LUOJIA Explorer : A Multi-robot Autonomous Exploration and Mapping System for Unknown Spaces

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Keywords: Multi-robot, Exploration, Mapping, Path Planning, Unknown Spaces.

Abstract

As human exploration of space advances, the exploration of unknown spaces and the construction of digital twins for these environments have become increasingly important. Autonomous exploration and mapping by unmanned systems is one of the key methods to achieve this, but existing single-robot exploration approaches are inefficient in large-scale scenarios or time-critical tasks. Multi-robot collaboration can effectively address this issue, but enabling fully autonomous multi-robot collaborative exploration of unknown spaces and constructing digital models of these spaces remain significant challenges. This paper introduces the Luojia Explorer system, a multi-robot autonomous exploration and mapping system for unknown spaces. At the algorithmic level, the system is primarily divided into two parts: multi-robot collaborative simultaneous localization and mapping (C-SLAM) and collaborative exploration and planning. Through the seamless integration of these two components, efficient multi-robot collaborative exploration of unknown spaces is achieved. Its effectiveness has been validated in campus scenarios, where it achieved an exploration efficiency of 38.15 m³/s.

1. Introduction

Digital twin dynamically maps and simulates physical entities through virtual models. It enables comprehensive perception and precise modeling of physical objects through real-time data support and feedback (Tao et al., 2022). Among various data representations, point cloud has become one of the key data foundations for digital twins due to its ability to accurately capture 3D spatial information (Bisheng et al., 2017).

As human exploration of space deepens, the exploration of unknown spaces, such as underground spaces and planetary environments, has become increasingly important. Moreover, constructing digital twin models for these spaces becomes increasingly significant. In the field of surveying and remote sensing, autonomous unmanned surveying using robotic systems has become one of the core methods for achieving digital twins of unknown spaces. This approach provides a digital foundation and construction basis for the creation of digital twins.

Traditional surveying methods typically rely on Terrestrial Laser Scanning systems to collect data for environmental reconstruction. However, these methods are inefficient and require significant human involvement. In recent years, mobile laser scanning systems, such as backpack or helmet-mounted scanning systems (Wu et al., 2023), have rapidly developed. While these systems have improved portability, they still cannot overcome the limitations of manual operation and remain difficult to deploy in the exploration of unknown spaces.

With the rapid advancement of mobile robotics, autonomous surveying based on diverse robots provides new opportunities for efficiently exploring and modeling unknown spaces. SLAM technology enables robots to perform real-time localization and construct maps in unknown environments using equipped sensors. Meanwhile, autonomous planning and exploration technologies enable robots to navigate and collect information autonomously in complex environments. These technologies have been widely applied in fields such as planetary exploration and underground mining, significantly improving the efficiency and accuracy of exploring unknown spaces.

Currently, many studies have developed single-robot systems capable of autonomous exploration (Cao et al., 2021; Sun et al., 2024). However, the exploration range and efficiency of single-robot systems are limited, making it difficult to meet the demand for efficient exploration in large-scale and complex environments. In contrast, multi-robot systems can leverage the advantages of heterogeneous unmanned platforms, offering high spatial exploration efficiency and a broad perception range (Xu et al., 2023). However, the increase in the number of robots also introduces more challenges in terms of SLAM, task planning, and collaboration strategies for multi-robot systems.

To address the challenges, we propose the Luojia Explorer system, a multi-robot autonomous exploration and Mapping system for unknown spaces. The system offers multi-robot collaborative autonomous exploration capabilities and efficient environment mapping, providing the data foundation for the efficient realization of digital twins in unknown environments. As shown in Figure 1, the hardware system consists of two unmanned vehicles: one with a four-wheel differential chassis and the other with a tracked chassis. The system is capable of

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multi-robot C-SLAM, as well as distributed collaborative exploration and planning based on LiDAR in unknown spaces. The proposed system has been effectively validated in a campus scenario and can provide data support for digital twins of unknown spaces.

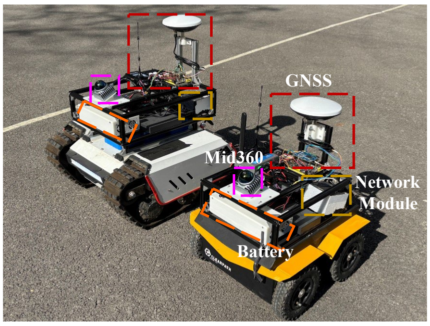


Figure 1: Hardware Composition of the Luojia Explorer System. The system consists of two unmanned devices, each equipped with a LiDAR and communication module.

2. Related Work

2.1 C-SLAM

Single-robot SLAM has evolved significantly over the years (Cong et al., 2024) , and based on this foundation, C-SLAM has also seen substantial development. LAMP 2.0 (Chang et al., 2022) is a multi-robot SLAM system developed for large-scale underground environments, designed to address challenges such as perceptual aliasing and data outliers. It features a robust and scalable loop closure detection module, an outlier-resilient pose graph optimization backend based on Graduated Non-Convexity, and is adaptable to different odometry sources. DOOR-SLAM (Lajoie et al., 2020) introduces a fully distributed SLAM system that integrates distributed outlier rejection and efficient data exchange, enabling accurate trajectory estimation and robust multi-robot collaboration in low-bandwidth and limited connectivity scenarios. DiSCo-SLAM (Huang et al., 2022) presents a distributed multi-robot SLAM framework that leverages the scan context descriptor for efficient LiDAR data exchange and employs a two-stage global-local optimization procedure for accurate and stable localization. Swarm-SLAM (Lajoie and Beltrame, 2023) develops a decentralized, sparse, and scalable C-SLAM framework for multi-robot systems, incorporating a inter-robot loop closure detection algorithm based on algebraic connectivity maximization, optimized to minimize communication overhead in large-scale swarm robotics deployments. SlideSLAM (Liu et al., 2024) introduces a real-time decentralized metric-semantic SLAM system for heterogeneous robot teams, utilizing sparse, lightweight object-level semantic maps for efficient inter-robot loop closure detection and seamless collaboration.

2.2 Multi-Robot Collaborative Exploration

In comparison with single-robot exploration, multi-robot exploration can offer enhanced efficiency and robustness. In recent years, a large number of multi-robot autonomous exploration methods have emerged. SMMR-Explore (Yu et al., 2021) proposes a submap-based DSLAM framework for efficient inter-robot communication and a Multi-robot Multi-target Potential Field strategy to improve exploration efficiency by optimizing goal selection and minimizing trajectory overlap. MUI-TARE (Yan et al., 2023) is a multi-agent exploration system that integrates adaptive sub-map merging and cooperative multi-agent planning to enhance exploration efficiency and sub-map merging robustness in large-scale 3D environments with unknown initial poses. FAME (Bartolomei et al., 2023) proposed a decentralized multi-robot exploration strategy that dynamically balanced cautious exploration and aggressive exploitation of the environment, achieving faster and more efficient forest coverage than existing methods. RACER (Zhou et al., 2023) introduces a decentralized multi-UAV exploration approach that utilizes pairwise interaction based on online hgrid space decomposition, a CVRP formulation for efficient task allocation, and a hierarchical planner to ensure fast, safe, and scalable exploration of unknown environments. GVP-MREP (Dong et al., 2024) introduces a multi-UAV exploration method that leverages a multi-robot dynamic topological graph for efficient communication and a hierarchical exploration strategy using graph Voronoi partition to enable effective task allocation.

3. System and Method

3.1 Luojia Explorer System Overview

This section introduces the composition of the Luojia Explorer system, including both hardware and algorithms. In terms of hardware, as shown in Figure 1, the system is configured with a mobile robot chassis, available in two types: a differential drive chassis and a tracked chassis. The high-performance computer is responsible for processing the data collected by the sensors and executing the system algorithms for data analysis. LiDAR and IMU sensors (the Livox Mid360 and its built-in IMU) are employed for robot localization and navigation. To enable multi-robot collaborative exploration and task execution, each robot is equipped with a 1.5G wireless Mesh self-organizing network node. On the hardware side, Mesh-based WLAN devices are used to facilitate multi-hop, multi-path connectivity, thereby significantly enhancing both communication robustness and real-time performance. On the software side, to overcome the limitations of ROS1, such as the necessity of a master node and potential issues with name conflicts or topic collisions, the system utilizes the ROS1_bridge for bidirectional mapping of ROS1 and ROS2 topics as shown in Figure 2. Additionally, it leverages the DDS-based distributed messaging system in ROS2 to enhance communication flexibility and scalability. To support distributed collaboration, each node autonomously configures Quality of Service (QoS) policies at the DDS layer, enabling message isolation and prioritization of topics based on specific requirements. This ensures the reliable delivery of critical data even under network congestion or instability. Furthermore, the use of custom configuration files allows for flexible QoS tuning for key topics, providing a scalable and robust communication framework for multi-robot collaborative exploration.

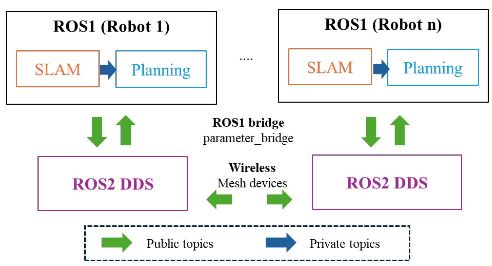


Figure 2: Communication flow diagram for the proposed multi-robot system.

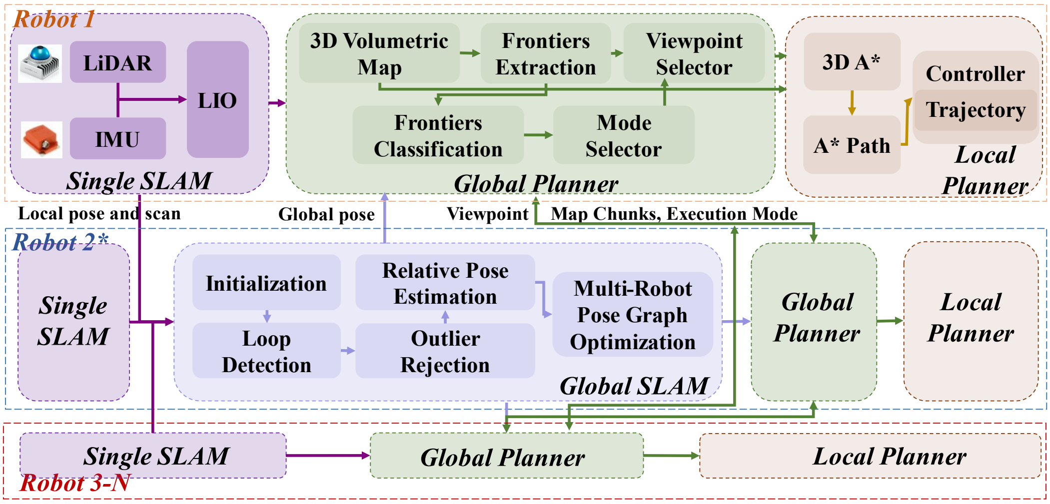


Figure 3: Algorithm diagram of the Luojia Explorer system, where * denotes the robot acting as the main node.

The Luojia Explorer system incorporates two key modules: multi-robot C-SLAM and collaborative exploration, as depicted in Figure 3. In the C-SLAM module, a centralized architecture is utilized, where each robot runs the single SLAM method to estimate its own local pose. The system designates the robot with the best performance, meaning the one with the highest computational efficiency, as the master node to execute the global SLAM algorithm. This master node processes the local poses and point cloud scans from all robots, estimates the global poses in the system, and shares this information with the other robots for subsequent planning. The collaborative exploration module is divided into global and local planning components. This approach employs a distributed framework, enabling each robot to analyze global data and plan its own trajectory. This design facilitates efficient autonomous exploration and mapping in unknown environments.

3.2 Collaborative SLAM

The main function of C-SLAM is to estimate the global pose of the robots and the global map based on the sensors carried by each robot. The C-SLAM algorithm employs a centralized architecture. Each robot runs a single SLAM module, utilizing LiDAR and IMU sensors for state estimation through LiDAR-Inertial Odometry, based on the Fast-LIO2 algorithm (Xu et al., 2022). However, the poses and point clouds obtained from the single SLAM are expressed in the robot's local frame. Therefore, global SLAM is required to align the local poses of all robots into a unified global frame. The robot with the best performance is designated as the main node, which receives local poses and scans from the other robots. The main node estimates the global pose using the global SLAM module and shares it with the other robots for further exploration and planning.

The global SLAM module consists of initialization, loop closure detection, relative pose computation, outlier rejection, and global pose graph optimization. First, if there are large overlapping areas between the initial regions of the robots, local poses and scans are accumulated to form submaps. By leveraging the overlap between the robot submaps and using the Fast-GICP algorithm (Koide et al., 2021), the initial relative poses between robots are computed, aligning the local frame to the global frame. Subsequently, the algorithm calculates reliable loop closure constraints between robots through loop detection, outlier rejection, and relative pose estimation modules. Finally, the multi-robot pose graph optimization module combines the odometry factors of the system, intra-robot and inter-robot loop closure constraints, solving for the globally optimal poses. A general likelihood model for these factors is defined as:

$$\mu(p) = \varphi\left(z_{\alpha_i\beta_j} \middle| p\right) \tag{1}$$

where $p = \{p_\alpha, p_\beta, \ldots\}$ represents the set of robot poses, and $z_{\alpha_i\beta_j}$ is the measurement model between the pose of robot α at time i and the pose of robot β at time j. The module optimizes the loop closure and odometry constraints to solve for the global pose p^* using the formula:

$$p^* = \arg\max_{p} \prod \mu(p) \tag{2}$$

The global poses are transmitted to the other robots for subsequent planning.

3.3 Multi-Robot Collaborative Exploration

In multi-robot collaborative exploration, we use the previously developed distributed multi-robot exploration algorithm DCARE (Zhao et al., 2024). At the mapping level, the unmanned robot team incrementally shares perceived information and merges local environmental data on each robot to generate a global 3D voxel map. At the global planning level, the robot team extracts frontiers of the known region in a distributed manner. A frontier is defined as a voxel on the boundary between free space and unknown space. The frontiers are then clustered into frontier clusters, which serve as rough targets for exploration. To determine the specific current target point, a cylindrical coordinate system is constructed at the origin of the frontier cluster, and a set of viewpoints is evenly sampled as the current candidate target set. Finally, an information gain function is used to assess the exploration value of each viewpoint, with the highest-scoring viewpoint being selected as the current exploration target. The specific definition of the information gain function is as follows:

$$\begin{aligned} G(c, P_i) = {} & \omega_{area} G_{area}(\mathcal{L}_{c,best}) - \omega_{dis} D_{dis}(p_i, \mathcal{L}_{c,best}) - \\ & \omega_o D_o(y_i, p_i, \mathcal{L}_{c,best}) - \omega_{goal} D_{goal}(g_i, \mathcal{L}_{c,best}) - \\ & \omega_{other} D_{other}(P) - \omega_{label} D_{label}(C, P) \end{aligned} \tag{3}$$

where c represents a frontier cluster, and $P_i = \{p_i,\ y_i,\ g_i\}$ denotes the state of robot i. Specifically, p_i, y_i, and g_i represent the robot's position, heading, and current goal, with the global pose from C-SLAM. $\mathcal{L}_{c,best}$ denotes the viewpoint with the highest gain corresponding to the frontier cluster c . G_{area} represents the information gain of the viewpoint, which corresponds to the volume gain achievable by the robot when heading to this viewpoint. D_{dis} is the path length to the viewpoint $\xi_{c,best}$, while D_o is the cost of direction change, which penalizes frequent turns. D_{goal} represents the cost of the previous goal, promoting goal consistency, and D_{other} accounts for the state set of other robots, encouraging team collaboration in decentralized exploration. D_{label} represents the cost of different execution mode. The weights ω_{area}, ω_{dis}, ω_o, ω_{goal}, ω_{other}, and ω_{label} are the corresponding positive weights.

To specify, D_{label} is calculated as follows. Frontiers are categorized into two types: large and small, based on their shape and location. In the default mode, robots in explorer mode prioritize the rapid coverage of unknown areas, focusing on large frontiers while ignoring small ones. However, if too many small frontiers are neglected, smaller but potentially significant features such as corridors or openings that lead to larger unexplored spaces may be overlooked. Therefore, when the number of small frontiers surrounding a robot exceeds a certain threshold, the system switches to collector mode, constructing a Traveling Salesman Problem (TSP) to cover all small frontiers. As a result, the expression for D_{label} is as follows:

$$D_{label} = \begin{cases} penalty_{small} & , explorer\ mode \\ penalty_{large} & , collector\ mode \end{cases} \tag{4}$$

where $penalty_{small}$ represents the penalty for neglecting small frontiers, and $penalty_{large}$ represents the penalty for neglecting large frontiers.

At the local planning level, we employ a heuristic path planning algorithm 3D A*, along with a probabilistic trajectory generation method to safely and stably navigate the robot to the selected target location. We use Falco method (Zhang et al., 2020) to generate trajectory and speed commands. Given the start state s_{start} and the goal state s_{goal} , the planner incrementally maximizes the probability of reaching the goal $\mathrm{P}(s_{goal}|\mathrm{s})$, generating the specific trajectory step by step. This process can be expressed as:

$$s_{next} = \arg max\ \mathrm{P}(s_{goal}|\mathrm{s}) \tag{5}$$

To specify, $\mathrm{P}(s_{goal}|\mathrm{s})$ is calculated using Monte Carlo sampling. We draw $\mathrm{n} \in Z^+$ samples $\theta_1, \theta_2, \ldots, \theta_n$ to estimate the reaching probability, where $\theta_1, \theta_2, \ldots, \theta_n$ represent the paths derived from the current state s, and $\mathrm{P}(s_{goal}|\theta_i)$ denotes the probability of θ_i successfully reaching the goal state s_{goal} . The reaching probability is approximated as:

$$\mathrm{P}(s_{goal}|\mathrm{s}) \approx_{n\uparrow\infty} \frac{1}{n}\sum_{i=1}^{n} \mathrm{P}(s_{goal}|\theta_i) \tag{6}$$

4. Experiments

4.1 Experimental Data Collection and Setup

To validate the effectiveness of the proposed Luojia Explorer system, we conducted a series of tests within our campus environment. The test scenario encompassed a variety of challenging features, including buildings, roads, vehicles, and open areas, with complex terrain that posed significant difficulties for multi-robot collaborative exploration and localization. The 3D reconstruction model of the scene, as shown in Figure 4, provides an accurate representation of the environmental complexity, which includes narrow passages and variations in terrain that are typical of real-world settings.

For the experiment, two robots were deployed, as illustrated in Figure 1. Each robot was equipped with essential sensors, including LiDAR and IMU, as well as communication devices and high-performance computing platforms for data processing. These sensors enabled the robots to perceive the environment, localize themselves, and perform real-time mapping. During the experimental setup, the robots were initially placed in close proximity at starting positions to begin autonomous exploration. The robots then autonomously navigated through the environment, collaborating with one another to explore and map the space efficiently.

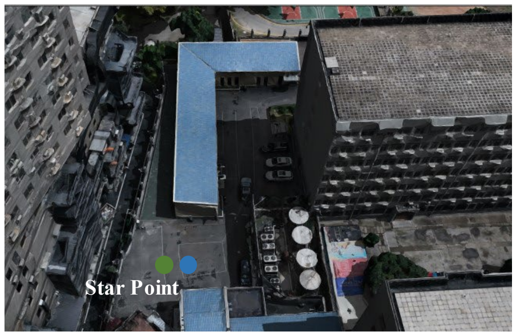


Figure 4. 3D model of the experimental scenario.

4.2 Results

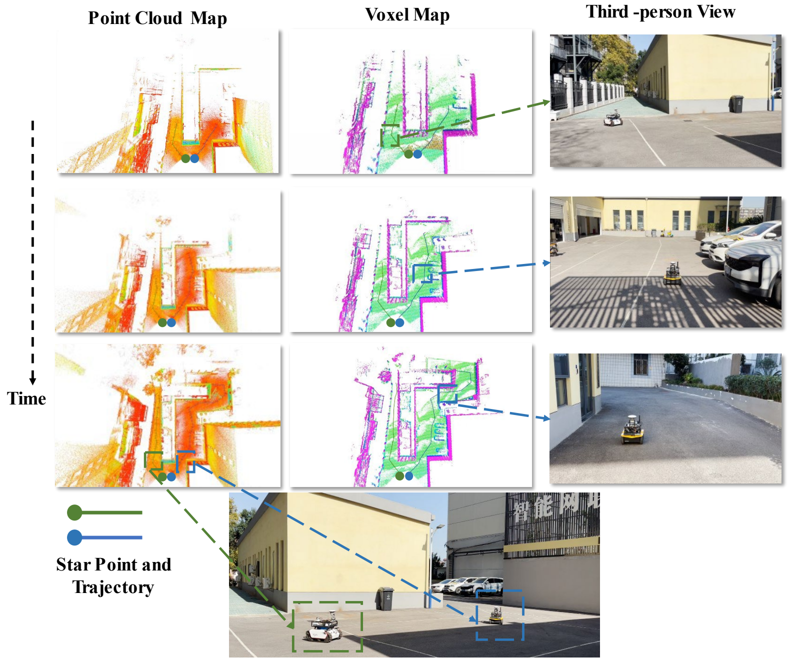
In the real-world experiment, our system successfully completes the autonomous exploration task within the campus environment. The experiment demonstrates that the two robots are able to autonomously choose different paths and explore distinct areas, achieving effective distributed cooperation. As shown in Figure 5, we present the robot exploration states at various time points, including point cloud maps, voxel maps, and third-person perspective exploration images. Over time, the area covered by the multi-robot autonomous exploration expands, ultimately leading to the successful completion of the exploration and the construction of the environment's 3D model. The system exhibits high adaptability, adjusting its exploration strategy in response to environmental changes.

In Figure 6, we present the final results of multi-robot collaborative mapping. As shown in Figure 6 (a), different color maps are used to represent the point cloud maps obtained by each robot. It is evident that the robots explore distinct areas, and the point clouds acquired by both robots are seamlessly integrated into the global frame, with no noticeable layering. Additionally, the global map is colored by Z-axis values, resulting in a uniform color distribution. A histogram of point count based on elevation is generated, with the majority of points distributed within the 0-10m range.

For the exploration task, we use exploration volume and path length as quantitative metrics. Exploration volume refers to the known volume in the voxel map with a resolution of 0.2m, while exploration efficiency represents the rate of increase in the explored volume. Path length effectively measures the quality of the exploration path, with the average path length representing the mean distance traveled by the two robots to complete the exploration. Our system completed the exploration and mapping of a 9557.09 m³ area in 250.45 s, with an average path length of 66.74 meters. The exploration efficiency reached 38.15 m³/s, demonstrating the system's high efficiency in large-scale spatial exploration, as shown in Figure 7. Compared to traditional single-robot exploration methods, the distributed collaborative strategy of this system significantly improves both task

https://doi.org/10.5194/isprs-archives-XLVIII-G-2025-269-2025 | © Author(s) 2025. CC BY 4.0 License.

completion efficiency and coverage, providing essential data support for digital twins.



Real-world scenario experiments

Figure 5: Real-world scenario autonomous exploration results

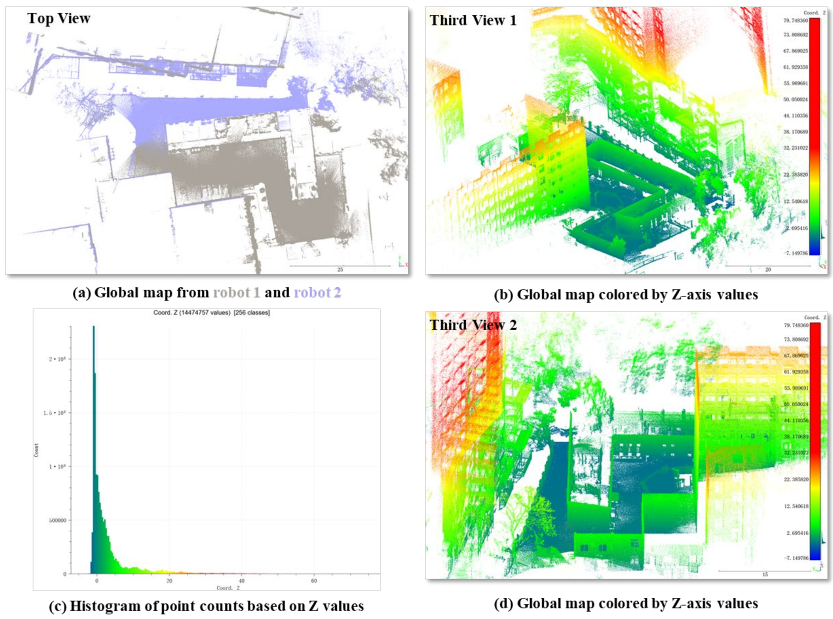


Figure 6: Multi-robot collaborative mapping results

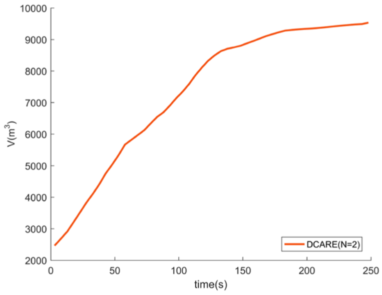


Figure 7: Exploration efficiency analysis

5. Conclusion

This paper presents the Luojia Explorer system, a multi-robot autonomous exploration and mapping system. The system enables multi-robot collaborative localization and mapping, as well as LiDAR-based collaborative exploration and planning in unknown spaces. Its effectiveness has been validated in campus scenarios, achieving an exploration efficiency of 38.15 m^3/s. Furthermore, the system provides critical data support for the development of digital twins in unknown environments. Future work will focus on optimizing the system's communication architecture to enhance overall performance.

Acknowledgements

This research was funded by the National Natural Science Foundation of China (No.U22A20568), the National Key RESEARCH and Development Program (No.2022YFB3904101), the Fundamental Research Funds for the Central Universities. This research was supported by LIESMARS Special Research Funding.

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