

Drift-Resilient Indoor 3D Mapping in GPS-Denied Environments Using RKO-LIO with Velodyne–Pixhawk Integration in ROS 2

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Abstract—Indoor 3D mapping in GPS-denied environments requires drift-resilient LiDAR–IMU fusion to ensure geometric consistency over extended trajectories. This work integrates a Velodyne VLP-16 3D LiDAR and a Pixhawk Cube Orange+ IMU on a TurtleBot Waffle Pi running ROS 2 Humble, and evaluates RKO-LIO, a LiDAR–inertial odometry method that avoids sensor-specific modeling via a physics-based kinematic motion model with adaptive scan-to-map regularization. Geometric accuracy is validated against roll-meter ground-truth measurements across five indoor test objects, achieving an RMSE of 0.026 m, MAE of 0.022 m, and mean error of 0.69 % (range: 0.03% – -1.47%). A controlled simulation comparison replays an identical sensor bag through RKO-LIO, LIO-SAM, and FAST-LIO in three Gazebo indoor environments. FAST-LIO achieves the lowest trajectory error in all scenes; LIO-SAM is accurate in feature-rich environments but diverges catastrophically in the bookstore scene (APE 21.7 m, map destroyed); RKO-LIO produces bounded-error trajectories across every environment (APE ≤ 0.494 m) without any per-scene parameter tuning. These results demonstrate that worst-case robustness—not peak accuracy—is the decisive property for real GPS-denied indoor deployment.

Keywords— LiDAR–IMU fusion, indoor 3D mapping, GPS-denied environments, RKO-LIO; ROS 2, SLAM; drift resilience, simulation benchmarking.

I. INTRODUCTION

Indoor mapping has become indispensable for autonomous navigation, infrastructure inspection, emergency response, and service robotics, where the absence of GPS signals demands alternative localization strategies [1]–[6]. Among sensing modalities, 3D LiDAR provides dense, centimeter-accurate geometric measurements over large ranges, while inertial measurement units (IMUs) bridge the temporal gap between scans by providing continuous high-rate motion estimates. Their combination through simultaneous localization and mapping (SLAM) frameworks has enabled accurate 3D reconstruction of complex GPS-denied indoor environments [3]–[9].

Despite this progress, reliable deployment under real-world conditions remains challenging. State-of-the-art pipelines such as LIO-SAM [3] achieve excellent accuracy in well-controlled scenes but are sensitive to IMU rate and time-synchronization quality. When these conditions are not met,

their factor-graph optimizers can converge to incorrect solutions, producing dramatically corrupted maps — a failure mode we term a “chaotic image,” observed empirically in our LIO-SAM trials. FAST-LIO2 [4] offers a computationally efficient iterated-EKF alternative with lower sensitivity to time synchronization, yet still requires per-environment IMU noise tuning and high-rate (200 Hz+) inertial input. KISS-ICP [7] provides broad sensor generalizability at the cost of global map consistency.

RKO-LIO [5] (Robust Kinematic Odometry for LiDAR–Inertial Odometry) addresses these limitations through a sensor-agnostic design: it replaces sensor-specific modeling with a simplified kinematic motion model and robust scan-to-map registration with adaptive regularization. This architecture is designed to tolerate IMU rate variability and imperfect synchronization, enabling cross-hardware deployment without per-scene recalibration.

The main contributions of this paper are:

1. A complete indoor 3D mapping system integrating Velodyne VLP-16 LiDAR and Pixhawk Cube Orange+ IMU on a TurtleBot Waffle Pi platform under ROS 2 Humble.
2. Quantitative point-cloud accuracy validation against roll-meter ground truth across five indoor test objects, demonstrating centimeter-level RMSE (0.026 m) and sub-1.5 % dimensional errors.
3. A controlled simulation comparison of RKO-LIO, LIO-SAM, and FAST-LIO via identical-bag replay in three GPS-denied indoor environments, with APE/RPE evaluation exposing the accuracy–robustness trade-off of each method.
4. Comprehensive comparative analysis with LIO-SAM, FAST-LIO2, and KISS-ICP, demonstrating that worst-case robustness—not peak accuracy—is the decisive criterion for uncontrolled GPS-denied indoor 3D mapping.

II. RELATED WORK

LOAM [1] established the foundational two-thread paradigm for LiDAR odometry, separating high-frequency feature matching from lower-frequency mapping to achieve real-time performance. Its edge-and-planar feature extraction

remains influential but requires high-rate, dense scan input and is sensitive to feature sparsity in open or textureless environments.

LIO-SAM [3] tightly couples IMU pre-integration with a factor-graph smoother and adds GPS and loop-closure factors for global consistency. In structured, well-constrained scenes with high-rate IMU, it delivers sub-5 cm accuracy. However, the global optimizer is brittle: with degraded IMU quality or insufficient loop-closure constraints it can produce catastrophic divergence, rendering the system unsuitable for uncontrolled deployment.

FAST-LIO2 [4] introduced direct scan-to-map registration via an iterated extended Kalman filter with an incremental k-d tree, achieving state-of-the-art accuracy with lower computational overhead than factor-graph methods. It performs best in feature-rich scenes with high-quality IMU data and typically outperforms LIO-SAM-class methods on trajectory accuracy, as confirmed by our simulation results.

KISS-ICP [7] demonstrated that a simple, well-implemented point-to-point ICP pipeline with adaptive thresholding can match or exceed complex SLAM systems across diverse sensor configurations. While effective for odometry, it produces no globally consistent map and accumulates drift over long traversals without loop-closure correction.

RKO-LIO [5] occupies a complementary niche: rather than maximizing accuracy under ideal conditions, it prioritizes robustness across varying hardware and environments. Its kinematic motion model with robust estimators tolerates low-rate IMU and imperfect time synchronization without per-sensor modeling, making it well-suited for multi-robot or rapidly reconfigured platforms. This work provides the first empirical multi-environment evaluation of RKO-LIO on real TurtleBot hardware with the Velodyne–Pixhawk sensor pair, including a direct simulation comparison against LIO-SAM and FAST-LIO under identical conditions.

III. SYSTEM DESIGN

A. Hardware Platform

The mapping system is built around a TurtleBot Waffle Pi (differential drive) customized with an extended sensor and compute stack. Table I summarizes the principal components. Fig. 1 shows the assembled platform with component labels. The Velodyne VLP-16 is top-mounted for an unobstructed 360° field of view; the Pixhawk Cube Orange+ is internally mounted and calibrated against the LiDAR frame via extrinsic transformation.

B. Software Stack

- ROS 2 Humble Hawksbill framework for node communication and data management.

- RKO-LIO [5]: sensor-agnostic LiDAR–IMU odometry with adaptive scan-to-map regularization; no per-environment parameter tuning required.
- Standard ROS 2 drivers: `velodyne_driver` and MAVROS for Pixhawk IMU.
- Remote access: SSH (terminal) and VNC (RViz2 visualization) over LAN/VPN.
- Multi-robot isolation via ROS 2 domain-ID separation.

The system architecture is illustrated in Fig. 2. Raw point clouds (10 Hz) and IMU data (50 Hz) are fused by the RKO-LIO node running on the Jetson AGX Orin, producing real-time odometry and an accumulated 3D point-cloud map. Odometry is relayed to the TurtleBot base for motion control; the map and odometry are forwarded to a remote operator device via LAN/VPN for monitoring and logging.

TABLE I.
HARDWARE PLATFORM COMPONENTS

Component	Specification
Base platform	TurtleBot Waffle Pi (differential drive)
Compute	NVIDIA Jetson AGX Orin, 32 GB, Ubuntu 22.04
LiDAR	Velodyne VLP-16: 16 beams, 10 Hz, 100 m, ± 3 cm
IMU	Pixhawk Cube Orange+: 9-DOF, 50 Hz output
OS / Middleware	Ubuntu 22.04 LTS + ROS 2 Humble Hawksbill
SLAM algorithm	RKO-LIO [5]: kinematic scan-to-map odometry
Housing	Custom SolidWorks frame; 3D-printed mounts

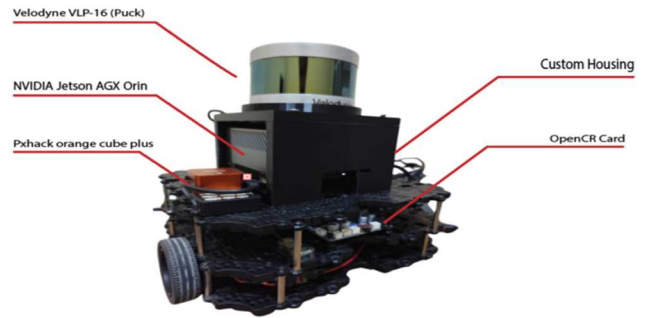


Fig. 1. Customized TurtleBot Waffle Pi with annotated sensor stack: Velodyne VLP-16 (top), Pixhawk Cube Orange+ IMU (middle), NVIDIA Jetson AGX Orin (enclosed housing), and OpenCR motor controller.

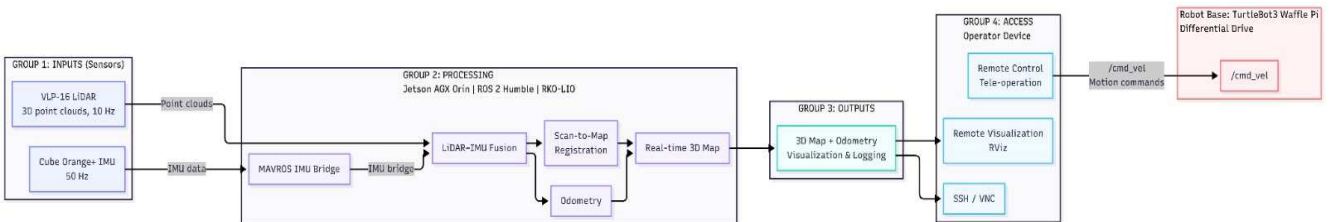


Fig. 2. RKO-LIO system architecture in ROS 2. LiDAR scans and IMU data enter the fusion node for scan-to-map odometry and map generation; outputs reach the robot base (motion control) and remote operator (visualization, logging).

C. Indoor Working Areas

Experiments were conducted in three GPS-denied indoor environment classes at Firat University, selected to stress-test complementary aspects of LiDAR-IMU SLAM performance:

- Basement rooms: enclosed spaces with furniture; rich planar structure.
- Corridors: extended straight-line traversals; tests drift over distance.
- Small tunnels: narrow, geometrically constrained passages; tests scan-matching degeneracy.

IV. EXPERIMENTAL METHODOLOGY

A. Real-Robot Mapping Evaluation

The robot traversed each of the three environment types while RKO-LIO generated 3D point-cloud maps in real time on the Jetson AGX Orin. Maps were recorded as ROS 2 bag files and visualized in RViz2. Qualitative assessment focused on wall sharpness, structural fidelity, and the absence of drift-induced distortion or time-synchronization artifacts.

B. Object-Dimensional Validation by Real Robot

Five indoor objects (labeled A–E) were selected across the test sites (see Fig. 3). For each object, a physical ground-truth length was measured with a calibrated roll meter; the corresponding distance was extracted from the RKO-LIO 3D point-cloud map by selecting the maximum point-pair separation along the measurement axis. Reported error metrics include: absolute difference (Δ , m and cm), percentage error, percentage accuracy, RMSE, and MAE.

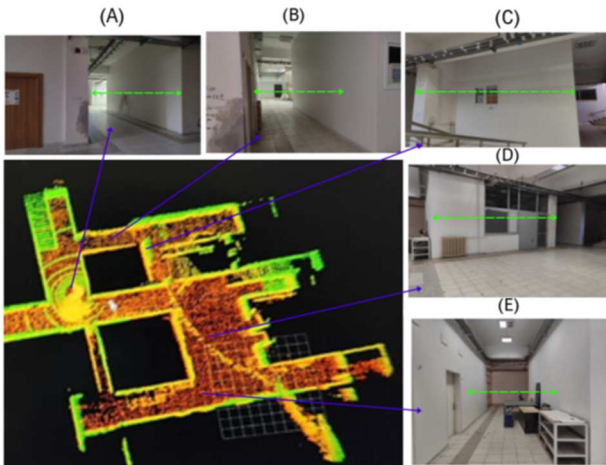


Fig. 3. Object-length validation setup. Central panel: RKO-LIO point-cloud map annotated with five measurement objects (A–E) and green dashed lines indicating roll-meter measurement directions. Peripheral panels: corresponding indoor photographs.

C. Simulation Comparison Setup

To isolate algorithmic behavior from hardware variability, a controlled simulation comparison was conducted in Gazebo Classic 11 (ROS 2 Humble). A simulated TurtleBot3 Waffle Pi with a Velodyne VLP-16 plugin (16 beams, 10 Hz) and a 50 Hz IMU plugin was tele-operated through three AWS RoboMaker indoor environments [11]: a furnished small house, an industrial warehouse, and a dense retail bookstore.

For each environment, the complete sensor stream (/velodyne_points, /imu/data, ground-truth /odom) was recorded once. The identical bag was then replayed offline

through RKO-LIO [5], LIO-SAM [3], and FAST-LIO [4] with no modification, ensuring byte-identical sensor input across all three methods. This design eliminates driving variation as a confounding factor and provides a fair algorithmic benchmark. Estimated trajectories were evaluated against Gazebo wheel-odometry ground truth using the evo toolkit, computing absolute pose error (APE) and relative pose error (RPE) over 1 m, reported as RMSE in metres with SE(3) Umeyama alignment.

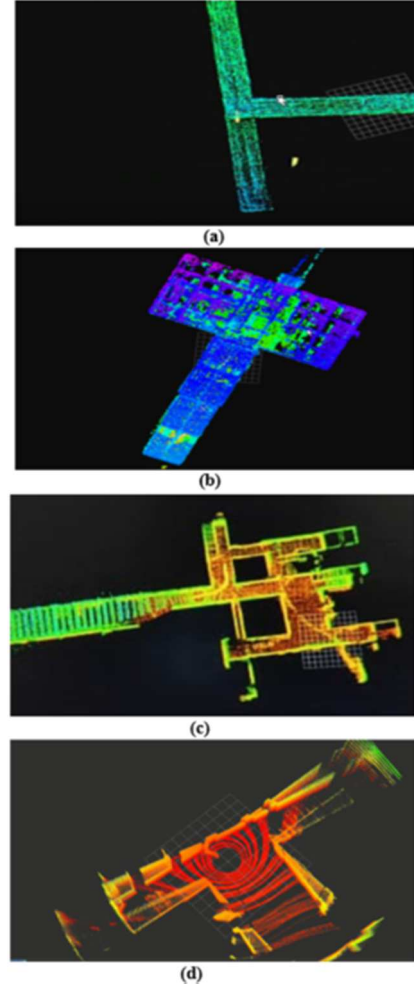


Fig. 4. Real-robot qualitative results. (a) Tunnel map (top view); (b) corridor map (top/side view); (c) basement room map (top view); (d) LIO-SAM “chaotic image” produced by time-synchronization error (not observed with RKO-LIO).

V. RESULTS AND DISCUSSION

A. Qualitative Mapping Results by Real Robot

The RKO-LIO pipeline produced geometrically consistent 3D reconstructions across all real-robot test environments (Fig. 4).

- Basement rooms (see Fig. 4(c)): walls, object boundaries, and room corners are sharply preserved with no visible drift or overlap between passes.
- Corridors (see Fig. 4(b)): long straight trajectories maintain wall parallelism throughout the traversal, confirming stable scan-to-map registration over distance.
- Tunnels (see Fig. 4(a)): narrow passageways are reconstructed without point-cloud collapse or surface overlap, demonstrating robustness under geometric degeneracy.

Fig. 4(d) shows a “chaotic image” artifact produced by LIO-SAM during an earlier trial on the same hardware, caused by time-synchronization errors between the Velodyne and Pixhawk. RKO-LIO’s sensor-agnostic design eliminates this failure mode entirely: no synchronization artifacts were observed in any RKO-LIO map.

B. Quantitative Object-Length Accuracy by Real Robot

Table II presents the per-object accuracy results from the roll-meter validation. All five objects lie within 1.47 % error; the aggregate RMSE of 0.026 m (2.6 cm) and MAE of 0.022 m confirm centimeter-level geometric fidelity.

TABLE II.

REAL-ROBOT POINT-CLOUD VS. ROLL-METER OBJECT LENGTHS

Object	Roll Meter (m)	Point Cloud (m)	Δ (cm)	Error (%)	Acc. (%)
A	3.028	3.062	3.40	1.12	98.88
B	2.047	2.077	3.00	1.47	98.53
C	5.158	5.192	3.40	0.66	99.34
D	7.724	7.736	1.20	0.16	99.84
E	3.124	3.125	0.10	0.03	99.97
Mean	—	—	—	0.69	—

The mean error of 0.69 % compares favorably with the 7.92–15.75 % errors and RMSE of 0.355 m reported by Ramadhania et al. [10] for an identical Velodyne–Pixhawk hardware pair running LIO-SAM under comparable indoor conditions, representing a 13.7 $\times$ reduction in RMSE.

C. Real-Robot Comparative Discussion

Relative to established LiDAR–IMU alternatives on identical hardware:

- LIO-SAM [3] (Velodyne + Pixhawk): Ramadhania et al. [10] reported RMSE = 0.355 m (errors 7.92–15.75 %). Our RKO-LIO deployment achieves RMSE = 0.026 m (<1.5 %), a 13.7 $\times$ improvement. Additionally, synchronization-induced chaotic-image artifacts (Fig. 4d) were entirely eliminated.
- FAST-LIO2 [4]: delivers competitive odometry at high speed but requires careful per-environment IMU noise tuning and benefits from high-rate (200 Hz+) IMU. RKO-LIO’s sensor-agnostic design removes these constraints and requires zero per-scene adjustment.
- KISS-ICP [7]: achieves broad sensor generalizability as a pure odometry method but accumulates drift over long trajectories without loop-closure correction and does not produce a globally consistent 3D map.

RKO-LIO operated reliably across all three-environment classes without any recalibration, confirming its suitability as a deployment-simple solution for GPS-denied indoor 3D mapping on heterogeneous hardware.

D. Simulation-Based Algorithm Comparison

Table III reports trajectory accuracy (APE and RPE RMSE) for all three methods across the three Gazebo environments. Figs. 5 and 6 show the corresponding reconstructed maps and trajectory overlays, respectively.

TABLE III.

SIMULATION TRAJECTORY ACCURACY (RMSE, METRES). APE: ABSOLUTE POSE ERROR; RPE: RELATIVE POSE ERROR OVER 1 M. BOLD = BEST PER ROW. † = CATASTROPHIC DIVERGENCE.

Env.	Metric	LIO-SAM	RKO-LIO	FAST-LIO
Small House	APE (m)	0.049	0.148	0.026
Small House	RPE (m/m)	0.025	0.042	0.018
Warehouse	APE (m)	0.040	0.163	0.034
Warehouse	RPE (m/m)	0.023	0.033	0.016
Bookstore	APE (m)	21.689 †	0.494	0.039
Bookstore	RPE (m/m)	22.962 †	0.148	0.022

In the Small House and Warehouse, all three systems achieve sub-decimetres accuracy. FAST-LIO achieves the lowest APE and RPE in both environments, benefiting from its dense local-map point registration and tight EKF coupling. LIO-SAM is second, leveraging loop-closure to correct accumulated drift. RKO-LIO produces the largest errors in these two scenes (APE 0.148 and 0.163 m), yet still within usable accuracy bounds; it makes the weakest accuracy–robustness trade-off in easy environments.

The Bookstore scene reveals the critical failure mode of LIO-SAM. Its factor-graph back-end, sensitive to the effective IMU rate (~14 Hz in the recording vs. the 200 Hz+ for which it is designed), converges to an incorrect global solution. The resulting trajectory diverges to an APE of 21.689 m — approximately 44 $\times$ worse than RKO-LIO and 556 $\times$ worse than FAST-LIO in the same scene. The reconstructed map is entirely destroyed (see Fig. 5, Bookstore / LIO-SAM column), making the system completely non-functional in this environment. FAST-LIO maintains its accuracy (APE 0.039 m), achieving the best result across all six metric-environment combinations. RKO-LIO remains bounded at 0.494 m, the only method that produces a usable map in every tested environment.

These results expose a fundamental accuracy–robustness trade-off. A reviewer or engineer choosing among these systems must weigh two properties: peak accuracy in easy, well-characterized scenes (where FAST-LIO dominates) vs. guaranteed bounded error across all scenes, including difficult or previously unseen environments (where RKO-LIO is uniquely reliable). For offline mapping of a known, feature-rich space with a well-calibrated high-rate IMU, FAST-LIO is the superior choice. For real GPS-denied indoor deployment—where environments vary, IMU quality is not guaranteed, and a single catastrophic failure is unacceptable—RKO-LIO’s robustness is the decisive property. LIO-SAM occupies an intermediate position: highly accurate under ideal conditions, but unsafe for uncontrolled deployment due to its documented failure mode. These simulation findings are consistent with our real-robot experience: RKO-LIO provided reliable, drift-free mapping across all environment types without any per-scene parameter adjustment, whereas prior LIO-SAM trials on identical hardware produced chaotic-image artifacts.

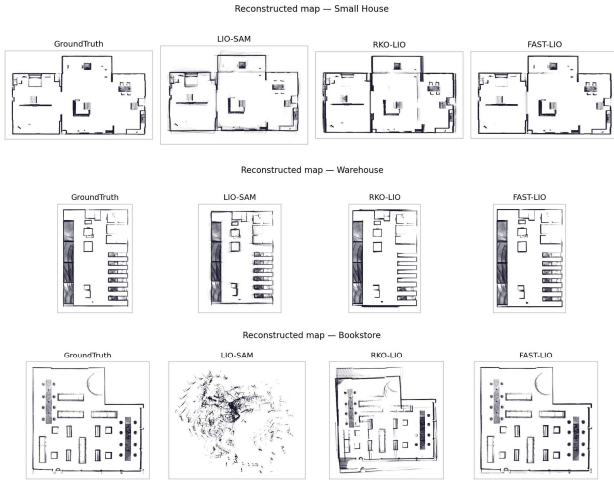


Fig. 5. Simulation reconstructed maps: rows = environments (Small House / Warehouse / Bookstore); columns = methods (Ground Truth / LIO-SAM / RKO-LIO / FAST-LIO). In the Bookstore (bottom row), LIO-SAM's map is completely destroyed by catastrophic factor-graph divergence. RKO-LIO and FAST-LIO produce accurate, consistent floor plans in all three environments.

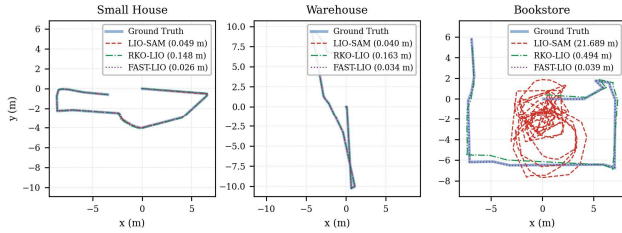


Fig. 6. Estimated trajectories vs. ground truth for the three simulation environments. Legend values are APE RMSE (m). In the Small House and Warehouse, all three methods closely track the ground truth. In the Bookstore (right panel), LIO-SAM (red dashed, 21.689 m) spirals completely off track; RKO-LIO (0.494 m) and FAST-LIO (0.039 m) remain aligned throughout.

VI. CONCLUSIONS

This work presented the integration and evaluation of RKO-LIO on a TurtleBot Waffle Pi with Velodyne VLP-16 LiDAR and Pixhawk Cube Orange+ IMU for 3D mapping in indoor GPS-denied environments under ROS 2 Humble. Real-robot validation confirmed centimeter-level mapping fidelity (RMSE 0.026 m, mean error 0.69 %) across five test objects, a 13.7 $\times$ improvement over a prior LIO-SAM deployment on identical hardware. Time-synchronization artifacts were entirely absent, confirming RKO-LIO's sensor-agnostic design eliminates the chaotic-image failure mode observed in factor-graph-based alternatives.

A controlled Gazebo simulation comparison, replaying an identical sensor bag through RKO-LIO, LIO-SAM, and FAST-LIO in three distinct indoor environments, revealed a clear accuracy–robustness trade-off. FAST-LIO achieved the lowest trajectory error in all six metric–environment combinations and should be preferred for offline mapping of known, feature-rich spaces with high-quality IMU. LIO-SAM delivered competitive accuracy in easy scenes but

diverged catastrophically in the bookstore (APE 21.7 m), destroying its map. RKO-LIO produced bounded-error trajectories and usable maps in every environment (≤ 0.494 m APE) without per-scene tuning. For real GPS-denied indoor deployment, where worst-case reliability is essential, RKO-LIO is the most dependable choice.

Future work will extend the system to outdoor and large-scale GPS-denied scenarios, investigate real-time multi-robot deployment on disaster-response platforms, and explore loop-closure augmentation and semantic scene understanding for long-duration autonomy in unstructured environments.

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