

# Evaluating Immersive Teleoperation Interfaces: Coordinating Robot Radiation Monitoring Tasks in Nuclear Facilities

Harvey Stedman<sup>1\*</sup>, Basaran Bahadir Kocer<sup>2,3\*</sup>, Nejra van Zalk<sup>4</sup>, Mirko Kovac<sup>2,5</sup>, Vijay M. Pawar<sup>1</sup>

**Abstract**—We present a virtual reality (VR) teleoperation interface for a ground-based robot, featuring dense 3D environment reconstruction and a low latency video stream, with which operators can immersively explore remote environments. At the UK Atomic Energy Authority’s (UKAEA) Remote Applications in Challenging Environments (RACE) facility, we applied the interface in a user study where trained robotics operators completed simulated nuclear monitoring and decommissioning style tasks to compare VR and traditional teleoperation interface designs. We found that operators in the VR condition took longer to complete the experiment, had reduced collisions, and rated the generated 3D map with higher importance when compared to non-VR operators. Additional physiological data suggested that VR operators had a lower objective cognitive workload during the experiment but also experienced increased physical demand. Overall the presented results show that VR interfaces may benefit work patterns in teleoperation tasks within the nuclear industry, but further work is needed to investigate how such interfaces can be integrated into real world decommissioning workflows.

**Index Terms**—Virtual reality and interfaces, telerobotics and teleoperation, human-centered robotics

## I. INTRODUCTION

Decommissioning historic nuclear facilities across the world is an expensive and complex problem. In the UK alone, the cost is estimated between £99-£232 billion over 120 years to decommission its historic nuclear facilities, and approximately 75% of this funding will be directed to Sellafield [2]. Sellafield is noted as a globally unique facility due to its size, age and international importance - it consists of over 1000 buildings which once housed nuclear weapons facilities and the world’s first commercial nuclear reactor. Decommissioning the site presents many dangers and logistical challenges. As site activities started in the 1940s and the facility evolved rapidly during its lifespan, documentation of the state of the facility is often not available or reliable. This means that inventories of buildings can be unknown before entry and that buildings must be physically entered to be documented and their content analysed, sorted and segregated [3]. Therefore, human workers are expected

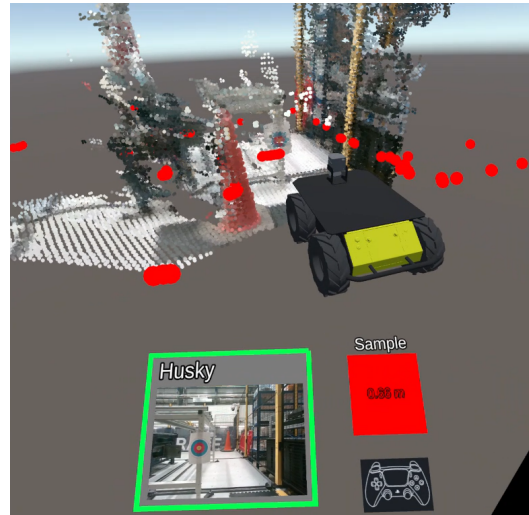


Fig. 1: Screenshot from the presented VR teleoperation interface during operation, including the generated VRTAB-Map pointcloud [1] (coloured pointcloud), LIDAR pointcloud (red pointcloud), video stream and Husky model. Additional sample and controller widgets are also shown.

to carry out manual assessments of buildings during the decommissioning process, along with repeated monitoring of radiation levels across the facility.

Many problems arise from the requirement of manual assessment. Firstly, this process will inherently risk exposing operators to radiation dosage even with personal protective equipment (PPE) procedures in place, and working under such conditions is both stressful and physically demanding [4]. Inspection areas including roofs, high walls and other positions at height pose challenges and safety risks during manual access [5], and some areas may not be safe for any human entry but will be required to be assessed nonetheless. The radiation monitoring procedure adds extra challenges to the work as it is both time-consuming and requires operator diligence to monitor over large areas [6]. Additionally, in many cases, secondary waste volumes from discarded PPE can be more than 10 times the volume of waste processed during decommissioning of the site [7].

Teleoperated robotic systems are noted for their potential to aid in monitoring, characterising and decommissioning nuclear facilities as they provide a means to navigate and interact with remote environments that are otherwise dangerous for humans [8]. In some cases, it is known that robotic systems are the only feasible option for entering facilities as

\* Authors contributed equally to this work

<sup>1</sup> Authors are with the Autonomous Manufacturing Laboratory within the Department of Computer Science, University College London, Gower Street, London WC1E 6BT, UK.

<sup>2</sup> Authors are with the Aerial Robotics Laboratory, Imperial College London, London SW7 2AZ, UK.

<sup>3</sup>Basaran Bahadir Kocer is with the Department of Aerospace Engineering, University of Bristol, Bristol, BS8 1TR, UK.

<sup>4</sup> Nejra van Zalk is with Dyson School of Design Engineering, Imperial College London, London SW7 1AL, UK.

<sup>5</sup> Mirko Kovac is with Laboratory of Sustainability Robotics at the Swiss Federal Laboratories for Materials Science and Technology, Switzerland.

the danger of nuclear radiation is too high for human workers [9]. Despite this, robotic systems are rarely applied in the nuclear industry in practice, and then they are usually chosen for their ruggedness and reliability at the expense of the operators' cognitive workload and situational awareness (SA) [4]. Recent research into immersive teleoperation interface designs that use virtual reality (VR) hardware has demonstrated that such systems can improve operator SA, cognitive load and teleoperation performance when compared to traditional interface design [10]. However, the effect of immersive interface designs in nuclear-decommissioning tasks, and the relationship of cognitive load and SA between immersive and non-immersive interfaces in this sector, is currently not well known.

Partnering with the UKAEA RACE facility, this work presents the results of a realised teleoperation user study investigating the effect of immersive teleoperation systems in nuclear monitoring and decommissioning tasks. Using a Clearpath Husky A200 and the proposed VRTAB-Map framework [1], a novel immersive teleoperation interface was designed that featured dense environment reconstruction and an efficient video streaming pipeline during operation. 18 trained robotic operators from RACE then participated in a realistic nuclear monitoring and decommissioning scenario, in which operators explored an unknown environment and completed simulated visual inspection and alpha radiation sampling tasks with the presented teleoperation system. The main contributions of this work are:

- Experimental validation of the VRTAB-Map immersive teleoperation framework in a realistic nuclear decommissioning scenario.
- A human factors analysis of operator performance to understand the relationship of teleoperation performance, cognitive load and SA between VR and non-VR interface designs within nuclear decommissioning teleoperation tasks.
- A discussion of physiological data collected from targeted users and challenges & future research areas for human-robot interaction in the nuclear sector.

## II. BACKGROUND

Understanding teleoperation interface designs that reduce cognitive load and increase SA remains a key focus of human-robot interaction and teleoperation research. SA relates to the operators' understanding of different elements and factors in a remote environment, and their capability to build an accurate model to make informed decisions [11]. Low levels of SA and high cognitive load from teleoperation interfaces have been found to negatively impact operator performance in teleoperation tasks [12]. This can then reduce operational efficiency and result in operation mistakes [13], which are particularly costly when operating a robotic system within a nuclear facility due to the high consequences associated with mission failure.

The advent of consumer VR hardware has sparked renewed interest in research exploring VR and teleoperation. VR systems are being studied as a potential solution

for reducing cognitive workload and enhancing situational awareness (SA) by immersing operators in a natural 3D environment with intuitive interfaces [10]. Previous research has demonstrated that VR interfaces can enhance teleoperation performance and SA in various domains such as pick and place tasks [14], industrial tasks [15], UGV navigation [16], and multi-robot control [17] when compared to traditional interface designs. Furthermore, VR interfaces have been implemented in the nuclear industry to operate robotic gloveboxes [18] and explore the potential of decontamination and decommissioning processes [19]. However, developing immersive interfaces featuring full environment reconstruction of unknown environments, a requirement for exploring undocumented nuclear sites, has historically been challenging due to computational complexity and large bandwidth requirements. Recent research has addressed this challenge by proposing scalable architecture based on SLAM methods for generating remote environments in real time for VR interfaces [20]. These studies have also investigated visual aids for immersive VR interfaces with environment reconstruction, and demonstrated their benefits in teleoperation compared to traditional 2D visualisations [21], [22]. Nevertheless, more extensive work is necessary to improve human factors within teleoperated systems for nuclear decommissioning tasks [23], and to understand how expert users interact with these interfaces in representative conditions [10].

## III. SYSTEM DESIGN

### A. Overview

The teleoperation system is based on the VRTAB-Map framework [1] and consists of a Clearpath Husky A200 and a custom Unity interface. A computer mounted on board the Husky runs the RTAB-Map algorithm [24] to build a dense pointcloud representation of the environment during operation, and streams pointcloud data into the Unity interface using WebSocket connections between a rosbridge-server and a ros-sharp Unity client [25]. Additional data from an onboard depth camera and LIDAR are also streamed to Unity and rendered in an intuitive ecological style interface design that overlays multiple data sources. Operators can then use the interface to understand the state of the remote environment and issue commands to the Husky through a wireless PS5 controller. The interface can be used through a traditional computer monitor setup or with SteamVR enabled VR hardware to immerse operators within the digital environment. A system diagram is presented in Figure 2 and an example of the interface output is presented in Figure 1.

### B. Husky Setup

The Clearpath Husky A200 was selected as the robot platform of choice due to its rugged offroad capabilities and large battery capacity, making it suitable for remote teleoperation studies in difficult environments. The Husky was mounted with a SICK LMS100 LIDAR system and a Realsense D455 stereo camera which, along with odometry generated from the ROS `ekf_localisation` package, were used as inputs into the RTAB-Map SLAM algorithm. A custom ROS package

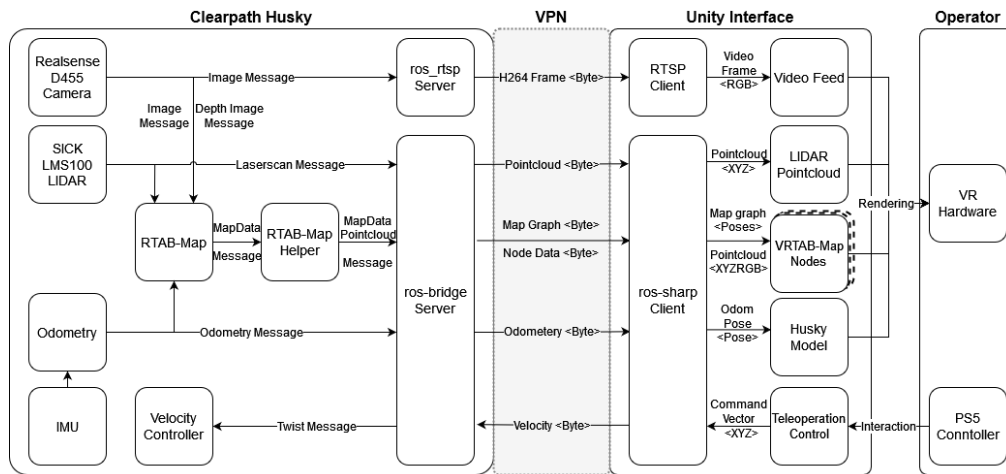


Fig. 2: System diagram of the presented VR teleoperation interface based upon the VRTAB-Map framework [1].

called RTAB-Map Helper subscribed to MapData messages from RTAB-Map, which consists of new RGB-D frames inserted into the algorithm’s graph and the optimised graph, and converted RGB-D frames into pointclouds to simplify the interface implementation. A rosbridge server then exposed all topics over a WebSocket connection to communicate with the Unity interface. An additional ros\_rtsp server [26] was used to stream images to the interface. It subscribed to image messages from the D455 camera, converted raw image frames into H.264 frames using FFmpeg and streamed data over a GStreamer RTSP server.

### C. Unity Teleoperation Interface

A ros-sharp client [25] was used to receive all ROS messages over WebSocket. The VRTAB-Map PointCloudMapData organiser [1] then generated new pointcloud frames within the Unity scene to reconstruct the RTAB-Map pointcloud map. LIDAR data was also rendered as a pointcloud and overlaid in the scene, and the Husky’s odometry data was overlaid with a robot model to represent its location within the sensor data. Using the VRTAB-Map TFOrganiser, relative transforms between different TF frames were represented in Unity’s Object Parenting hierarchy to ensure that sensor data was overlaid correctly during operation.

Along with the ROS data, a separate RTSP client also received and decoded the ros\_rtsp H.264 video frames using FFmpeg and rendered RGB data on a texture within the interface to represent the live video feed during operation.

1) *Experiment Additions:* In addition to the baseline processes outlined above, extra functionalities were implemented for the designed user study. A sampling widget was created to simulate an alpha radiation sampling procedure. This calculated the distance between the Husky’s location and the closest point within the LIDAR pointcloud. As the accuracy of alpha radiation sampling is highly related to the distance between the sample location and the sensor, a sliding scale was designed for the widget. The user could not get a sample when it is taken out of the 0.5m range and the sampling accuracy, represented by a red-green colour change,

improved as the distance is reduced. After a successful sample collection, a marker representing the sample location was rendered in the interface.

For user-friendly VR design, an additional controller widget was implemented using the Unity input system to provide line of site visualisation of button presses. To reduce motion sickness, operators in the VR interface were disconnected from the location of the Husky’s odometry position. Therefore, a teleportation function was also added, allowing operators to teleport to positions based on their viewpoint.

## IV. EXPERIMENTAL PROCEDURE

Partnering with UKAEA’s RACE facility, a user study was completed to analyse the effectiveness of immersive interface design against traditional monitor-based interfaces in a simulated initial entry and inspection mission in an undocumented nuclear facility. Users operated the interface from a UKAEA climate-controlled robotics control room, commanding the Husky located in an experimental robot cell in a separate building through a secure VPN connection. Therefore, the operators had to rely solely on data being streamed into the interface to complete the task. The experiment course was designed to test the operators’ capabilities at navigating difficult obstacles and completing simulated sampling missions. A diagram of the experiment course is presented in Figure 3.

### A. Course Design

The course was designed with one linear critical path, along which the operators encountered two distinct sampling tasks:

- **Alpha Sampling** - Traffic cones represented locations of interest for alpha sampling. Users were tasked with moving as close as possible to the location and taking a sample using the interface’s sampling widget.
- **Visual Inspection** - Targets represented locations of interest for visual inspection. Users were tasked with orienting the robot in front of the target using the

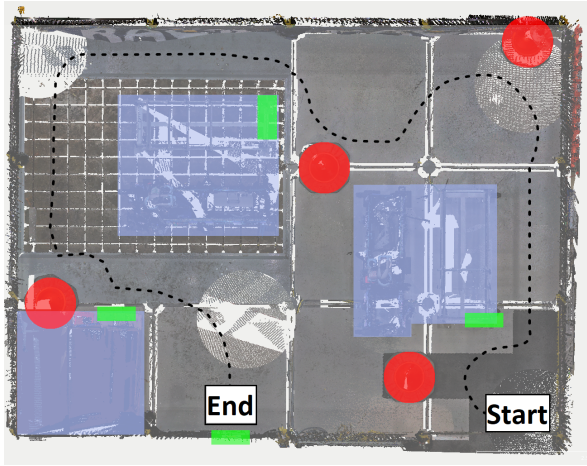


Fig. 3: Pointcloud capture of the experiment course. *Red Circles*: Traffic cones for simulated alpha sampling. *Green rectangles*: Paper targets for simulated visual inspection. *Blue*: Immovable obstacles and barriers within the experiment course. *Black dotted line*: Critical path of the teleoperated robot.

generated map and video feed and taking a picture in the interface.

### B. Experiment Methodology

After entering the robotic control room, each user was randomly assigned into VR or non-VR experimental groups and asked to fill out an initial questionnaire to assess their technical background with robots and virtual reality systems. After this, baseline physiological data was recorded for 1 minute using the Empatica E4 system. Users were then introduced to their corresponding interface and full functionalities were explained and explored. A training session was then conducted to allow users to understand how the interface worked, gain experience with the interface visualisation and practice the experiment sampling procedures. When the users were happy to proceed with the experiment, the Husky and interface were restarted and experiment conditions were put in place. They then explored the course and completed the tasks as they appeared to them. The Empatica E4 system was kept on the users during the whole operation but the recording is activated for each baseline, training and the test case individually. Once the end of the course was reached, the experiment was completed. Users then filled out the final questionnaire including NASA TLX to analyse subjective cognitive workload [27], Situation Awareness Rating Technique (SART) to analyse subjective SA [28] and usability questions to understand interface preferences. After the experiment sessions, short-term heart rate variability (HRV) was calculated by analysing the root means square of successive differences (RMSSD) of R-R intervals [29] measured by the Empatica E4:

$$\text{RMSSD} = \sqrt{\frac{\sum_{i=1}^{N-1} (RR_i - RR_{i+1})^2}{N-1}} \quad (1)$$

where  $RR_i$  is the time interval between adjacent R waves,  $RR_{i+1}$  is the next R-R interval, and  $N$  is the number of R-R intervals.

### C. Experiment Metrics

The following data was collected from each participant:

- User background questionnaire including experience with robotic systems, virtual reality and video games.
- Time required to complete the course.
- Number and locations of collisions.
- Sampling accuracy for each alpha radiation location.
- Log file of all commands issued during the experiment.
- RMSSD HRV [29] calculated from R-R intervals measured by the Empatica E4.
- Accelerometer data measured from the Empatica E4.
- NASA TLX [27] and SART questionnaire [28].
- Usability questionnaire to assess interface preferences and additional qualitative feedback.

### D. System Implementation

In all experiments, the ROS nodes were executed in ROS Melodic on a Ubuntu 18 machine equipped with an Intel i7-9750H CPU and 32GB DDR4 RAM connected by ethernet to the Husky's base machine. The Husky's local network was then connected wirelessly to RACE's VPN system through which it communicated with the remote robot control room. Both VR and non-VR teleoperation interfaces were executed in Unity 2019 LTS on a Windows 10 machine equipped with an Intel i7-9750H CPU, 16GB DDR4 RAM and an NVIDIA GeForce RTX 2070 Max-Q GPU. Operators viewed the VR interface through a HTC Vive headset.

## V. RESULTS AND DISCUSSIONS

### A. Participant Demographics

Using RACE's operations team as a participant pool, 18 participants volunteered for the study (16 identified as male and 2 identified as female, age range 20-57 years old, mean age  $31.83 \pm 10.47$  years). As part of the operations team, every participant had VR and robotic teleoperation experience within a nuclear setting, with a mean  $3.06 \pm 1.84$  years of experience at RACE.

### B. Results Evaluation

Comparisons between groups were done through independent samples t-tests, with statistical significance set at  $P = .050$ .

1) *Teleoperation Performance Metrics*: Results presented in Table I and Figure 4 show that operators in the VR condition generally took longer to complete the task ( $M = 257.33 \pm 66.67s$ ,  $P = .002$ ) with fewer collisions ( $M = -2.11 \pm 0.77$ ,  $P = .020$ ). Additionally, operators in the VR condition had a smaller number of inputs per second ( $M = -0.41 \pm 0.32$ ,  $P = .242$ ) and no difference in mean sampling distances ( $M = -0.02 \pm 0.03m$ ,  $P = .634$ ), though these findings were not significant. It has previously been suggested that the higher degree of immersion in VR interfaces may encourage more time consuming inspections in an interface [20], which could explain the increase in time and decrease in collisions in the VR condition. The reduction

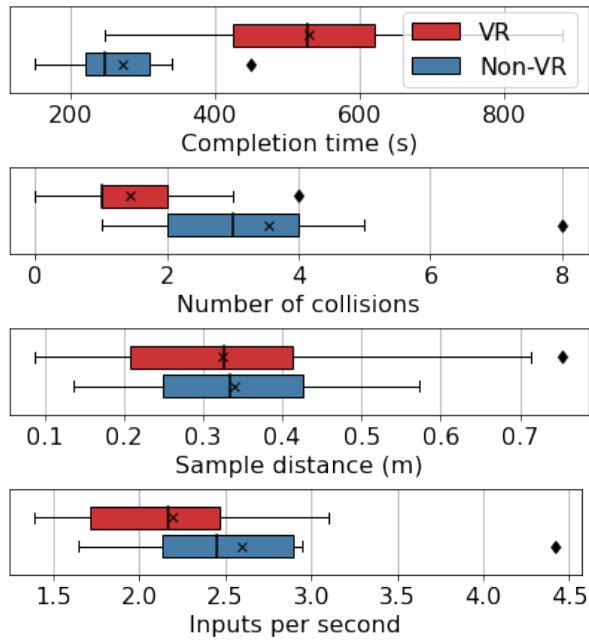


Fig. 4: Box plots of teleoperation performance metrics. Includes mean marked with a  $\times$ , median, lower and upper quartile, lower and upper whiskers and outliers marked with a  $\diamond$ .

TABLE I: Summary of experiment results. All values represent the mean difference between VR and Non-VR performance.

Metric	Mean	$P$ -value
Completion time (s)	$257.33 \pm 66.67$	.002
Collisions per trial	$-2.11 \pm 0.77$	.020
Alpha sampling distance (m)	$-0.02 \pm 0.03$	.634
Inputs per second	$-0.41 \pm 0.32$	.242
NASA TLX score	$0.07 \pm 0.34$	.844
SART score	$-0.46 \pm 0.65$	.652

in collisions especially would suggest that operators had a lower cognitive load and higher SA. However, operators in the VR condition reported slightly higher NASA TLX Scores ( $M = 0.07 \pm 0.34$ ,  $P = .844$ ) and lower SART scores ( $M = -0.46 \pm 0.65$ ,  $P = .652$ ), corresponding to higher perceived cognitive load and lower SA, though the results were not significantly different across the conditions. Regarding individual NASA TLX and SART categories, the physical demand in the NASA TLX was significantly different between the two conditions, with operators in the VR group reporting a greater physical demand ( $M = 1.00 \pm 0.31$ ,  $P = .008$ ). This is understandable, as the VR interface requires operators to physically move to orientate themselves in the interface.

2) *Interface Preferences*: Results from the post-experiment questionnaire about interface preferences are presented in Table II and Figure 5. For the VR group, the pointcloud map was the most preferred data source ( $M = 90.13 \pm 7.44$ ) followed by the camera

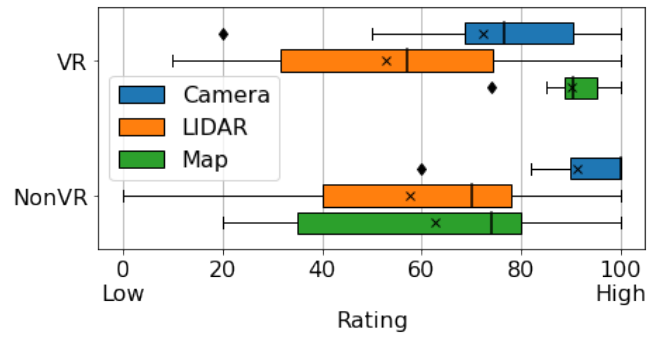


Fig. 5: Box plots of interface preferences. Includes mean marked with a  $\times$ , median, lower and upper quartile, lower and upper whiskers and outliers marked with a  $\diamond$ .

TABLE II: Comparison of preferences of data sources within the interface. All values represent the mean difference between VR and Non-VR groups.

Data Source	Mean	$P$ -value
Camera Feed	$-18.83 \pm 9.59$	.076
Lidar Pointcloud	$-4.79 \pm 15.83$	.781
Map Pointcloud	$27.35 \pm 8.94$	.015

feed ( $M = 72.50 \pm 24.35$ ) and the LIDAR pointcloud ( $M = 52.88 \pm 30.99$ ), but for the non-VR group, the camera feed was the most preferred ( $M = 91.33 \pm 12.68$ ) followed by the pointcloud map ( $M = 62.78 \pm 25.64$ ) and LIDAR pointcloud ( $57.67 \pm 34.28$ ). Comparing preferences of data sources directly between conditions, a notable difference is found for the camera feed ( $M = -18.83 \pm 9.59$ ,  $P = .076$ ) and a significant difference for the pointcloud map ( $M = 27.35 \pm 8.94$ ,  $P = .015$ ). In an additional question in the post-experiment questionnaire, it was found that operators in the VR group expressed a higher feeling of presence compared to the non-VR group ( $M = 1.67 \pm 0.59$  increase on a 1-7 Likert scale,  $P = .017$ ).

It is hypothesised that the interface preferences results are linked to the teleoperation performance results presented in section V-B.1; it is known that increasing an operator's depth perception can reduce operational mistakes during teleoperation tasks with a UGV [30]. Therefore, as VR operators had a higher preference to use the generated 3D map during the experiment, a reduction in collisions is expected. The differences in data preferences between conditions also highlight that interface designs for traditional teleoperation systems cannot be assumed to translate into VR styles, and that future work should continue with inter-VR studies that take advantage of immersive rendering and natural input mediums.

3) *Physiological Metrics*: Results presented in Table III and Figure 6a show that users in the VR group experienced higher HRV than the non-VR group in both the training sessions ( $M = 20.87 \pm 14.10$ ms,  $P = .249$ ) and the experiment ( $M = 13.27 \pm 23.31$ ms,  $P = .629$ ), which indicates a lower cognitive workload [31], though the findings were not

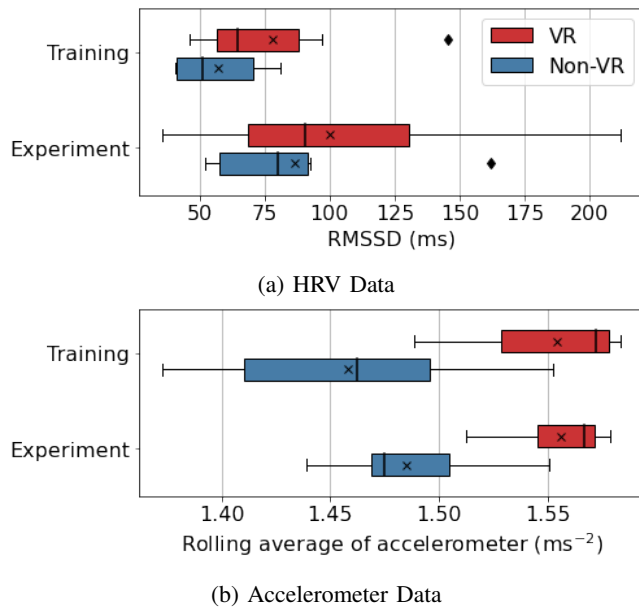


Fig. 6: Box plots of data physiological data derived from Empatica E4. Includes mean marked with a  $\times$ , median, lower and upper quartile, lower and upper whiskers and outliers marked with a  $\diamond$ .

TABLE III: Summary of physiological results. All values represent the mean difference between VR and Non-VR conditions.

Metric	Mean	$P$ -value
HRV during training (ms)	$20.87 \pm 14.10$	.249
HRV during experiment (ms)	$13.27 \pm 23.31$	.629
Accelerometer during training ( $\text{ms}^{-2}$ )	$0.096 \pm 0.021$	< .001
Accelerometer during experiment ( $\text{ms}^{-2}$ )	$0.071 \pm 0.013$	< .001

significant. Interestingly, this observation goes against that of the subjective NASA TLX scores explored in section V-B.1, suggesting a disassociation between objective and subjective measures of cognitive load [32].

Additionally, there was an increase in HRV between training sessions and experiment sessions for both VR ( $M = 22.11 \pm 21.41\text{ms}$ ,  $P = .377$ ) and non-VR ( $M = 29.71 \pm 16.84\text{ms}$ ,  $P = .168$ ) conditions. This indicates that users were more relaxed in the experiment sessions and had a reduced cognitive workload when compared to the training sessions. As HRV has been linked with performance in repeated tasks [33], [34], this suggests that the training sessions were adequate for introducing the operators to the teleoperation system and the experimental process. Approximate training times were 6 and 4.5 minutes for VR and non-VR cases.

The small sample size may explain why the above trends were not statistically significant. Short team HRV analysis is known to be heavily impacted by sample size, and in some cases user studies can require almost 100 participants to find significant results [35]. However, our participant population comprises targeted users (i.e., specialist robotics operators)

within the nuclear sector, making a user study of this scope difficult to organise. Understanding the trade-off between expertise and sample size might be useful for designing targeted teleoperation studies in the future.

Inspecting the rolling average values of the Empatica E4 accelerometer presented in Table III and Figure 6b, users in the VR condition experienced larger changes of acceleration in both the training ( $M = 0.096 \pm 0.021 \text{ms}^{-2}$ ,  $P < .001$ ) and experiment sessions ( $M = 0.071 \pm 0.013 \text{ms}^{-2}$ ,  $P < .001$ ) when compared to the non-VR condition. This matches the results of the VR condition experiencing higher physical demand and can be attributed to the requirement for operators to physically move within the interface during the operation. Therefore, the VR interface is expected to be more tiring over large periods of operation due to the accumulation of physical fatigue. High levels of fatigue during teleoperation have been found to reduce the confidence and quality of an operator's decisions and commands [36] and increase operational mistakes when operating a UGV [37]. Nevertheless, as our experiment was relatively short in duration, the influence of physical fatigue on teleoperation performance was minimal when compared to the benefits of immersion within the interface.

## VI. CONCLUSION

This paper presents the findings from a user study that examined the impact of immersive interface design on nuclear monitoring and decommissioning tasks. The teleoperation interface, which incorporated dense 3D environment reconstruction and an efficient video streaming pipeline, was employed to conduct simulated radiation and visual inspection tasks in controlled remote operation conditions. Our results demonstrate that VR interface designs hold promise for improving teleoperation workflows for nuclear monitoring and decommissioning tasks, albeit with the potential to increase operator fatigue during operation. Further research should explore the impact of these teleoperation systems on long-term operations using larger participant pools and consider the influence of other field teleoperation factors, such as latency, on mission performance.

## ACKNOWLEDGEMENTS

This work was approved by UCL Research Ethics Committee (ID 13305.003). This work made use of equipment provided by the UK National Nuclear User Facility through the UK Atomic Energy Authority. We thank UKAEA and RACE for their support and guidance, and the ORCA Partnership Resource Fund for our project "Mixed-Reality Enhanced Telepresence for Remote Inspection and Monitoring with Multiple Aerial Robots". We acknowledge the funding of EPSRC (award no. EP/R009953/1, EP/L016230/1, EP/R026173/1 and EP/S031464/1), NERC (award no. NE/R012229/1) and the EU H2020 AeroTwin project (grant ID 810321). For the purpose of open access, the author(s) has applied a Creative Commons Attribution (CC BY) license to any Accepted Manuscript version arising.

## REFERENCES

- [1] H. Stedman, B. B. Kocer, M. Kovac, and V. M. Pawar, "VRTAB-Map: A Configurable Immersive Teleoperation Framework with Online 3D Reconstruction," in *2022 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct)*. IEEE, 2022, pp. 104–110.
- [2] GOV.UK, "Nuclear Provision: the cost of cleaning up Britain's historic nuclear sites," 2019. [Online]. Available: <https://www.gov.uk/government/publications/nuclear-provision-explaining-the-cost-of-cleaning-up-britains-nuclear-legacy/nuclear-provision-explaining-the-cost-of-cleaning-up-britains-nuclear-legacycosts-for-decommissioning-other-uk-nuclear-sites>
- [3] A. Shaukat, Y. Gao, J. A. Kuo, B. A. Bowen, and P. E. Mort, "Visual classification of waste material for nuclear decommissioning," *Robotics and Autonomous Systems*, vol. 75, pp. 365–378, 2016. [Online]. Available: <http://dx.doi.org/10.1016/j.robot.2015.09.005>
- [4] S. Watson, B. Lennox, and J. Jones, "Robots and Autonomous Systems for Nuclear Environments," 2019.
- [5] P. G. Martin, J. Moore, J. S. Fardoulis, O. D. Payton, and T. B. Scott, "Radiological assessment on interest areas on the sellafeld nuclear site via unmanned aerial vehicle," *Remote Sensing*, vol. 8, no. 11, pp. 1–10, 2016.
- [6] B. Bird, A. Griffiths, H. Martin, E. Codres, J. Jones, A. Stancu, B. Lennox, S. Watson, and X. Poteau, "A robot to monitor nuclear facilities: Using autonomous radiation-monitoring assistance to reduce risk and cost," *IEEE Robotics and Automation Magazine*, vol. 26, no. 1, pp. 35–43, 2019.
- [7] M. Talha, "Human Factors Issues in Telerobotic Decommissioning of Legacy Nuclear Facilities," Ph.D. dissertation, 2018.
- [8] I. Tsitsimpelis, C. J. Taylor, B. Lennox, and M. J. Joyce, "A review of ground-based robotic systems for the characterization of nuclear environments," *Progress in Nuclear Energy*, vol. 111, no. November 2018, pp. 109–124, 2019. [Online]. Available: <https://doi.org/10.1016/j.pnucene.2018.10.023>
- [9] D. W. Seward and M. J. Bakari, "The use of robotics and automation in nuclear decommissioning," *22nd International Symposium on Automation and Robotics in Construction, ISARC 2005*, vol. 44, no. 0, 2005.
- [10] M. Wonsick and T. Padir, "A systematic review of virtual reality interfaces for controlling and interacting with robots," *Applied Sciences (Switzerland)*, vol. 10, no. 24, pp. 1–17, 2020.
- [11] M. R. Endsley, "Toward a theory of situation awareness in dynamic systems," *Human Factors*, vol. 37, no. 1, pp. 32–64, 1995.
- [12] A. W. W. Yew, S. K. Ong and A. Y. C. Nee, "Immersive augmented reality environment for the teleoperation of maintenance robots," *Procedia CIRP*, vol. 61, pp. 305–310, 2017.
- [13] S. Shao, Q. Zhou, and Z. Liu, "Study of mental workload imposed by different tasks based on teleoperation," *International Journal of Occupational Safety and Ergonomics*, vol. 0, no. 0, pp. 1–11, 2020. [Online]. Available: <https://doi.org/10803548.2019.1675259>
- [14] J. I. Lipton, A. J. Fay, and D. Rus, "Baxter's Homunculus: Virtual Reality Spaces for Teleoperation in Manufacturing," *IEEE Robotics and Automation Letters*, vol. 3, no. 1, pp. 179–186, 2018.
- [15] Q. Wang, W. Jiao, R. Yu, M. T. Johnson, and Y. Zhang, "Modeling of Human Welders' Operations in Virtual Reality Human-Robot Interaction," *IEEE Robotics and Automation Letters*, vol. 4, no. 3, pp. 2958–2964, 2019.
- [16] G. Baker, T. Bridgwater, P. Bremner, and M. Giuliani, "Towards an immersive user interface for waypoint navigation of a mobile robot," *Proceedings of VAM-HRI*, p. 9, 2020. [Online]. Available: <http://arxiv.org/abs/2003.12772>
- [17] J. J. Roldán, E. Peña-Tapia, A. Martín-Barrio, M. A. Olivares-Méndez, J. del Cerro, and A. Barrientos, "Multi-robot interfaces and operator situational awareness: Study of the impact of immersion and prediction," *Sensors (Switzerland)*, vol. 17, no. 8, pp. 1–25, 2017.
- [18] O. Tokatli, P. Das, R. Nath, L. Pangione, A. Altobelli, G. Burroughes, E. T. Jonasson, M. F. Turner, and R. Skilton, "Robot-assisted glovebox teleoperation for nuclear industry," *Robotics*, vol. 10, no. 3, 2021.
- [19] J. Petereit, J. Beyerer, T. Asfour, S. Gentes, B. Hein, U. D. Hanebeck, F. Kirchner, R. Dillmann, H. H. Gotting, M. Weiser, M. Gustmann, and T. Eglloffstein, "ROBDEKON: Robotic Systems for Decontamination in Hazardous Environments," *2019 IEEE International Symposium on Safety, Security, and Rescue Robotics, SSR 2019*, pp. 249–255, 2019.
- [20] P. Stotko, S. Krumpfen, M. Weinmann, and R. Klein, "Efficient 3D reconstruction and streaming for group-scale multi-client live telepresence," *Proceedings - 2019 IEEE International Symposium on Mixed and Augmented Reality, ISMAR 2019*, vol. 25, no. 5, pp. 19–25, 2019.
- [21] P. Stotko, S. Krumpfen, M. Schwarz, C. Lenz, S. Behnke, R. Klein, and M. Weinmann, "A VR System for Immersive Teleoperation and Live Exploration with a Mobile Robot," *IEEE International Conference on Intelligent Robots and Systems*, pp. 3630–3637, 2019.
- [22] S. Livatino, D. C. Guastella, A. Member, G. Muscato, S. Member, V. Rinaldi, L. Cantelli, C. D. Melita, A. Caniglia, R. Mazza, and G. Padula, "Intuitive Robot Teleoperation Through Multi-Sensor Informed Mixed Reality Visual Aids," *IEEE Access*, pp. 25 795–25 808, 2021.
- [23] M. Talha, E. A. Ghalamzan, C. Takahashi, J. Kuo, W. Ingamells, and R. Stolkin, "Towards robotic decommissioning of legacy nuclear plant: Results of human-factors experiments with tele-robotic manipulation, and a discussion of challenges and approaches for decommissioning," *SSRR 2016 - International Symposium on Safety, Security and Rescue Robotics*, pp. 166–173, 2016.
- [24] M. Labbé and F. Michaud, "RTAB-Map as an open-source lidar and visual simultaneous localization and mapping library for large-scale and long-term online operation," *Journal of Field Robotics*, vol. 36, no. 2, pp. 416–446, 2019.
- [25] Siemens, "ros-sharp." [Online]. Available: <https://github.com/siemens/ros-sharp>. [Accessed 12-Jun-2022]
- [26] CircusMonkey, "ros\_rtsp." [Online]. Available: [https://github.com/CircusMonkey/ros\\_rtsp](https://github.com/CircusMonkey/ros_rtsp). [Accessed 09-Sep-2022].
- [27] S. G. Hart and L. E. Staveland, "Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research," *Advances in Psychology*, vol. 52, no. C, pp. 139–183, 1988.
- [28] R. M. Taylor, "Situational awareness rating technique (SART): The development of a tool for aircrew systems design," in *Situational awareness*. Routledge, 2017, pp. 111–128.
- [29] A. B. Ciccone, J. A. Siedlik, J. M. Wecht, J. A. Deckert, N. D. Nguyen, and J. P. Weir, "Reminder: RMSSD and SD1 are identical heart rate variability metrics," *Muscle and Nerve*, vol. 56, no. 4, pp. 674–678, 2017.
- [30] Y. Luo, J. Wang, H. N. Liang, S. Luo, and E. G. Lim, "Monoscopic vs. Stereoscopic views and display types in the teleoperation of unmanned ground vehicles for object avoidance," *2021 30th IEEE International Conference on Robot and Human Interactive Communication, RO-MAN 2021*, pp. 418–425, 2021.
- [31] S. Delliaux, A. Delaforge, J. C. Deharo, and G. Chaumet, "Mental Workload Alters Heart Rate Variability, Lowering Non-linear Dynamics," *Frontiers in Physiology*, vol. 10, no. MAY, pp. 1–14, 2019.
- [32] A. Luque-Casado, J. C. Perales, D. Cárdenas, and D. Sanabria, "Heart rate variability and cognitive processing: The autonomic response to task demands," *Biological Psychology*, vol. 113, pp. 83–90, 2016.
- [33] R. Castaldo, L. Montesinos, S. Wan, A. Serban, S. Massaro, and L. Pecchia, "Heart rate variability analysis and performance during a repeated mental workload task," *IFMBE Proceedings*, vol. 65, pp. 69–72, 2017.
- [34] B. B. Kocer, H. Stedman, P. Kulik, I. Caves, N. Van Zalk, V. M. Pawar, and M. Kovac, "Immersive View and Interface Design for Teleoperated Aerial Manipulation," in *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2022, pp. 4919–4926.
- [35] G. D. Pinna, R. Maestri, A. Torunski, L. Danilowicz-Szymanowicz, M. Szwoch, M. T. La Rovere, and G. Raczak, "Heart rate variability measures: A fresh look at reliability," *Clinical Science*, vol. 113, no. 3–4, pp. 131–140, 2007.
- [36] S. Liu, Y. Xie, Y. Jia, N. Xi, and Y. Li, "Effect of training on the quality of teleoperator (QoT)," *2015 IEEE International Conference on Cyber Technology in Automation, Control and Intelligent Systems, IEEE-CYBER 2015*, pp. 1928–1933, 2015.
- [37] C. Ju and H. I. Son, "Evaluation of Haptic Feedback in the Performance of a Teleoperated Unmanned Ground Vehicle in an Obstacle Avoidance Scenario," *International Journal of Control, Automation and Systems*, vol. 17, no. 1, pp. 168–180, 2019.