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BIM-BASED HUMAN-ROBOT COLLABORATION FOR BUILDING INSPECTIONS USING MIXED REALITY

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Abstract

Human-robot collaboration (HRC) may be leveraged to improve building inspections by allowing robots and humans to perform inspections jointly. However, HRC methods lack intuitive interfaces for seamless collaboration and contextual building information exchange, limiting collaboration and inspection efficiency. This paper proposes a BIM-based HRC framework using mixed reality (MR), enabling operators to visualize inspection data, control robots, and to monitor inspection processes in real time. The BIM-based HRC framework is implemented using MR headsets and validated through collaborative inspections of an indoor environment, showcasing the potential of the framework to advance collaborative building inspections and improve inspection accuracy and efficiency.

Introduction

Buildings and civil infrastructure require routine inspections during and after construction, which are typically performed manually (Halder and Afsari, 2023). However, due to the time-consuming and costly nature of manual inspections (Tandon et al., 2024), robots have been proposed to assist human inspectors in performing building inspections (Smarsly et al., 2023). Human-robot collaboration (HRC) may be used to delegate repetitive or physically demanding tasks to robots, enhancing inspection efficiency and reducing human workload. To achieve efficient HRC, intuitive control of robots is required (Sarida et al. 2024), with mixed reality (MR) being one of the most promising technologies in this direction (Delmerico et al., 2022).

Mixed reality provides a promising paradigm for enhancing HRC in domains requiring spatial reasoning and shared situational awareness. MR enables merging digital information with the physical environment and has the potential to facilitate intuitive interaction between human operators and robotic systems, particularly in tasks such as inspection, construction, and maintenance. In such domains, MR interfaces enable intuitive and context-aware interaction, enabling humans to visualize robot intentions, results of commanded tasks, and planned trajectories in real-time. In Tadeja et al. (2024), the use of MR to enhance HRC in assembly tasks has been investigated by contrasting eye-gaze and hand-ray pointing methods. The study concluded that using MR has reduced cognitive load and enabled effective collaboration by improving user experience and task accuracy. In Delmerico et al. (2022), the role of spatial computing in enabling intuitive interaction through MR interfaces has been emphasized, allowing users to visualize and command robots in a shared spatial context. The study elicits the role of MR in supporting natural methods of interaction, such as gaze, gesture, and spatial cues, critical for reducing cognitive load and improving task performance in HRC settings.

While MR has been investigated in several studies for enabling HRC, MR-based HRC for building inspections has received little attention. In general, employing MR for building inspections has predominantly relied on building information modeling (BIM), which is increasingly adopted in the construction industry, as BIM models contain valuable contextual building information to improve building inspections (Theiler and Smarsly, 2018). MR technologies and BIM have been employed to manage building inspections remotely. In Nguyen et al. (2022), BIM models of bridges, including damage reports mapped on the models, are displayed using an MR headset. In Halder et al. (2022), quadruped robots equipped with 360° cameras are controlled remotely to monitor construction progress. Thereby, the camera images are overlaid with the BIM models of the buildings for inspection. As using MR devices on site requires localization of operators wearing the MR devices relative to BIM models, in Einizinab et al. (2024), wireframes are extracted from camera sensors built in MR devices and matched against wireframes extracted from BIM models. In Tao et al. (2024), operators wearing MR headsets localize themselves relative to BIM models using fiducial tags, i.e., easily recognizable artificial markers, to confirm the location of electrical sockets and switches. In Girgin et al. (2023), a case study is presented to detect issues with mechanical, electrical, and plumbing installations using MR devices. In summary, despite the research on using MR and BIM to support operators directly in manual building inspection processes or to enable remote control of quadruped robots to perform building inspections, MR-based HRC for building inspections has yet to be investigated.

In this paper, a BIM-based HRC framework using MR to enable collaborative and effective building inspections is proposed. Inspection tasks are automatically extracted from building elements represented in BIM models. Fiducial tags are employed to enable localization of both MR devices and robots with respect to common reference frames established by the BIM models. Intuitive MR interfaces are developed to control multiple robots, to assign inspection tasks to the robots, and to visualize information relevant to the inspection tasks and the robots. The remainder of this paper is organized as follows: In the next section, the design and the implementation of the HRC framework are described. Then, validation tests conducted in an indoor office environment are presented, and the results are summarized and discussed. Finally, conclusions are drawn and potential future research directions are proposed.

A BIM-based human-robot collaboration framework using mixed reality

The HRC framework proposed in this paper utilizes BIM models as a shared reference coordinate system, referred to as the BIM model frame **B**, as shown in Figure 1. Inspection tasks are linked to building elements represented in the BIM models, and both humans wearing MR headsets and robots localize themselves with respect to the BIM model frame **B**. In the following subsections, (i) the extraction of building elements that require inspection from BIM models, (ii) the virtual world alignment and localization of MR headsets, (iii) the frame alignment of maps for robot navigation and BIM models, (iv) the development of intuitive MR interfaces for visualization and control, and (v) the assignment of inspection tasks to multiple robots are discussed.

Extraction of target building elements from BIM models

BIM models include digital representations of building elements that require inspections, hereinafter referred to as "target building elements". To identify and extract the target building elements, including spatial and relational information, the hierarchical structure of BIM models is traversed. Based on the type of the target building elements, inspection routines are derived. For example, target building elements associated with visual inspections require generating inspection poses, ensuring that cameras face the target building elements from an appropriate distance. To generate the inspection poses with reference to the BIM model frame, a transformation matrix containing a pre-defined distance and orientation to the target building elements is multiplied by the pose of the target building elements in the BIM models. The BIM models, employed for the proposed HRC framework, are managed based on the Industry Foundation Classes (IFC) standard. IfcOpenShell is utilized to extract target building elements, including the poses in the BIM model frame (IfcOpenShell, 2024).

Virtual world alignment and localization of mixed reality headsets

In MR, maintaining a stable alignment between virtual objects and the real world is essential for immersive and interactive experiences. Furthermore, the alignment between the virtual world and the real world is critical for accuracy when controlling robots with MR devices. In the proposed HRC framework, the alignment between the virtual world and the real world is obtained through world locking and localization of MR devices. World locking ensures virtual objects remain fixed in the physical environment by providing a fixed coordinate system, referred to as the virtual world frame or the MR headset origin frame **HO**, relative to the BIM model frame **B**. The world locking process determines the fixed transformation $^{B}\mathbf{T}_{HO}$ between the BIM model frame **B** and the MR headset origin frame **HO**. World locking is achieved via the Microsoft World Locking Tools

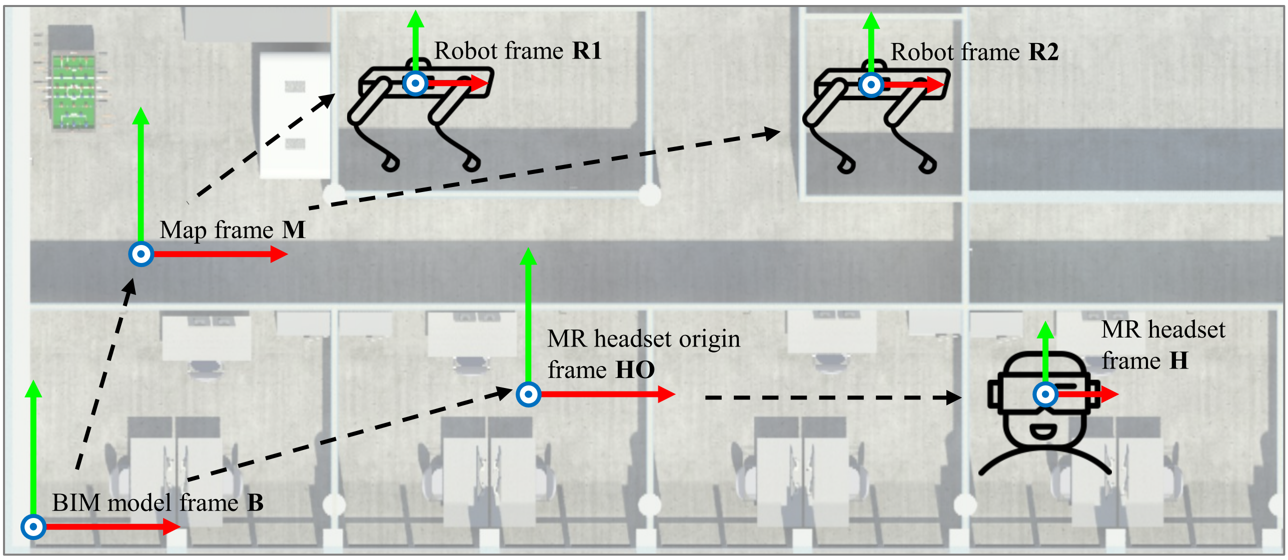

Figure 1: Overview of coordinate frames in the HRC framework

(Microsoft, 2024a) by scanning multiple QR codes of artificial markers with MR headsets that correlate to Unity *QR Space Pins* in the virtual world to anchor BIM-based virtual world models to the physical world. Furthermore, localization is essential to track the dynamic movement of the MR headsets. To localize MR headsets in the fixed MR headset origin frame **HO**, visual inertial odometry is performed using sensor data recorded by depth cameras and inertial measurement units integrated within the MR headsets.

Frame alignment for robot navigation

Typically, robot navigation utilizes maps devised for efficient localization, path planning, and obstacle avoidance. The maps are created from cameras and/or lidar sensors mounted on robots, and the coordinate system of the maps is referred to as the map frame **M**. In this study, to enable robots to navigate to the inspection poses defined in the BIM model frame **B**, the transformation matrix ${}^{\mathrm{B}}\mathbf{T}_{\mathrm{M}}$ describing the relative poses between the BIM model frame **B** and the map frame **M** for alignment is obtained using fiducial tags. The fiducial tags are placed at the same locations in the BIM model and in the corresponding physical building. Robots observing "real-world" fiducial tags placed in the physical buildings leverage the "virtual" tags placed in the corresponding BIM models to set up a chain of transformations to estimate the matrix ${}^{\mathrm{B}}\mathbf{T}_{\mathrm{M}}$. Since calculating ${}^{\mathrm{B}}\mathbf{T}_{\mathrm{M}}$ from a single tag is prone to misalignments, multiple tags are considered by calculating the mean transformation matrix ${}^{\mathrm{B}}\overline{\mathbf{T}}_{\mathrm{M}}$ when a new tag is observed. AprilTags are employed as fiducial tags (Olson, 2011), placed in the BIM models, which are retrieved and located using IfcOpenShell. The calculation of the mean transformation matrix ${}^{\mathrm{B}}\overline{\mathbf{T}}_{\mathrm{M}}$ is formulated as an optimization problem and solved using the *scipy.optimize.least_squares* package in Python (SciPy, 2024).

Intuitive MR interfaces for visualization and control

To achieve efficient HRC for building inspections, intuitive MR interfaces are required. In the proposed HRC framework, a graphical user interface is developed that allows users wearing MR headsets to interact with the target building elements using hand gestures and digital interfaces. Furthermore, to enable individual control of the robots, users can define goal inspection poses in the virtual world and assign the goal inspection poses to the physical robots using MR interfaces. To enable robot control and navigation to user-defined poses in the map frame **M**, the transformation matrix ${}^{\mathrm{HO}}\mathbf{T}_{\mathrm{M}}$ describing the relative poses between the virtual world frame **HO** and the map frame **M** for alignment is calculated using Unity *QR Space Pins* by scanning QR codes placed on the robot frame **R1**. Once a QR code is scanned, the transformation ${}^{\mathrm{H}}\mathbf{T}_{\mathrm{R1}}$ relating the robot frame **R1** to the MR headset frame **H** is determined. The transformation ${}^{\mathrm{HO}}\mathbf{T}_{\mathrm{H}}$ relating the MR headset frame **H** and the virtual world frame **HO** is obtained using the localization system of the MR headset. Similarly, the transformation ${}^{\mathrm{M}}\mathbf{T}_{\mathrm{R1}}$ relating the robot frame **R1** to the map frame **M** is obtained using the localization system of the robots. Therefore, the transformation matrix ${}^{\mathrm{HO}}\mathbf{T}_{\mathrm{M}}$ aligning the map frame **M** to the virtual world frame **HO** can be determined using the following:

$$ {}^{\mathrm{HO}}\mathbf{T}_{\mathrm{M}} = {}^{\mathrm{HO}}\mathbf{T}_{\mathrm{H}}\,{}^{\mathrm{H}}\mathbf{T}_{\mathrm{R1}}\,{}^{\mathrm{M}}\mathbf{T}_{\mathrm{R1}}^{-1} \in \mathrm{SE}(3) \quad (1) $$

After the transformation matrix ${}^{\mathrm{HO}}\mathbf{T}_{\mathrm{M}}$ has been determined, robots can be commanded directly using MR interfaces within the MR headset frame **H** and virtual world frame **HO**. The MR interfaces are implemented

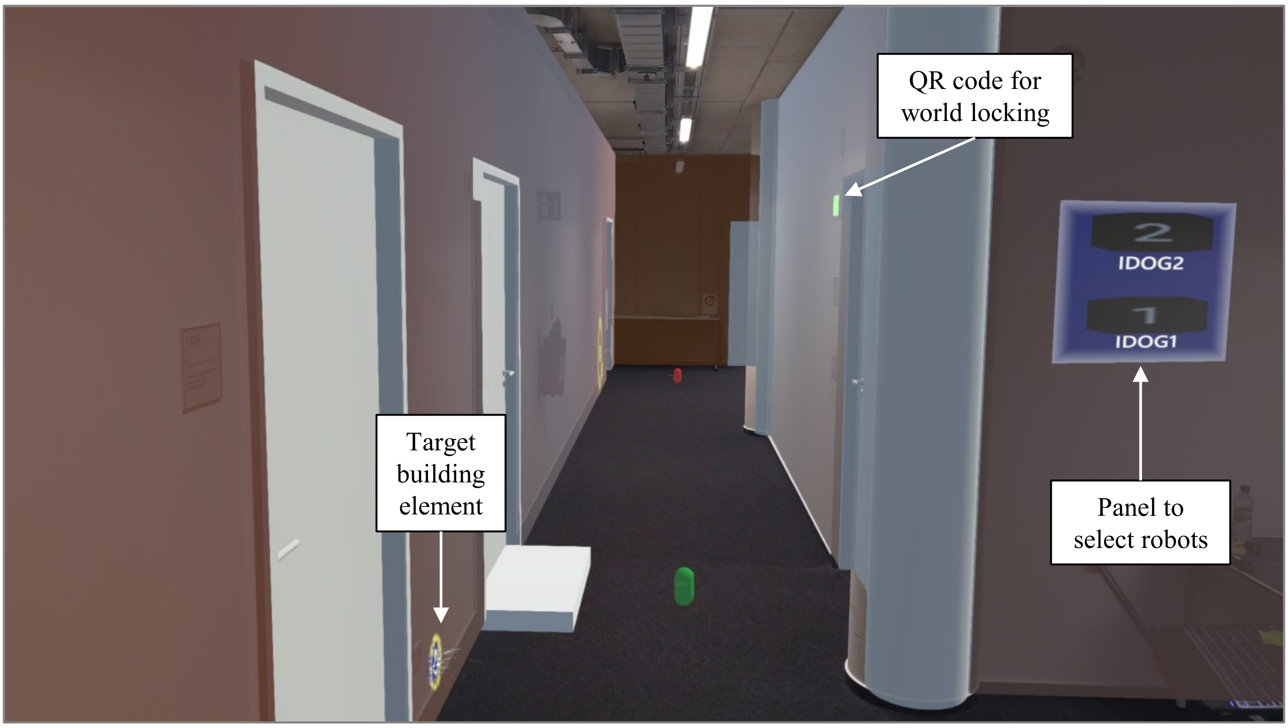

Figure 2: Accuracy when superimposing the virtual world model on the real world

using the game engine Unity (Unity, 2025), with the target building elements extracted from BIM models and inserted as Unity *GameObjects*. To couple the MR interfaces with the software systems on the robots running the Robot Operating System (ROS) framework (Quigley, 2009), the ROS-TCP-Endpoint (ROS-TCP-Endpoint, 2022) system is utilized.

Assignment of inspection tasks to multiple robots

To accelerate the inspection of buildings, robots can be deployed in multi-robot teams alongside human operators, enabling parallel execution of inspection tasks. Inspection tasks may be distributed among humans and multiple robots, based on the type of inspection tasks and capabilities of the robots. Deploying robots in multi-robot teams within a common environment offers the advantage of sharing maps among robots ("shared maps"). A shared map enhances robot coordination by ensuring the use of consistent coordinate frames, improving fault tolerance, and enabling real-time map updates for better navigation and task execution. In the shared map, which is hosted centrally on a map server within a common network, individual robots access the map server as clients. Individual robots use local simultaneous localization and mapping (SLAM) to build submaps independently, while the global SLAM process is managed by the map server, which integrates submaps into a unified global map. The map server receives trajectory nodes and submaps from clients, performs global optimization, and incorporates updates into the global map. The distributed architecture enables real-time collaboration, allowing robots to share map updates, resolve task or navigation conflicts, and maintain consistent maps across large and dynamic environments.

In the HRC framework, the gRPC Remote Procedure Call (gRPC) architecture is utilized with the Cartographer (Cartographer, 2018) SLAM algorithm to enable distributed SLAM and communication between multiple robots using a client-server architecture in the multi-robot system (MRS). The MRS is implemented using the ROS framework. To implement the MRS, two robots are wirelessly connected to the same local network. The map server is configured to operate locally on the first robot. Both robots are then able to connect to the map server running on the first robot to subscribe to the global map and corresponding updates. The motion planning framework described in Tandon et al. (2024) is deployed to plan and execute navigation plans in the map. ROS namespaces are utilized for each robot to isolate task execution and motion planning, thereby promoting scalability and modularity in the MRS.

The accuracy and efficiency of the HRC framework are demonstrated through validation tests, which are described in the next section.

Validation tests and results

This section presents the validation tests conducted to validate the HRC framework. First, the objectives of the tests and the metrics used in this study are discussed. Next, the test environment, hardware, and procedure are described. Finally, the results are presented, analyzed, and discussed.

Objectives and metrics

The objectives of the validation tests include assessing the human-robot collaboration outcome, quantified through the accuracy of robots reaching inspection poses, and the efficiency of collaborative inspections, performed by operators and multiple robots in parallel.

In the first validation test, the *accuracy* of robots reaching inspection poses, both generated from target building elements and user-defined by an operator wearing an MR headset, is assessed. For each inspection pose, the accuracy is measured as the distance of the poses (generated or user-defined) to the inspection pose reached by the robots. The overall accuracy results from reaching multiple inspection poses are calculated using the root mean square error (RMSE) of the distances of all poses. In the second validation test, the *efficiency* of the robots performing visual inspection tasks is assessed by performing inspections collaboratively, involving multiple robots and human operators.

Test environment, hardware, and procedure

The validation tests are conducted in an indoor office environment with dimensions 39 m × 16 m, represented by a BIM model, created in Autodesk Revit. The hardware used for the tests includes the Microsoft HoloLens 2 (HL2) MR headset (Microsoft, 2024b) and two quadruped robots of type IDOG ("Intelligent DOcumentation Gadget"), which have been used in previous work of the authors (Tandon et al., 2024).

The ***first validation test*** is conducted as follows: The BIM model of the indoor office environment, exported in the IFC format, is queried for elements of type *IfcOutlet* and the inspection poses are generated at 1-m distances in front of all *IfcOutlet* elements. Subsequently, the human operator wearing the HL2 MR headset scans the QR codes to perform world locking to align the virtual world frame **HO** with the real world. To assess the alignment of the virtual world frame **HO** with the map frame **M**, the QR code on the IDOG is scanned to determine the transformation matrix $^{HO}\mathbf{T}_{M}$. The IDOG is subsequently commanded to navigate to the corresponding location of the map frame **M** in the virtual world. The deviation between the calculated map frame, denoted **MC**, in the virtual world frame **HO** and the observed map frame **M** is noted. The aforementioned procedure is repeated three times, and the results are compared.

Figure 2 shows the view of the operator wearing the MR headset after performing world locking. As can be seen, the virtual world model is superimposed on the real world with accuracy, and the *GameObjects*, for interacting with the target building elements and for assigning corresponding inspection tasks, are coincident with building elements in the real world.

Figure 3 illustrates the navigation accuracy to inspection poses, upon performing the alignment between the virtual world frame **HO** and the map frame **M**. As observed, the

IDOG successfully navigates to the inspection poses within an error range reasonable for visual inspections.

In the ***second validation test***, typical inspections are carried out collaboratively by multiple robots and human operators, as will be elucidated in detail in the following paragraphs through Figures 4-7. First, the IDOG is devised to visually inspect electrical outlets under the supervision of the operator. Hereby, the operator has access to the camera feed of the IDOG, and the inspection poses and target building elements are highlighted (Figure 4).

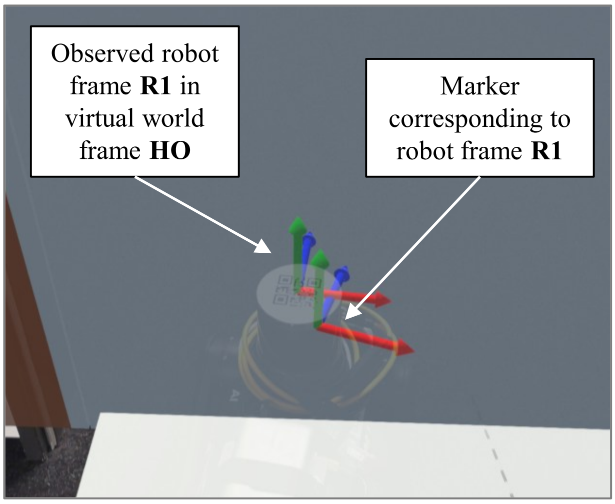

Figure 3: Accuracy when navigating to the inspection poses

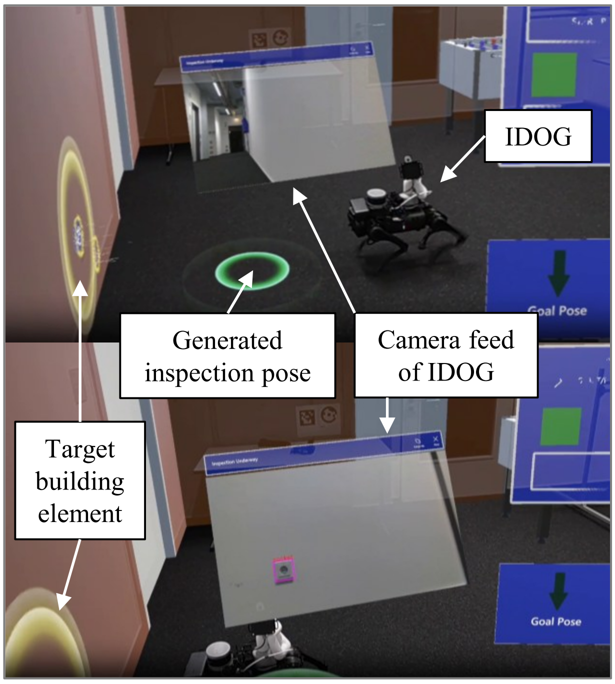

Figure 4: Supervising the IDOG in performing inspection tasks, top: IDOG moving to the inspection pose, bottom: Inspecting target building elements

Figure 5 shows a user-defined inspection pose supplied manually by the human operator. The human operator utilizes the MR interfaces to dynamically reassign inspection tasks among multiple IDOGs, to command the

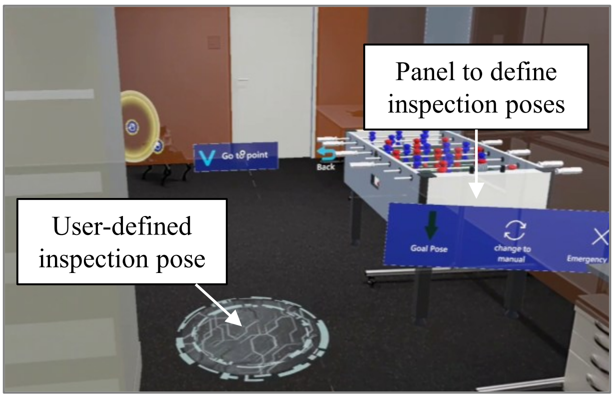

Figure 5: Defining inspection poses for the IDOG

IDOGs to different inspection poses, and to override motion commands in the case of manual control.

Figure 6 shows collaborative inspections between human operators and an IDOG using mixed reality interfaces. The IDOG is assigned to visually inspect building elements based on sensor payload and robot capabilities. As the IDOG performs visual inspections of the electrical outlet, the human operator performs an RFID sensor-based data acquisition task to collect structural health monitoring data from sensors attached to the walls. If corresponding inspection poses are unreachable (e.g., when the wall-mounted sensors are too far away), the IDOG is unable to accomplish the inspection task, which is then performed by the human operator, thereby leveraging the unique capabilities of robots and humans for collaborative inspection.

Figure 6: Collaborative building inspections

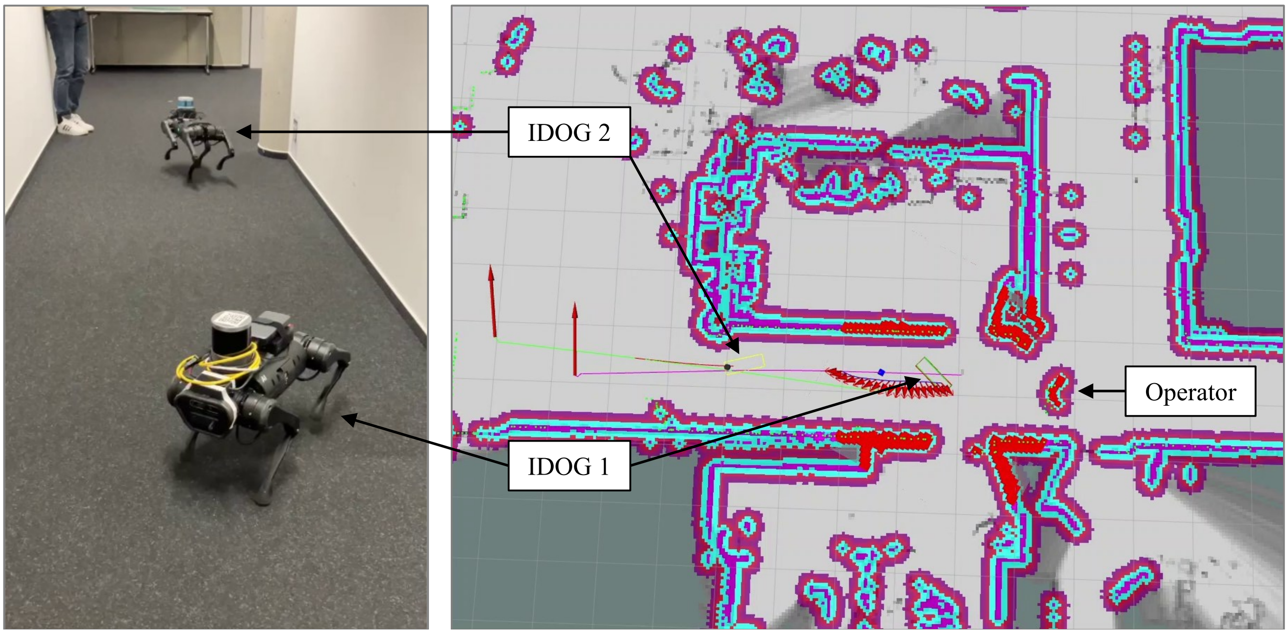

Figure 7: Multi-robot inspections

Figure 7 shows the operation of multiple IDOGs on a common map within a multi-robot system for the collaborative execution of inspection tasks. The human operator assigns different inspection tasks to the IDOGs to be performed concurrently, while the human operator performs inspection tasks that may be either unsuitable or not possible for the IDOGs and may be better suited to human inspectors than robots.

Results and discussion

The results of the first validation test are summarized in Table 1, which shows the quantitative measurements of the *accuracy* of alignment of the map frame **M** and virtual world frame **HO**. The deviations in observed map frame **M** are caused due to residual errors from the world locking process that aligns the virtual world frame **HO** to the real-world building. Deviations between the calculated map frame **MC** and map frame **M** are of the magnitude of standard errors in the localization of the IDOG. Thereby, the alignment is considered successful for visual inspections.

*Table 1: Distances (d) between the calculated map frame **MC** in the virtual world frame **HO** and the observed map frame **M** (in meters)*

Test	M_x	M_y	M_z	MC_x	MC_y	MC_z	*d*
1	-2.45	-0.57	7.45	-2.46	-0.67	7.47	0.103
2	-2.44	-0.56	7.44	-2.51	-0.56	7.42	0.072
3	-2.27	-0.47	7.36	-2.47	-0.57	7.33	0.226

The results of the second validation test (Figures 4-7) are indicative of the efficiency of the BIM-based HRC framework. The division of inspection tasks among humans and robots enhances overall efficiency by leveraging the autonomous capabilities of the robots alongside the adaptability and contextual understanding of human inspectors. The results specifically reflect fundamental principles of HRC, such as dynamic task allocation, complementarity, adaptability, and the use of intuitive interfaces for communication. By enabling the distribution of inspection tasks between human operators and multiple IDOGs, the system ensures robust, concurrent, and efficient execution even in complex or unstructured environments. The next section summarizes the paper, draws conclusions, and presents future work directions.

Summary and conclusions

Buildings and civil infrastructure require routine inspections. Human-robot collaboration may improve building inspection productivity by allowing robots and human workers to perform specialized inspection tasks concurrently. This paper has presented a BIM-based HRC framework using mixed reality, enabling operators to visualize inspection data, to control robots, and to monitor inspection processes in real-time. The validation tests have demonstrated the accuracy and efficiency of the HRC framework.

While the BIM-based HRC framework using MR demonstrates promising results in a controlled indoor environment, limitations must be addressed for real-world deployment. For example, scalability to large, complex, and dynamic environments may pose challenges, and factors such as variable lighting conditions and varying network connectivity may adversely affect the usability and reliability of MR interfaces. Practical considerations, such as the limited battery capacity of robots and MR headsets, may limit the applicability of the BIM-based HRC framework, thereby constraining operations to small buildings. Network connectivity in large buildings or with extensive metal structures may experience deterioration in the quality of service, thereby hindering communication between robots and MR devices and impacting real-time data transfer and collaboration. Apart from technical constraints, high costs, training requirements for operators, safety certifications, and compliance with regulatory standards may pose barriers to the adoption of the framework in practice.

In future work, the accuracy of the HRC framework may be improved by adding localization constraints between MR devices and robots. Additionally, the usability of the HRC framework and the potential increase in cognitive load for human operators using MR during collaborative human-robot inspections may be investigated. Furthermore, safety-related factors of human-robot collaboration may be integrated, facilitating the safety of collaborative inspections.

Acknowledgments

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