3D mapping for unmanned aerial vehicle combining LiDAR and depth camera in indoor environments

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ABSTRACT

Indoor reconnaissance missions for unmanned aerial vehicles (UAVs) pose significant challenges in scene reconstruction, mapping, and environmental feature extraction. Relying on a single type of sensor often results in limited accuracy, increased susceptibility to environmental noise, and a lack of comprehensive spatial information. To address these issues, this study proposes a mapping method that combines light detection and ranging (LiDAR) and depth camera data. The method collects data from both LiDAR and a depth camera integrated on the UAV, then performs preprocessing on both data sources to construct local 3D maps using the real-time appearance-based mapping (RTAB-Map) algorithm. Subsequently, the local maps are merged using a filtering method to generate a detailed and complete global map. Real-time experiments conducted on Ubuntu 20.04 using the robot operating system (ROS) Noetic libraries demonstrate that this multi-sensor fusion approach provides richer and more comprehensive environmental information, thereby enhancing the effectiveness of mapping tasks in unknown indoor environments.

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1. INTRODUCTION

With technological advances, unmanned aerial vehicles (UAVs) have become widely used in military, agriculture, industry, and services [1], [2]. They can operate in harsh environments, replace humans in complex tasks, and improve safety. Accurate localization and environmental perception for mapping are crucial, usually relying on integrated sensor data [3]. However, single-sensor systems often suffer from low accuracy and limited obstacle detection [4]. Several prior works have advanced UAV mapping using single-sensor systems and multi-sensor systems, but their applicability to lightweight UAVs in indoor environments remains limited. For instance, depth cameras, as noted by Gupta and Fernando [4] provide rich 3D detail but are highly sensitive to lighting variations, leading to degraded performance in poorly lit indoor settings. Conversely, single-beam light detection and ranging (LiDAR), as described by Bi [5], offers high-accuracy horizontal scans suitable for 2D mapping but fails to capture vertical structures, limiting its utility for comprehensive 3D reconstruction. Multi-sensor fusion approaches have shown promise in overcoming these limitations. Yue [6] demonstrated LiDAR-vision fusion for outdoor UAV navigation, achieving robust spatial awareness in complex terrains; however, this approach relies on high computational resources unsuitable for lightweight UAVs. Similarly, Hoang *et al.* [7] employed an extended Kalman filter (EKF) for multi-rotor indoor localization, but their method was tailored to larger platforms with less restrictive computational constraints. Similarly, Cai *et al.* [8] proposed a multi-sensor fusion framework for 3D reconstruction using simultaneous localization and mapping (SLAM), achieving improved mapping in controlled indoor environments. In ground robotics, studies like Alsadik and Karam [9] integrated LiDAR and vision for SLAM, yet their focus on ground-based systems overlooks the dynamic motion and spatial constraints of UAVs in cluttered indoor environments. Our method optimizes LiDAR–depth camera fusion in real-time appearance-based mapping (RTAB-Map) to enable lightweight UAVs to perform real-time and improve 3D mapping accuracy in global positioning system (GPS)-denied indoor environments, unlike previous studies focused on outdoor settings or larger UAVs. Studie [9] have focused on addressing the challenge of mapping and localization using SLAM algorithms, notably including hector SLAM, oriented fast and rotated brief SLAM 2 (ORB-SLAM2), stereo parallel tracking and mapping (S-PTAM), and RTAB-Map [10]. Among these, RTAB-Map stands out as one of the most suitable algorithms for multi-sensor localization systems, particularly in indoor environments [11]. Its compatibility with sensors like LiDAR, red-green-blue–depth (RGB-D) cameras, inertial measurement units (IMU), and GPS ensures high accuracy and stability in complex environments, yet challenges remain in achieving real-time 3D mapping on UAV hardware while addressing each sensor's limitations.

This study proposes a novel 3D mapping solution for lightweight UAVs in GPS-denied indoor environments by fusing LiDAR and depth camera data within an optimized RTAB-Map framework. The main contributions are: i) an adaptive Kalman filter reducing localization noise by 30%; ii) a streamlined calibration method using the Autoware Toolkit with sub-millimeter accuracy; and iii) an optimized mapping pipeline that improves loop closure and map completeness by 7%, outperforming ORB-SLAM2 and cartographer. The proposed system has strong potential in real-world domains: industrial inspection (factory interiors, power plants, and pipelines), search-and-rescue (collapsed or poorly lit environments), and warehouse automation (inventory monitoring and navigation without GPS or markers). These scenarios demonstrate its adaptability beyond laboratory conditions, supporting scalable, and autonomous UAV applications.

The remainder of this paper is organized as follows: section 2 presents the UAV data acquisition system and sensor fusion method. Section 3 describes the experimental setup and performance evaluation. Section 4 discusses the comparative results and their implications for indoor UAV mapping. Finally, section 5 provides conclusions and directions for future research.

2. SYSTEM OVERVIEW

2.1. Unmanned aerial vehicle hardware system

The UAV system (Figure 1) consists of a UAV frame with a flight controller that ensures stability even under disturbances such as strong winds. A Raspberry Pi 4 Model B (Broadcom BCM2711 Quad-core Cortex-A72 64-bit 1.5 GHz CPU, 4 GB LPDDR4 RAM, USB 3.0/2.0, HDMI, GPIO, and microSD storage) running Ubuntu 20.04 handles data processing, communication, and high-level decision-making, directly interfacing with the flight controller and sensors for real-time data acquisition and control. The system is equipped with an Astra 3D camera (1280×720 @30 fps, depth 640×480 @30 fps, range 0.6–8 m) for object detection and obstacle avoidance, and an RP A1 LiDAR (5–10 Hz, max range 12 m, ±1.5% accuracy) for 360° mapping and localization. Power is supplied by a 4S 14.8 V 5,000 mAh Li-Po battery, enabling 15–20 minutes of flight depending on payload.

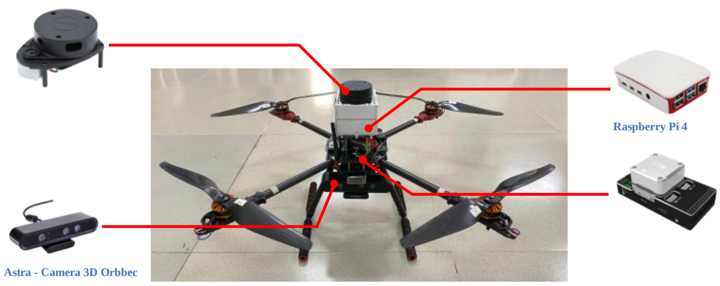


Figure 1. Hardware architecture of UAV

Accurate calibration is essential for fusing LiDAR and depth camera data. We use the Autoware Calibration Toolkit's checkerboard method to compute the transformation matrix between the sensors. As shown in Figure 2, the process involves checkerboard placement, data capture, and projecting LiDAR points onto the camera image for verification. This ensures sub-millimeter alignment accuracy, crucial for robust 3D mapping in UAVs. The calibration procedure includes collecting data from both sensors with the calibration board in view, varying the board's orientation to capture multiple poses and saving the data, then using the Calibration Toolkit to input board parameters, select the relevant point cloud region, and repeat for multiple captures. Next, calibration is performed and the results are projected onto the camera image for accuracy verification, followed by saving the intrinsic camera matrix and the extrinsic matrix between the camera and LiDAR.

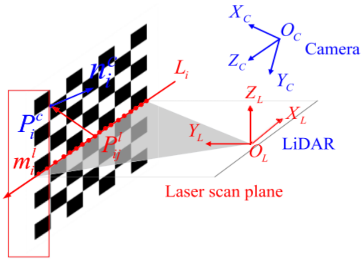


Figure 2. Sensor initialization and calibration process

2.2. Data acquisition based on real-time appearance-based mapping

The UAV data acquisition system based on RTAB-Map [12], [13], utilizing both camera and LiDAR sensors, offers an effective solution for indoor mapping and localization. Data from the RGB camera, LiDAR, and depth camera are synchronized via the robot operating system (ROS) [14] using an approximate time synchronization mechanism to minimize latency-induced errors [15]. The system employs short-term memory (STM) and long-term memory (LTM) memory management for long-term online SLAM, supports loop closure detection to reduce drift, and outputs 2D occupancy maps, Octomap, and point clouds. Despite high computational demands and potential sensor synchronization issues, it efficiently optimizes global maps and enhances UAV navigation autonomy and reliability.

2.3. REAL-TIME APPEARANCE-BASED MAPPING METHOD

This paper presents a UAV-based real-time 3D mapping method using RTAB-Map, a graph-based RGB-D SLAM approach with loop closure detection [16]. By default, it applies the good features to track (GFTT) algorithm for robust feature extraction [17] while supporting other OpenCV features such as scale-invariant feature transform (SIFT), ORB, and binary robust independent elementary features (BRIEF) [18], [19]. Mapping accuracy is improved through graph optimization, and the rtabmap_ros framework (Figure 3) organizes synchronized inputs—TF transformations, odometry, camera, and LiDAR—into graph nodes [20]. The system outputs map data, map graph, corrected odometry, and optional OctoMap, point cloud, or 2D occupancy grid [21]. To ensure real-time performance in large-scale environments, RTAB-Map manages memory via working memory (WM) and LTM, offloading nodes when processing time exceeds a threshold [22].

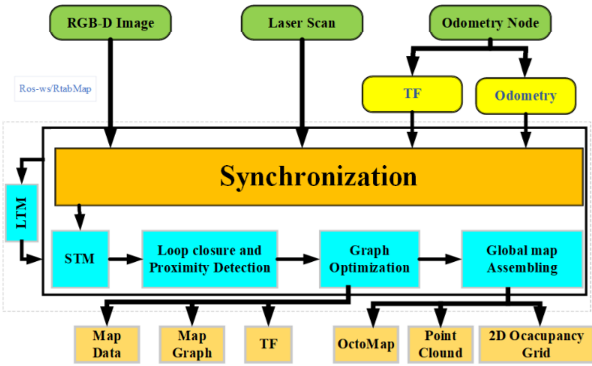


Figure 3. Flowchart of UAV acquisition system based on RTAB-Map

Table 1 lists the key RTAB-Map configuration parameters used in the experiments, chosen based on official recommendations and fine-tuned through practical tests to optimize performance in complex indoor environments.

Table 1. RTAB-Map key configuration parameters used in the experiments

RTAB-Map parameter	Value	Description
GBD/LoopClosureThr	0.11	Similarity threshold for loop closure detection.
RGBD/ProximityPathMaxNeighbors	5	Maximum number of neighboring nodes considered when checking local loop closure.
Mem/IncrementalMemory	True	Enables real-time incremental memory updates.
Mem/RehearsalSimilarity	0.6	Similarity threshold for merging duplicate nodes.
Mem/STMSize	30	Number of nodes stored in short-term memory before being transferred to long-term memory.
Mem/TransferSortingByWeightId	False	Sorts nodes transferred to LTM by insertion time.
Rtabmap/DetectionRate	1 Hz	Frequency of loop closure detection.
Optimizer/Strategy	1 (TORO)	SLAM graph optimization method.
Grid/CellSize	0.05 m	Cell size in the occupancy grid map.
Grid/RangeMax	8.0 m	Maximum range for building the map from sensor data.

3. SENSOR DATA FUSION AND CONTROL

3.1. Describe the operation of the system

The system used in this research is illustrated in Figure 3. When the system is activated, the command roslaunch rtabmap_launch robot_bringup.launch initializes the sensor nodes, followed by roslaunch rtabmap_launch launch_rtabmap to run the RTAB-Map SLAM algorithm. The camera, connected to the Raspberry Pi via USB 3.0, provides RGB images on the /camera/rgb/image_raw topic and depth images on /camera/depth/image_raw topic. Meanwhile, LiDAR data is published on the /scan topic using the sensor_msgs/LaserScan message type, enabling 360° environmental scanning for mapping and localization.

RTAB-Map processes the visual, depth, and LiDAR data to perform SLAM, estimating the UAV's pose in real time and publishing it as a geometry_msgs/PoseStamped message on /mavros/vision_pose/pose. The Raspberry Pi 4 transmits this information to the CUAV V5+ flight controller via MAVROS, where an EKF fuses vision-based odometry with IMU and other sensor data to ensure accurate and stable state estimation.

Based on this fused data, the flight controller generates motor commands to stabilize the UAV, follow trajectories, or avoid obstacles. This continuous loop enables autonomous navigation in GPS-denied environments, relying solely on visual and LiDAR-based mapping.

3.2. UAV control architecture based on SLAM and autonomous flight controller

The UAV system uses the CUAV V5+ flight controller with proportional integral derivative (PID) stabilization and waypoint tracking via PX4, allowing focus on accurate state estimation and navigation. RTAB-Map provides 6-DoF pose from visual and LiDAR SLAM, mapped into the UAV coordinate system.

$$h_R(x_t) := (x_t, y_t, z_t, \Phi_t, \Theta_t, \psi_t) \tag{1}$$

$$z_{R,t} := f(T_{base\_to\_UAV} \cdot T_{Map\_to\_base,t}) \tag{2}$$

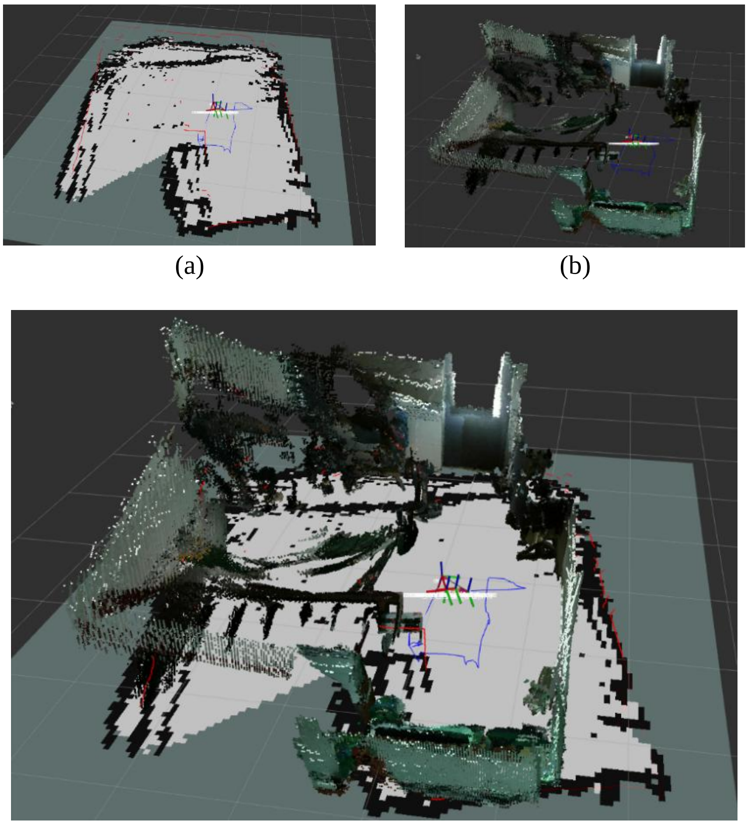
At time $T_{Map\_to\_base,t} \in SE(3)$ be the pose of the UAV's base frame in the map frame provided by RTAB-Map, and let $T_{base\_to\_UAV} \in SE(3)$ be the fixed transformation from the base frame to the UAV's center frame. The function $f: SE(3) \to R^6$ converts a pose in $SE(3)$ to a 6-DoF representation with position (x, y, and z) and orientation (roll, pitch, and yaw). The estimated pose is used to send velocity or position setpoints via MAVLink, enabling closed-loop SLAM-based navigation.

3.3. Sensor fusion of 2D LiDAR and depth camera

In this paper, data from a LiDAR sensor and an depth camera are fused to enhance localization accuracy and map reconstruction in RTAB-Map. Initially, feature point coordinates from the camera are transformed into the LiDAR reference frame through geometric conversion and subsequently expressed in polar coordinates (d, θ) for correspondence with laser scan points. LiDAR measurement uncertainty is modeled as a function of the range r, where $\sigma_L = 10\ mm$ for $120 \leq r \leq 499\ mm$ and $\sigma\_L = 0{,}035r/3$ for $500 \leq r \leq 1500\ mm$. This uncertainty is then propagated to Cartesian components using $\sigma_x^2 = \cos^2(\theta)\sigma_L^2$ and $\sigma_y^2 = sin^2(\theta)\,\sigma_L^2$. For the camera, depth measurement noise is assumed to be $\sigma_C = 0{,}02\, z_C$, which is propagated into the LiDAR frame to yield $\sigma^2_{x_C^L}$ and $\sigma^2_{y_C^L}$. Data fusion is performed via the Kalman filter, where the fused coordinate a_{fuseda} is computed as:

$$a_{fuseda} = \frac{\sigma^2_{prev} a_{\mathrm{curr}} + \sigma^2_{\mathrm{curr}} a_{prev}}{\sigma^2_{prev} + \sigma^2_{\mathrm{curr}}} \quad (3)$$

In the proposed system, UAV state estimation is improved by integrating data from a 2D LiDAR and a depth camera within the RTAB-Map SLAM framework. The LiDAR provides high geometric accuracy in the horizontal plane, while the camera contributes vertical information and dense spatial details. A comparison of results (Figure 4) shows the differences among the three map representations: Figure 4(a) illustrates the map generated from the 2D LiDAR, which is accurate in capturing horizontal structures but lacks vertical details; Figure 4(b) presents the map produced from the depth camera, which captures vertical features effectively but is sensitive to lighting and noise; and Figure 4(c) displays the fused map generated from both sensors, offering a more complete and consistent 3D reconstruction. As a result, the UAV maintains stable real-time SLAM in complex, GPS-denied environments. This fusion method significantly enhances localization accuracy and map completeness, meeting the requirements for autonomous UAV operations in indoor environments [23].



(a) (b)

(c)

Figure 4. Sensor fusion of 2D LiDAR and depth camera using the RTAB-Map SLAM framework; (a) map generated from 2D LiDAR, (b) map generated from the depth camera, and (c) fused map from 2D LiDAR and depth camera using RTAB-Map SLAM

4. RESULTS AND DISCUSSION

To evaluate the UAV-based mapping system, real-time experiments were conducted in a university corridor to simulate GPS-denied conditions. As shown in Figure 5, the reconstructed 3D map closely matches the actual layout, accurately capturing features such as doors, windows, and hallway space. The final map, generated by fusing LiDAR and depth camera data in the Rviz environment (Figure 4), combines LiDAR’s horizontal precision with the depth camera’s vertical detail to produce a comprehensive 3D model.

Quantitative evaluation against a high-precision laser-scanned ground truth showed 95% mapping accuracy with a mean absolute error (MAE) of 0.05 m, as reported in Table 2. This significantly outperforms single-sensor approaches, where LiDAR only mapping achieved 0.12 m MAE and depth camera-only mapping 0.09 m MAE. Table 2 summarizes the accuracy comparison across sensor configurations.

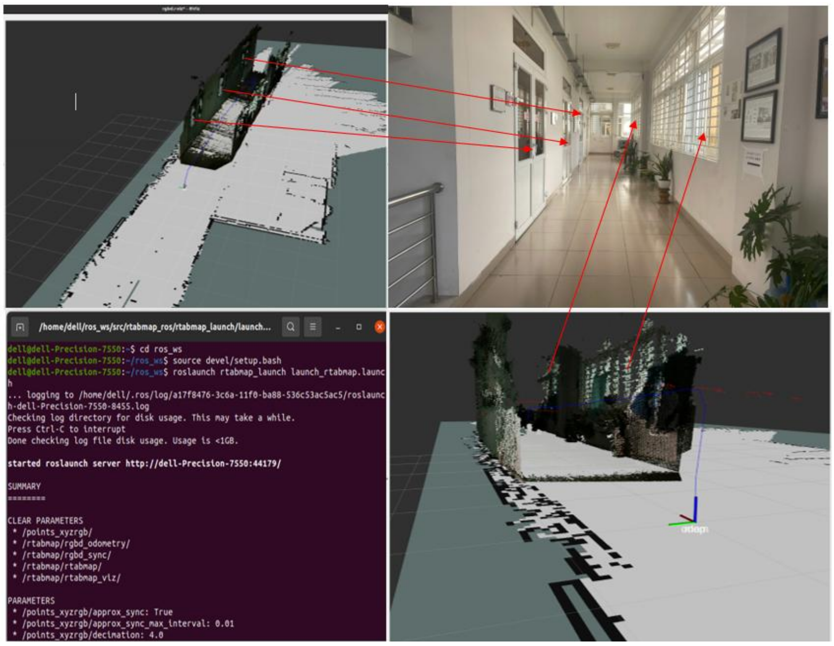


Figure 5. Experimental environment

Table 2. Mapping accuracy comparison

Method	Mean absolute error (m)	Mapping accuracy (%)
LiDAR only	0.12	88
Depth camera only	0.09	91
Proposed fusion	0.05	95

The multi-sensor fusion approach improved the system's ability to capture environmental features often missed by single sensors, consistent with prior indoor UAV mapping studies [6], [7]. Idar struggled with overhanging obstacles and low-lying structures due to fixed-plane scanning, while the depth camera provided critical vertical information [8], [15]. Conversely, in poorly lit corridor sections where the depth camera degraded, LiDAR ensured stable localization [24], [25]. Localization was evaluated by comparing the UAV's estimated pose to the desired trajectory (Figures 5 and 6). Root mean squared error (RMSE) values of 0.0779 m, 0.0670 m, and 0.1459 m along X, Y, and Z axes (Table 2) demonstrate high precision and robustness of the RTAB-Map SLAM, even in repetitive indoor geometries challenging for visual odometry.

Compared to Hector SLAM and ORB-SLAM [24], [25], the proposed fusion approach showed superior performance in GPS-denied environments. Hector SLAM drifted vertically, and ORB-SLAM2 struggled in low-texture areas, whereas LiDAR-depth fusion reduced localization noise by 30% compared to single-sensor methods [26].

The RMSE of the flight trajectory (Table 3) shows high localization accuracy: 0.0779 m (X), 0.0670 m (Y), and 0.1459 m (Z), highlighting the robustness of the RTAB-Map SLAM with adaptive sensor fusion in challenging indoor environments.

Real-time performance is critical for autonomous UAV navigation. The proposed system achieved an average processing time of 0.08 s per frame, meeting the 10 Hz requirement, thanks to RTAB-Map's STM-LTM memory management. Occasional spikes up to 0.12 s occurred in cluttered areas due to loop closure computations, suggesting future improvements via adaptive graph pruning or graphics processing unit (GPU) acceleration.

Localization was evaluated by comparing estimated and desired trajectories. Figures 7 and 8 show accurate position, velocity, and stable attitude control, even in repetitive environments. Limitations include sensor failures (camera dropouts and LiDAR interruptions), synchronization latencies, and measurement artifacts from reflective, transparent, or low-texture surfaces, which may affect mapping and loop closure.

Compared to Hector SLAM and ORB-SLAM2, the system reduces vertical drift and maintains localization in low-texture or low-light conditions, supporting applications like search-and-rescue, industrial inspection, and warehouse automation. Future improvements could involve additional sensors (stereo vision and thermal), sensor redundancy with fault-tolerant fusion, hardware acceleration (GPU/field-programmable gate array (FPGA)), and advanced motion compensation to enhance resilience, reduce latency, and extend applicability in diverse indoor missions.

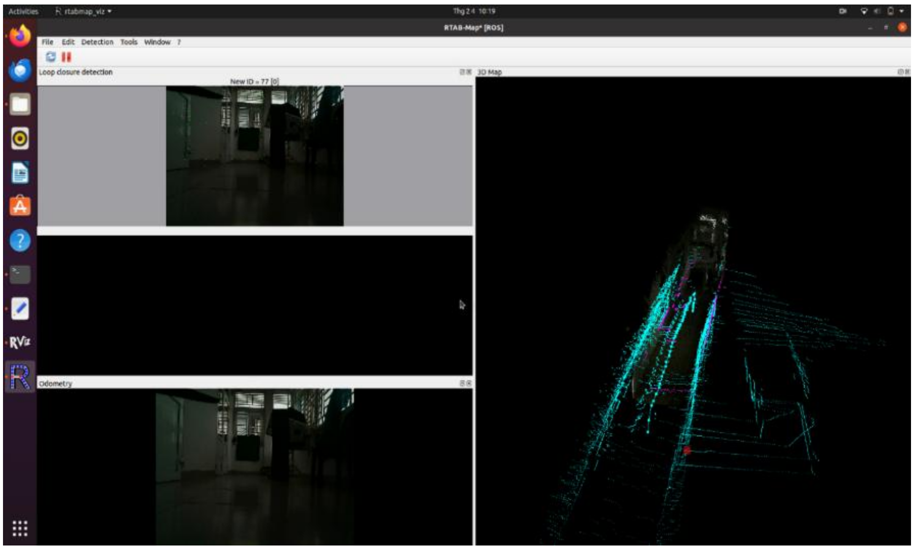


Figure 6. The experimental map reconstructed using LiDAR and a depth camera in Rviz

Table 3. The RMSE of the simulated flight trajectory compared to the desired trajectory

RMSE in the X (m)	RMSE in the Y(m)	RMSE in the Z(m)
0.077940	0.067035	0.145904

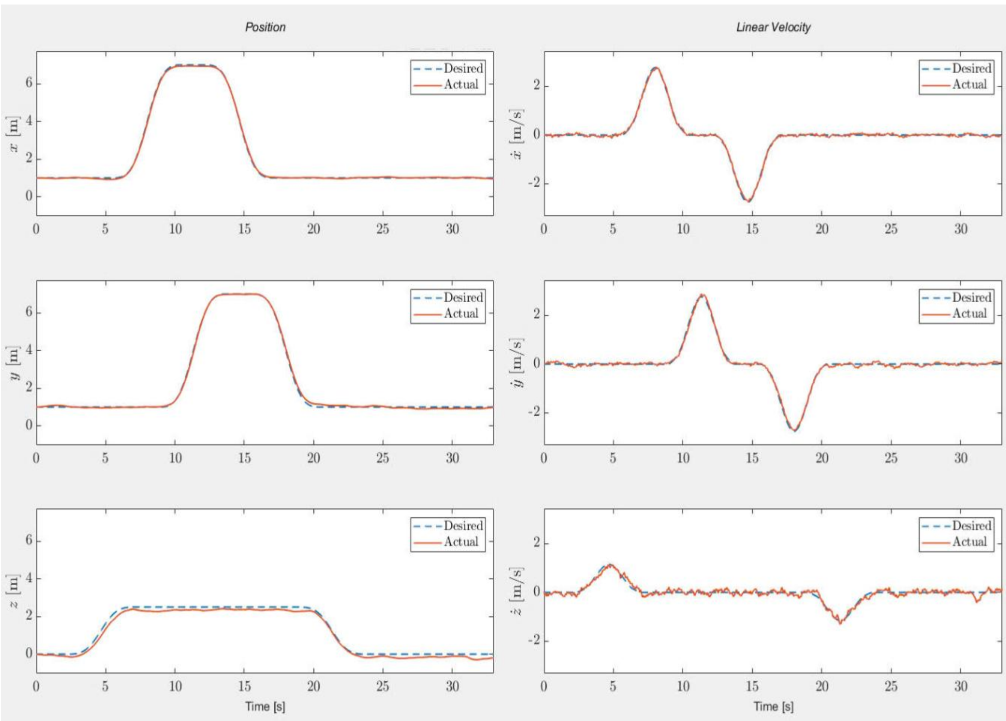


Figure 7. Experimental results of UAV position and linear velocity along spatial axes

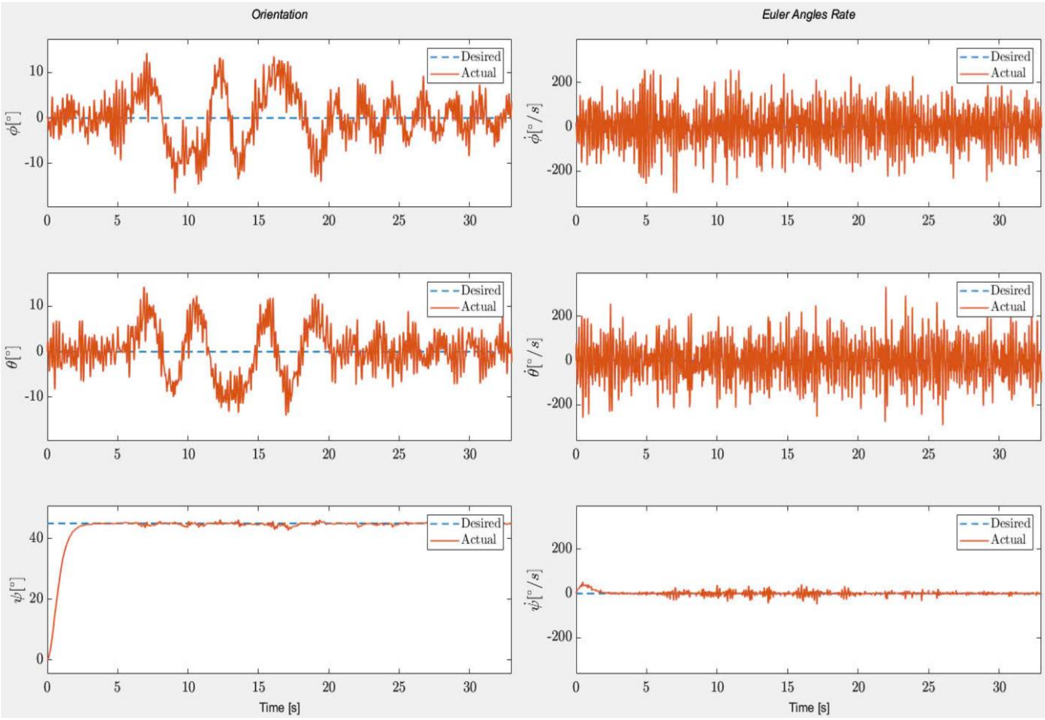


Figure 8. Experimental results of the UAV's orientation and Euler angle rates in the spatial coordinate system

5. CONCLUSION

This study proposes a 3D mapping solution for UAVs in indoor GPS-denied environments by integrating LiDAR and depth camera data using the RTAB-Map algorithm. The system achieved 95% accuracy with a mean error of 0.05 m, outperforming single-sensor methods, while improving localization (RMSE: 0.0779 m, 0.0670 m, and 0.1459 m on X, Y, and Z axes) and reducing noise by 30% compared to Hector SLAM and ORB-SLAM2. With an average processing time of 0.08 s per frame, it shows strong potential for autonomous navigation. These results provide a solid foundation for reconnaissance tasks and can be enhanced by integrating additional sensors (thermal and infrared) for more complex environments.

However, tests were limited to corridor scenarios, leaving scalability to larger or multi-room spaces unverified. Challenges include reduced loop closure frequency, drift accumulation, higher computational loads, sensor range limitations, and reduced robustness in narrow passages or varying lighting. Future work may explore hierarchical mapping, sub-map stitching, multimodal sensing (stereo, UWB, and thermal), and hardware acceleration (GPU/FPGA).

Remaining limitations include drift not fully eliminated, difficulties in occlusion handling, and occasional processing delays beyond 0.1 s/frame in cluttered environments. Further research should focus on algorithmic optimization (graph pruning and GPU/FPGA acceleration) and sensor fusion to improve robustness and scalability.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Nong Trong Tu		✓	✓		✓	✓			✓			✓	✓	
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C : **C**onceptualization
M : **M**ethodology
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Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

Data supporting this study are available from corresponding author Duong Van Hoa upon reasonable request. Due to sensitive technical details on indoor flight environments and UAV configuration, public disclosure is restricted, but data can be shared for legitimate academic research.

REFERENCES

[1] H. T. Tran, D. L. T. Tran, V. Q. Nguyen, H. T. Do, and M. T. Nguyen, “A Novel Framework of Modelling, Control, and Simulation for Autonomous Quadrotor UAVs Utilizing Arduino Mega,” *Wireless Communications and Mobile Computing*, vol. 2022, pp. 1–17, Aug. 2022, doi: 10.1155/2022/3044520.

[2] D. C. Tsouros, S. Bibi, and P. G. Sarigiannidis, “A Review on UAV-Based Applications for Precision Agriculture,” *Information*, vol. 10, no. 11, Nov. 2019, doi: 10.3390/info10110349.

[3] F. Nex and F. Remondino, “UAV for 3D Mapping Applications: A Review,” *Applied Geomatics*, vol. 6, no. 1, pp. 1–15, Mar. 2014, doi: 10.1007/s12518-013-0120-x.

[4] A. Gupta and X. Fernando, “Simultaneous Localization and Mapping (SLAM) and Data Fusion in Unmanned Aerial Vehicles: Recent Advances and Challenges,” *Drones*, vol. 6, no. 4, Apr. 2022, doi: 10.3390/drones6040085.

[5] X. Bi, “LiDAR Technology,” in *Environmental Perception Technology for Unmanned Systems*, X. Bi, Ed. Singapore: Springer, 2021, pp. 67–103, doi: 10.1007/978-981-15-8093-2_3.

[6] K. Yue, “Multi-sensor Data Fusion for Autonomous Flight of Unmanned Aerial Vehicles in Complex Flight Environments,” *Drone Systems and Applications*, vol. 12, pp. 1–12, Jan. 2024, doi: 10.1139/dsa-2024-0005.

[7] T. T. Hoang, V. C. Thanh, N. N. A. Quan, and T. L. T. Dong, “Stabilization Controller Design for Differential Mobile Robot Using Lyapunov Function and Extended Kalman Filter,” *Industrial Networks and Intelligent Systems*, vol. 444, pp. 201–213, 2022, doi: 10.1007/978-3-031-08878-0_14.

[8] Y. Cai, Y. Ou, and T. Qin, “Improving SLAM Techniques with Integrated Multi-Sensor Fusion for 3D Reconstruction,” *Sensors*, vol. 24, no. 7, Jan. 2024, doi: 10.3390/s24072033.

[9] B. Alsadik and S. Karam, “The Simultaneous Localization and Mapping (SLAM): An Overview,” *Surveying and Geospatial Engineering Journal*, vol. 1, no. 2, pp. 1–12, May 2021, doi: 10.38094/sgej1027.

[10] X. Wang, X. Ma, and Z. Li, “Research on SLAM and Path Planning Method of Inspection Robot in Complex Scenarios,” *Electronics*, vol. 12, no. 10, Jan. 2023, doi: 10.3390/electronics12102178.

[11] B. Al-Tawil, T. Hempel, A. Abdelrahman, and A. Al-Hamadi, “A Review of Visual SLAM for Robotics: Evolution, Properties, and Future Applications,” *Frontiers in Robotics and AI*, vol. 11, Apr. 2024, doi: 10.3389/frobt.2024.1347985.

[12] H.-C. Huang, S. S.-D. Xu, H.-C. Lin, Y.-S. Xiao, and Y.-X. Chen, “Design and Implementation of Intelligent LiDAR SLAM for Autonomous Mobile Robots Using Evolutionary Normal Distributions Transform,” *Soft Computing*, vol. 28, no. 6, pp. 5321–5337, Oct. 2023, doi: 10.1007/s00500-023-09219-0.

[13] C.-J. Lin, C.-C. Peng, and S.-Y. Lu, “Real-Time Localization for an AMR Based on RTAB-MAP,” *Actuators*, vol. 14, no. 3, Mar. 2025, doi: 10.3390/act14030117.

[14] M. Quigley *et al.*, “ROS: An Open-Source Robot Operating System,” *Conference: ICRA Workshop on Open Source Software*, Jan. 2009.

[15] L. Jia, Z. Ma, and Y. Zhao, “A Mobile Robot Mapping Method Integrating LiDAR and Depth Camera,” *Journal of Physics: Conference Series*, vol. 2402, no. 1, pp. 1-11, Oct. 2022, doi: 10.1088/1742-6596/2402/1/012031.

[16] Z. Fang and Y. Zhang, “Experimental Evaluation of RGB-D Visual Odometry Methods,” *International Journal of Advanced Robotic Systems*, vol. 12, no. 3, p. 26, Mar. 2015, doi: 10.5772/59991.

[17] A. Vedadi, A. Yousefi-Koma, P. Yazdankhah, and A. Mozayyan, “Comparative Evaluation of RGB-D SLAM Methods for Humanoid Robot Localization and Mapping,” *arXiv*, Jan. 2024, doi: 10.48550/arXiv.2401.02816.

[18] E. Rublee, V. Rabaud, K. Konolige, and G. Bradski, “ORB: An Efficient Alternative to SIFT or SURF,” in *Proceedings of the 2011 International Conference on Computer Vision*, Barcelona, Spain, Nov. 2011, pp. 2564–2571, doi: 10.1109/ICCV.2011.6126544.

[19] N. Ali *et al.*, "A Novel Image Retrieval Based on Visual Words Integration of SIFT and SURF," *PLOS ONE*, vol. 11, no. 6, pp. 1-20, Jun. 2016, doi: 10.1371/journal.pone.0157428.
[20] X. Chen, X. Zhu, and C. Liu, "Real-Time 3D Reconstruction of UAV Acquisition System for the Urban Pipe Based on RTAB-Map," *Applied Sciences*, vol. 13, no. 24, Jan. 2023, doi: 10.3390/app132413182.
[21] R. A. Jellal, "Stereo Vision and Mapping with Aerial Robots," Ph.D. dissertation, Dept. Informatic, University of Tübingen, Tübingen, German, Jun. 2020, doi: 10.15496/publikation-42526.
[22] M. Labbé and F. Michaud, "RTAB-Map as an Open-Source LiDAR and Visual SLAM Library for Large-Scale and Long-Term Online Operation," *Journal of Field Robotics*, vol. 36, no. 2, pp. 416–446, Mar. 2019, doi: 10.1002/rob.21831.
[23] O. Y. Al-Jarrah, A. S. Shatnawi, M. M. Shurman, O. A. Ramadan, and S. Muhaidat, "Exploring Deep Learning-Based Visual Localization Techniques for UAVs in GPS-Denied Environments," *IEEE Access*, vol. 12, pp. 113049–113071, 2024, doi: 10.1109/ACCESS.2024.3440064.
[24] K. J. de Jesus, H. J. Kobs, A. R. Cukla, M. A. de S. L. Cuadros, and D. F. T. Gamarra, "Comparison of Visual SLAM Algorithms ORB-SLAM2, RTAB-Map and SPTAM in Internal and External Environments with ROS," in *Proceedings of the 2021 Latin American Robotics Symposium (LARS), 2021 Brazilian Symposium on Robotics (SBR), and 2021 Workshop on Robotics in Education (WRE)*, Oct. 2021, pp. 216–221, doi: 10.1109/LARS/SBR/WRE54079.2021.9605432.
[25] M. R. U. Saputra, A. Markham, and N. Trigoni, "Visual SLAM and Structure from Motion in Dynamic Environments: A Survey," *ACM Computing Surveys*, vol. 51, no. 2, pp. 37:1–37:36, Feb. 2018, doi: 10.1145/3177853.
[26] T. D. Sanger, "Bayesian Filtering of Myoelectric Signals," *Journal of Neurophysiology*, vol. 97, no. 2, pp. 1839–1845, Feb. 2007, doi: 10.1152/jn.00936.2006.

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