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ROV Teleoperation in the Presence of Cross-Currents Using Soft Haptics

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ABSTRACT

The remote operation of underwater vehicles at depth is complicated by the presence of invisible and unpredictable environmental disturbances such as cross-currents. Communicating the presence of these disturbances to an operator on the surface is made more difficult by the nature of the disturbances and the lack of visible features to highlight in the visual display presented to the operator. Here we explore the use of a novel interactive soft haptic touchpad that utilizes vibration and particle jamming to provide information about the presence and direction of cross-currents to the operator of an ROV (remotely operated vehicle). An in-water experiment using a thruster-based ROV and artificially generated cross-current was performed with nonexpert ROV operators to evaluate the effectiveness of multimodal haptic feedback to communicate complex environmental information during high-risk operations. Advanced haptic displays can signal both the presence of external factors as well as their direction, information that can enhance operational performance as well as reduce operator cognitive load. Using haptic feedback resulted in a statistically significant reduction in cognitive load of 24.3% and an increase in positioning accuracy of 28.3% for novice operators. Deviation from an ideal path was also reduced by 29.5% for experienced operators when using haptic feedback compared to without. While this experiment took place in controlled conditions with a fixed direction cross-current and haptic interface, this approach could be extended to communicate real-time environmental information in real-world unstructured environments.

1 | Introduction

Underwater robots or remotely operated vehicles (ROVs) are mobile robots generally intended for deep sea exploration, underwater biological surveys and underwater structure inspection. These tasks require significant precision in some of the most hostile conditions that a robot or remotely teleoperated device can encounter. Limited visibility, floating debris, complex environmental geometry, and invisible water currents are among the hazards that a mobile robot may encounter when operating at depth. To address these and other challenges posed by operating ROVs, researchers are beginning to consider haptic feedback to convey additional state and environmental information to a remote human operator.

Teleoperation remains the preferred mode of controlling ROVs in many contexts, even when autonomous operation is available (Yuh 2000). Giving real-time control of a robot to a human operator may be preferred where tasks are safety-critical, require an established chain of liability, are likely to become complex and require human intervention, or for extended operations in complex, unstructured environments. For example, a recent review of underwater robot sensor technology given in Cong et al. (2021) identified widespread limitations in modern sensors' range, accuracy, efficiency and robustness. Teleoperation is essential as direct sensing of environmental characteristics underwater is often insufficient to build a complete and trustworthy model of a robot's surroundings. An even more recent review of underwater localization techniques further makes the distinction between clear and cluttered environments, warning that autonomous robots may struggle to operate safely in complex environments with many hazards (Wu et al. 2024). These reviews further highlight that multiple streams of information are often needed to completely and correctly understand an underwater environment, indicating that multiple streams of information output, including haptics, are likely to be useful when teleoperating a robot underwater.

By way of a concrete example of a challenging underwater operation, operating a tethered ROV through a shipwreck at depth, such as shown in Figure 1 presents a significant HRI challenge. The ROV must be operated in a very controlled manner, avoiding obstacles in the environment while progressing towards an identified target—in this case a safe exit from the wreck. The confined nature of the shipwreck causes currents that impact ROV performance. Transitions in the underwater environment—such as the point at which the ROV exits the wreck—can be associated with significant cross currents, which can impact vehicle performance, threatening mission success and even the vehicle itself by pushing or pulling it away from the operator's intended and expected path, often without strong visual cues to serve as a warning to the operator.

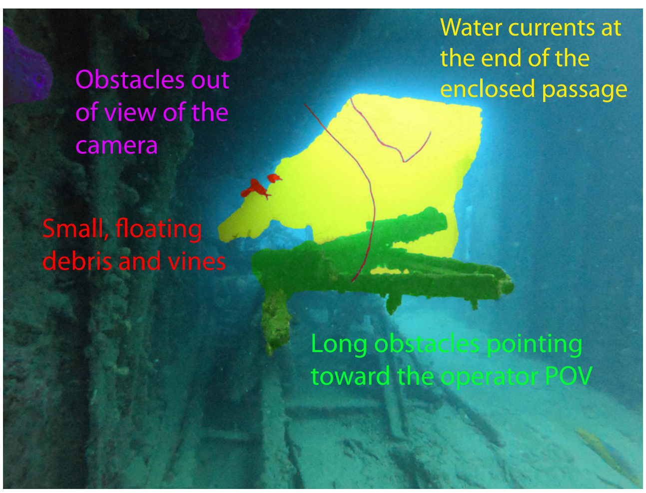

FIGURE 1 | A typical remotely operated vehicle (ROV) operating environment with a number of hard-to-visualize hazards. The operator must use available sensory feedback from the ROV to drive the robot to a goal—here an exit from the wreck—while avoiding collisions with long, forward facing obstacles, floating and moving debris and peripheral objects that are about to pass out of the camera's field of view, highlighted in green, red, and purple. The constrained nature of the environment can focus currents in the wreck with openings, such as those highlighted in yellow, associated with significant changes in current that can cause the vehicle to move in unexpected ways. [Color figure can be viewed at wileyonlinelibrary.com]

Most recent and ongoing HRI (human–robot interaction) research relevant to underwater robots focusses on the communication from a human to a robot, for example to deliver instructions. Most existing means for underwater robots to relay information to human operators are visual, such as relaying of an onboard camera feed to a control post, or flashing onboard lights at a diver in the water (Birk 2022). Above the surface, haptic feedback has been shown to impart safety-critical information to a remote robot operator including presence of obstacles (Lamam et al. 2007; Tang et al. 2009; Farkhatdinov et al. 2008), unsafe roll and pitch (Corujeira et al. 2018), and loss of traction (Luz et al. 2018). Beyond the robotics domain, tactile feedback has been used to alert drivers to changing road conditions and even to return their attention to the road if the driver appears unfocused (Ho et al. 2005; Spence and Ho 2008). Haptic feedback has also been employed to relay information about the robot's state that may not be obvious from conventional visual feedback, such as velocity when climbing stairs (Horan et al. 2008) and complex pose information to avoid self-collisions (Selvaggio et al. 2017). Advanced haptic interfaces such as Spiers and Dollar (2017), Corujeira et al. (2018), and Stanley et al. (2014) can be used to provide complex time-varying haptic signals in navigation and teleoperation tasks. Such devices can be used to signal the presence and nature of unusual environmental conditions, which could lead to improvements in vehicle operations as well as reduced load on the operator. There is however very little empirical evidence for this, especially in the case of ROVs, where experiments are rarely conducted in-water with a real robot (Zhou et al. 2022).

The work presented here aims to address the challenge of teleoperating an ROV through an invisible cross-current by presenting environmental information nonvisually via advanced, multimodal haptic feedback. This question is addressed by a controlled in-pool experiment using an ROV operated towards a visual target in the presence (or absence) of a cross-current. Conventional visual feedback is given, but advanced haptic feedback is also provided by an experimental vibrating and hardness-changing touchpad.

The study demonstrates that advanced haptic information can enhance operational accuracy as well as reduce cognitive load on the operator. Given the cost and complexity of ROV operations, and the risk of potential vehicle loss, the integration of sophisticated haptic cues within the teleoperation interface is appropriate to aid the operator in complex underwater vehicle deployments.

The remainder of this paper is organized as follows. Section 2 reviews the experimental vibrating and hardness-changing haptic device used in this work. Section 4 describes the experimental method in detail. Section 5 provides the results, while Section 6 summarizes the key results and suggests directions for future research.

2 | Background

The underwater environment presents unique challenges for the safe and efficient teleoperation of underwater vehicles. These include severe mechanical constraints that govern the design of underwater electronics enclosures, which limits the options for mounting cameras and providing the operator a clear view of the environment. This issue was partially addressed in the early 21st century through the use of three-dimensional (3D) models of the ROV and environment to create a virtual third person view of the robot and environment (Lin and Kuo 1997, 2001). At about the same time, force feedback was proposed as a means of warning operators of the presence of obstacles outside the robot's field of view (Diolaiti and Melchiorri 2002). Communication with ROVs is also difficult, with most wireless communication systems being unable to penetrate the water column and provide the desired communication bandwidth. Shared control has been proposed as a means of compensating for this communication issue by generating commands automatically while waiting for user input (Di Lillo et al. 2018, 2021). Haptic feedback has also been used to support multiple operators working with the same vehicle (for instance to distribute motion and manipulation tasks) (Stewart et al. 2016; Ryden et al. 2013). Semi-autonomous action by the robot itself can also be encoded through advanced haptic feedback, with the autonomous actions taken by a robot signaled to the operator by forces applied to the control joystick (Konishi et al. 2020). Although not all of these systems have been evaluated with users, those that have were found to produce measurable improvements in performance (Sakagami et al. 2022), estimated task difficulty, and error rates (such as collisions) (Huang et al. 2019).

Teleoperated manipulation in underwater environments has also been addressed through haptics, with sophisticated multi-DoF haptic robots being used to maintain safe paths and keep-out zones during object handling tasks, though not tested in-water (Ryden et al. 2013). Force-feedback through a haptic interface has also been found to be beneficial for manipulation tasks when visibility is limited—a common problem in deep-sea operations (Utsumi et al. 2002). Upcoming work, which is yet to be published, extends this concept to OceanOneK, an advanced humanoid ROV (Khatib et al. 2016), which uses a pair of 6DoF force feedback interfaces to replicate physical interactions between the robot's two dexterous hands and the environment (Wu 2022). Tactile sensors have been added to underwater manipulators, potentially allowing higher-definition haptic feedback to be provided during teleoperated manipulation tasks (Kampmann and Kirchner 2015; Lin et al. 2020). This concept has been extended more recently with a whole body haptic interface being proposed to relay the automatic actions of an ROV's manipulators back to the user via haptic feedback (Brantner and Khatib 2021). Finally, face movements and hand gestures have been proposed as an intuitive means of commanding an ROV underwater (Kapicioglu et al. 2021; Jenkin and Codd-Downey 2023).

Haptics, the process of transmitting information in a user interface through the sense of touch, has a long history in robotics and virtual reality (see Stone 2001; Hamza-Lup et al. 2019; and Hayward et al. 2004 for a review of the literature). Often, haptic feedback is based on very simple tactators or vibrators, such as those found in video game controllers or mobile phones. However, more sophisticated haptic devices have been developed (Hamza-Lup et al. 2019). Haptics has been found to be an effective mechanism for human–machine interaction in a wide range of different applications (see Okamura and Chang 2003; Dongseok et al. 2005; Kim et al. 2001; Pacchierotti and Prattichizzo 2024). While early haptic devices could only provide limited haptic feedback such as a short pulse of vibration, more modern devices are capable of providing complex haptic signals to encode information and accurately replicate real-world interactions.

Haptic feedback is rarely incorporated into commercially available teleoperation systems, leading to poor operator performance in many real-world tasks. For example, whilst many popular systems use gamepad-style controllers with built-in vibrating motors to command an ROV neither the Dronecode QGroundControl or Blue Robotics Cockpit software applications provide any facility to drive this feedback without custom commands (Dronecode 2019; Blue Robotics 2024). Higher-end, fully integrated solutions such as DexROV do support haptic feedback via proprietary hardware devices that are tailored to specific use cases. For example, the DEXO haptic exoskeketon integrates closely with the DexROV software and Underwater Dexterous Gripper (DexROV 2025). This has been shown to improve performance in inspection and manipulation tasks (Gancet et al. 2015), however it is a highly specialized device that does not provide any haptic feedback that could support maneuvering tasks that are made hazardous by the presence of obstacles and unpredictable currents (Xia et al. 2022, 2023).

Of particular interest here is the development of haptic devices that can communicate via multiple, simultaneous haptic cues. One such class of devices are those which borrow heavily from the flexible and modifiable technologies emerging from research in soft robotics, such as particle jamming (Biroli 2007). Haptic interfaces based on particle jamming are widely used to create the sensation of softness under a user's finger or hand (Follmer et al. 2012; Brown and Bello 2024a) but with the inclusion of other technologies, they can also change shape (Stanley et al. 2013; Stanley and Okamura 2017; Li et al. 2014) or vibrate (Brown and Farkhatdinov 2020, 2022; Kurihara et al. 2014) to introduce other tactile sensations. Particle jamming haptic interfaces have also been used in kinesthetic interfaces to restrict the movement of joints in haptic gloves (Zubrycki and Granosik 2017; Simon et al. 2014) and exosuits (Al Maimani and Roudaut 2017) by stiffening strategic areas of the suit with a small mass of particles.

3 | Soft Haptic Touchpad

To demonstrate and evaluate this concept, a prototype soft haptic touchpad has been developed that can provide 2D touch input (finger position and force magnitude) interaction while providing physical feedback to the user by altering the hardness of the surface using the particle jamming effect, and using a voice coil motor to produce a vibration over this surface. The touchpad design is unusual in a teleoperation interface, which would normally use a gamepad or joystick style device, or potentially a keypad for input. A number of studies have evaluated and compared such interfaces in teleoperation contexts (Kechavarzi et al. 2012; Bonaiuto et al. 2017; Amaya et al. 2021). The selection of a touchpad style interface was intentional as these have been shown to be less intuitive to use in teleoperation tasks (Kechavarzi et al. 2012), so this interface goes some way to negate potential performance differences between participants who may have prior video game, remote control vehicle or teleoperation experience, and those who don't, whilst offering the multiple degrees of tactile feedback that are needed to evaluate the hypothesis of this study.

3.1 | Operating Principles

The device consists of three major sub-systems that provide two distinct haptic sensations as well as accepting user input. First, particle jamming is used to effect controllable hardness-change in the touch surface of the device. Particle jamming—the action of changing the viscosity of a granular fluid by compressing its constituent grains—is a popular approach to hardness change in the soft robotics community. Here, a rigid, airtight container is filled with particles (e.g., seeds) which are compressed by the soft touch surface under the action of low air pressure inside the device.

Vibration is afforded by the inclusion of a large voice coil motor within the particles. When this vibrates, it agitates the particles, transmitting a vibration to the user's finger via the touch surface. Prior work has demonstrated that the jamming effect can reduce the amplitude of these vibrations, but does not significantly alter the received frequency (Brown and Farkhatdinov 2022). This effect allows complex vibration signals to be produced and transmitted to the user.

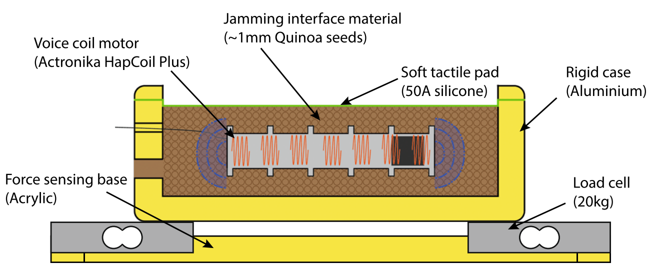

FIGURE 2 | A schematic view of the soft, multimodal haptic touchpad, with a large voice coil motor suspended in a granular fluid and a force sensing base measuring user interaction. [Color figure can be viewed at wileyonlinelibrary.com]

User input is received in two dimensions—position and force. Both are measured by a pair of load cells fixed under the touchpad. This arrangement, a simplified version of that demonstrated in Schmidt et al. (2003), allows for the fingertip position from left-right to be calculated as the ratio of force detected on each side of the touchpad, with the magnitude taken as an average of the two forces. This allows a user to move their finger from left to right to give input in one dimension, whilst pressing down harder or more softly yields an input in a second dimension.

All three of these sub-systems are shown in Figure 2. As a haptic interaction device, this allows the interface to provide multiple streams of information encoded as separate cues (e.g., distance to a goal location signaled by surface hardness and the presence of a cross-current by manipulating the vibration of the interaction surface) whilst simultaneously recording input from the user (e.g., yaw of a robot commanded by moving a finger left or right and the speed of a robot by applying more or less force to the touchpad).

3.2 | Prototype Design and Construction

The prototype itself consists of a rigid aluminum box with an internal cavity measuring 120 mm(w) × 70 mm(d) × 30 mm (h) which is filled with particles (quinoa seeds of approximately 1.5 mm in diameter) that provide the hardness-changing effect via jamming and covered with a soft, 3D printed silicone touch surface (of shore hardness 50A) and thickness 1.5 mm. The particle fluid also transmits the motion of the voice coil motor (Actronika HapCoil Plus) within the device to the user. The voice coil motor is encased in a ribbed plastic sleeve (3D printed plastic) which acts as a mechanical antenna to better agitate the particles radially to the motor during vibration (Figure 3a). The hardness and vibration of the interaction surface is altered through control of air pressure via a vacuum pump (single stage, 7 CFM (cubic feet per minute), min pressure 5 Pa) and regulator (SMC ITV0090-3BS) and voice coil motor driven by a high impedance sound card (Actronika HSD-Mk1). Two beam-style load cells (each rated for 20 kg with Mantracourt ICA2H amplifiers) attached to a large, stiff plastic base, monitor the user's interaction with the device and report their finger position accurate to approximately ±0.06 mm and force magnitude accurate to approximately 0.1 μN.

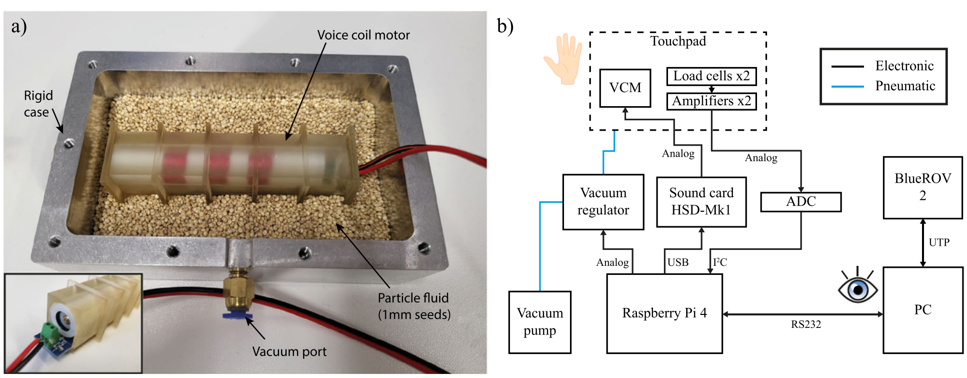

FIGURE 3 | Haptic touchpad. (a) shows the touchpad with the cover and most seeds removed. Insert: the voice coil motor (VCM) inside the vibration transferring sleeve. (b) the underlying control for the touchpad and its connection to the remotely operated vehicle (ROV). [Color figure can be viewed at wileyonlinelibrary.com]

The haptic touchpad is controlled by a Raspberry Pi 4 with an additional ADC module (32-bit Texas Instruments ADS1263 connected via an SPI interface) to read the load cells. The Linux install on the Raspberry Pi supports a range of software frameworks including ROS, MAVlink and simple TCP/IP communication (Figure 3b).

3.3 | Limitations

Whilst effective in presenting haptic feedback via multiple modalities—the central aim of this study—the multimodal haptic touchpad does have two key limitations. First, as stated previously, the touchpad design is known to be less intuitive to use in teleoperation tasks than more conventional gamepads and joysticks. This was a necessary scientific handicap to place on users in the context of a scientific study. However, in real-world use, where no such constraints exist, the same types of haptic feedback could and should be integrated into a more typical and comfortable interface.

Second, particle jamming-based devices are known to be slow to actuate, with a full hard-soft transition in the touchpad taking 2–3 s[1]. This was not a significant limitation in the context of the experiment, as hardness changed gradually as the robot approached the touchpad, an activity that could be expected to take at least 15 s; however, recent research has identified mechanical approaches to particle jamming that can be actuated much more quickly, so future extensions or deployments of this technology could be able to adjust their hardness much faster (Brown and Bello 2024b).

4 | User Study

4.1 | Participants

Eight participants (five self-reported as male and three self-reported as female) between the ages of 26–65 were recruited from York University and Seneca College, both in in Toronto, Canada. Five participants (four males) reported experience playing 3D video games. No participant reported impaired visual or tactile sensation or motor skills. Participants read and signed an informed consent form before participating in the experiment. The experiment was approved by the York University Ethics Board with certificate number e2022-266.

4.2 | Setup

4.2.1 | Environment

The experiment was conducted in indoor swimming pools at York University and Seneca College to achieve an isolated, controllable environment in which artificial hazards could be induced in a predictable manner. A visual target was positioned 4 m ahead of the robot's starting position, indicated by a red ball suspended in the water. A cross-current was generated halfway between the robot and the target by a fixed thruster (Blue Robotics T200) to provide an optional invisible force that would push the robot off the operator's desired course (depicted in Figure 7b). This length of trial was expected to take 30–60 s to complete, which is short enough to allow multiple repeated trials to be conducted without causing participant fatigue and improving the reliability of the data collected. An operator station was established on the pool deck such that the operator did not have a direct view of the robot operating and would only receive information from the ROV via the visual and haptic feedback available at the operator's console.

4.2.2 | ROV

A Blue Robotics Blue ROV2, (Figure 4 insert) was maneuvered in this environment at a constant depth between the starting point and the target. The Blue ROV2 was configured to provide six degrees of movement, however depth was automatically maintained at 1.5 m (the depth of the ball) and automatic stabilization was applied to both roll and pitch. Lateral movement and stabilization were deactivated in software so that the robot would be displaced by the external current. A front-facing RGB camera and four spotlights were used to capture the view in front of the robot and relay visual feedback to the operator console.

4.2.3 | Visual Feedback

Visual feedback was provided via the ROV's onboard camera. This streamed the view in front of the ROV to both the participant and experimenter at 30 frames per second at a resolution of 1280 h × 720 v pixels. The participant's view was augmented with a red circle in the center of the video feed (visible in the display shown in Figure 5 to provide visual guidance when attempting to align the robot with the target. This was presented at the native resolution of a 22” computer monitor behind the haptic touchpad.

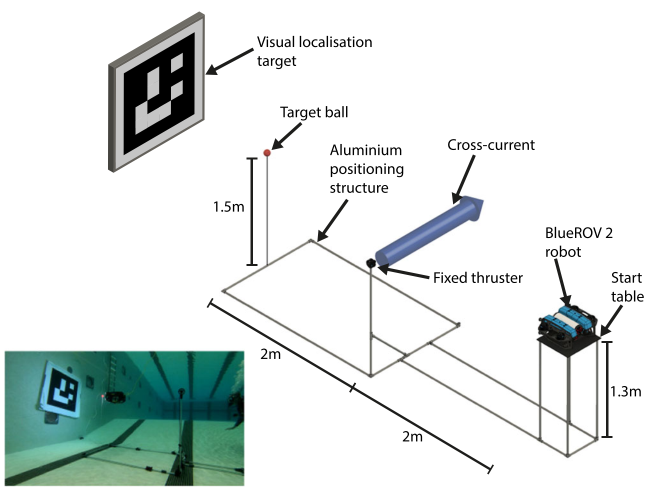

FIGURE 4 | The remotely operated vehicle (ROV) was operated from a starting table to a red ball target suspended in front of it. A large visual target was used to localize the ROV. A fixed thruster was used to induce cross-current. Insert shows the the ROV operating in the set up. [Color figure can be viewed at wileyonlinelibrary.com]

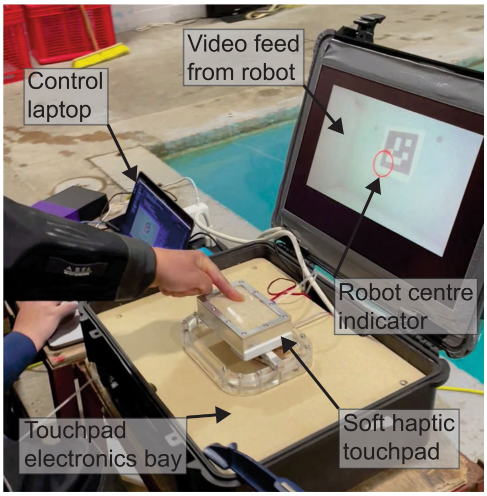

FIGURE 5 | The operator (participant) control station set up on the pool deck. [Color figure can be viewed at wileyonlinelibrary.com]

4.2.4 | Haptic Touchpad

Haptic feedback was provided by a soft haptic touchpad (adapted from Brown and Farkhatdinov 2021, see Figure 5) to indicate the presence and direction of this current in some trials, as well as the distance to the target position. The selection of the touchpad interface was intentional. While such devices are common on laptop computers, they are not at all widely used in teleoperator systems. This makes it less likely that any participant will enter the study with experience controlling robots in this way, making it possible to observe learning effects. When present, haptic feedback was presented in two modalities. First, the touchpad was made to vibrate when the robot entered the cross-current. To cue directionality, an asymmetric sine wave was used to drive the vibrating linear motor such that the touchpad exerted a net force on the fingertip from left to right (Tappeiner et al. 2009; Culbertson et al. 2016). This was in the same direction as the current in the teleoperator's view when the cross-current was present.

4.3 | Procedure

Each participant operated the ROV from the displays shown in Figure 5 without direct sight of the robot operating in the pool. Three different operating conditions were presented:

- **Control**: Visual feedback was provided via the robot's forward-facing camera. No cross-current was generated and no haptic feedback was provided.
- **Cross-current**: Visual feedback was provided and a cross-current was created flowing left-to-right, midway between the robot and the target. No haptic feedback was provided.
- **Haptics + current**: Visual and haptic feedback (vibration signaling the cross-current and hardness signaling distance to target) were provided and a cross-current was created between the robot and the target.

Visual feedback was provided in all conditions for two reasons. First, the haptic feedback provided in this task was designed to complement visual feedback rather than to replace it (e.g., the hardening of the touchpad doesn't indicate what direction the target is in, only that it is getting closer or farther away), meaning that a non visual condition would have been too difficult for operators, providing little additional scientific insight. Second, the number of conditions needed to be constrained to allow sufficient time to conduct repeat trials ensuring scientific reliability without fatiguing participants.

Each condition was presented 10 times in two blocks of five presentations. The first block (repeats 1–5) in each condition was labeled the "familiarization" phase whilst the second (repeats 6–10) was labeled the "experienced" phase. All three familiarization blocks were presented, followed by the three experienced blocks. In this way, broad changes in performance could be observed as participants became acquainted with the robot and control interface. Within each phase, the order of presentation of blocks was randomized for each candidate, with the requirement that the order of block presentation for a given candidate did not present the same condition in sequence.

Each experimental condition involved having the operator teleoperate the ROV from the start table to the target ball (see Figure 4) relying only on the tactile and visual cues provided by the operator interface shown in Figure 5. The operator was screened from the operation of the ROV so as to not be able to view the ROV operating directly. At the end of each condition, the robot was moved manually by a diver back to the start table for the next condition. Each experimental condition took approximately 30 s for the participant to drive the robot from the start table to the target. When driving the robot the operator had control of the direction of motion (yaw) and forward speed, but roll, pitch, heave and sway were held constant and out of their control. After each block of five trials in each experimental condition, participants were asked to complete the NASA Task Load Index (TLX) survey which is an established tool for assessing the cognitive load associated with a defined task (Hart and Staveland 1988).

Telemetry from the robot was logged. This consisted of the robot's heading, ground speed, angular velocity in each axis (roll, pitch, and yaw), acceleration in each axis of the robot frame and absolute position and orientation in the world frame, obtained by visual pose estimation using a 1.2×1.2 m ArUco marker (Romero-Ramirez et al. 2018) located at the end of the experiment area, beyond the red ball target. The ArUco target was used to estimate the robot's pose underwater, and the robot's final position was estimated from the ArUco target using a seven point sample moving average filter to remove jitter, primarily caused by visual artefacts inherent in video recorded underwater (Leonard and Bahr 2016; Hogue et al. 2007; Emberton et al. 2018). The touchpad inputs (finger position and force) and outputs (vibration and hardness) were also logged and synchronized with robot telemetry.

5 | Results

Performance was assessed via a number of indicator metrics relevant to either the specific task being performed or characteristics of successful and efficient robot operation. Results are presented in terms of the familiarization and experienced phases of the study, as well as aggregated over both blocks. All inferential statistics were computed with MATLAB R2022b using the Statistics and Machine Learning Toolbox.

5.1 | Cognitive Load

After the familiarization and experienced sessions, cognitive load was assessed using the NASA TLX scale—a self-reported assessment of cognitive workload measured across six dimensions (mental, physical, and temporal demand, perceived performance, required effort, and frustration) and summarized as a weighted workload score between 0 and 100 (lower scores indicate a lower workload, which is better) (Hart and Staveland 1988). See Figure 6 and Table 1 for overall workload results in each condition and phase. The NASA TLX scale is a well established means of assessing cognitive workload in a variety of HCI and psychological domains, including teleoperation (Shao et al. 2021; Zhu et al. 2021; Whitney et al. 2020) and has been in widespread use for over 20 years (Hart 2006). NASA TLX was used over secondary task performance as the inclusion of a secondary task would have represented too much of a departure from real-world operating conditions and because the complexity involved in selecting a task that would fairly compete with the multisensory (visual and tactile) interactions in the main task (Esmaeili Bijarsari 2021). EEG-based evaluation of cognitive load was not used due to the significant complexity of setup and operation alongside an already complex in-water experiment, potential participant risk, and limited reliability of EEG data outside of a tightly controlled lab environment (Antonenko et al. 2010).

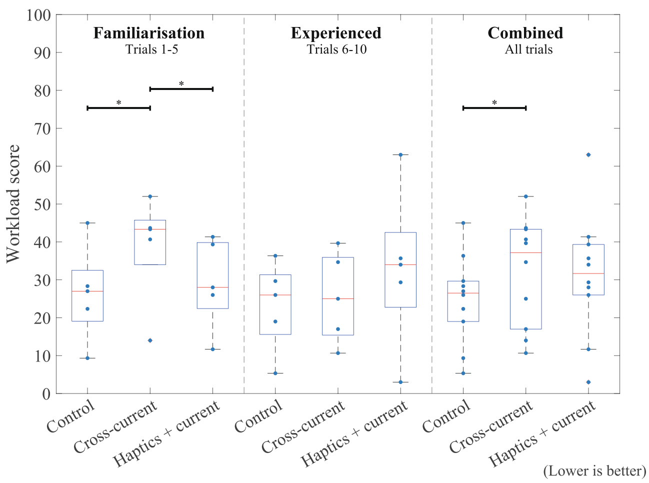

FIGURE 6 | Cognitive workload (NASA TLX) scores reported in each condition and phase. *Denotes a statistically significant difference in results with a 95% confidence interval ($p < 0.05$). **Denotes a 99% confidence interval ($p < 0.01$). [Color figure can be viewed at wileyonlinelibrary.com]

Differences in the familiarization, experienced and combined conditions were analyzed using a two-tailed, paired *t*-test. There were significant differences between the control and cross-current conditions overall ($p = 0.0262$) and specifically in the familiarization phase ($p = 0.0149$). Providing haptic feedback in the Haptics + current condition yielded a significant reduction in workload compared to the cross-current alone in the familiarization phase ($p = 0.0261$) but a slight (nonsignificant) increase in the experienced phase. Haptic feedback slightly improved workload overall, but this was not significant. There were no significant differences between the control and Haptics + current conditions either overall or in either learning phase.

5.2 | Performance

5.2.1 | Missing Data in Quantitative Analysis

In total, 240 trials (participants (8) × conditions (3) × phases (2) × repeats (5)) were run. A small number of trials were aborted due to the participant straying too far off course to be able to locate the target, or due to the participant giving up out of frustration (Control—14, Cross-current—23, Haptics + current—18) resulting in a total of 185 valid trials. In the quantitative analyses below, responses more than 1.5*IQR below the 25th percentile or above the 75th percentile were identified as outliers and also excluded from analysis. For the purposes of this study, IQR is defined as the difference between the 75th and 25th percentiles. Given the missing data, statistical analysis of quantitative results could not be performed using ANOVA tests.

5.2.2 | Accuracy

Accuracy was measured as the Euclidean distance between the robot's final position and the target ball, projected onto the horizontal plane. This is shown in green in Figure 7b.

A Jarque-Bera test indicated that the final distance results from each condition were not normally distributed at the 5% confidence level in all conditions (Control: $p = 0.0674$, Cross-Current $p = 0.0088$, Haptics + current: $p = 0.1426$). Therefore, the non-parametric Kruskal–Wallis test was used to determine statistically significant differences between conditions. Mean accuracy results are summarized in Table 2 and are plotted in Figure 8.

TABLE 1 | Cognitive workload by condition.

	Mean cognitive load (NASA TLX scale)		
Condition	**Familiarization**	**Experienced**	**Combined**
Control	26.4	23.3	24.8
Cross-current	38.7	25.4	32.1
Haptics + current	29.3	33.0	31.1

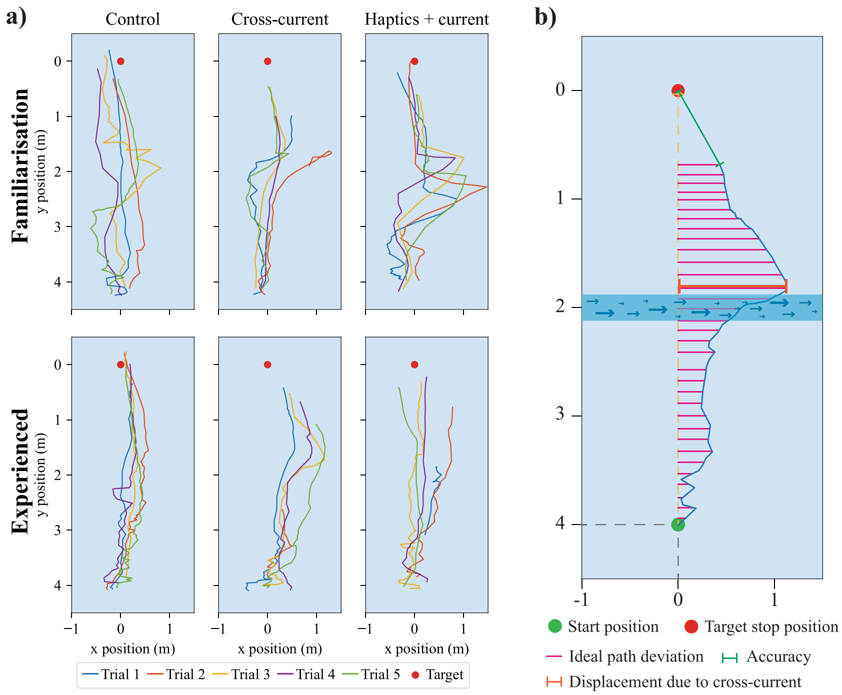

FIGURE 7 | (a) Recorded robot paths from a representative participant based on visual odometry. (b) An example path annotated to demonstrate key performance indicators (accuracy, ideal path deviation, and maximum lateral displacement) and the location of the cross-current. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 2 | Mean remaining distance to target at the end of the experiment.

	Distance (m)		
Condition	**Familiarization**	**Experienced**	**Combined**
Control	0.38	0.37	0.37
Cross-current	0.60	0.49	0.54
Haptics + current	0.43	0.43	0.43

Most participants ended the task less than 1 m away from the target, though there are high variances across all conditions, possibly due to differences in performance characteristics (visual acuity, fine motor control, reaction time, hand-eye coordination, etc.) between participants. In the control condition, participants finished on average 0.37 m away from the target, with the best trial ending 0.08 m from the ball. Participants performed best in the control condition across both phases. The mean errors were not significantly different in the familiarization and experienced phases of the experiment. With the cross-current applied, accuracy worsened with an overall average of 0.54 m (familiarization: 0.60 m; experienced: 0.49 m). With haptic feedback indicating the cross-current and ball position, the average distance remaining to the ball was reduced to 0.43 m, which is consistent in both familiarization and experienced phases.

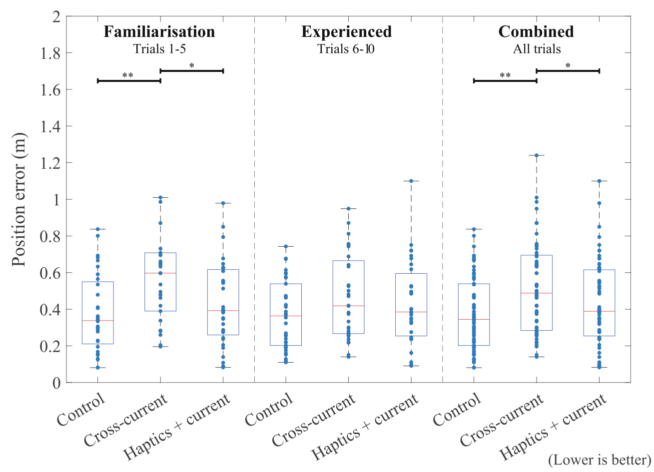

FIGURE 8 | Accuracy: remaining distance to target at the end of each trial (with outliers removed). *Denotes a statistically significant difference in results with a 95% confidence interval ($p < 0.05$). **Denotes a 99% confidence interval ($p < 0.01$). [Color figure can be viewed at wileyonlinelibrary.com]

Participants performed significantly worse when the cross-current was turned on compared to the control condition, both in the combined group ($p = 0.0008$) as well as during the familiarization phase ($p = 0.0029$). Haptic feedback was found to yield a statistically significant improvement in accuracy compared to the cross-current without haptic feedback overall ($p = 0.0468$) and during the familiarization phase ($p = 0.0172$). There were no statistically significant differences between conditions in the experienced phase. There was no significant difference between performance in the control condition (still water) and with the cross-current present and represented by haptic feedback, although the results suggest a slight increase in positional error.

5.2.3 | Ideal Path Deviation

The ideal path in this study is a straight line 4 m ahead of the robot, shown in orange in Figure 7b. Whilst achievable, operator error and displacement due to the cross-current could move the robot off this course, increasing the path length and completion time, and in a real world scenario increasing the risk of a collision with an obstacle in the robot's periphery. Paths taken by a representative participant in each condition are shown in Figure 7a. This path error was quantified as the root mean square error (RMSE) between the ideal path and the actual path taken by the robot, as recorded by visual odometry.

A Jarque-Bera test indicated that the RMSE path deviation results from each condition were normally distributed at the 5% confidence level (Control: $p = 0.0017$, Cross-Current $p < 0.001$, Current + Haptics: $p = 0.0011$). Therefore, a two-tailed, paired t-test was used to determine statistically significant differences between conditions. Mean displacement results are summarized in Table 3 and are plotted in Figure 9.

Deviation from the ideal path was low in the control condition (expectedly, as there was no cross-current) but significantly worse with the cross-current, both overall ($p = 3.5e^{-4}$) and in the familiarization phase of the experiment ($p = 0.0027$),indicating that the cross-current with haptic feedback reduced the straight line deviation significantly both overall ($p = 0.0165$) and in the experienced phase ($p = 0.0492$).

5.2.4 | Displacement Due to Current

The maximum displacement due to the cross-current is also a useful metric. This records the maximum sideways perturbation, as shown in Figure 7b. Here, a larger displacement indicates that the robot operator was slower or otherwise less able to correct the robot's course, whilst a lower number indicates that that the operator made course corrections quickly and effectively.

A Jarque-Bera test indicated that the maximum path deviation results from each condition were normally distributed at the 5% confidence level (Control: $p < 0.001$, Cross-Current $p = 0.0141$, Current + Haptics: $p = 0.0058$). Therefore, a two-tailed, paired t-test was used to determine statistically significant differences between conditions. Mean displacement results are summarized in Table 4 and are plotted in Figure 10.

As would be expected, maximum displacement was significantly lower in the control condition than both the cross-current (overall: $p = 1.1664e^{-7}$, familiarization: $p = 0.0017$, experienced: $p = 1.4469e^{-5}$) and Haptics + current (overall: $p = 8.4436e^{-7}$, familiarization: $p = 1.1120e^{-4}$, experienced: $p = 0.0026$) conditions. Lateral movement was significantly lower in the haptics + current condition compared to the cross-current condition but only in the experienced phase of the experiment ($p = 0.0422$).

6 | Discussion and Future Work

The experimental results point to two conclusions. First and foremost, there are clear improvements in ROV operator performance when haptic feedback is available and used to convey environmental information. Accuracy, path efficiency and resistance to the perturbation were all improved when haptic feedback was offered. Visual feedback was deemed essential for this task, so it was provided in all conditions. Previous studies have investi-

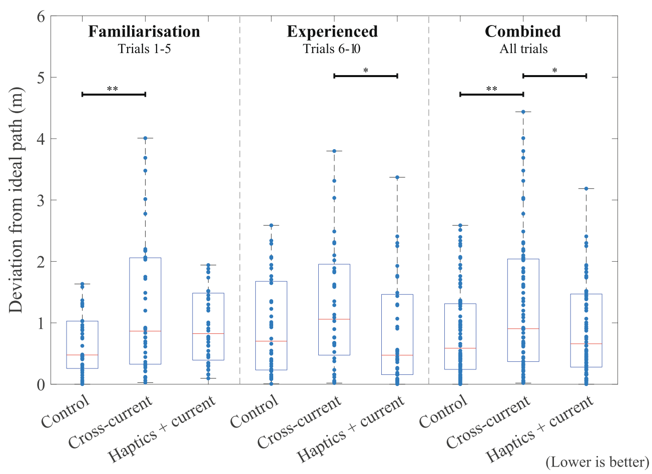

FIGURE 9 | RMSE from an ideal straight line path for each condition and phase (with outlier values beyond 1.5*IQR from the mean removed). *Denotes a statistically significant difference in results with a 95% confidence interval ($p < 0.05$). **Denotes a 99% confidence interval ($p < 0.01$). IQR, interquartile range; RMSE, root mean square error. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 3 | Mean root mean square (RMS) deviation from an ideal straight line path.

	Mean RMS deviation (m)		
Condition	**Familiarization**	**Experienced**	**Combined**
Control	0.75	0.99	0.87
Cross-current	1.34	1.39	1.36
Haptics + current	1.03	0.93	0.98

TABLE 4 | Maximum lateral displacement in the cross-current.

Condition	Mean displacement (m) Familiarization	Experienced	Combined
Control	0.12	0.09	0.10
Cross-current	0.29	0.31	0.30
Haptics + current	0.34	0.23	0.28

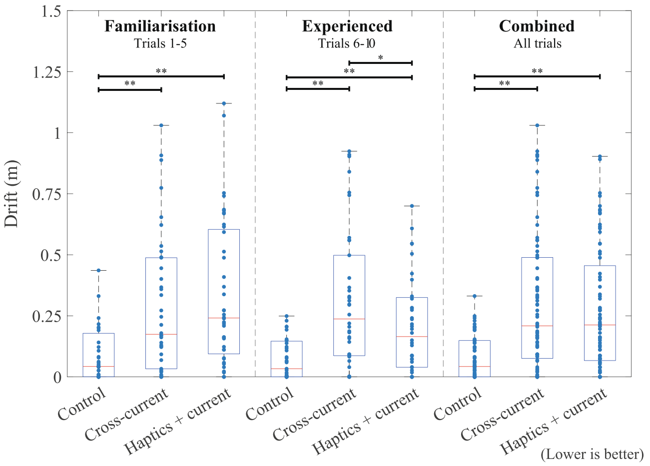

FIGURE 10 | Maximum lateral displacement in the cross-current for each condition and phase (with outlier values beyond 1.5*IQR from the mean removed). *Denotes a statistically significant difference in results with a 95% confidence interval ($p < 0.05$). **Denotes a 99% confidence interval ($p < 0.01$). [Color figure can be viewed at wileyonlinelibrary.com]

gated the individual roles of visual and haptic feedback in teleoperation tasks and shown that robot operators consistently express a preference to be given visual feedback, even when not relevant to the task or performance metrics in question (Glover et al. 2009). Studies have also shown that adding haptic feedback to visual feedback improves performance but increases perceived task difficulty across a variety of haptic and visual feedback modalities and task scenarios (Gibbs et al. 2022; Al-Mouhamed et al. 2010), which is broadly in line with the results of this study.

That being said, the specifics of how environmental information was presented by the haptic interfaces in this study may or may not be optimal, and there is much room for future work to investigate, for example, what vibrotactile signals would best indicate the cross-current, or what modalities of haptic feedback may best encode each relevant characteristic of the robot's or environment's state. Significant further technical work would be required to engineer additional haptic signals into the touchpad to allow this to be investigated.

Second, the learning effects observed in this study point to differences in how novice and experienced operators make use of haptic feedback. The performance indicators described above can broadly be linked to two separate haptic effects. Accuracy (final distance to the target) was most affected by tactile hardness (encoding distance to the target). Likewise, path accuracy and resistance to perturbation were most affected by vibration (encoding interaction with the cross-current). The results above show that accuracy was most improved by haptic feedback during the familiarization phase of the study, when participants were intentionally unfamiliar with the control interface, task and environment. Conversely, resistance to the perturbation and the ideal path error were most improved during the experienced phase of the study. This distinction could be explained by the notion of where, in the interaction flow, the haptic feedback was inserted. Hardness change was designed to make it physically harder to depress the touchpad, forcefully encouraging operators to slow down and stop as they got close to the target. The vibration on the other hand did not move the operator's finger to steer them back on course, but merely communicated that they were drifting to the side and that they needed to correct. We hypothesize that novice robot operators benefit most from haptic assistance that physically interacts with them close to the input interface, whilst experienced operators benefit most from haptic feedback that relays information which they must then act on. If proven by a more targeted study, this could have implications for the deployment of ever more popular force-feedback interfaces, which may be of limited use in professional grade teleoperator systems that are usually intended for professional robot operators.

Future research in this area could extend these findings to other classes of mobile robots. Drones and ROVs share many common configurations and kinematics, and ground-based mobile robots are not immune from hazardous situations or complex environments. The concept of using advanced haptic interfaces to relay environmental information is also very relevant to the operation of other manned vehicles which could benefit from haptic assistance systems. Moreover, visually impaired pedestrians currently receive very limited information about their environment from a white cane or guide dog. As environmental mapping sensors become smaller and more portable, this type of haptic communication could be of great value to those who cannot benefit from visual information about the world around them.

The haptic feedback used in this study was developed from the design principle of natural mapping (Norman 1991), supported by several short pilot studies. In addition to the application of this research, future studies could more extensively investigate optimal parameters for haptic communication through multiple different modes of physical feedback. This would allow interaction designers to better communicate environmental information to the operators of vehicles, making interfaces quicker to learn and haptic signals easier to interpret in real-time.

6.1 | Limitations

A key limitation of the study is the limited sample size of eight participants. This is a consequence of the cost and complexity of undertaking an in-water experiment with a real robot, and limits the generalizability of the results presented above. However, statistically significant results were obtained from this small study group.

An additional limitation is the choice of haptic display/input touchpad. The touchpad design was selected to provide an artificial usability handicap on the system, which could be improved by the selection of a more user-friendly device in real-world use. The underlying technology (particle jamming and vibration) has been shown to behave in broadly the same way regardless of form factor (Brown and Farkhatdinov 2022).

A minor limitation is the use of the NASA TLX assessment tool to measure participant's cognitive load. Whilst this tool is well established and has been widely used in similar studies (Shao et al. 2021; Zhu et al. 2021; Whitney et al. 2020), it is limited in that it only provides an overview of the user's cognitive load during the task as a whole, and is reliant on users self-reporting cognitive load reliably and accurately. Its ability to produce meaningful overall assessments of cognitive load compared to the individual dimensions of workload reported by participants has also recently been questioned, although no alternative questionnaire-based assessment of cognitive workload has emerged in response (Bolton et al. 2023).

Finally, the study only investigated one specific environmental configuration. This was done to improve the reliability and reproducibility of the data whilst maintaining a manageable scope for the study. Future work could usefully consider the issue of different directions/intensities of cross currents, or cross-currents acting in different directions or locations. Moving targets could be investigated to examine the utility of the hardness-changing feedback to understand a dynamic quantity. Additional environmental characteristics such as depth or the presence of obstacles could be introduced via additional haptic channels (force feedback, shape-change, etc.) to probe the limitations of information delivery via the haptic channel.

6.2 | Extending to Real-World Use

Future application of this technique to real-world underwater teleoperation scenarios is possible, but the techniques and methodologies described above would require some extension and modification to be applicable in the real world.

First, the haptic feedback provided only represented a cross-current acting in one dimension and with constant intensity. The intensity of the current could be indicated by varying the strength of the vibration, however this would need to be evaluated experimentally. Currents acting in different directions could be represented by vibrations in different directions, either produced by a 2D array of vibrating motors, or a mechanized motor that can be re-oriented to match the current direction. Presenting 3D currents on a 2D touchpad would be difficult, and gesture or multi-DoF robotic interfaces might be better suited to this. It is useful to note that even if an area of water is subject to multiple currents in different directions, the robot will only be pushed in a single vector so the 1D voice coil motor remains a suitable vibration source for real world use.

Second, the haptic feedback was generated artificially by the experiment control software rather than being generated dynamically from the robot's sensor data. The two environmental features under investigation—distance to a target or obstacle and interaction with cross-currents—could be easily obtained from sensor data. Sonar is a well developed technique for detecting underwater objects and performing underwater localization (relative to a target position), whilst onboard IMU, propellors or doppler sensors would be able to measure currents and their impact on an ROV.

Third, the experiment reported here was performed in an indoor pool environment rather than open water. Whilst less realistic than open water, the pool was selected for this study to ensure scientific rigor by providing a controlled environment in which identical cross-currents could be generated for each participant, and additional apparatus could be deployed to support the tracking of the robot's movements. Performing the experiment in open water would also have compromised the safety of the dive team and left the experiment vulnerable to adverse weather and other operational challenges. The controlled, directed currents used in this experiment would not have affected the robot differently in either setting.

Finally, the particle jamming mechanism implemented here relies on a large and heavy vacuum pump to actuate the jamming effect. Whilst this works in controlled environments, it is very inconvenient for a portable interface that may need to be deployed rapidly in remote locations. Fully mechanical approaches now exist for actuating a particle jamming system, though these only came to light following the completion of this study (Brown and Bello 2024a).

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] This data was obtained from observation and comparison of published performance data from similar devices and systems. It was not possible to measure dynamic hardness-change during this study.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.