrodynamic features in VR digital twin. A whole-body coverage haptic feedback is generated to provide sufficient environmental information for ROV operation. With this integrated VR-Haptic sensory feedback system, the human sensation of the robot workspace is extended, which will benefit ROV teleoperation for future complex subsea operations.

2. Literature review

2.1. ROV operations and controls

ROVs are a common type of unmanned underwater vehicles (UUVs) that are widely used in a wide range of subsea applications. These applications include underwater intervention, exploration and surveys, equipment installation and retrieval, sample collections, and photography/filmography, to name a few (Brun, 2012; NOAA, 2021). The differentiating characteristics of ROVs from autonomous underwater vehicles (AUVs), the other common type of UUVs, include their large numbers of maneuvering degrees of freedom; expendability to be outfitted with a wide range of monitoring and navigational payloads; and versatility in fulfilling needs for underwater intervention and manipulation tasks when equipped with manipulators (Azis et al., 2012; Brun, 2012; Paull et al., 2013). As the name indicates, ROVs are designed to be remotely operable through a tether connecting the vehicle and the remote operator. For larger ROV systems that need to be deployed from a surface vessel, an intermediate cable management system is often necessary to reach deeper depths. The umbilical cable provides a high-speed data connection between the vehicle and the remote operator, making real-time data streaming and high-frequency remote control possible (Filaretov et al., 2018; Song et al., 2020).

ROVs can be classified differently depending on their typical dimensions, costs, functionalities, etc. Based on their main purposes, existing ROV platforms can be loosely categorized as education/hobbyist-class, inspection/survey-class, and work-class (Song et al., 2020). Education-class ROVs are often smaller in size and designed with an open architecture, making them an ideal platform for universities and research institutes that desire low-cost platforms with good expendabilities (Wang et al., 2019). The BlueROV series by Blue Robotics is an example of this type of platform (BlueRobotics, 2021). Inspection/survey-class ROVs are often equipped with different types of sensing instruments for data collection and monitoring (Capocci et al., 2017). A wide range of ROVs is full within this category, including the commercially available Sabertooth ROV by Saab Seaeye (Johansson et al., 2010). The work-class ROVs are the most versatile ones that are often equipped with underwater manipulation capabilities. They play an essential role nowadays in many of the routine operations of oil and gas industries and the ocean science community (Nakajoh et al., 2012). An emerging category is the residential-class ROVs that are designed to be deployed at the work site for an extended period with support from underwater docking stations and subsea cables for power and communication (Jacoff et al., 2015).

Although ROVs vary in their sensing and actuation capabilities, they typically have basic capabilities such as maneuverability along more than one principal axes, state estimation, and communication through the umbilical cable or additional wireless means. For work-class ROVs, more sophisticated actuation and sensing capabilities are often available to ensure operational accuracy and improve system reliability (Finney, 2015). For instance, to improve the vehicle control robustness in dynamic and uncertain conditions, a disturbance rejection controller can be implemented to improve the maneuvering accuracy in the event where unknown environmental forces appear to act on the vehicle (Cao et al., 2020). This capability becomes very essential to ROVs when performing intervention or manipulation tasks, where the body of the ROVs needs to hold its position to allow precise control of the end effector. However, existing station holding controllers often act as after-the-effect disturbance compensators, meaning that the controller will not take effect until a position holder error appears due to disturbances (Caccavale and Villani, 2002; Wang et al., 2017). Such a vehicle stabilization method creates control delays and inaccuracies for ROVs. Similarly, more capable ROVs are equipped with navigational sensors with improved range, precision, and long-term accuracy. These navigational sensors allow the ROVs to maintain a better positioning accuracy, which is of utmost importance for underwater navigation where satellite-based localization services are not available and persistent localization is inherently challenging (Paull et al., 2013).

ROV technologies have gradually matured over the past few decades. Nonetheless, operating an ROV is still a challenging and demanding task even for experienced ROV pilots with years of background in ocean engineering, especially for complex subsea inspection, installation and maintenance tasks. Operations in these tasks can entail risks of complacency, misjudgment and loss of manoeuverability due to a lack of environmental information (Utne et al., 2019). However, current efforts in ROV technologies development do not help reduce the high barriers to entry for ROV piloting. On the one hand, many studies focused on improving traditional visual feedback and joystick controller, such as photo-model-based stereo-vision 3D perception (Tian et al., 2019) and extra steering for ROV control systems by tracking the gamepad orientation (Abdulov and Abramenkov, 2021). These methods highly relied on operators' skills and did not resolve the perceptual-motor malfunction problem (Finney, 2015). On the other hand, more and more studies focused on autonomous algorithms, including automatic docking (Qomaruzzaman and Mardiyanto, 2018), autonomous inspection (Amundsen et al., 2021), and autonomous manipulation (Yeu et al., 2019). Yet, the subsea environment is much more complex than the traditional engineering workplace, such as highly dynamic fluid environments with many unknown disturbances. It is extremely hard for autonomous algorithms to cover all the work requirements, and human operators are necessary in the loop. Future ROVs should possess high levels of autonomy with human control in the loop and be capable of relaying underwater perceptions of different modalities back to the human operator in real time, creating an intuitive and immersive piloting experience.

2.2. VR-based robot teleoperation

Traditional robot teleoperation, especially ROV teleoperation, highly relied on camera view display and all kinds of joystick panel control (Kent et al., 2017). Many studies focused on improving teleoperation by designing efficient teleoperation interface (Kent et al., 2017; Labonte et al., 2010) and additional workload analysis (Lin et al., 2019). These kinds of control methods still lacked sufficient sensory feedback, which might result in lower spatial perception in complex environments (Lathan and Tracey, 2002). Virtual Reality (VR) is an emerging human-computer interface for rendering realistic environment scenes and for providing rich spatial information (Brooks, 1999; Zheng et al., 1998). VR for human-robot collaboration (HRC) has brought the benefits of coupling the perception and controls between human agents and robots (Chakraborti et al., 2017). Such a close sensation pairing can result in a better plan of motions and interactions in difficult tasks that require both robotic and human intelligence (Williams et al., 2019). For robot teleoperation, compared to traditional 2D imagery or video feedback above, the advantage of VR is to provide a direct and immersive 3D visualization of the target object or scene within the surrounding workplace, therefore converting richer environmental information and relationship between multi objects to human users, and lowering the communication and control barriers (Kaminka, 2013).

In addition to augmenting visual feedback, it is recently noted that VR can also serve as the platform for multisensory augmentation, i.e., providing multimodal visual, auditory, and haptic cues associated with an intended action to improve the motor performance (Sugiyama and Liew, 2017; Zhou et al., 2020a, 2020b; Zhu et al., 2021). Especially, haptic devices combined with a VR simulation can generate haptotactile stimulation (e.g., vibrations and force feedback) on the user's body in correspondence with the occurring events (Tian et al., 2017, 2021). These haptotactile signals may be used as feedback cues signing for the human operator's sensation to help understand the motion and status of ROVs, which is expected to further improve human spatial awareness and control ability of ROVs. In fact, some studies have already tested the efficacy of capturing underwater environmental information and sending the simulated haptic signals back to humans. For example, a linear-oscillating actuator using asymmetric drivers was developed to create equivalent pressure signals (Ciriello et al., 2013), such as pushing or hydrostatic pressure in remote system operations. A gyro effect haptic actuator was tested to simulate torque feedback even when ungrounded (Shazali, 2018). The combined pressure and torsion forces applied to the user's body can produce the illusional feeling of external force and incorporated by the user's proprioceptors, generating a kinesthetic perception of the ROVs (Amemiya and Maeda, 2009). These preliminary "one-size-fits-all" efforts could only work in the pre-designed workspace with limited depth and zones, which could hardly capture multi-level hydrodynamic features in underwater workplaces. Lacking detailed information for different spatiotemporal scales, these methods may not be effective for ROV operations occurring in diverse and complex workspaces. Given the emergence of resident ROV systems, challenges for the large-scale ROV navigation and precision operations such as docking/undocking are both significant, which is missing in the current sensory feedback methods. A system is needed to capture high-fidelity hydrodynamic data at both the micro and macro levels, as well as simulations to create a unique immersive sensory-rich environment for ROV operators. The system should also be able to augment human ability in critical decision-making such as navigation path planning. We propose to utilize the framework of digital twin simulation to integrate the data processing and decision-making needs in the VR.

2.3. Digital Twin for complex work interface

Digital Twin (DT) is a comprehensive digital representation connecting to physical products. It includes properties, conditions, and behaviors of the real-life object through models and data (Haag and Anderl, 2018; Tao et al., 2018). An effective DT should have basic functions of modeling, simulation, verification, validation, accreditation (VV&A), data fusion, interaction and collaboration, and service (Jones et al., 2020; Tao et al., 2018). In practice, DT is a great tool for data fusion and augmentation, including integrating different sources of data and filling gaps in the collected data. For example, for geometrical variations management, a concept of Skin Model Shapes was proposed to connect all different views throughout the product life-cycle and operations in a comprehensive model that incorporates manufacturing process planning and inspection process planning (Schleich et al., 2016; Schleich et al., 2017). To monitor machining operations and predict surface roughness, a method was developed by Cai et al. and Tao et al. to integrate sensor data and manufacturing data as the basis for building the DT of a vertical milling machine (Ricks et al., 2015; Tao et al., 2018). Especially for subsea environment data, there is much-complicated information from a variety of sensors and methods. Tremendous data is obtained by different kinds of sensors for all purposes, including temperature sensors, hydro pressure sensors, acoustic doppler for turbidity, etc. (Williamson et al., 2015). Multiple methods are applied to predict ocean conditions, such as machine learning methods for modeling a bigger range of workplaces (Brunton et al., 2020) and Smoothed Particle Hydrodynamics (SPH) for simulating free surface flows (Liu and Liu, 2010). Such a huge amount of data results in a burden on data perception and analysis for human operators. Therefore, it deserves a further investigation to integrate all kinds of data in DT and send it to human operators effectively for future ROV subsea tasks.

Plus, DT can be used as an effective optimization tool. For example, DT for manufacturing can offer an opportunity to simulate and optimize the production system, including logistical aspects and visualization of the manufacturing process (Kritzinger et al., 2018). In robot applications, DT can serve as a platform for path planning. Simulated environments can be built in DT based on the physical environment, and path planning algorithms such as A* (Tseng et al., 2014) can be integrated to generate the shortest route path to target points. For example, a robot path planning algorithm that integrates human-predicted trajectories by a context-aware Long Short-Term Memory (LSTM) model was successfully designed by Hu et al. to navigate a robot at an unstructured construction site (Hu et al., 2020). However, for subsea environment path planning, it is more challenging due to the complexity of the subsea environment and the unique locomotion features of ROVs. Except for obstacles, potential dangers such as high turbidity areas are required to be avoided as well for ROV navigation. These kinds of information are lacking in current ROV operation studies. Therefore, further efforts are necessary to develop a multi-level hydrodynamic information display method and a subsea-adapted path plan function in the DT module.

3. System design

3.1. System architecture

The existing ROV control and feedback systems still focus on the camera view display and joystick controller. Although efforts were paid to efficient UI design (Labonte et al., 2010), workload analysis (Riddle, 2002) and autonomous algorithms (Amundsen et al., 2021; Qomaruzzaman and Mardiyanto, 2018), these methods could not provide enough sensory feedback for effective environmental spatial perception.

Especially, the complexity of the subsea environment, such as the dynamic internal currents, low visibility, and unexpected contact with marine life, may undermine the stability of the ROVs and result in a high career barrier. A new method is necessary to provide human operators with sufficient and immersive feedback of the surrounding workspace. Therefore, this study presents the design of a system combining the VR simulation and a whole-body haptic device to augment the human operator's sensation in ROV teleoperation. Fig. 1 illustrates the architecture of the proposed human-robot sensory transfer system for simplifying ROV teleoperation. The proposed system consists of five modules, including *Subsea Sensing Module, ROV module, Robotic Simulation, and Control Module*, *Workplace Model*, and *User Interface*. The details of each module are described as follows.

VR and haptic feedback methods have been commonly used in robot teleoperation, such as robotic arms (Zhou et al., 2020) and snake robot teleoperation (Zhu et al., 2022). Compared to these studies, our system contributes in two aspects. Firstly, previous studies consider VR as an immersive visual augmentation method, while our system improves it as a DT simulator and data center. Different kinds of sensory data are sent to VR and used to reconstruct a realistic subsea environment, including not only visual objects but also hydrodynamic features. Several algorithms are developed to categorize all kinds of data and generate multi-level feedback based on hydrodynamic features, such as micro-field haptic glove feedback, near-field haptic suit feedback, and far-field visual augmentation feedback. Secondly, many haptic-related studies are limited to a hand-held level, i.e., developing hand-held haptic device (Chen et al., 2019) and robotic arm sensory feedback (Li et al., 2019). Except for the hand-held device, our system extends the haptic feedback to a whole-body level. Several algorithms are developed to adjust hydrodynamic features to body-covered haptic intensity values.

3.2. Subsea sensing module

Subsea workplaces will be substantially different from our established workplaces, and thus the human operator may not perceive the environmental data in the desired way. As a result, we expect the sensing system to capture the key characteristics of a dynamic underwater environment for sensory augmentation. The Subsea sensing module builds on a multi-level sensor network to collect real-time subsea environmental data pertaining to the hydrodynamic features and temperature changes. The sensor network captures three levels of sensor data to meet the sensing needs, including far-field hydrodynamic status based on an acoustic Doppler current profiler (ADCP) (Kostaschuk et al., 2005) to collect underwater wave profiles in the 3–20 m proximity; and near field (0.1–3 m) and micro field (<0.1 m) turbulence based on in-situ sensors equipped on the ROVs. The far-field sensing aims to identify the sudden change of underwater waves on a bigger scale or the so-called "seamount". The existence of seamounts often poses significant risks to the teleoperation of ROVs as they usually intensify the tidal flow and water stratification, interrupting the ongoing ROV operation profiles. As for the in-situ sensor, we leverage an artificial skin – an innovative distributed sensor system that allows a flexible add-on sensor package. It uses an array of paired differential pressure sensors mounted on electronics boards. The boards are embedded in elastomers with hardware that allow them to connect to a 3D printed scaffolding or a custom shell. A hydrodynamic force measurement module is fabricated and installed onto the ROVs to enable the vehicle to sense near-field flows and hydrodynamic forces. Different scales of flow sensing measurements are collected by the sensor module and sent to the DT simulation and optimization module for data fusion, smoothing, and reconstruction. The artificial skin sensing system enables fast disturbance detection and rejection to improve vehicle control accuracy. The design of the in-situ sensor is based on our previous works (Krieg et al., 2011; Krieg et al., 2019; Krieg et al., 2015) on lateral-line sensory mechanisms within fish which consist of specialized "hair cells"

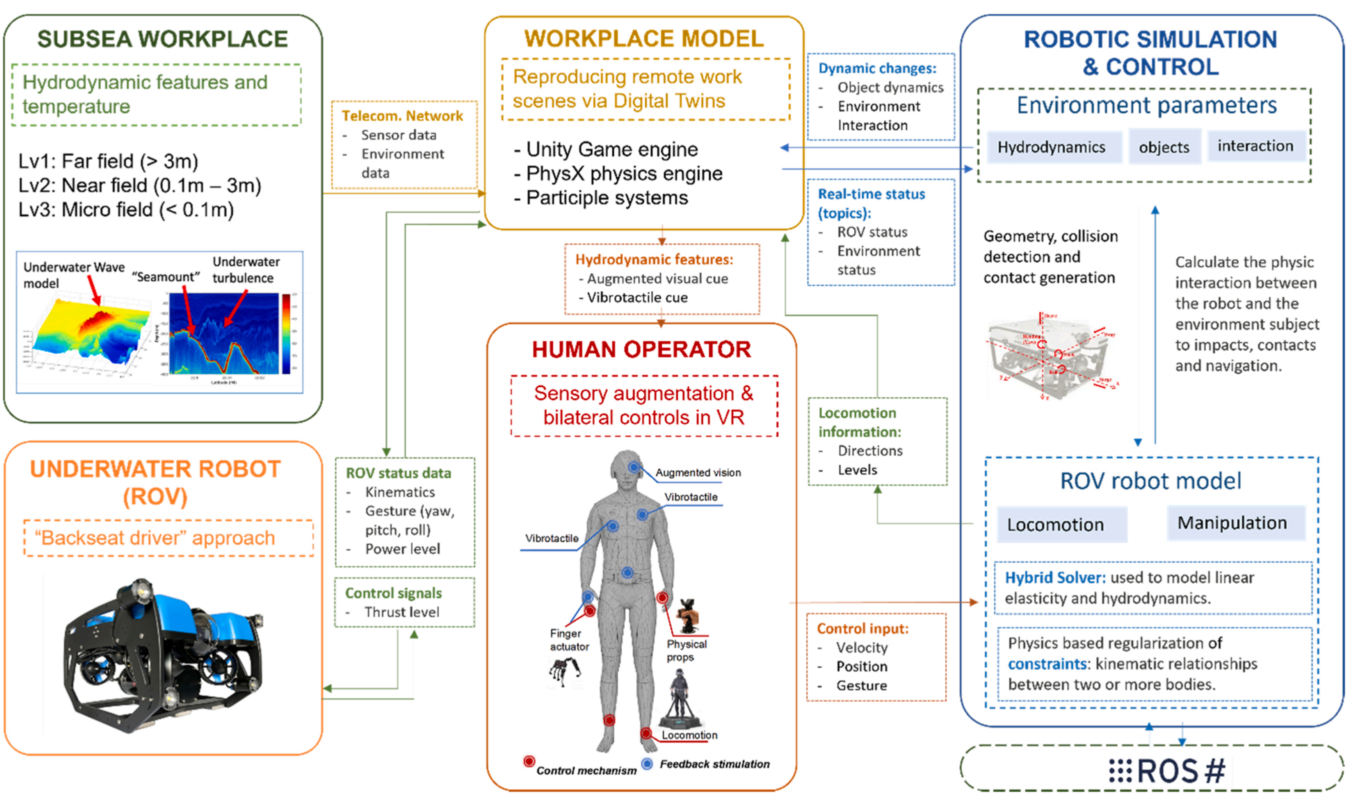

Fig. 1. Proposed underwater human-robot interaction for enhanced ROV teleoperation.

throughout the body surface capable of detecting pressure gradients and shear stress. Sensing signals include temperature, pressure gradient, and shear stress sensors distributed throughout a custom shell designed to fit the surface of the ROVs. All these visual and haptic feedbacks is sent to the operation module to generate a real-time and realistic sense of the ROV workspace for humans through multi-modal sensory devices. In addition, to enable the continuous operation and long-term availability, the proposed system is designed to be a resident system with a docking station that can be deployed for long terms and tasked remotely from a remote station on land (Song et al., 2020). The docking station can utilize power and communication interfaces available from existing cabled subsea observatories (Pawlak et al., 2009), marine renewable energy harvesting systems, or inter-continental telecommunication infrastructure (Wallen et al., 2019). The ROVs can be connected to a docking station through a cable management system for high reliability and bandwidth in data transfer, and the docking station is connected to a remote human operator via the Internet. The bioinspired flow sensing system is integrated with the vehicle to provide in-situ hydrodynamic force measurements. In addition, the DT simulated environment can be also used as a fast training of new operators and provide pre-mission evaluation for operation plans.

3.3. ROV module

The vehicle used in this project is based on a BlueROV2 platform with a heavy configuration. The BlueROV2 is an open-source underwater vehicle equipped with six thrusters in a vectored configuration. The heavy configuration provides control in all six DOFs. The based vehicle is powered by an onboard 18Ah battery, giving 2–3 h of battery life with a single charge. On top of the base platform, our vehicle is upgraded with a Jetson Xavier NX backseat computer (NVIDIA, 2021) to perform high-level sensor fusion and closed-loop control autonomy. The vehicle is outfitted with a bottom-facing single-beam echosounder that measures distances concerning the seafloor for up to 50 m, and a 360-degree scanning imaging sonar for underwater perception. In addition, the vehicle is equipped with a Nortek Doppler velocity log with current profiling capability that allows the vehicle to measure the relative velocity concerning the seafloor as well as the far-field flow velocity for augmenting the operator's situational awareness in the digital-twin environment. The vehicle is outfitted with forward and bottom-facing cameras, a 360-degree scanning sonar for obstacle detection, collision avoidance, and mapping, a custom-integrated wireless charging and communication system, and a 1-MHz compact acoustic Doppler current profiler (ADCP) to provide volumetric far-field flow measurements. The near-field flow and hydrodynamic force sensor are added to the vehicle as a separate module at locations free from structural obstructions, which may create vortex shedding and affect the sensing quality. This novel sensor system allows the vehicle to directly measure the hydrodynamic disturbances and compensate accordingly before positioning error starts to appear (Krieg et al., 2019), improving the vehicle control accuracy and responsiveness. We developed a "backseat driver" computing method to realize the open-loop control needs. As discussed earlier, there may be a disconnection between the control commends issued by the human operator and the actual reaction of the ROVs due to the changing hydrodynamic conditions in the subsea workplace. As a result, a resolver is used to generate the correct rendering of ROV kinematics in VR. The same applies to the controlling of the real ROVs, as the real system also needs to match the control commands and mirror the behaviors in the VR environment. The same hybrid solver will be applied to the backseat driver's computer. In addition, near-field flow sensing measurements can be reflected on the haptic suite and gloves on the pilot to enhance the situational awareness of the pilot.

3.4. Robotic simulation and control module

Physics engine simulation data and sensor data from the remote ROVs need to be transferred to Robot Operating System (ROS) seamlessly to enable ROV simulation and controls. Building on our previous work (Zhou, 2020), we will examine a data synchronization system for VR and robotic systems. The system features two functions: converting environmental parameters extracted from the workplace model (hydrodynamics, objects, and interactions) to ROS to rebuild the 3D scene in ROS Gazebo for robot simulation, and to enable the control commands for the ROVs. Rosbridge is used to provide a JSON API for transferring data between ROS and Unity (Crick et al., 2017). Rosbridge also provides a WebSocket server for web browsers to interact with, serving as a connection between ROS and the network (Crick et al., 2017). ROS server converts ROV dynamics data into JSON messages via rosbridge and publishes it to the website or receives JSON message from the Internet and converts it to ROS message (Crick et al., 2017; Quigley et al., 2009). On the Unity side, we use ROS#, a set of open-source software libraries in C#, for communicating with ROS from.NET applications, in particular, Unity (GitHub, 2019). ROS# establishes a WebSocket in Unity so that Unity can connect to a computer with a specific IP address through the network and transfer data. It also helps build nodes that publish and subscribe to topics from ROS in Unity. ROS# converts data into JSON and publishes it or converts the received data into the original format. We grant the ROS server and Unity's WebSocket the same IP address so that the ROS server can publish the processed topics to the ROS platform, and Unity can subscribe to all topics on ROS platforms through ROS#.

The robotic simulation and control module also supports an intuitive control of the remote ROVs via natural body motions. As shown in Fig. 2. Human control input parameters, including local rotation of HTC trackers, body postures, and a secondary auxiliary controller, are designed to match ROV control parameters such as rotation, moving, and some specific control functions. The local rotation of the human body is sent to ROVs for pitch, roll, and yaw control, which ensures ROVs' orientation consistent with human body motion. Human body postures are designed to control ROVs moving in the subsea environment. For example, ROV pitches down when the human operator leans forward. A secondary auxiliary control method, the HTC VIVE controller is introduced for vertical up and down operations and function control. Specifically, the y-axis input value of the touchpad was used to control up and down for ROVs, with the x-axis value for speed control. The Boolean value of the trigger button was designed to control the system on and off. This kind of control method requires long time engagement in VR with body motion, which might not be feasible for humans with motion sickness or missions lasting for hours. A practical application in the future is to integrate this control method with autonomous system to reduce operation time and human fatigue.

Another need for seamless ROV teleoperation is to render the kinematics features of the remote ROVs in VR (e.g., speed, gesture, etc.). This is because the locomotion control signals from the human operator are not always realized on the remote ROVs due to the dynamic subsea environment. For instance, a human operator may lean forward by 10 degrees to command the corresponding 10-degree negative pitch of the ROVs. Nonetheless, the real ROVs may only demonstrate a 5-degree pitch due to the liquid viscosity underwater. As such, the reactions of the ROV kinematics must be regenerated despite what controls are given by the human operator. In our system, we don't rely on the real ROV kinematics data (collected from the onboard sensors) because of the possible tracking errors or telecommunication latencies. Instead, we rely on the real-time ROS Gazebo simulation to recover the predicted ROV kinematics status. The challenge would be to reproduce the robotic dynamics in ROS Gazebo in a precise and accurate manner. We will use a hybrid solver that solves both the linear elasticity and hydrodynamic changes of the simulated ROVs in Gazebo, such as (Chitta et al., 2012).

3.5. Workplace model module

The real-time sensor data is then used to model spatiotemporal

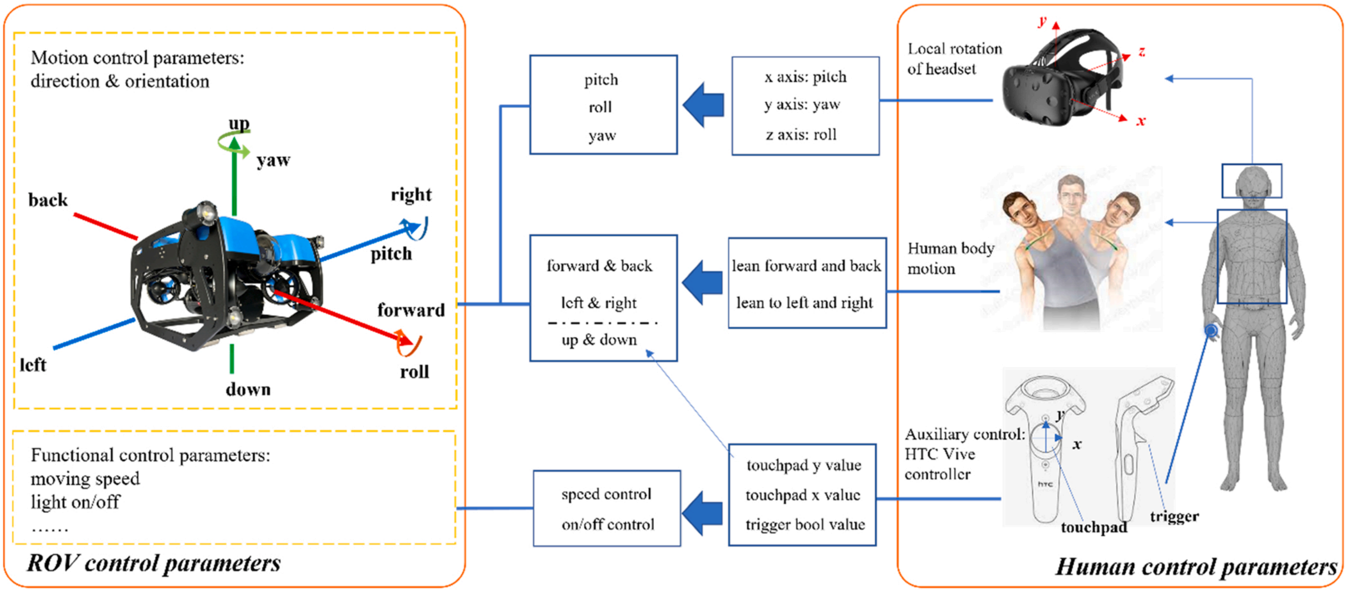

Fig. 2. Map of natural body-motion parameters to ROV control parameters.

dynamics of a subsea zone in the vicinity of the robot. To generate an immersive visualization of the subsea workplace, a game engine Unity v2020.1 (Unity, 2022) is used. Unity can model the far-field sensor data as vectors and render the entire space as Virtual Reality displays. Another key feature of the proposed system is to convert the hydrodynamic features into human-perceivable sensations, i.e., vibrotactile cues. To realize this function, a physics game engine NVIDIA PhysX is used (version 9.19) to simulate underwater (PhysX, 2022). Especially the smoothed particle hydrodynamics (SPH) method (Monaghan, 1992) of PhysX is used to simulate the hydrodynamic changes based on the sensor data. The raw data is used to determine the initial conditions of the particle emitters. Then a collision detection mechanism is used to examine the collision events between each particle and the virtual ROV model. The collision frequency and magnitude will be used to generate haptics of different levels (see the next section).

The proposed human-underwater robot interaction requires real-time modeling and visualization for “making sense” of the dynamic, dangerous, and underexplored subsea workplaces. It needs to address the challenges of both data sparsity and data overload that could happen and are equally destructive in the effort of modeling the subsea workspace. A unique challenge of HRC in subsea operations is the overwhelming data that needs to be processed and digested instantaneously. The stepstone for a better underwater HRC is reducing the complexity of underwater data processing via what we call "sparse data modeling". Therefore, this digital twin simulation and optimization module is developed to integrate sensor data and hydrodynamic model for a better quality of workspace modeling.

In offshore environments, invisible flow structures are generated at different spatiotemporal scales, such as internal waves and shear instabilities. Intense internal waves can impact the navigation safety and operation of underwater robots. Shear instabilities can greatly enhance turbulence generation, which can result in high turbidity that scatters light and affects water clarity and optic sensors. The location and timing of these underwater processes are hard to predict; however, they often leave unique surface signatures that can be detected by remote sensing imagery (Chickadel et al., 2011; Klemas, 2012; Plant et al., 2009). It is therefore important to integrate local sensors with ocean observation network data to provide accurate descriptions of the working environment. We propose a hierarchal process to model subsea workplaces: (i) For modeling an environment in close proximity to the underwater robot, we will apply the robot-carried sensors to infer the turbidity, pressure, and temperature with hydrodynamic numerical simulation. The idea is to estimate workplace characteristics within a small radius (<3 m) centered around the underwater robot. (ii) For modeling the bigger range of the workplaces (>3 m), we propose to relate the surface roughness information with hydrodynamic processes in the water column. How to integrate data from observation networks with in-situ measurement by underwater robots and visualize the data to provide workers direct link on how the magnitude, extent, and process of large hydrodynamic events affect the operation of underwater robots remains a great challenge. Statistical and numerical models are powerful tools to forecast ocean conditions, but the hydrodynamic numerical simulations are expensive and too slow for real-time underwater robot simulation and controls. As a result, we use reduced-order models (Noack et al., 2011) to efficiently capture low-dimensional descriptions of the essential flow patterns at a fraction of the cost. With the large volume of data from observation networks and high-resolution numerical simulations in the vicinity of the underwater robot, we developed a physics-informed data-driven model. The model is based on the physical principles (conservation laws), and the low-dimensional model approximate is implemented using the Deep Convolutional Generative Adversarial Network (DCGAN) machine learning techniques (Brunton et al., 2020; Loiseau et al., 2018). We applied the validated high-resolution numerical simulation data to train the network offline. The DCGAN network first extracts the spatial-temporal coherent flow structures of the high-dimensional fluid fields as low-dimensional latent variables. The governing equation of the low-dimensional representation of fluid field is solved following the same physical principles. The low-dimensional results are then projected back to the high-resolution space to provide an accurate prediction of key characteristics of the flow that are important to workers. The data-driven model can be used to forecast circulation patterns, sea state, and turbidity that affects optical sensors on underwater robots. In addition, using in-situ data collected by robots, the data-driven model could better capture and predict extreme events that are difficult to predict by classic hydrodynamic models.

3.6. User interface module

VR and haptic devices are applied in this module. Compared to other studies, this system considers VR as an DT simulator and data center instead of immersive visual augmentation method. Due to the complexity and uncertainty in subsea tasks, much more levels of information would be involved in the system, especially hydrodynamic features. VR is the great tool for data fusion and augmentation to reconstruct a realistic DT environment with physically information. Specifically, the proposed sensor module provides all kinds of necessary fluid information at different spatiotemporal scales. However, data collected by ROV sensors are spatially and temporally sparse, resulting in an incomprehensive sensory coverage and a low refresh rate of haptic feedback. Therefore, after the data fusion in the DT simulation and optimization module, improved data will be sent to the operator module for generating real-time and high-refresh-rate feedback. Fig. 3 demonstrates the architecture of the user interface module.

The VR environment is adjusted to the subsea workspace. The interactive VR system is developed based on our previous works (Du et al., 2016, 2017, 2018a, 2018b; Shi et al., 2018; Zhou et al., 2020a, 2020b; Zhu et al., 2021). A set of scripts have been developed for the ROV locomotion and navigation controls in the VR environment. The rendering of the subsea environment changes accordingly to provide a realistic sense of navigation in the simulation environment as in the real remote workplace. In addition, a hierarchical particle fluid simulation system is developed to receive real sensor data and generate a simulated flow, which hits sensors around the ROV model and creates denser data (in addition to the raw sensor data) with a higher refresh rate. This shows the first function we plan to achieve with the DT module, i.e., augmenting the raw sensor data with additional simulated data points. The user interface module is further realized with a Unity data augmentation system and haptic feedback system, as described later.

3.6.1. Unity data augmentation system

As shown in Fig. 4, the Unity data augmentation system includes the far-field visual augmentation and the near-field particle simulation. Another ROV model was used in the Unity DT fluid simulation. For the far-field data, a series of vectors are visualized to indicate the overall hydrodynamic patterns necessary for the operator's navigation decision-making, including fluid directions, speed, and hydrodynamic gradient extensions. Vector arrows are rendered in the DT simulation as shown in Fig. 4b. These vectors change the direction the same as flow data, with the length of the vector indicating the flow speed. Specifically, vectors with longer lengths indicate faster and stronger water flows. Compared to traditional camera view feedback, VR provides more enriched spatial information with immersive and interactive visual feedback. Besides, the VR system can provide the path planning function by displaying the identified optimal trajectories to the operator. The operator then has the option to either use these optimal trajectories as references during manual piloting or convert to autonomous controls that allow the autopilot of the ROVs to follow those trajectories. By allowing the operator to configure the priorities of optimization (e.g., prioritizing travel distance over energy consumption), the proposed system frees the operator from low-level vehicle maneuver controls ta high-level mission control. Such a hierarchical system design can simplify the overall piloting effort during routine operations and reduce operation inaccuracy due to human errors.

On the other hand, for the near-field waterbody surrounding the ROVs, a position-based particle system is applied to simulate the physical interactions with the ROVs in a realistic way (Fig. 4a). Position-Based Dynamics (PBD) is a proper method to simulate realistic fluid conditions, which allows the similar incompressibility and convergence in result compared to the Smoothed Particle Hydrodynamic method (Macklin and Müller, 2013). In this study, Obi Fluid (Obi, 2019; VirtualMethod, 2021) is selected as the core near-field particle simulation method. The activated particle number is set to 650 for balancing the simulation fidelity and CPU cost. Virtual particles can physically interact with ROV models in Unity as shown in Fig. 4c. The simulated emitter parameters would be used to fill the data gaps in raw sensor data (such as before real raw data was received or the gaps in sensor placement), but the raw sensor data still shares a higher priority. If any divergence between the DT simulation and raw data is sensed, raw data will override DT simulation results.

To be noted, the ROV-equipped sensors are effective in providing pressure descent data, and hence are effective for constructing realistic fluid meshes. But the raw sensor data would not provide parameters indicating flow intensity which is also needed for the DT simulation. Therefore, a script is developed to extract near-field particles' velocity when they collide with sensors around the ROV model. The flow intensity is calculated as Eq. 1:

$$F_{sensor} = \sum m_i * \hat{v}_i \tag{1}$$

Where m_i is the mass of particle I, $\hat{v}_i$ is the normal vector of the velocity of particle I, i.e., the projection of speed perpendicular to the contact surface, as shown in Fig. 5. In this equation, for each virtual sensor, a sum of normal momentum for all the particles colliding with the senor, $\sum m * \hat{v}_i$, is calculated as the representation of flow intensity. In this particle fluid simulation, the mass difference of each particle does not need to be considered because the hydrodynamic features are manifested as the pressure gradient. As a result, the mass m can be equally set to 1.0 in the equation. All the virtual sensors around the ROVs collect particle velocity data when a collision happens, and the final sum value is sent to haptic devices with a haptic intensity value from a proper range. With this method, human operators can feel the changes in the strength and direction of the water flow.

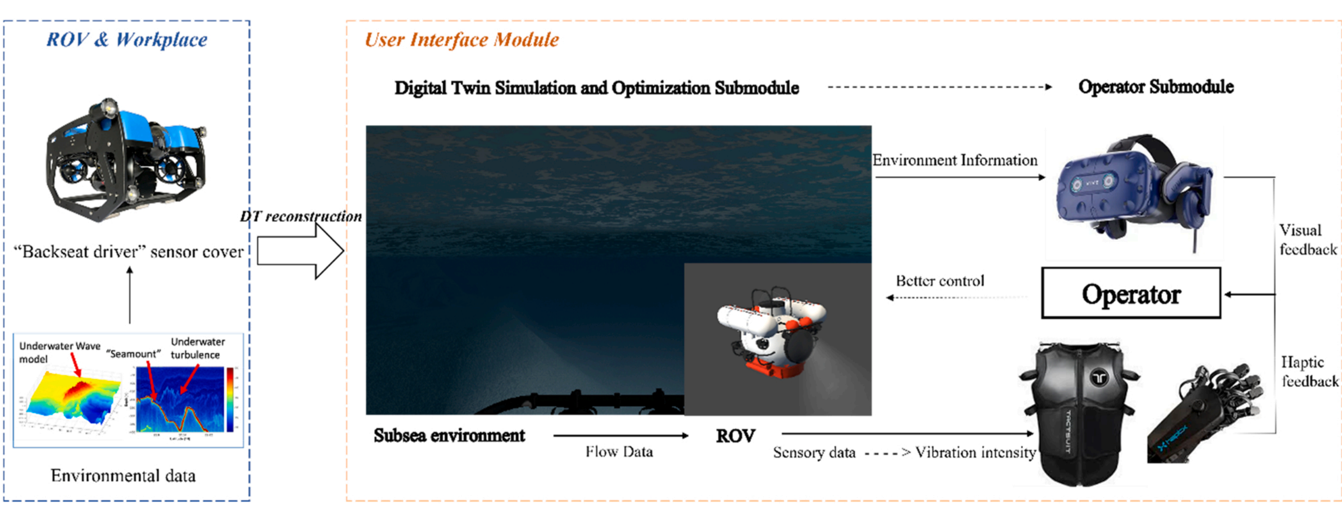

Fig. 3. Integrated multi-level VR-Haptic system, including digital twin simulation environment and haptic emulator.

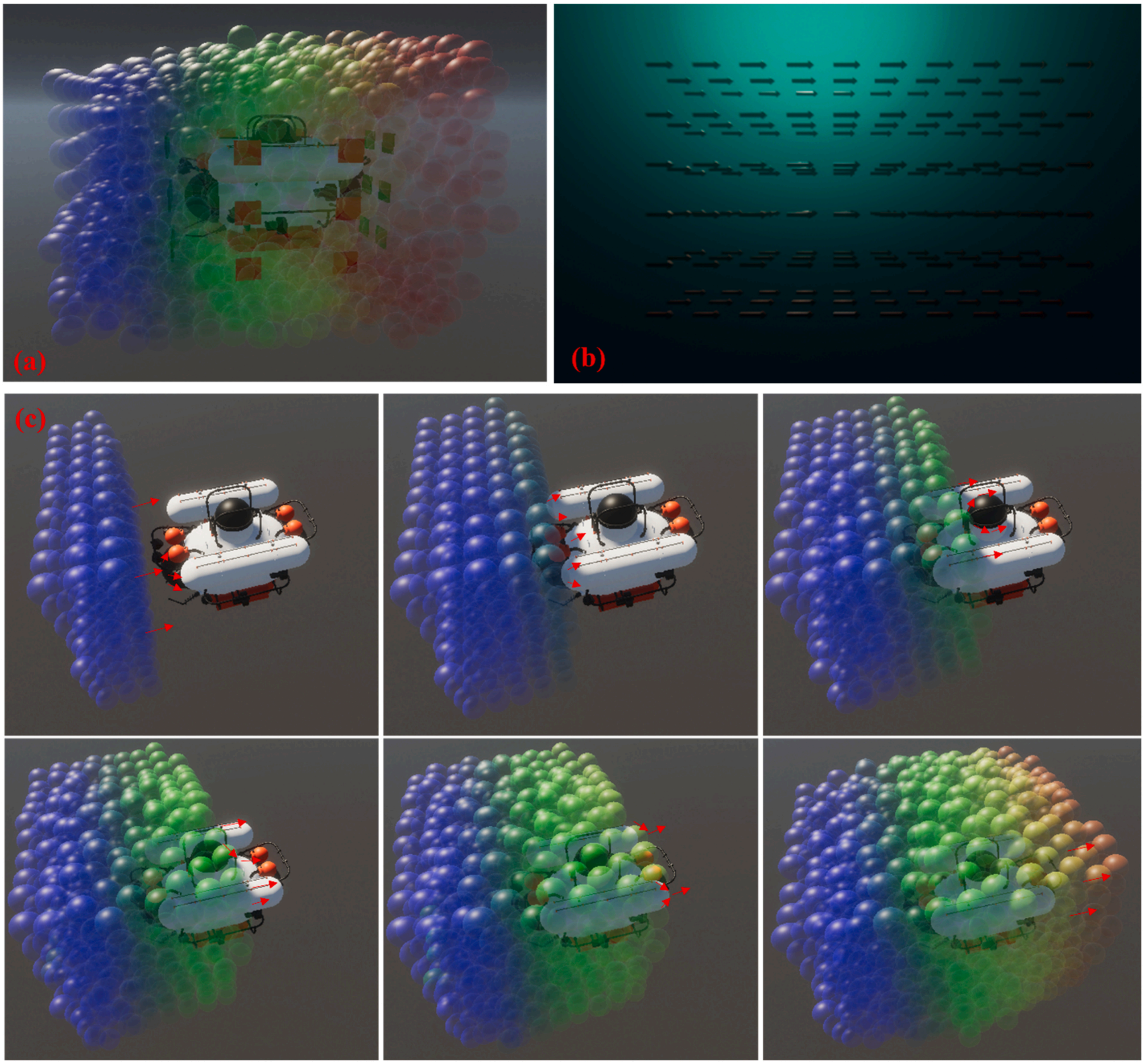

Fig. 4. Hierarchical fluid simulation in the Digital Twin reconstruction with another ROV model. (a) Near-field particle simulation. (b) Vector field for far-field visual augmentation. (c) Particle interactions with the ROV model.

Fig. 5. Example of virtual sensor intensity in DT module: normal vector for intensity calculation.

Similarly, the micro-field haptic glove feedback is realized with the same method. We used HaptX gloves as the user interface. Each HaptX Glove features over 130 discrete points of tactile feedback that physically displace the user's palm up to 2 mm (HaptX, 2021). HaptX Gloves also feature the strong force feedback, with exo-tendons that apply up to 40 pounds of dynamic force feedback per hand (8 lbs./35 N per finger) (Fig. 6). A haptic glove location model is created in VR to reflect the motions of operator's hands. When virtual fluid collides with the virtual glove model in Unity, the system generates a higher resolution haptic cue for simulating the micro-scale haptic feedback. To be noted, the same particle system is used for glove-based haptic stimulation but with a higher resolution, as hands are more sensitive to bodies in terms of haptic sensation.

3.6.2. Haptic feedback system

Different from other haptic related studies, except for hand-held level haptic feedback, this system also develops a whole-body coverage haptic map to hydrodynamic features. Fig. 7 demonstrates the user setup for haptic feedback system. The motion of fluid surrounding the ROVs can be sensed with virtual sensor objects in the Unity game engine. A total of 40 sensors on the haptic suit are matched with 24 virtual sensors equipped on the ROV model in VR. Since it is CPU-consuming for an increased number of sensors which could significantly decrease system performance. In addition, the haptic sensory channel of the human body is not sensitive enough to sense minor differences between adjacent sensors. As a result, we designed a mapping method to project the data of four virtual sensors to eight vibrators in two rows on the haptic suit for the upper and lower parts of the body, as shown in Fig. 7. In total, there are 12 virtual sensors on each side of the ROV to trigger all 40 vibrators on the haptic suit. The haptic suit will vibrate based on the flow intensity parameters sent by virtual sensors. At the same time, human operators can sense the micro-turbulence via the haptic gloves. With vibrating intensity changing on both sides of the human body, operators can easily sense the hydrodynamic changes and reactively maneuver ROVs for other tasks. We use a dynamic collision detector, to examine whether a particle collided with the dynamic rigid body (i.e., the virtual ROV model) during the last simulation step. Then two methods from PhysX are used to read position and velocity information.

To be noted, the flow intensity representation generated in DT cannot be directly used for triggering the haptic suit. The haptic intensity should be set in a proper range, otherwise, human operators would feel uncomfortable due to the strong vibrations. We estimated that a comfortable upper limit for the vibration should be no more than 1.5 cm/s^2 according to our user experience test. Aimed to convert flow intensity to the identified haptic intensity range, a formula was developed to adjust the values as Eq. 2. The purpose is to discount the large range of the raw flow data to a proper range for haptic intensity, where F_{sensor} represents the flow intensity sent by the sensors.

$$Intensity = 1.5\frac{e^{F_{sensor}} - 1}{e^{F_{sensor}} + 1} \quad (2)$$

For micro-field haptic stimulation, a haptic glove device HaptX was selected to generate micro-turbulence haptics. As mentioned, HaptX is a pneumatic haptic glove with air channels to deliver high resolution and high displacement tactile feedback (Perret and Vander Poorten, 2018). Facebook Meta lab has also shown a prototype VR glove with inflatable plastic pads arranged to fit the wearer's palm and generate force feedback (Robertson, 2021). All these devices have improved with a better tactile feedback accuracy and can extend Human-VR interaction. In our design, HaptX glove was used because of its full palm and fingers covering air channels design. Human operator wearing the haptic gloves can move their hands to where he/she wants to perceive minor hydrodynamic changes at the micro-level. Micro-scale turbulence data is sent to haptic glove actuators, where palm-level haptics are generated for the human operator. There are two main advantages of this multi-level design. On one hand, accurate and high-fidelity hydrodynamic features are required for specific ROV tasks, such as docking, and underwater inspection in an environment with many obstacles. Lack of accurate and high-resolution turbulence information may undermine

Fig. 6. User setup with HTC Vive, haptic suit, and haptic gloves.

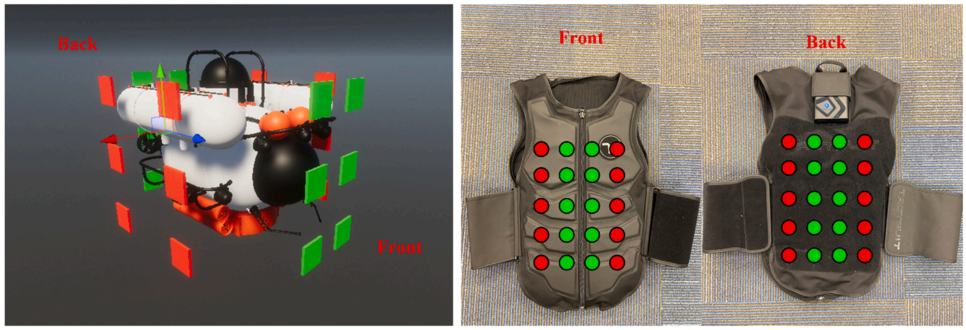

Fig. 7. Map of virtual sensors in DT module matching haptic suit vibrators.

the human perception of the potential danger, resulting in improper decision-making and failure of collision avoidance. On the other hand, too much information could induce cognitive load and mental fatigue. For example, for simple inspection and routine navigation tasks, such kind of micro-scale turbulence information is of no use to send to the human operator. With haptic gloves and multi-level design, the human operator can decide when to use what levels of sensation (far-field, near field, and micro-level), based on the task context.

4. Demonstration case

A case study was performed to test the system's effectiveness in a simulated ROV navigation task. Practically, drift caused by unpredictable subsea currents is a great challenge for current subsea ROV operations (Leabourne et al., 1997). Deviating from the target route may cause stabilization problems and disorientation (Capocci et al., 2018; Leabourne et al., 1997). This case study aimed to augment the human sensation of subsea currents with the new-designed feedback system and assist human operators in resisting drift. The subjects were required to control the ROV model in the VR environment for straight-line navigation in the x direction. Five checkpoints were distributed on a straight line at $x = 8\ m$, $x = 20\ m$, $x = 35\ m$, $x = 60\ m$, and $x = 90\ m$. Multiple current fields were set along the route, and the component on the z direction caused the drift from the straight line. Subjects were asked to control the ROV by joystick with (test condition) and without the proposed augmented sensory system (control condition) respectively. The flow components in these two conditions were shown in Table 1. The current fields distribution was designed with the same number of total fields and the same average flow speed, but with different velocities in each single field area. Such kind of design is to eliminate human learning effect in the second condition. In total, we tested 10 subjects for this case study. Besides, a body motion control case demo with the proposed sensory augmentation methods was also demonstrated.

Fig. 8 showed the overall performance of body motion control & sensory augmentation system on aspects of control, deviation and feedback values. Definitions of axis of rotation and directions of movement was shown in Fig. 9a. The haptic intensity values were updated 13.3 Hz. With the intuitive feeling of the human body, the operator could react rapidly to haptic intensity changes, as illustrated in Fig. 8a. Operator's body motion control could generally resist the drift caused by the current speed in the z direction. Besides, the deviation can be controlled at a relatively low level. The deviation, absolute deviation, and average deviation were plotted in Fig. 8b. The final average deviation was about 0.9163 m. Fig. 8c and Fig. 8d demonstrated the haptic intensity changes during the case study. The total 24 sensors were grouped into 4 areas based on their positions on human bodies. The changes in flow speed in different directions could trigger different sensor areas, which could be easily sensed. For example, an increasing flow speed on the positive z direction represented a stronger flow colliding with the right part of human bodies, and the average haptic intensity of 6 sensors on the right part would increase significantly.

As for the subjects' performance in the case study, we plotted trajectory patterns of two conditions in the same figure, and calculated average deviation for all subjects as task performance measurement. As demonstrated in Fig. 9b, the red point represented the trajectory of the control condition, and the blue point represented the trajectory of the test condition. The trajectory of test condition was significantly concentrated to the straight line while the control condition trajectories were more scattered. Specifically, the average deviation of the control condition was 4.9933 m and the average deviation of the test condition was 1.6006 m. With our sensory augmentation system, subjects could intuitively sense the flow intensity and control the ROV to resist the drift effect as well as keep straight-line navigation.

In conclusion, the result showed that there was a significant difference in vibration patterns for different flow conditions, indicating an effective way of using haptics to transfer underwater hydrodynamic conditions. Besides, the participants could easily identify different ROV positions and locomotion conditions based on the information provided by the multi-level sensory feedback system, which helped them understand ROV work status and thus engage in the most proper control operations in future diverse and complex work environments.

5. Discussion and conclusions

This paper introduces the design of an innovative system for the intuitive teleoperation of subsea ROVs with VR and haptic simulation. Multi-level sensory data from ROVs is collected and sent to a digital twin simulation environment for data augmentation. Three types of sensory augmentation methods, namely far-field augmented visual feedback, near-field haptic suit feedback, and micro-field haptic glove feedback, are generated to enhance human situational awareness of the ROV workspace with higher efficiency compared to traditional 2D video streaming feedback. This VR-Haptic integrated environment immerses the human operator in a high-fidelity sensory stimulation system,

Table 1
Current fields distribution and speed components in two directions.

Currents range x (m)		0–8	8–20	20–26	26–34	35–45	45–51	52–58	61–71	72–82	84–90
Control condition	$V_x(m/s)$	0.15	0.1	-0.2	-0.35	0.15	0.25	-0.2	-0.05	0	-0.067
	$V_z(m/s)$	0.45	-0.3	0.5	0.2	0.3	-0.35	-0.55	-0.5	0.2	0.2
Test condition	$V_x(m/s)$	0	0.3	0.3	-0.35	-0.4	0.25	0.2	0.1	-0.1	-0.33
	$V_z(m/s)$	0.45	-0.3	0.2	0.55	0.15	0.2	-0.7	-0.6	0.45	0.15

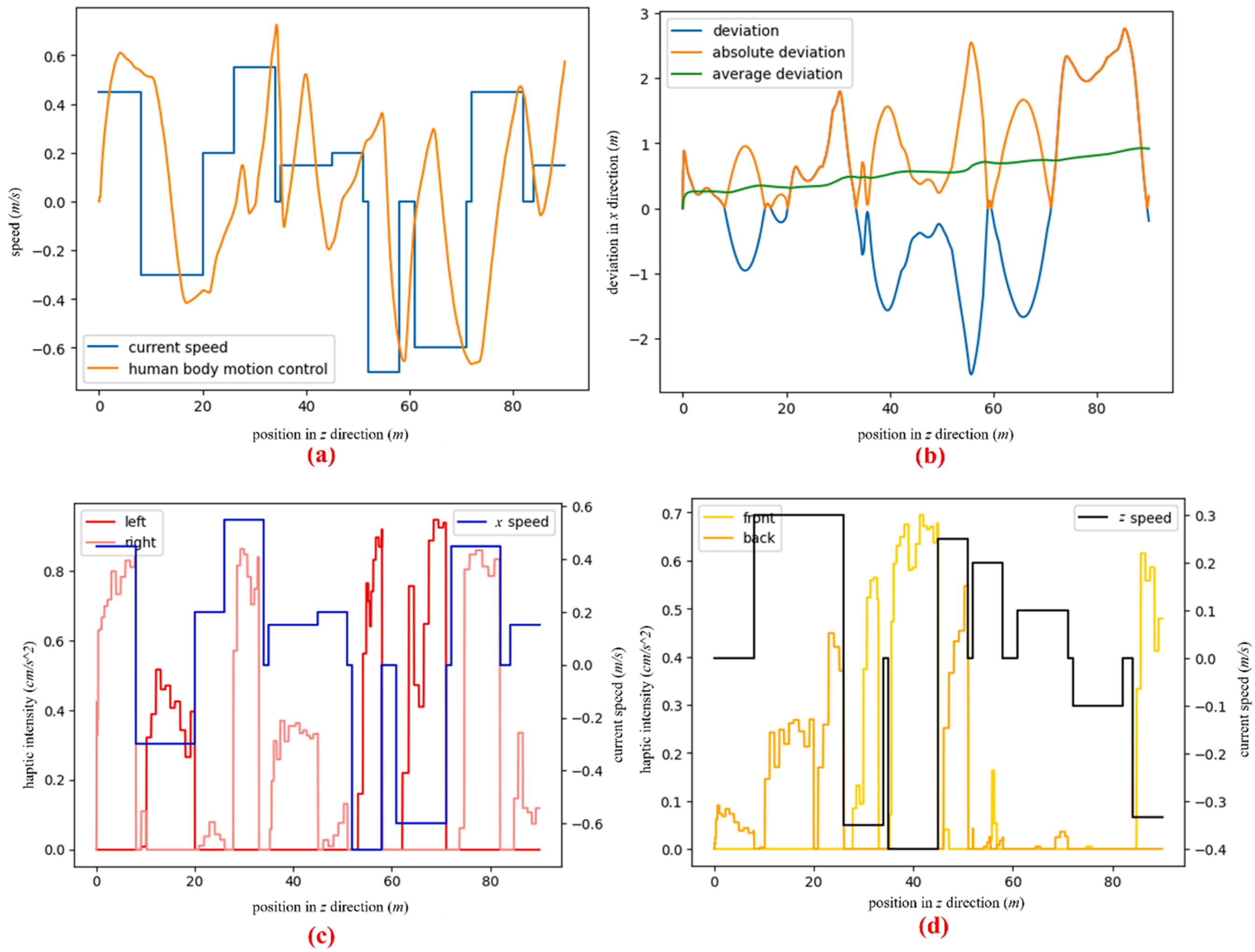

Fig. 8. Demo case result of body motion control. (a) Human body motion control speed change. (b) Deviation. (c) Haptic intensity changes in z direction. (d) Haptic intensity changes in x direction.

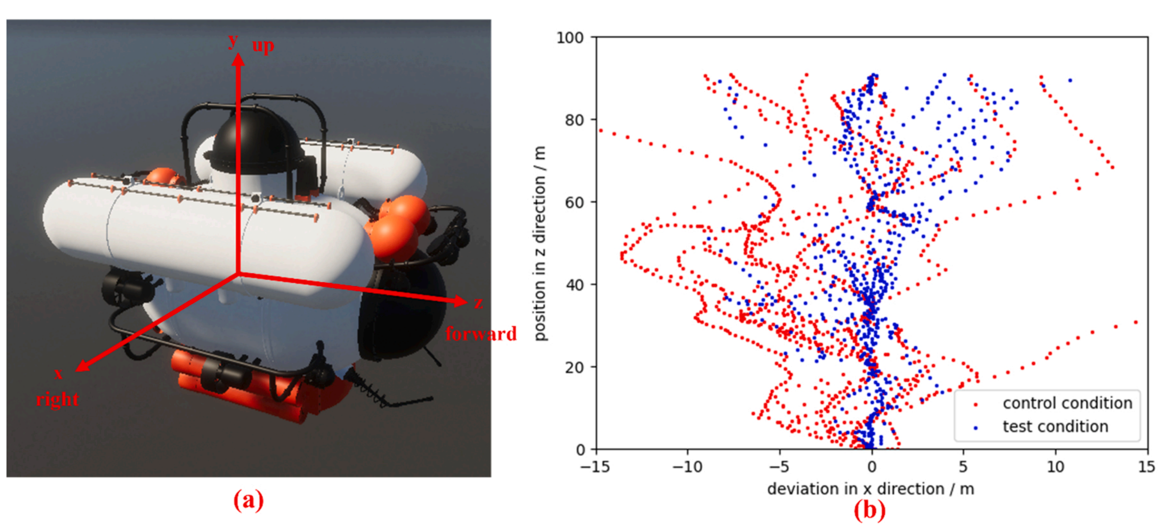

Fig. 9. (a) Axis of rotation and directions. (b) Trajectory patterns for control condition and test condition.

streamlining the HRC workflow. As a result, the human operator can easily sense the state of ROVs through visual and haptic channels and intuitively issue adequate control commands. Literature has verified that this kind of multi-sensory feedback system could increase situational awareness of human operators (Xia et al., 2022; Zhu et al., 2021; Zhu et al., 2022), which enables future engineers to enter a subsea era in a safer, less costly way. And our case study also verified the effectiveness of the proposed system. In conclusion, by integrating multi-levels of sensory information and feedback, this research provides an immersive and interactive control system for future ROV operations. This research is strongly positioned for better accessibility and inclusion because it aims to lower the career barrier for a traditionally highly professional area. The proposed underwater human-robot interaction approach will greatly simplify the requirement of engineering, science, and robotics knowledge for subsea engineering and underwater robot operation jobs. The sensory augmentation method for robotic control will mitigate the age requirement, promoting career longevity. The new technology will also help salvage the careers of experienced workers who have suffered from career injuries, such as diving diseases. In addition, the system could be used as a platform for fresh operator training as well to lower the training cost.

Besides, neurophysiological sensors are expected to be adopted to help assess the functions and performance of human operators during ROV operations using our system. It is expected that by integrating the robot control systems with the Unity engine, VR-Haptic-assisted ROV teleoperation can be accomplished in a participatory and inclusive way. With the increasing adoption of VR and haptic methods, the enhanced sensory feedback can help future engineers manage complex underwater tasks with ease. This ROV teleoperation system will ultimately lead to a Robot as a Service (RaaS) model that consists of a cyber-physical unit to facilitate the seamless integration of underwater robots and human operators into a shared cloud environment. It is envisioned that this RaaS model will greatly diversify the subsea workforce and broaden participation in subsea engineering, inspection, and scientific discovery.

There are still many challenges for us to resolve to make this technology viable. The first challenge relates to the technological maturity. Realizing the proposed system would require a significant change to the current ROV designs, including equipping the ROV systems with new sensors that can collect high-fidelity underwater environment data, such as pressure sensors on the surface of ROVs and Doppler sensors for far field hydrodynamic sensing. A new data and telecommunication infrastructure is also needed for transferring the potentially big amount of data to support the human-robot sensory transfer. Transforming current systems to new proposed system required time and money, and the initial cost may become a burden for many businesses. On the other hand, this method also has limitation in weariness after long time operation in VR. Human operators might get fatigue after missions of several hours. Autonomous technologies should be involved to reduce human operation time and workload in the future.

CRediT authorship contribution statement

Jing Du: Conceptualization, Methodology, Writing – review & editing. **Pengxiang Xia**: Investigation, Data Analysis, Visualization, Writing – original draft. **Fang Xu:** Investigation, Visualization. **Zhuoyuan Song:** Writing – review & editing, Visualization. **Shuai Li:** 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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