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Visual-haptic feedback for ROV subsea navigation control

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ABSTRACT

Subsea engineering operations, including subsea inspection, installation and maintenance, heavily rely on the seamless interaction between remotely operated vehicles (ROV) and human operators. Subsea ROV control has always been a great challenge to human operators due to the dynamics of the subsea environment such as uncertainty of turbulence, affected visibility and interference with subsea ecosystems. Compared to engineering work on the ground, subsea engineering tasks are usually finished in a limited vision field with drift and localization problems. However, the traditional ROV feedback system, the live video streaming, cannot provide direct and intuitive perceptions of remote ROV workspace as well as a clear indication of the workspace uncertainties. Therefore, this research proposes a Virtual Reality augmented visual feedback system with haptic simulators to generate immersive, intuitive and effective feedback for human operators. The system can generate visual and haptic feedback as indications of flow conditions based on sensory data. A human subject experiment was performed to verify the effectiveness of this system. The result indicated that this system could significantly assist human operators in precepting the flow conditions in the ROV workspace in a more immersive and intuitive way.

1. Introduction

Subsea engineering, i.e., activities below waterline related to the construction, inspection, and manipulation of manmade systems, plays a vital role in offshore energy, aquaculture, sustainability, disaster preparedness, seafloor mining and cabling, and maritime transport [11,38,39]. Currently, subsea engineering operations highly rely on remotely operated vehicles (ROV), i.e., underwater teleoperated robotic systems [4]. Due to the rapidly decreasing cost of deployment and improved versatility of ROVs, in certain subsea areas, the global ROV market has observed a substantial growth with emerging engineering applications at scale [8]. It is expected that the next-generation subsea engineering will be greatly benefited from the broader utilization of ROVs with desired agility, safety and endurance [33]. However, despite the promising benefits of the broader and increasing utilization of various ROV systems in the future subsea engineering, the ROV operator remains a highly specialized area with a high barrier to broader participation. Most ROV-related jobs require strict professional preparation (ocean sciences, mechanical engineering, and diving knowledge) that takes many years of training. The existing ROV service workforce consists of marine engineers, professional divers, and robot service providers, and only a small portion holds licenses for certain tasks. Provided the increased demand for subsea engineering workforce, there is a foreseeable shortage of ROV operators in the near future. A recent survey shows that the need for ROV pilots is expected to increase 130% on an annual basis [31]. It has also been noted that the harsh subsea environment and difficult robot controls are major obstacles for the future subsea workforce to utilize or team up with underwater ROVs.

The fundamental problem of ROV operations is related to the lack of effective human-robot interaction (HRI) methods to meet the unique challenges of subsea workplaces. With the traditional ROV control system, an operator controls the ROV on a vessel above sea level with the assistance of live video streaming captured by the camera equipped on ROVs [70]. However, the complex information of the subsea environment, such as dynamic internal currents, low visibility, and unexpected contacts with marine lives, cannot be fully transited by 2D videos, which might undermine human sensation of subsea environments and result in inappropriate operations [26,32,49]. Human operators often lose sense of orientation due to subsea currents without assistance from the system. And for subsea manipulation, installation, and maintenance, it is extremely hard for human operators to stabilize the ROV in volatile body of water only based on live videos. Such an inability to directly sense

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water flows can break the feedback loop for accurate ROV control actions, resulting in an induced *perceptual-motor malfunction* [25]. For complex motor tasks, humans rely on multi-sensory channels, such as visual and somatosensory feedback, to make sense of the consequence of any initiated action [63]. Literature has well recognized the benefits of simulating multi-sensory feedback, including visual, auditory and haptic feedback, as augmented HRI methods for robot teleoperation to improve motor performance [72]. But it is less clear whether the knowledge gained from land applications can be readily transferred to the subsea ROV interface designs, as many characteristics of subsea environment can be considered novel and alien to human operators, such as the feeling of hydrodynamic forces. It is also unknown how the multi-sensory feedback system can be optimized to improve human ROV control performance in the subsea engineering.

This paper proposes a sensory augmentation system that converts novel subsea environmental parameters into human-perceivable sensations, including simulating the hydrodynamic features as visual feedback and haptic feedback. Based on the novel design, an experiment was performed to compare how different modes of sensory feedback could influence the human sensations of hydrodynamic features, and ultimately, how it could assist in ROV navigation in the subsea environment with low visibility. Human operators were asked to control the ROV for straight-line navigation with traditional visual feedback, haptic feedback, augmented visual (vector-field) feedback, and a combination of haptic with visual visualization respectively in a high-fidelity Virtual Reality (VR) environment. The remainder of the paper introduces the point of departure, the design of the sensory augmentation system, the human-subject experiment and the findings.

2. Literature review

2.1. Remotely operated vehicles (ROV) for subsea operations

ROV is a type of tethered underwater vehicle designed for underwater intervention, exploration, equipment installation and data collection [8,42,43]. ROVs can be classified differently depending on the size, the cost, and the designed functionalities. Based on their working depth and payloads, ROVs can be categorized as 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) [43]. Based on their main designed functionalities, ROVs can be further classified as education class, inspection class and work class [59]. Inspection class ROVs are the most widely used type for subsea exploration and offshore inspection. Especially for oil and gas companies, in order to prevent financial and environmental disasters caused by leaking, ROVs are frequently used for the inspection of thousands of kilometers of pipelines, and the inspection tasks can be performed 24 h and 7 days sometimes [69]. Inspection class ROVs are usually equipped with various sensors for data collection and monitoring [10]. Work class inspection ROVs are the most versatile ones equipped with underwater manipulation capabilities, such as robotic arms. They are capable of heavy operation works like subsea maintenance for oil and gas industries and the ocean science community [30].

Although vary in capabilities and sensors carried on, all types of ROVs have basic capabilities of maneuverability along more than one principal axis and state estimation. Usually, pilots on a vessel above sea level control the ROV with the assistance of live video streaming captured by equipped cameras. However, this traditional vision-based feedback could only provide limited information for human operators. Especially in the subsea environment, low visibility would undermine the human perception of the workspace, and 2D video provides little information about ocean waves and currents [13,34]. Such inconsistency between the ROV workspace and human perception can break the feedback loop for accurate ROV control actions, resulting in an induced perceptual-motor malfunction (Finney 2015). The lack of necessary information is a critical problem for certain kinds of tasks. For example, for subsea pipeline inspection and maintenance, the body of the ROV needs to hold its position stably, which requires a better perception and understanding of the surrounding environment [9,34]. Besides, complex and high-turbidity currents can significantly influence ROV's self-stabilization and cause disorientation in subsea exploration [61].

Currently, literature shows that more efforts have been made on improving ROV algorithms, such as self-stabilization using adaptive nonlinear feedback controller [54], disturbance rejection controller to improve maneuvering accuracy [9] and vision-based color correction and tracking algorithm for high depth and low light ecosystems [3]. These algorithms are aimed at controlling problems of the system and to some extent resolving the low visibility vision challenge. However, humans are the commander of the ROV system and are responsible for all the important control actions. Improving ROV algorithms but lack of effort in transferring environmental information to human operations can still undermine control operations in the complex and dynamic subsea environment. Effective methods for transferring main hydrodynamic features data to humans in an intuitive way, and how this new feedback could influence human navigation and control performance in complex subsea navigation are still largely unknown.

2.2. ROV drifting in navigation

Navigation planning are critical for ROV teleoperation in subsea engineering. However, due to the low visibility and subsea currents, precise navigation controls in the subsea environment are extremely challenging compared to applications on land [32]. Drifting is a prevailing issue in ROV navigation. Subsea engineering would not always take place in static flows. Currents can push the ROV away from its original route [35], and high-turbidity currents can also bring an extreme burden on subsea installations and maintenance [27]. The drifting rate caused by subsea currents can be several kilometers per hour sometimes [15]. All these factors make ROV navigation in subsea environments nontrivial.

At present, there are two main methods for subsea anti-drifting correction in ROV navigation. One method is to utilize Simultaneous Localization and Mapping (SLAM) to extract visual feature points and establish a subsea map [40]. This process can be integrated with high-accuracy sensor data, such as Doppler Velocity Log (DVL), for a better mapping result [58]. The problem with this method is the lack of visual objects in subsea environments from which visual SLAM can extract sufficient feature points. And the integration with high-accuracy sensors could be too expensive for inspection-class vehicles. Another method is closed-loop controls based on machine learning [24]. A representative method is the predictive coding (PC)/biased competition (BC)-divisive input modulation (DIM) system [1]. Instead of using visual data, this method fuses multi high-accuracy sensor data such as the inertial measurement unit (IMU), differential global positioning systems (DGPS), ultra-short baseline (USBL) and DVL data, to enable automated pose and position correction of ROV at the low error rate to a mean of 3.96 m [1]. Although improved a lot in accuracy compared to previous SLAM method, the machine learning based closed-loop control method requires a large number of high-accuracy sensors, and thus the cost could be an adoption obstacle. Besides, most existing ROV anti-drifting and localization methods focus more on an automated workflow instead of incorporating human-in-the-loop needs. There is no effective interface design for human operators to visualize and comprehend the navigational decisions made by SLAM and automated control algorithms. Such a lack of automation transparency may result in extra cognitive load, reduced situational awareness, and worsened trust and performance [14]. Despite the advances of automated anti-drifting and localization methods, a better human-machine interaction method is needed to grant human operators with the ability to intuitively sense the surrounding environment without distracting attention in ROV operations.

2.3. VR-based ROV teleoperation

Virtual Reality (VR) is an emerging human-computer simulated interface widely used in medical, flight simulation, automobile industry design and military training purposes [45], for rendering realistic scenes and providing rich spatial information [7,71]. Literature has shown a great interest in utilizing VR in robot teleoperation due to the benefits of coupling perception and controls between humans and robots [12,17,72]. Such a close sensation pairing can assist in better planning motions and interactions in difficult tasks that require both robotic and human intelligence [62]. In ROV teleoperation, VR has been considered a promising solution for lowering the barriers to human-in-the-loop ROV teleoperation [64,65]. Several studies have tested the advantages of utilizing VR in ROV teleoperation in different tasks, such as underwater capture tasks [23] and deep ocean remote control [36].

Compared to traditional video streaming, VR can be programmed to provide additional visual feedback such as user interface (UI) design for work progress [44,67] and path optimization plan [60]. In addition, VR can also serve as a multisensory augmentation platform, i.e., providing multimodal visual, auditory, and haptic feedback associated with an intended action to improve motor performance [50,72,73]. Haptic devices can be integrated with VR platforms to generate haptotactile stimulation (e.g., vibrations and force feedback) on the user's body in correspondence with the occurring events [51,52]. Specifically, in ROV control, VR-based sensory stimulation can generate feedback such as the indication of hydrodynamic conditions, which may significantly improve human sensation and spatial awareness. Pilot efforts have been done to capture underwater environmental information and apply corresponding haptic feedbacks to human operators. For example, Amemiya and Maeda designed a system to combine pressure and torsion forces and generate an illusional feeling of external force for a kinesthetic perception of the ROV [2]. Ciriello et al. developed a linear-oscillating actuator using asymmetric drivers to create equivalent pressure signals [16]. Shazali tested a gyro effect haptic actuator to simulate torque feedback even when ungrounded [46]. However, these preliminary efforts were only tested in the limited pre-designed workspace and were not integrated with the VR system for more immersive visual-haptic feedback. To provide environmental information more efficiently to human operators for decision-making, we propose a VR augmented visual and haptic integration feedback system for subsea ROV navigation control.

3. Human-subject experiment and system

3.1. Overview

Due to the insufficiency of the current ROV teleoperation system in immersive, intuitive, and effective feedback, we have developed a VR-based sensory augmentation system that provides both augmented visual feedback and haptic feedback for a shared perception between the remote ROV system and the human operator. In order to compare how different types of feedback affect ROV operations, a benchmarking human-subject experiment was performed based on a sensory augmentation system as shown in Fig. 1. First, a realistic subsea environment was developed based on the crest ocean system [28] with multi predesigned subsea current areas, and a virtual sensory system was developed and embedded in the Unity game engine [55]. The sensory augmentation system can obtain the hydrodynamic forces of the water body in the close proximity of the ROV, and convert the raw sensor data into human-perceivable sensations as augmented visual feedback (i.e., displayed as visuals in a VR headset) and as haptic feedback (i.e., vibrations on the haptic suit). More details about the sensory augmentation system can be found in our previous publications [74,75]. In this paper, we focus on reporting the human subject experiment performed to verify the effectiveness of the proposed system.

Specifically, participants were required to operate an ROV in a VR simulator for a straight-line navigation task. To finish the task successfully, human subjects must be able to resist the drift caused by subsea currents based on the feedback signals provided by the system. Each subject was asked to complete four experiment trials in a shuffled order, including the *Control* condition with only the video streaming from the ROV, the *Visual* condition that visualized hydrodynamic flows as vector arrows in the VR headset, the *Haptic* condition that simulated the hydrodynamic forces as haptotactile feedback of different directions and

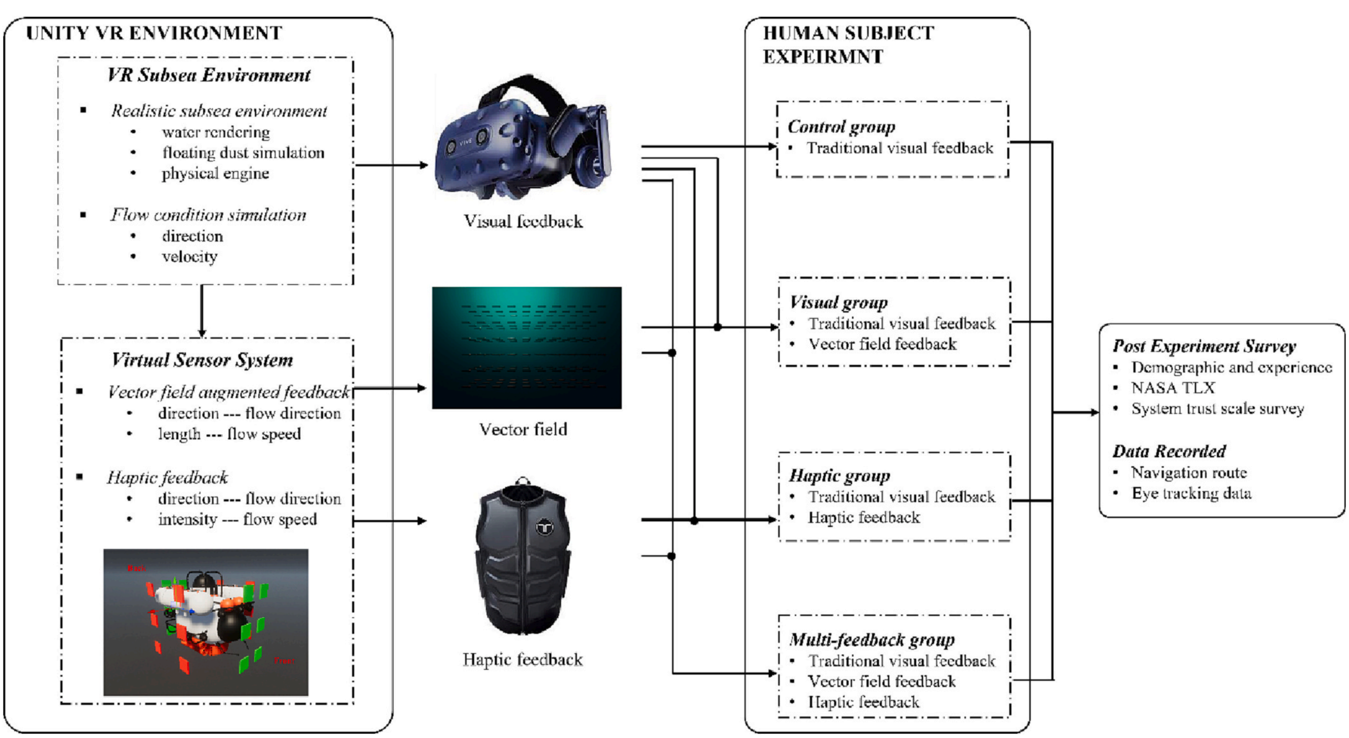

Fig. 1. System architecture and experiment design for VR-haptic feedback system for ROV teleoperation.

magnitude on the haptic suit, and the *Multi-Feedback* conditions that provided both the visual and haptic feedback. Performance and human function data were collected automatically via the VR system, including navigation route, time of completion, eye tracking data, as well as psychometric surveys about demographic information, Trust Scale questionnaire [41] and NASA Task Load Index (NASA-TLX) [29].

3.2. VR environment

The subsea VR environment was developed in Unity 2020.4.25f based on our previous systems [19–22,47,66]. As shown in Fig. 2, a realistic subsea environment was developed based on the crest ocean system [28], which ensured a high-fidelity ocean wave simulation and subsea light rendering. The background watercolor and effective camera field of view (FOV) could be adjusted to users' needs. In the experiment, the camera FOV was set to the range of 0 to 5 m to simulate visibility conditions in most offshore subsea environments. Besides, the Unity visual effect graph (VFX) [56] was applied to simulate the floating dust that human operators usually rely on for locomotion controls of ROV.

The device setup is demonstrated in Fig. 3. For ROV control, a joystick control method was designed based on the real ROV control system [6]. A bHaptics suit [5] was used for generating haptic feedback. Aiming to obtain the ROV trajectory data and human performance data, a system integrating an HTC VIVE head mounted display (HMD) with the Tobii Pro eye tracker [53] in Unity was used in the experiment. Several C# scripts were developed to collect the ROV navigation trajectory data as well as humans' eye movement and pupil size at a frequency of 50 Hz.

Fig. 3. ROV operation device setup.

3.3. VR-based sensory augmentation system

In order to test how different immersive and intuitive feedback could affect the ROV operation performance, we deployed a comprehensive VR-based sensory augmentation system, including the virtual ROV operation module, visual module, particle flow simulation module, virtual sensor module and haptic suit module. The system architecture is demonstrated in Fig. 4. Experiment participants could control the virtual ROV in VR with joysticks. User inputs, as well as hydrodynamic conditions, determined the ROV movements in the simulation environment. Augmented visual feedback, i.e., the visual condition, and virtual particle flows for simulating the hydrodynamic interactions were generated based on the particle systems of the physics engine. Particularly, the simulated particle flows would physically interact with the ROV model and hence the virtual sensors could capture the key parameters of the hydrodynamic flows. Finally, the dynamic data was sent to the haptic suit plugin via Python Unity Socket [48] and the corresponding vibration intensity was generated and sent to the haptic suit.

For the visual feedback, except for the basic visual indications such as the floating dust (Fig. 5a), this system also provided a visual (Fig. 5b) to indicate the flow speed and directions. Each arrow in the visual 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.

For haptic feedback, a particle flow and virtual sensor system was designed to simulate the hydrodynamic conditions and generate the corresponding haptic feedback. Data collected by ROV sensors are usually spatially and temporally sparse, resulting in incomprehensive sensory coverage and a low refresh rate of haptic feedback. As a result, a data augmentation process is necessary to enhance the data density, feedback coverage and refresh rate. In our system, the particle system was applied to simulate the physical interactions with the ROV in a realistic way, as demonstrated in Fig. 6. The particle simulation was based on the acoustic Doppler current profiler (ADCP) data, which contained flow direction and magnitude. The particle emitter would generate particle flows with same direction and magnitude around virtual ROV model. The particle flows could physically perform as real based on Unity physical engine, and virtual sensor system recorded physical interaction events and converted them to haptic intensity. To balance the simulation fidelity and the CPU cost, the activated particle number was set to 800 and the refresh rate was set to 2 Hz. A series of

Fig. 2. Example scene of subsea environment reconstruction.

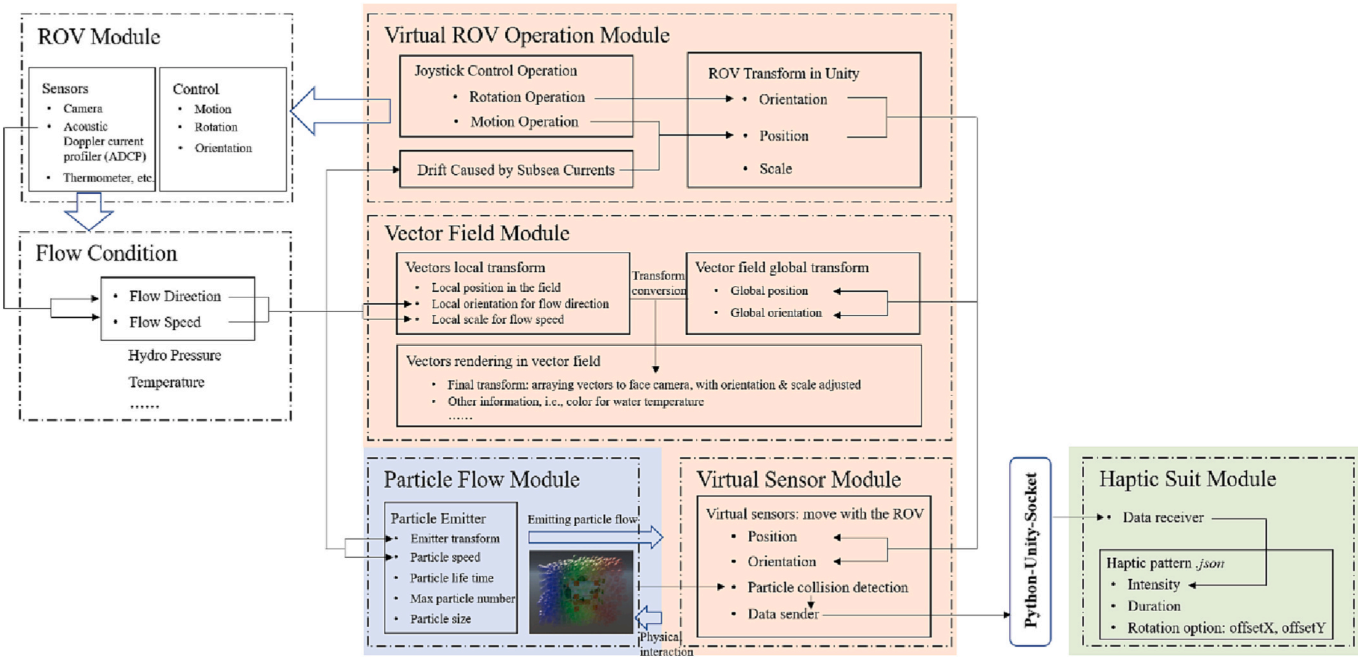

Fig. 4. Architecture of VR-Haptic feedback system.

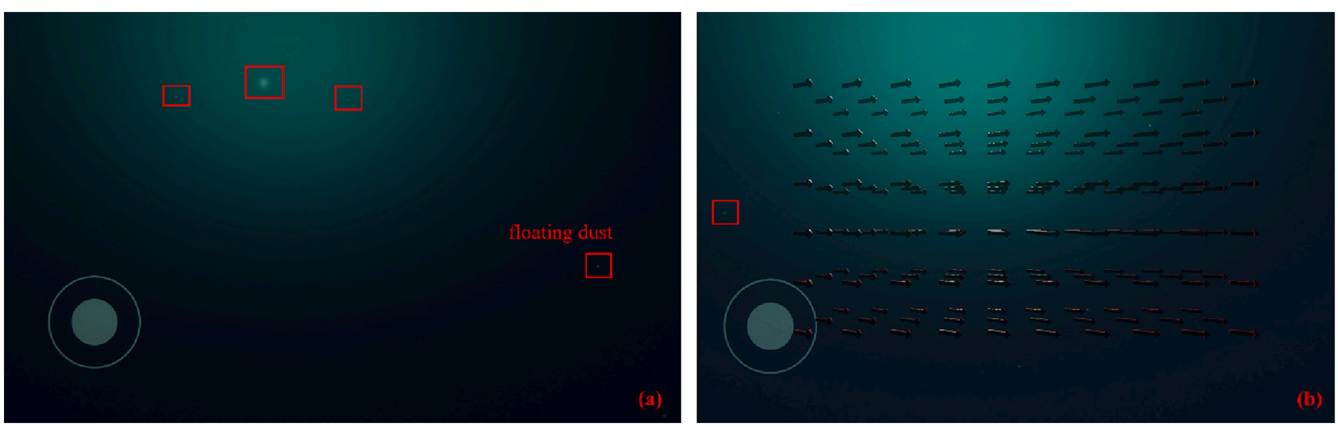

Fig. 5. Visual feedback examples: (a) Control condition: only floating dust; (b) Visual condition: vector field with floating dust.

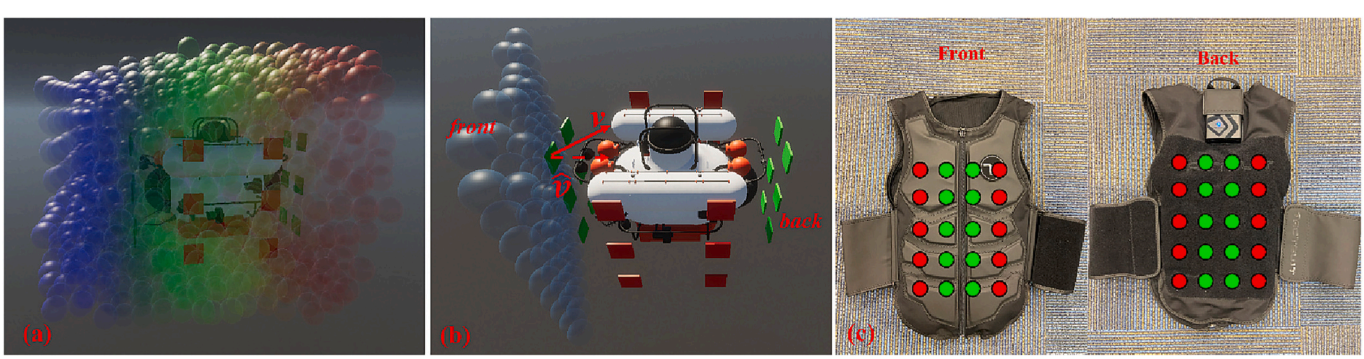

Fig. 6. Virtual sensory system and device mapping: (a) Particle flow; (b) Virtual sensory distribution and normal velocity projection; (c) Haptic suit sensor mapping.

virtual sensors were distributed around the ROV model (Fig. 6b). A mapping method was developed to map the data from the virtual sensors to the haptic suit (Fig. 6b&c). In total, there were 12 virtual sensors on each side of the ROV to trigger all 40 vibrators on the haptic suit. A script was developed to extract near-field particles' velocity when they collide with each virtual sensor. The flow intensity is calculated as Eq. 1:

$$M_{sensor} = \sum m_i * \widehat{v}_i \quad (1)$$

Where m_i is the mass of particle i, $\widehat{v}_i$ is the normal vector of the velocity of particle *i*, which is the projection of speed perpendicular to the contact surface, as shown in Fig. 5b. When particles collide with the virtual sensor, the sum of normal momentum $\sum m^{*}\hat{v}_i$ is calculated as the representation of the flow intensity. No mass difference was designed in this particle system because the hydrodynamic features were manifested as the pressure gradient, so the mass *m* can be equally set to 1.0 in practice. Each virtual sensor collected particle data when a collision happened. To map the haptic suit output range, a conversion function was applied to discount the larger raw flow intensity data to a range of 0 to 1 cm/sˆ2:

$$I = \frac{e^{0.33^{*}M_{sensor}} - 1}{e^{0.33^{*}M_{sensor}} + 1} \quad (2)$$

Where M_{sensor} represents the flow intensity sent by the sensors calculated in Eq. 1.After the intensity value of each virtual sensor was calculated in Unity, the intensity array was sent to the Python terminal via the Python-Unity-Socket [48] to trigger the haptic suit. With this system being well designed, operators could clearly feel the changes in the strength and direction of the water flow with their body feeling.

In summary, differentiation of particle flow direction and strength via visual and haptic feedback was achieved in this system. Virtual arrows were utilized in VR to indicate the direction of flow, with the length of the arrows representing the flow strength. Additionally, a haptic suit with 40 vibrating units was used to provide haptic feedback to the operator. A virtual sensor system with 24 virtual sensors was created in VR, which mapped to the 40 real units on the haptic suit. The virtual sensors were able to physically interact with particles in VR based on a physical engine, and the particle data was recorded to generate haptic feedback on the haptic suit. The use of this haptic suit allowed for the simulation of realistic oceanic sensations for the operator. For example, a strong vibration in the front represents that a strong flow is pushing operators backward. For the reference of feedback system demo, please refer to this link (https://drive.google.com/file/d/1PNwltmf9QbNdM5_Be4AOUnAvLP5xc2Bf/view?usp=share_link).

3.4. Data collection and analysis

The experiment was a straight-line navigation task with multiple checkpoints. Straight-line navigation is an essential skill for novice ROV operators before they could handle complex control actions, and is basic for many ROV operation tasks, such as pipeline inspection and ocean exploration. Besides, straight-line navigation task is a relatively simple and basic task for novices, which is less influenced by human knowledge and experience, and is a proper metric to evaluate the effect of sensory augmentation method. Specifically, a total of five checkpoints as well as several subsea current zones were aligned along the way for each of the experiment trials. Participants were required to operate the ROV for straight-line navigation, and to resist the effect of subsea currents to reach all the checkpoints along the line. The experiment was based on within-subject design, with a minimum sample size as 25 based on power analysis (significance level as 0.05, desired power as 0.8, and effect size as 0.8) [57]. 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. The training session was repeated three times to ensure that participants fully adapted to different kinds of feedback methods. After that, subjects were asked to finish four experiment trials in a random order, including the control condition, the visual condition, the haptic condition, and the multi-feedback condition. This kind of random design aimed to eliminate potential learning effect. The flow patterns were designed different between each experiment condition, but the average flow speed was calibrated as 0 m/s and the maximum flow magnitude was calibrated as 0.75 m/s in every condition to ensure a similar difficulty level. For each condition, realistic underwater renderings were optimized to support basic ROV navigation with camera streaming, including the rendering of floating dust and air bubbles to indicate the waterflow directions and speed. The distance and the number of subsea current zones (i.e., indicating current waterflow directional changes) between each pair of checkpoints are shown in Table. 1. The total distance was 90 m and the average ROV navigating speed was set to 1 m/s. The estimated finishing time for each condition without any delay would be 1.5 min. The difficulty of the task gradually increased along the navigation, with a longer distance to arrive at the next checkpoint and with more subsea current direction changes as disturbances.

During the experiment, our system could automatically record the ROV trajectory, the number of checkpoints reached, and human assessment data (such as gaze tracking). The average deviation from the straight line d_{avg} was used to evaluate the overall task performance in terms of keeping the straight-line navigation, which was the sum deviation of each frame divided by the total number of frames. As shown in Eq.3, d_i is the deviation from the straight line in each frame and I_{total} is the total frame number.

$$d_{avg} = \frac{\sum |d_i|}{I_{total}} \quad (3)$$

The number of checkpoints reached in the experiment was used as a secondary metric for task performance evaluation. Besides, the pupillary size was used for cognitive load analysis. As the literature indicates, pupillary diameter and eye blink rate are closely related to cognitive load and mental fatigue levels [68]. After each experiment trial, participants were asked to finish two surveys, including a NASA-TLX [29] for the workload level evaluation and a Trust Scale survey [41] for trust level analysis. Besides, they were asked to finish a demographic survey before the experiment, including information about gender, age, college major, experience and self-evaluation. At the end of the entire experiment, they were also asked to provide retrospective opinions about the proposed system and the suitability of haptic intensity. All results were analyzed with the Wilcoxon tests as preliminary analysis found that data did not satisfy the normality assumption [18].

4. Results

4.1. Participants

In total, 30 participants were recruited for the human subject experiment. As shown in Table 2, all participants were aged from 19 years old to 37 years old (mean = 25.2, std. = 4.06). There were 18 males and 12 females respectively. Among all participants, most were from engineering majors (25 or 86.7%) such as Civil Engineering and Aerospace and Mechanical Engineering, and a small portion of participants (5 or 16.7%) were recruited from non-engineering majors such as digital arts and law. Despite the difference in educational background, all participants were trained carefully until they reported that they felt fully adapted to the control of the ROV navigation with our system.

To be noted, we found a significant individual difference among the participants in terms of preference to the provided feedback methods. At the end of the entire experiment, participants were asked about their overall preference of feedback systems. In the follow-up analyses, we further found that the performance and human assessment data showed a significant difference among different preference groups. As a result, we will present the aggregated analysis results that incorporated all preference groups, and preference-based analysis for each of the preference groups. The method for clustering participants into preference groups will be introduced in detail later.

4.2. Aggregated analysis

First, we analyzed the task performance in terms of deviation and number of checkpoints reached. We tracked the deviation of ROV navigation path from the desired straight line, as shown in Fig. 7. The average deviation (m) per navigated distance (m) for the control, haptic, visual and multi-feedback conditions were 7.739 *m*, 2.714 *m*, 3.514 *m*

Table 1
Distance (m) and number of subsea current zones between each pair of checkpoints.

Areas	start ~ checkpoint1	checkpoint 1 ~ checkpoint 2	checkpoint 2 ~ checkpoint 3	checkpoint 3 ~ checkpoint 4	checkpoint 4 ~ end
Distance	8	12	15	25	30
No. of subsea current zones	1	1	2	3	3

Table 2
Background information of participants ($n = 30$).

Category	Item	Number	Percentage
Gender	Male	18	60.00%
	Female	12	40.00%
Age	Under 20	1	3.33%
	20 to 29	24	80.00%
	Above 30	5	16.67%
College Major	Engineering	25	83.3%
	Non-Engineering	5	16.7%
Feedback Method Preferred	Control Condition	0	–
	Haptic Feedback	10	33.33%
	Visual Feedback	7	23.33%
	Multi-Feedback	13	43.34%
VR/3D Gaming Experience	Quite Familiar	10	33.33%
	Several Trials	17	56.67%
	Never	3	10.00%

and 2.282 *m* respectively. A significant improvement in terms of drifting control was observed in the haptic condition and the multi-feedback condition. The result showed that it was harder for participants to localize the next checkpoint without additional feedback provided. It was because the drifting due to the changing hydrodynamic flows kept pushing the ROV from the desired path. In addition, because the visibility was low, participants could not see the checkpoint unless the ROV was close enough (within 5 m given the visibility range). Given the haptic feedback and/or the additional visual feedback, participants could maintain a relatively smooth path of the ROV in a trajectory closer to the desired straight line, and thus had a better chance of visualizing the next checkpoint.

We also analyzed the number of checkpoints reached, as shown in Fig. 8a. The Wilcoxon test showed significant differences between the control condition and the haptic condition ($p < 0.0001$), between the control condition and the visual condition ($p = 0.0002$), and between the control condition and the multi-feedback condition ($p < 0.0001$). However, there was no significant difference between the haptic condition and the visual condition ($p = 0.19$), between the haptic condition and multi feedback condition ($p = 0.65$), or between the visual condition and the multi feedback condition ($p = 0.10$).

As for the average deviation, as shown in Fig. 8b, there was a significant difference between the control condition and the haptic condition ($p < 0.0001$), between the control condition and the visual condition ($p = 0.0007$), and between the control condition and the multi-feedback condition ($p < 0.0001$). There was not a significant difference between the haptic condition and the visual condition ($p =$

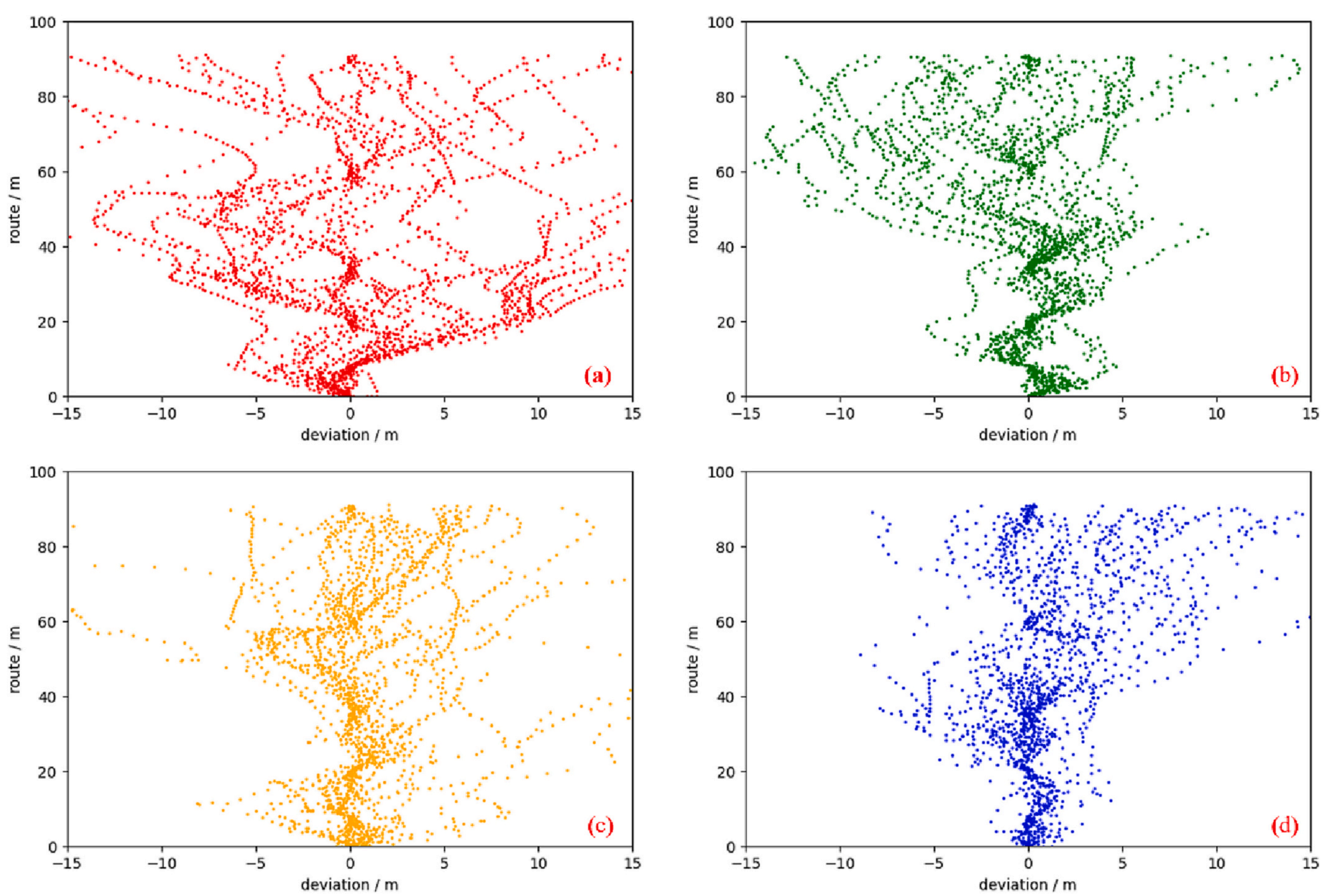

Fig. 7. ROV navigation trajectories of the four conditions: (a) Control condition (deviation per navigated meter: 7.739 m); (b) Haptic condition (deviation per navigated meter: 2.714 m); (c) Visual condition (deviation per navigated meter: 3.514 m); (d) Multi-feedback condition (deviation per navigated meter: 2.282 m).

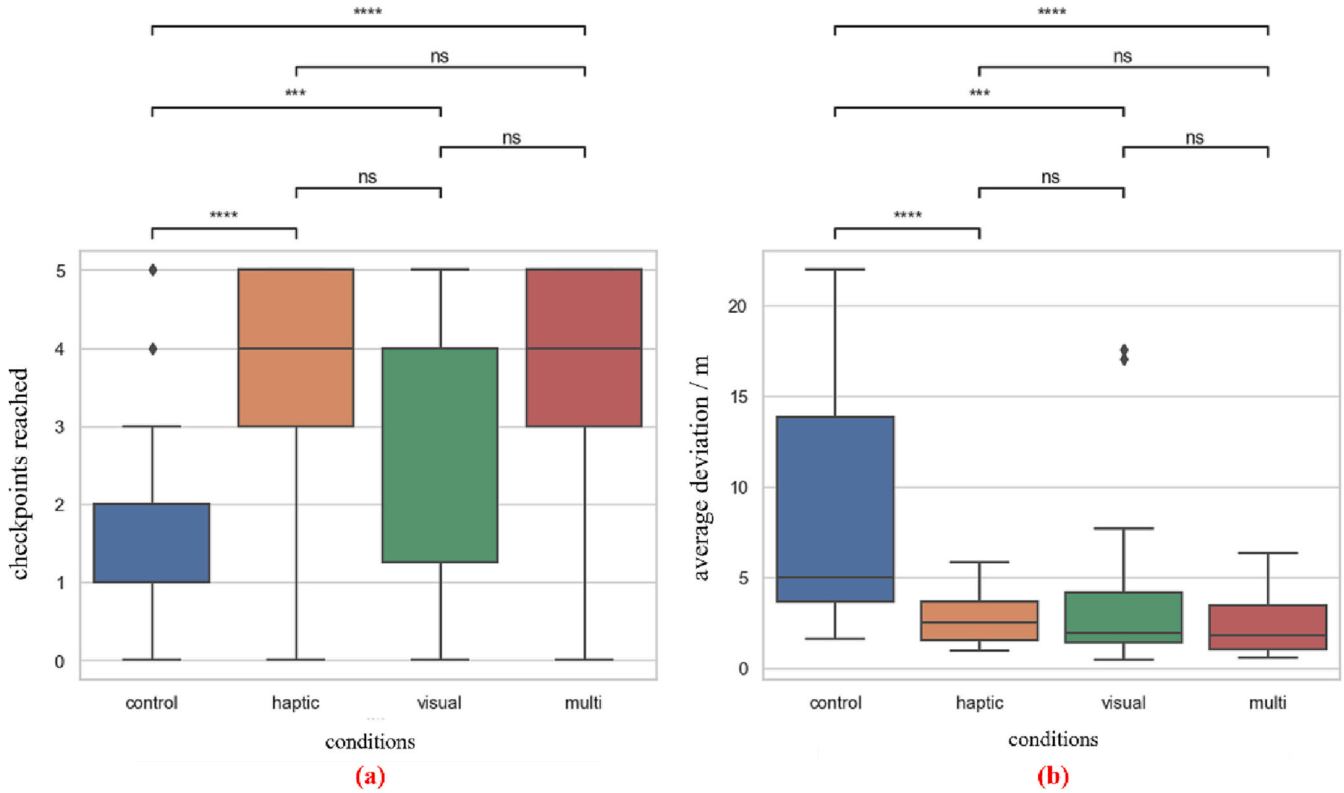

Fig. 8. Performance result: (a) number of checkpoints reached; (b) Average deviation.

0.70), between the haptic condition and multi-feedback condition ($p =$ 0.30), or between the visual condition and the multi-feedback condition ($p = 0.21$) in terms of the average deviation.

Then we analyzed the cognitive load based on the pupillary size and survey data, as shown in Fig. 9. For the cognitive load, which is represented by the pupillary diameters shown in Fig. 9a, participants showed a lower cognitive load in the haptic condition ($p < 0.0001$), the visual condition ($p = 0.0033$) and the multi feedback condition ($p = 0.002$) compared to the control condition. There was no significant difference between the haptic condition and the visual condition ($p = 0.89$), between the haptic condition and multi-feedback condition ($p = 0.52$), or between the visual condition and the multi-feedback condition ($p =$ 0.78). The NASA-TLX workload analysis showed a similar result as demonstrated in Fig. 9b. Participants reported a lower workload in the haptic condition ($p = 0.0003$), the visual condition ($p = 0.0004$), and the multi-feedback condition compared to the control condition ($p =$ 0.0006). As for the trust scale analysis in Fig. 9c, there were significant differences between the control condition and the haptic condition ($p <$ 0.0001), between the control condition and the visual condition ($p <$ 0.0001), and between the control condition and the multi feedback condition ($p < 0.0001$). In addition, participants also showed higher trust levels in the haptic condition ($p = 0.047$) and in the multi feedback condition ($p = 0.0002$) compared to the visual condition.

In general, with the sensory augmentation methods (including the

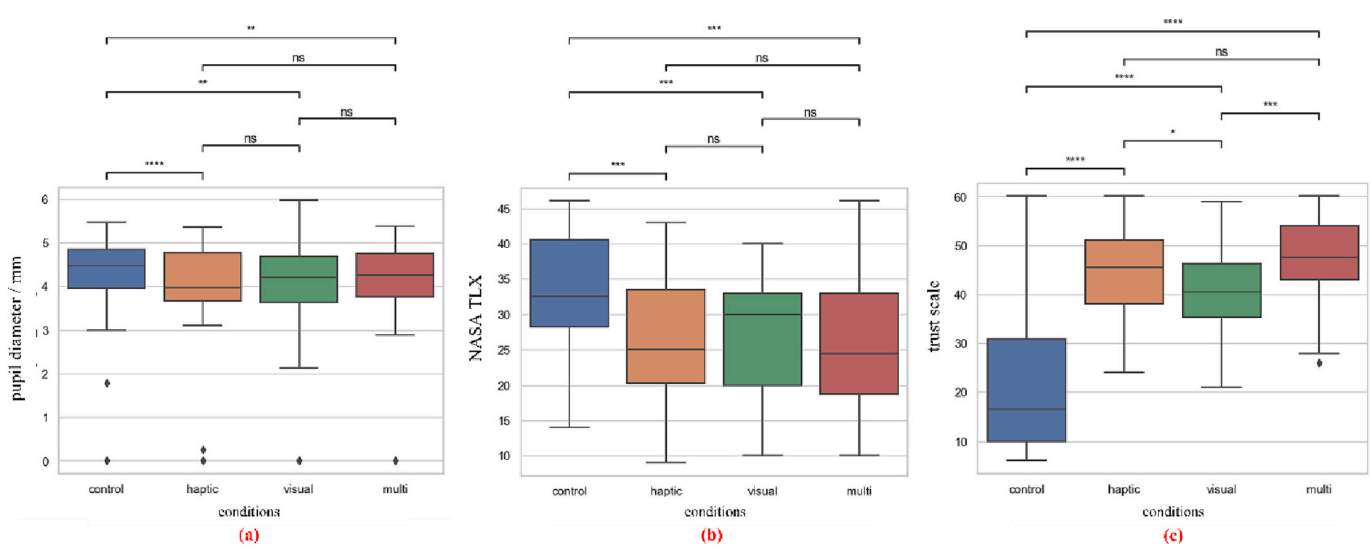

Fig. 9. Cognitive load and survey results: (a) Pupillary size; (b) NASA TLX survey; (c) Trust scale survey.

haptic feedback, visual visualization and multi-feedback), task performance, cognitive load and perceived trust were significantly improved in all the metrics. Yet, no significant difference was observed among the three sensory augmentation conditions. Participants only showed a lower trust with the visual feedback compared to the haptic feedback and the multi feedback. As discussed earlier, participants reported significantly different preferences to the provided sensory feedback methods. As such, we analyzed the performance and perception data for each of the preference groups.

4.3. Preference group based analysis

Although no significant differences in terms of performance and perception data were observed among the three sensory augmentation conditions, we found that participants reported distinct preferences for the provided sensory augmentation methods. It suggests that participants may have presented different abilities to digest spatial information from different modes of data (i.e., visual and haptic data), resulting in a vast individual difference within the haptic condition or the visual condition. For example, certain groups of people may be more sensitive to the haptic feedback than others, and hence tend to perceive the spatial information provided by the haptic feedback in a more effective way. We performed a post-experiment survey to solicit their perceived benefits and difficulties with the haptic and visual feedback provided in the experiment, as a basis for clustering participants into different preference groups.

We first found a split of preferences for different feedback methods as shown in Table 2. Specifically, the result showed that 10 participants (33.33%) preferred haptic feedback, 7 participants (23.33%) preferred visual feedback, and 13 participants (43.33%) preferred the multi-feedback method. We further found that participants also reported problems or concerns with different feedback methods. As shown in Table 3, 8 participants (26.67%) reported that the haptic intensity was improper (either too strong or too weak to be informative), labeled as "problems with haptic feedback", 10 participants (33.33%) reported that the visual feedback shown as visual were confusing and/or blocked their views, labeled as "problems with visual feedback", 3 participants (10.00%) reported issues with both haptic and visual feedback, labeled as "problem with both feedback", and 9 participants (30.00%) did not report any problems, labeled as "no concerns".

We found that data about concerns or problems does not completely compatible with the preference results. For example, a person could report a preference for haptic feedback but still complained about problems with the haptic feedback (too strong or too weak). It indicates that each participant may have inclined to a certain feedback method with some level of concerns. In order to roughly quantify the inclination to a certain feedback method, we defined a rating method to incorporate both the reported preference and reported concerns. Specifically, if a participant reported a preference for a certain feedback method and did not report any problems with the preferred feedback method, it would be marked as a high level of preference. If a person reported a preference for a certain feedback method, but also reported certain problems with the same feedback method, it would be marked as a medium level of preference. The rest would be marked as low levels of preference. And in a more special case, when a person reported preferring to the multi-feedback method, but reported perceived problems with a certain feedback mode (haptic or visual feedback), then the person would be assigned to the preference group with no reported problems. In this way, we have clustered 30 participants into two preference groups, namely the "visual preference group" and "haptic preference group" as shown in Table 4.

Then we compared the two preference groups in terms of performance and perception results, as illustrated in Fig. 10. As for the number of checkpoints reached, the visual preference group outperformed the haptic preference group with the visual feedback ($p = 0.018$), but no significant difference was observed with the haptic feedback. On the other hand, the haptic preference group ended up with a higher average deviation with the visual feedback ($p = 0.0005$). Besides, there was a significant difference in the trust scale survey. The visual preference group trusted visual feedback significantly more. No significant difference was observed in the pupillary diameters and NASA TLX survey results. Generally, the two preference groups showed significantly different performance patterns. It suggests that users could be categorized based on their preference for the feedback method, and personalized feedback solutions should be applied to each individual depending on the specific preference and potential problems with any feedback method.

We also analyzed performance and perception results for each preference group. As shown in Fig. 11, in the haptic preference group, participants reached a higher number of checkpoints in the haptic condition than the control group ($p = 0.0004$) as well as the visual condition ($p = 0.0052$), while maintaining a significantly lower average deviation in the haptic condition than the control condition ($p < 0.0001$) as well as the visual condition ($p = 0.0079$). The number of checkpoints reached in the multi-feedback condition was significantly higher than the control condition ($p = 0.0014$) as well as than the visual condition ($p = 0.018$), and the average deviation was significantly lower in the multi-feedback group than the control group ($p = 0.0079$). Besides, subjects showed a higher trust level in the haptic group ($p = 0.0022$) and multi-feedback group ($p = 0.0038$) compared to the visual group in this category. On the other side, there was no significant difference between the control group and the visual group ($p = 0.093$ for the checkpoints reached and $p = 0.26$ for average deviation), and between the haptic group and the multi-feedback group ($p = 0.66$ for the checkpoints reached and $p = 0.75$ for average deviation). In general, for those who highly relied on haptic feedback, visual augmentation could not provide effective information for their operations. They showed significantly poorer performance as well as lower trust in the visual feedback. When visual feedback was integrated with the haptic feedback, subjects' performance was not influenced and they could keep a similar deviation and trust in the system. For this category, both the haptic feedback system and the multi-feedback system could be the effective design for sensory augmentation in subsea engineering.

Different from the haptic preference group, the visual preference group showed a significantly different behavior pattern. As shown in Fig. 12, for the checkpoints reached in the experiment, there was not a significant difference between the haptic group and multi-feedback group ($p = 0.24$), between the haptic group and the visual group ($p = 0.066$), and between the visual group and multi-feedback group ($p > 0.9$). On the other hand, no significant difference was observed in the average deviation between the visual group and the multi-feedback group ($p = 0.45$), but it was significantly lower in the visual group ($p = 0.0012$) and the multi feedback group ($p = 0.040$) compared to the haptic group. There is an additional finding in this preference group that, although subjects showed a better performance with visual feedback, they did not show higher reliability on the visual system. For the

Table 3
Subjects' comfortability with haptic and visual augmentation feedback.

Reported Problems	Number	Percentage
No Concerns	9	30.00%
Problems with Haptic Feedback	8	26.67%
Problems with Visual Feedback	10	33.33%
Problems with both Feedback	3	10.00%

Table 4
Feedback method preference group.

Preference groups	Number	Percentage
Visual preference group	13	43.33%
Haptic preference group	17	56.67%

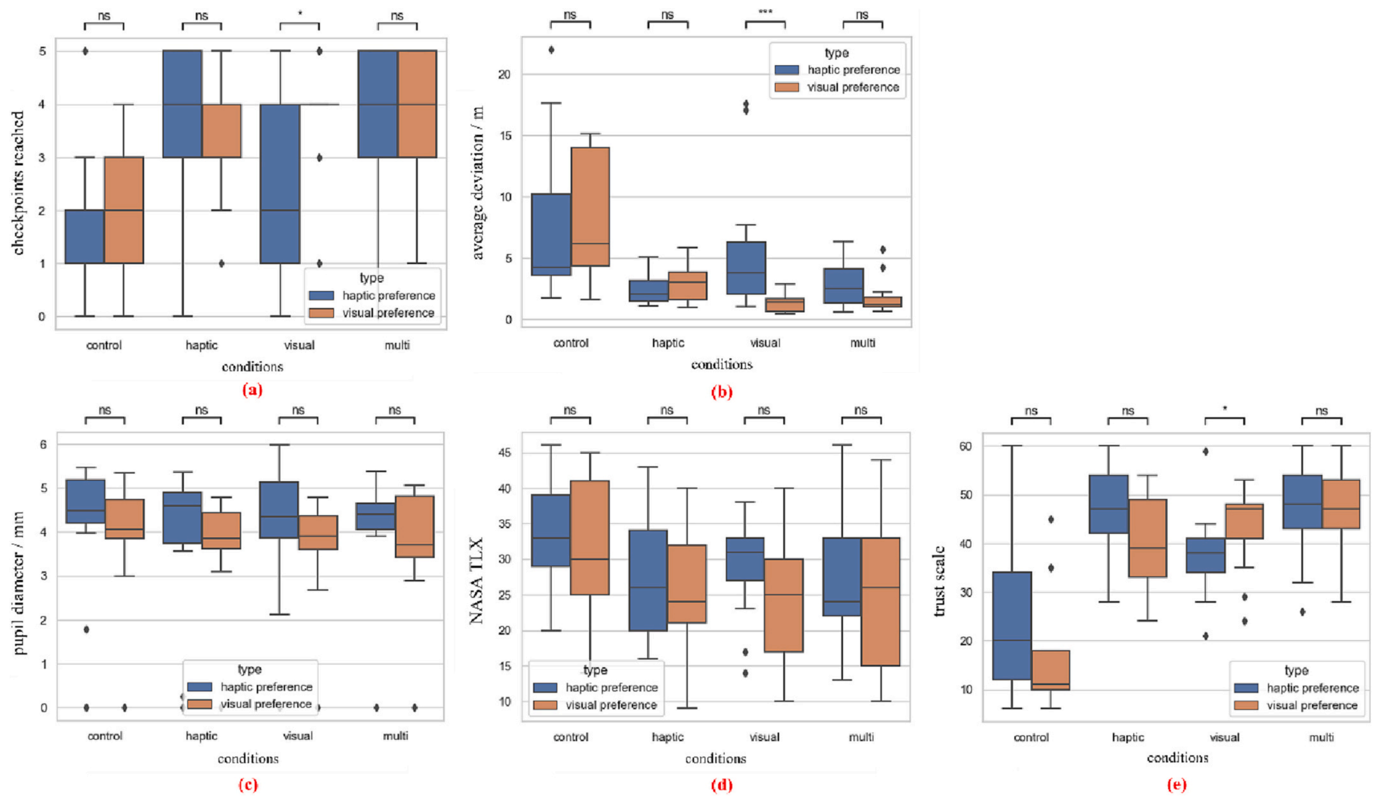

Fig. 10. Performance difference in two categories. (a) Numbers of checkpoints reached. (b) Average deviation. (c) Pupil diameters. (d) NASA TLX results. (e) Trust scale survey results.

trust scale survey, there was a similar score between the haptic group and the visual group ($p = 0.34$). Nonetheless, subjects showed higher trust in the multi-feedback group than in the visual group ($p = 0.017$) and the haptic group ($p = 0.030$). In general, although a relatively better performance was observed in the visual group, the performance difference was not as significant as that in the haptic preference group. Especially, subjects were not that reliant on visual feedback. Taking both the operation performance and subjects' evaluation of trust into consideration, the best design for this preference group should be the multi-feedback system.

Although our results indicated that the population could be divided into two different groups, measured by their subjective preferences, and such a categorization may significantly affect the level of benefits of different sensory augmentation feedback methods, we could not explain what demographic factors the root cause of different preferences could be, including gender, college majors, age, etc. Mann-Whitney analysis [37] was applied to test if the above factors are determinants of the two preference groups. Unfortunately, there was not any relationship between the preference groups and gender ($p = 0.55$), learning background ($p = 0.76$), VR/3D-gaming background ($p = 0.25$) as well as age ($p = 0.96$). We also analyzed eye tracking pattern for human navigation preference and strategy, but there was still no difference. Operators were keeping looking around trying to find checkpoints no matter what kind of feedback they were relying on.

5. Discussions

In general, the experiment results revealed the potential benefits of integrating sensory augmentation methods in current ROV control systems. The results verified that with sensory augmentation feedback, either haptic feedback, visual feedback, or a combination of both, to indicate hydrodynamic conditions in the proximity, the performance and perception results of ROV operators could be significantly improved in ROV navigation operations and the anti-drifting operations. Specifically, the number of checkpoints reached, average deviation, and trust levels were all improved with haptic, visual and multi-feedback methods, in comparison with the control condition where only camera feedback was used. Nonetheless, no significant differences were observed between the visual and haptic methods. We further found that participants reported different preferences to the provided feedback methods, and/or problems with a certain feedback method. Based on the reported preference and concerns, we categorized the participants into two preference groups, namely the “visual preference group” and the “haptic preference group”. The visual preference group showed a subjective inclination to use visual feedback, and the haptic preference group showed a subjective inclination to use haptic feedback. Based on the categorization of preference, we further analyzed the performance and perception data for each preference group. We found that personal preference indeed affected the impact of different feedback methods. Specifically, haptic feedback tended to lead to better task performance and a higher trust level for those who reported a preference for haptic feedback or companied less about the haptic feedback method. Similarly, visual feedback tended to lead to better task performance and a higher trust level for those who reported a preference for visual feedback or companied less about the visual feedback method. We also observed similar patterns in the cognitive load data measured by NASA TLX and pupillary dilation.

We also found that the multi-feedback method seemed to be the most favorable and practical sensory augmentation method for all participants. Therefore, we propose a reasonable design for the next-generation sensory augmentation system for the ROV controls. Firstly, since combining multi-feedback does not seem to distract operators or decrease operation effectiveness, a reasonable solution is to provide both haptic and visual augmentation feedback to provide as much assistance as possible. On the other hand, an ON/OFF switch function could be designed in the system if necessary. For example, not all the

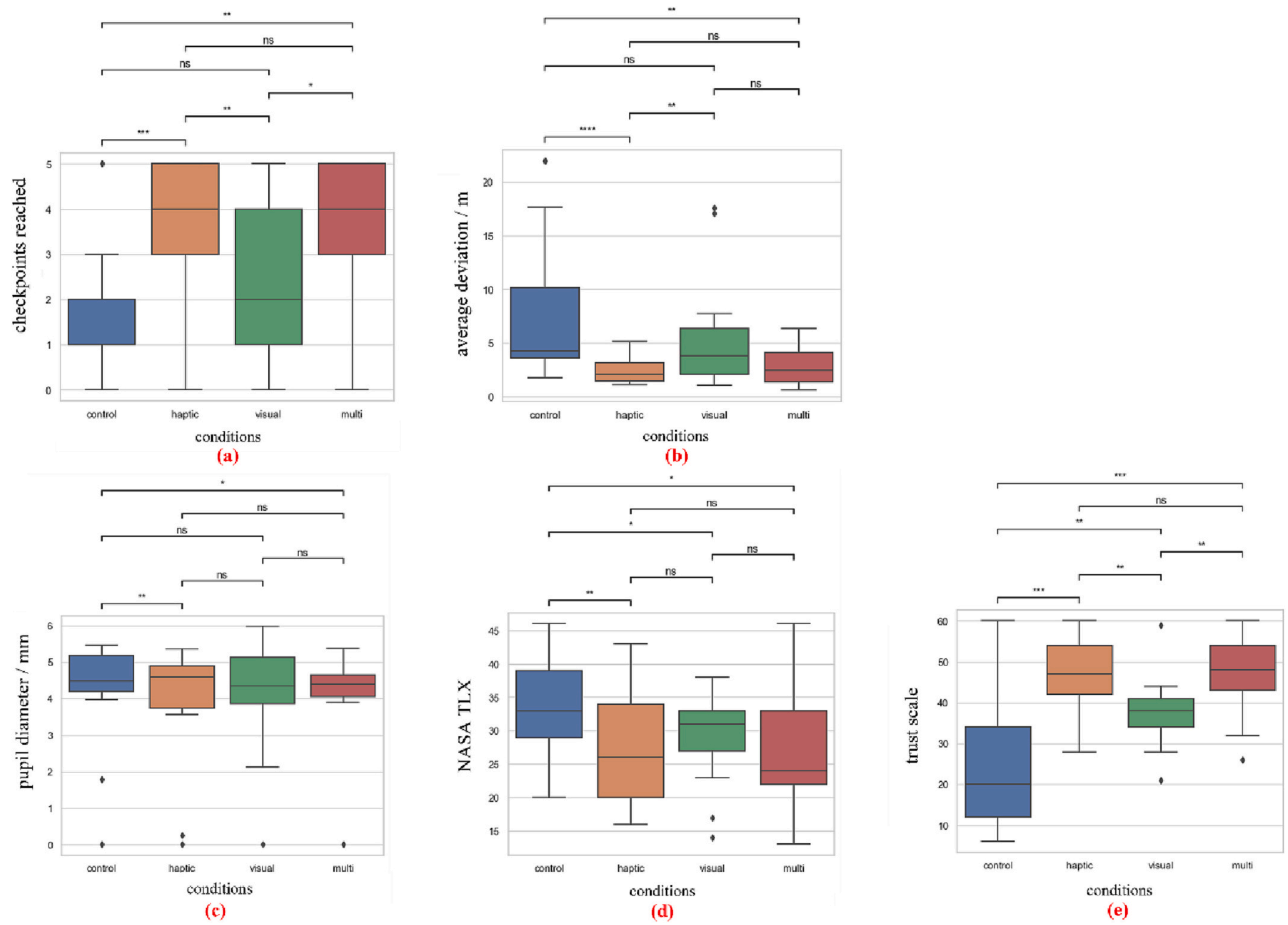

Fig. 11. Results for the haptic preference group. (a) Numbers of checkpoints reached. (b) Average deviation. (c) Pupil diameters. (d) NASA TLX results. (e) Trust scale survey results.

operators preferred to rely on visual feedback and too many visualization elements (such as vector field) would also block operators' views or make them confused, as 43.33% of subjects had complained in the experiment. Therefore, haptic feedback could be designed as the fundamental sensory augmentation method as an indication of hydrodynamic conditions. An ON/OFF function could be designed for turning on additional visual cues when needed. In contrast, for those who rely more on haptic feedback, visual feedback could be designed as the basic feedback method with haptic feedback as the secondary guilds. Another reasonable design is to differentiate the application proximities of the two feedback methods. For example, the visual can be designed to represent far-field flow conditions while haptic feedback can be used as an indicator of near-field interactions between currents and the ROV system.

There are also some limitations and future works for this study. The experiment only tested a most simple task condition. The experiment result is sufficient to support our system effectiveness in routine navigation tasks, where only motion and rotation actions are involved and flow conditions are often stable. However, ROV operators are facing so many unique challenges, and they need to take different control actions based on task requirement. There are also complex stabilization/docking tasks involving physical interaction with the environment and complex dynamic flow conditions, which cannot be represented by this simple experiment. Therefore, in the future, we will develop a real ROV teleoperation system with this proposed sensory augmentation system, based on a mini class ROV, BlueROV2, and test the system efficiency on those complex ROV operations. Besides, we will further improve the system to fit those unique task features by enhancing simulation data resolution and developing more intuitive control method.

6. Conclusions

Subsea engineering is highly dependent on ROVs. At present, ROV control mainly relies on traditional control kiosks and feedback methods, such as the use of joysticks and camera displays equipped on a surface vessel. However, due to the complexity of the subsea environment, including dynamic internal currents, low visibility, and unexpected contact with marine lives, traditional 2D video streaming method cannot provide enough information for human awareness of subsea environments, which might result in decreased performance or safety issues in ROV operations. This paper proposes a sensory augmentation method to enhance the ROV operator's perception through novel feedback methods, including simulating the hydrodynamic features of the surrounding subsea environment as visual feedback, haptic feedback, or a combination of both. To verify which feedback method is appropriate for ROV navigation control tasks, a human subject experiment was performed to test if the human operator could resist drift and keep straight-line navigation with haptic feedback, visual feedback, and multi-feedback. The result showed that with sensory augmentation methods, human operators' performance was significantly improved. We also found that personal preference to or concerns about a specific feedback method could affect the level of benefits of the corresponding

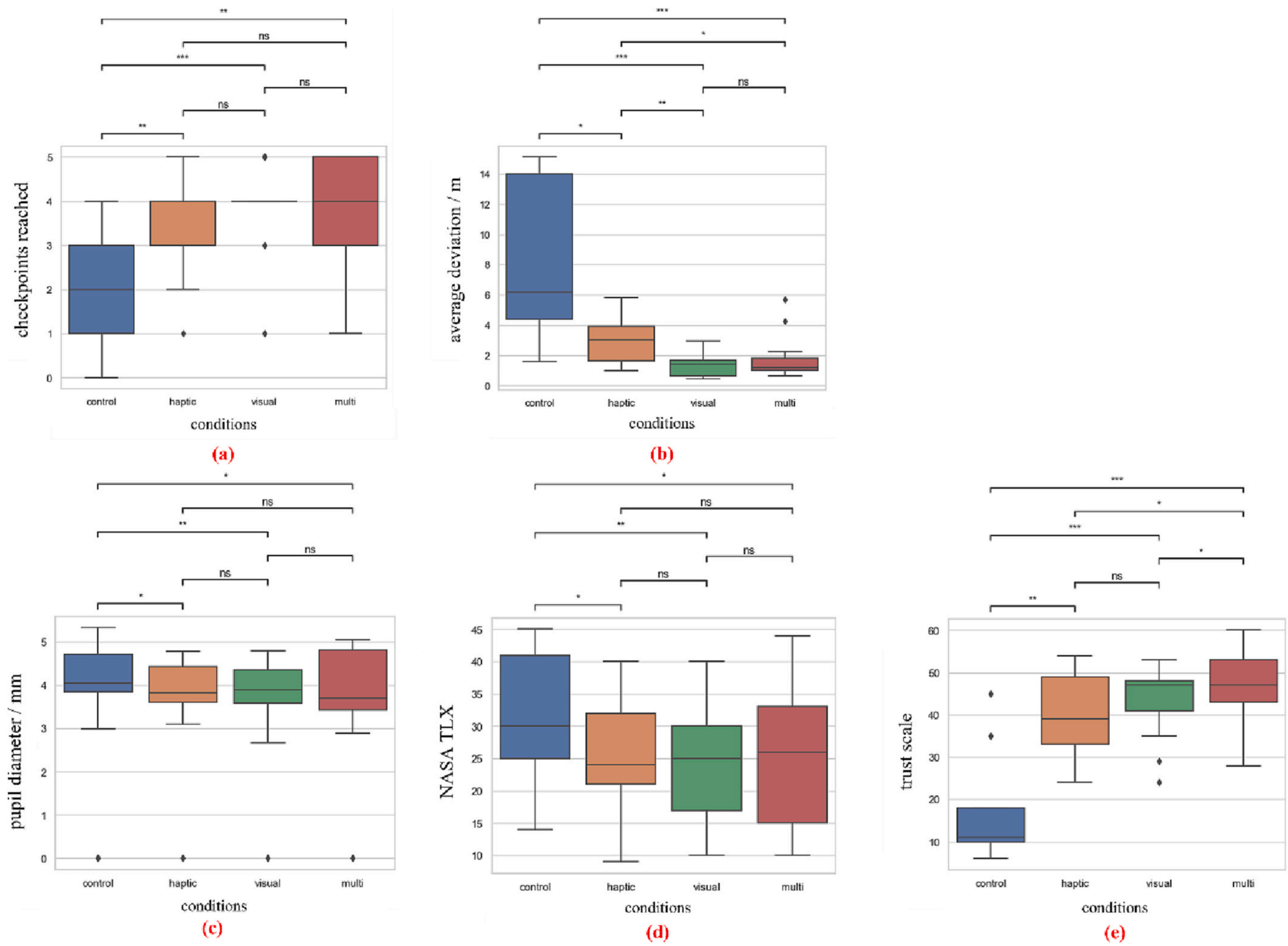

Fig. 12. Results for the visual preference group. (a) Numbers of checkpoints reached. (b) Average deviation. (c) Pupil diameters. (d) NASA TLX results. (e) Trust scale survey results.

feedback method. The limitation of this study is that the root cause for different preferences was not discovered by our data. There was no relationship between performance and the surveyed demographic factors including gender, age, college major backgrounds as well as subjects' self-evaluation. Further studies are needed.

In conclusion, with the urgent need for subsea engineering, new human-robot interaction designs are needed to enhance the human sensation of the subsea environment. We expect that the proposed new method of ROV feedback and controls can help advance a booming subsea engineering industry that requires a strong integration between human intelligence and robots to tackle environmental complexity and task dynamics. Without losing the generalizability, this method is expected to enable a much closer human-ROV collaboration for subsea inspection and survey, i.e., the maneuver and navigation controls of remote ROVs for sensor data collection and scanning of vessels and subsea structure inspection in offshore zones. It can make the key tasks easier, including navigation (localization and state estimation), control (path planning and maneuvering through complex environments) and perception (for robot position control and the inspection task). 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 sensory augmentation method for robotic 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.

Declaration of Competing Interest

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Data availability

Data will be made available on request.

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