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A ROS2-Based Architecture for Indoor 3D Mapping and Autonomous Navigation with Azure Kinect and LiDAR

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About the presenter

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Research focus

The research lines focus on the development of intelligent systems based on wireless communications and machine learning. In particular, work has been carried out on indoor localization and detection using Wi-Fi signals, applying fingerprinting techniques and classification methods such as decision trees and neural networks. In addition, IoT architectures and low-cost sensing systems have been developed for environmental monitoring and intelligent assistance applications, together with the use of data mining and computational intelligence techniques for analysis and prediction. Recent work also includes the development of 3D mapping and environment reconstruction systems using ROS 2, LiDAR sensors, and Time-of-Flight (ToF) cameras.

IDeTIC & DRyST division

Institute for Technological Development and Innovation in Communications (IDeTIC)

IDeTIC is a multidisciplinary University Institute, with research in various scientific, technological, innovation and technology transfer fields

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Telematic Networks and Services Division (DRyST)

Originated from the Telematic Networks and Services Research Group, created in 2008.

The division specializes in the study and analysis of wireless network protocols and indoor localization.

Motivation & problem statement

Previous approach:

Based on two Raspberry Pi 4 Model B devices (low-cost architecture).

Used simple Delta LiDAR 2A and a PMD CamBoard PicoMonstar Time-of-Flight (ToF) camera.

Raspberry Pi

pmd
can you imagine

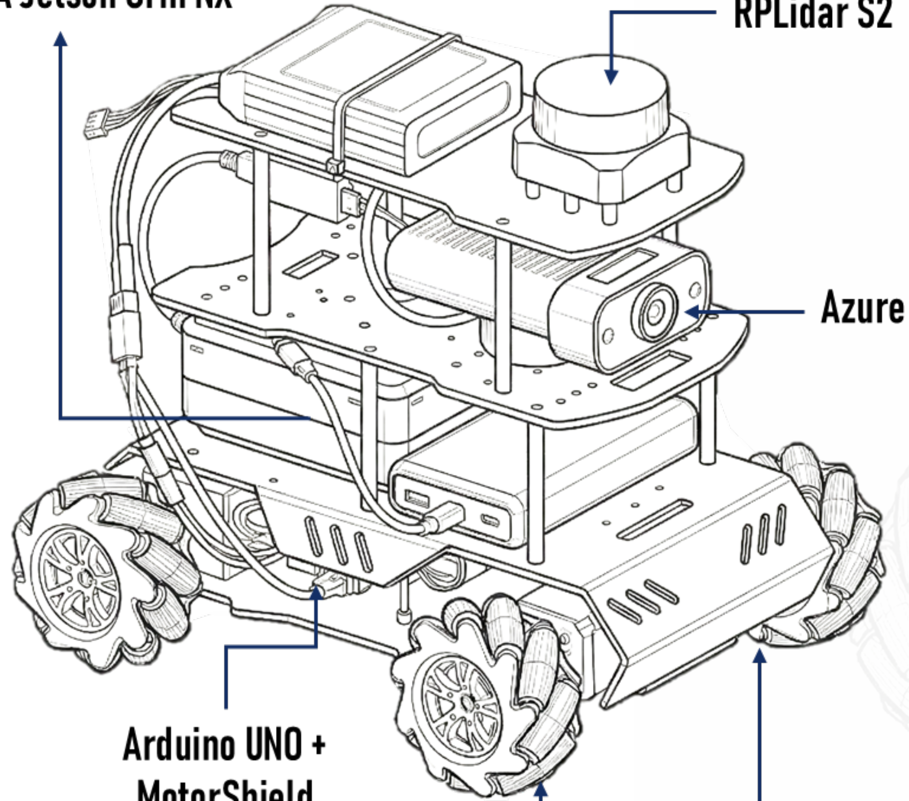
Identified limitations:

Bandwidth Saturation: Simultaneous processing of LiDAR (~70 KB/s) and RGB-D streams saturated the CPU.

Latency Issues: The DDS middleware in ROS2 caused message drops and serialization delays on low-power ARM CPUs.

Lack of Detail: Impossible to perform onboard dense 3D reconstruction or run semantic AI (YOLO) for accessibility.

Hardware architecture



Processing Unit: NVIDIA Jetson Orin NX

Selected for its AI capabilities and high I/O bandwidth (~5.7 Mbps throughput handling).

Primary Sensors

RGB-D: Azure Kinect DK. Provides dense point clouds and high-res RGB for 3D mapping (Fixed at 15 FPS to ensure stability).

LiDAR: RPLidar S2. Operates at 10 Hz for precise geometric 2D scanning and obstacle avoidance.

Actuation

Custom base with Mecanum wheels for omnidirectional movement.

Low-level control via Arduino UNO (bridge to ROS2 environment).

Software architecture (ROS2)

Middleware: Migrated to ROS2 Humble

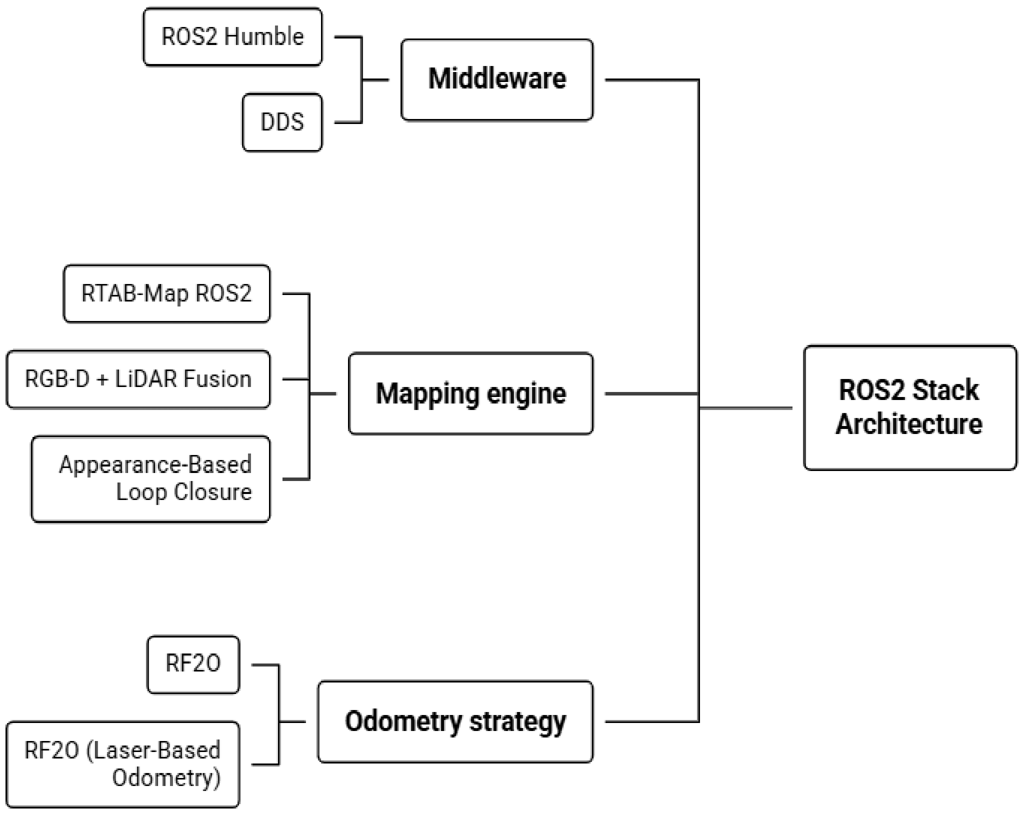
Offers deterministic communication and better data distribution (DDS) for high-bandwidth sensors.

Mapping engine: RTAB-Map ROS2

Fused RGB-D + LiDAR for Graph-Based SLAM. Handles loop closure detection visually (Appearance-Based).

Odometry Strategy: RF2O (Range Flow-based 2D Odometry)

We replaced unreliable wheel encoders with laser-based odometry. Estimates planar motion (x, y, yaw) purely from consecutive LiDAR scans at 10 Hz.



Odometry & synchronization

The mechanical failure

Mecanum wheels suffered from severe wiring issues and slippage, rendering standard wheel odometry unusable for SLAM. This forced the system to rely entirely on the 10 Hz LiDAR scans for localization (RF2O).

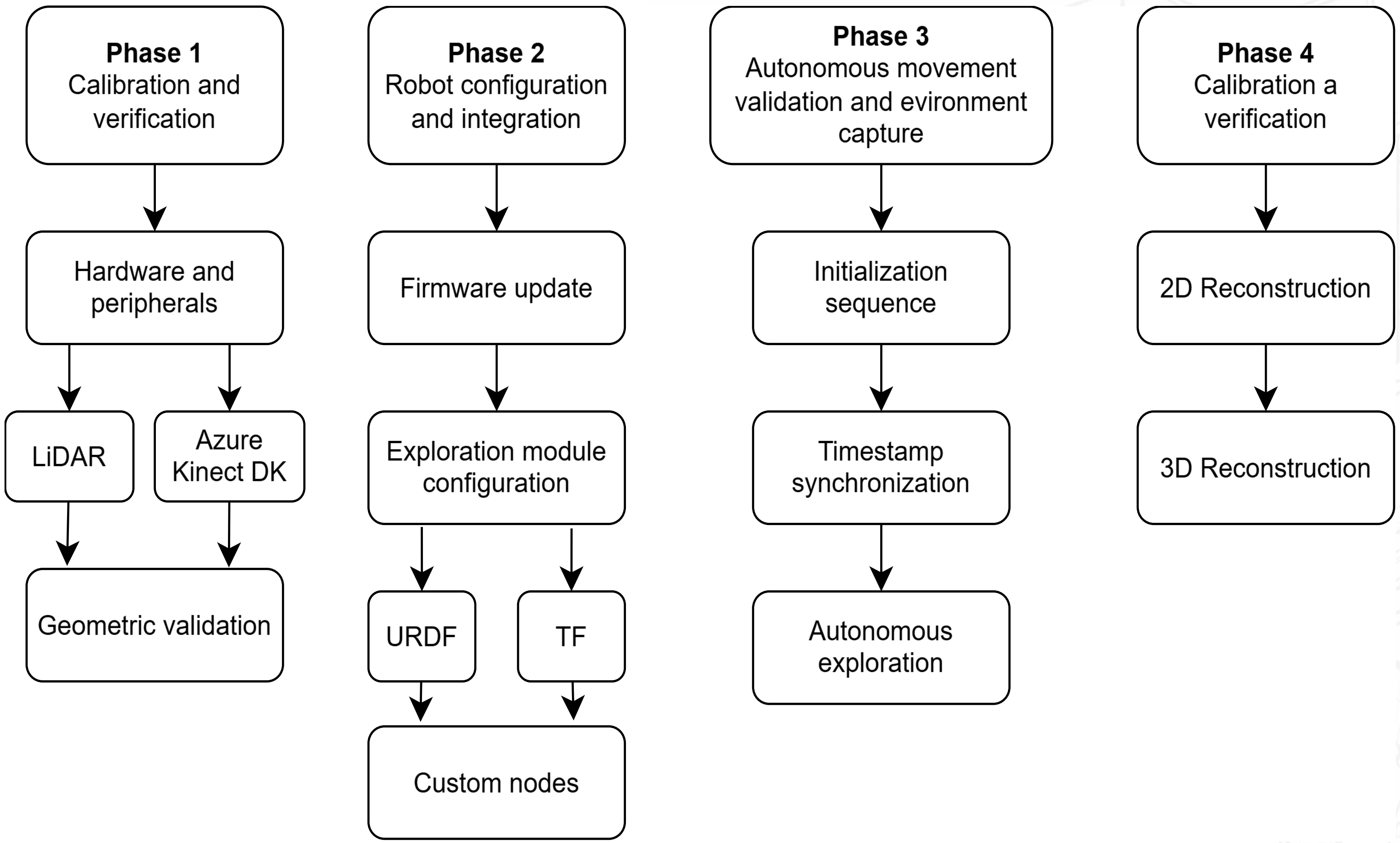
Sensor synchronization & TF Tree

Without wheel encoders, maintaining a consistent transformation tree (TF) required strict synchronization between the `robot_state_publisher` and sensor timestamps. Simulated joint states had to be published at 10 Hz to prevent errors in RViz2 and Foxglove.

Bandwidth management

The DDS middleware can easily saturate under high data loads. To prevent message drops, the Azure Kinect DK was capped at 15 FPS (depth-only), maintaining system-wide bandwidth at a stable ~5.7 Mbps.

Operational workflow



Phase 1. Calibration & verification

Ensures TF tree consistency and synchronizes sensor timestamps (RGB-D @ 15 FPS, LiDAR @ 10 Hz).

Phase 2. System launch

Initializes the ROS2 computation graph without Nav2 (to avoid wheel odometry dependency).

Phase 3. Autonomous exploration

Drives the robot to unexplored areas while avoiding obstacles using raw LiDAR data.

Phase 4. Reconstruction

Generates the final dense 3D map and semantic data offline.

System performance

Stable ROS2 pipeline

The ROS2 communication pipeline demonstrated stable performance under sustained operation, without message loss or DDS instability.

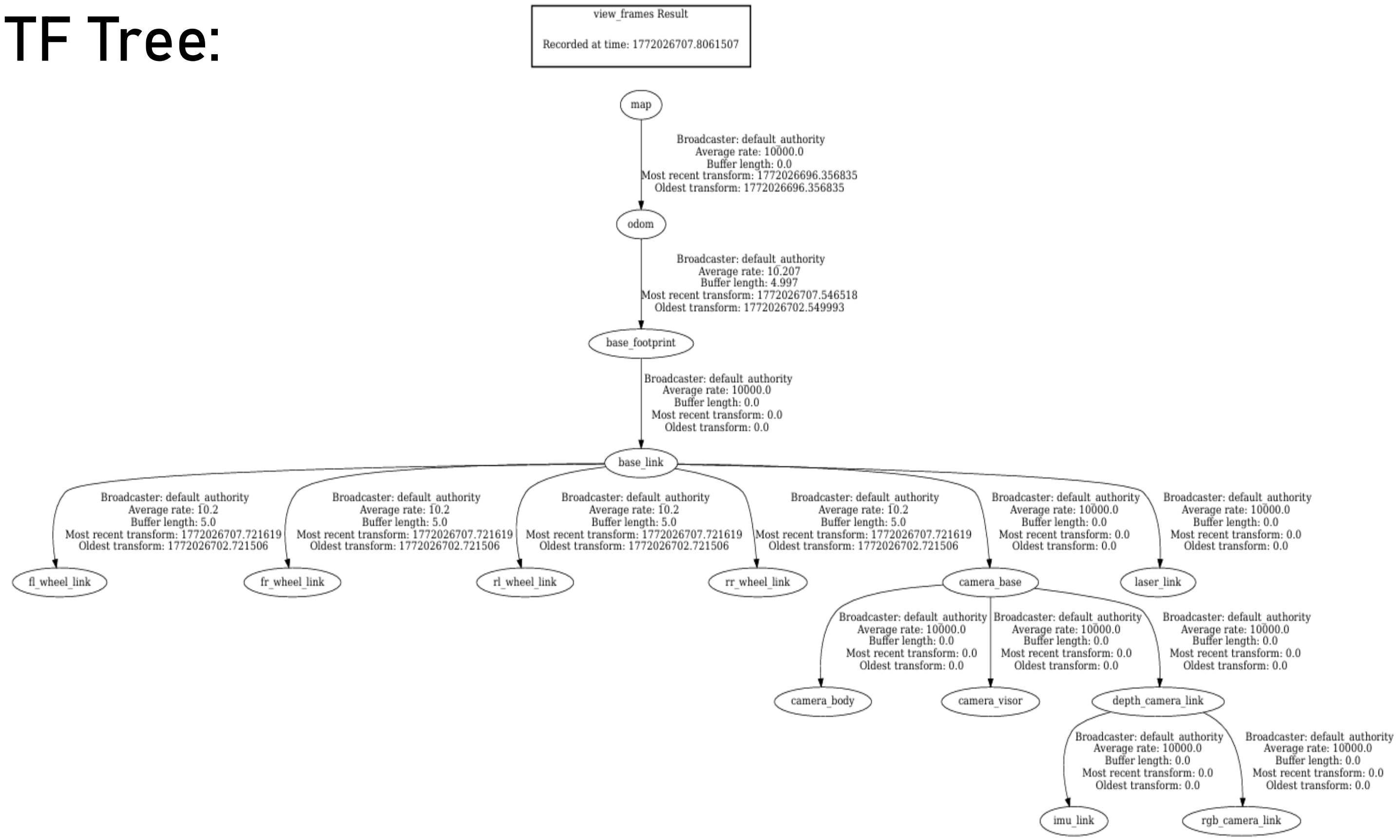
Key stability metrics

LiDAR processing: Stable scans at 10 Hz with an average throughput of 135 KB/s.

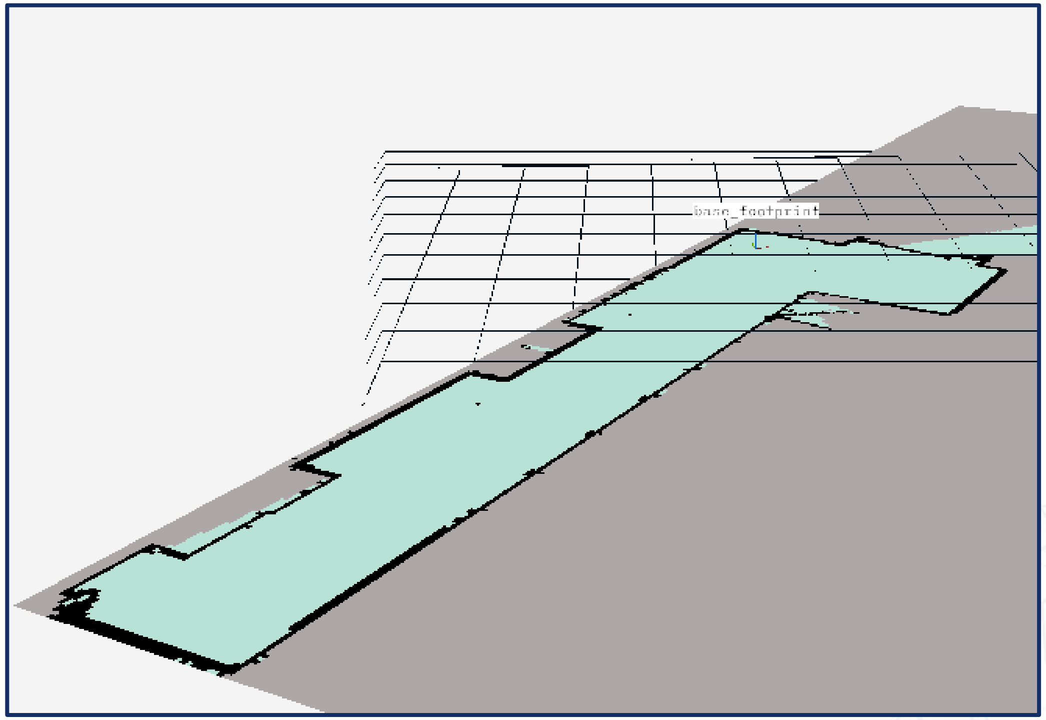
Odometry loop: RF2O generated /odom updates consistently at 10 Hz (~6-7 KB/s), crucial for SLAM convergence.

Vision stream: Azure Kinect DK operated flawlessly at 15 FPS, resulting in a data rate of ~5.2 MB/s.

TF Tree:

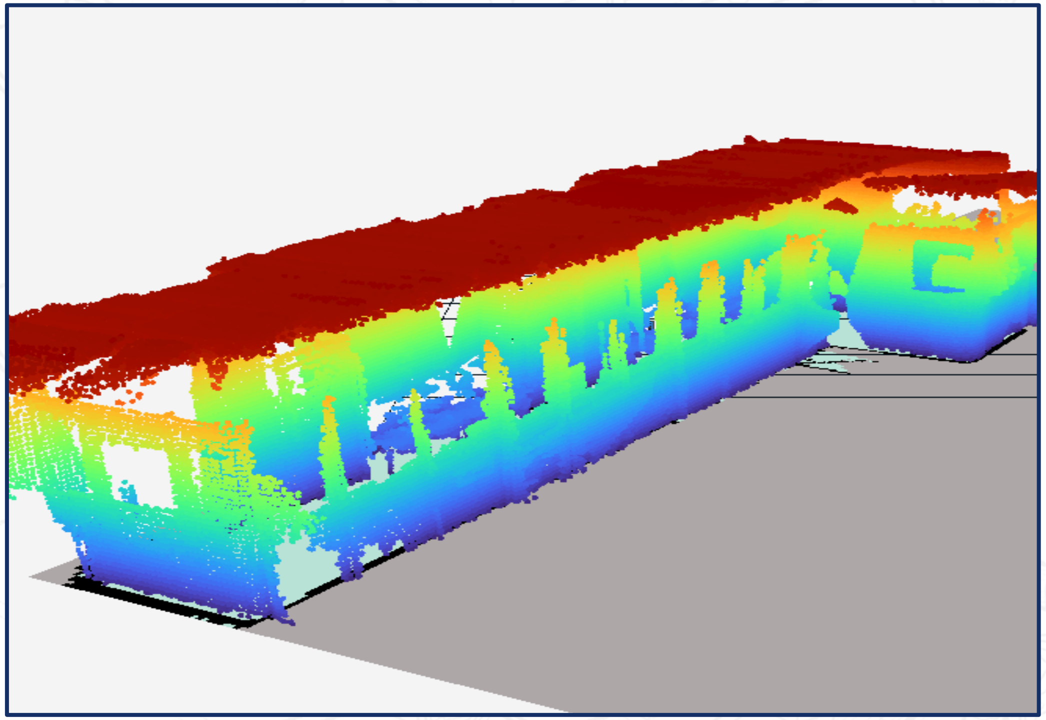


Mapping results (2D & 3D)



2D localization & mapping

Generated using SLAM Toolbox with a resolution of 0.05 m/cell. Maintained global consistency with low drift over short trajectories.

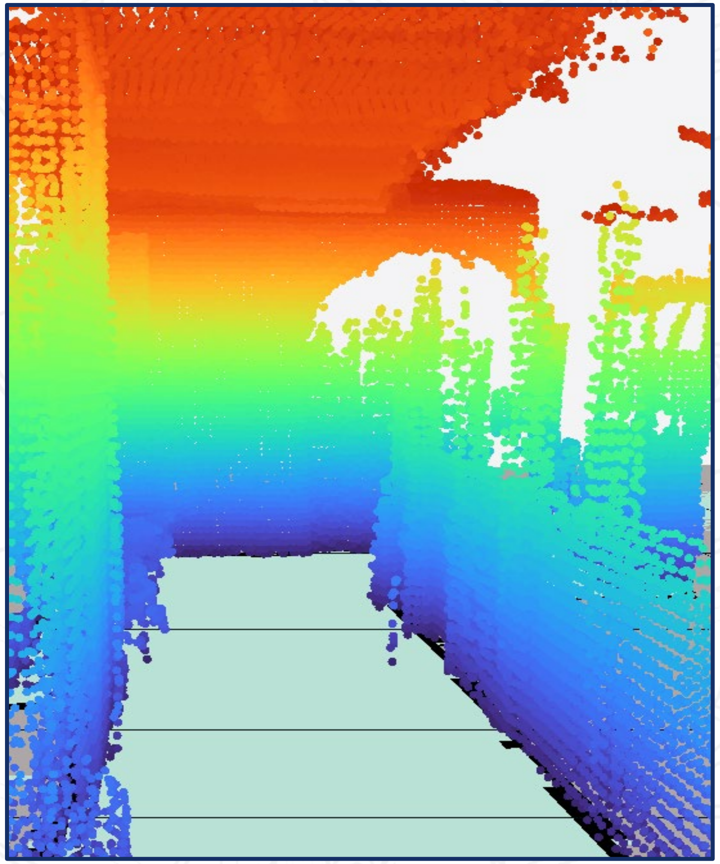


3D perception pipeline

RTAB-Map successfully generated local point clouds aligned with RF2O odometry data. Registered valid loop-closure hypotheses.

Fidelity

Original environment



3D Map

Justifying the hardware investment

Redefining the “robot”

This robot is designed to create the essential facility maps once. It does not need to be a low-cost device for every user; it's the professional tool for building the infrastructure.

The data asset

High-density point clouds allow offline semantic identification and barrier classification (doors, ramps, stairs) that cheap sensors simply cannot detect.

Eliminates wheel encoder dependency and localization drift, ensuring that the generated map is globally consistent for precise positioning.

Long-term cost efficiency

The high-fidelity map generated by this platform reduces the computational load and complexity of the mobile end-user application. All semantic barriers are already pre-labeled and perfectly aligned. Future user devices can be low-cost (e.g., standard smartphones).

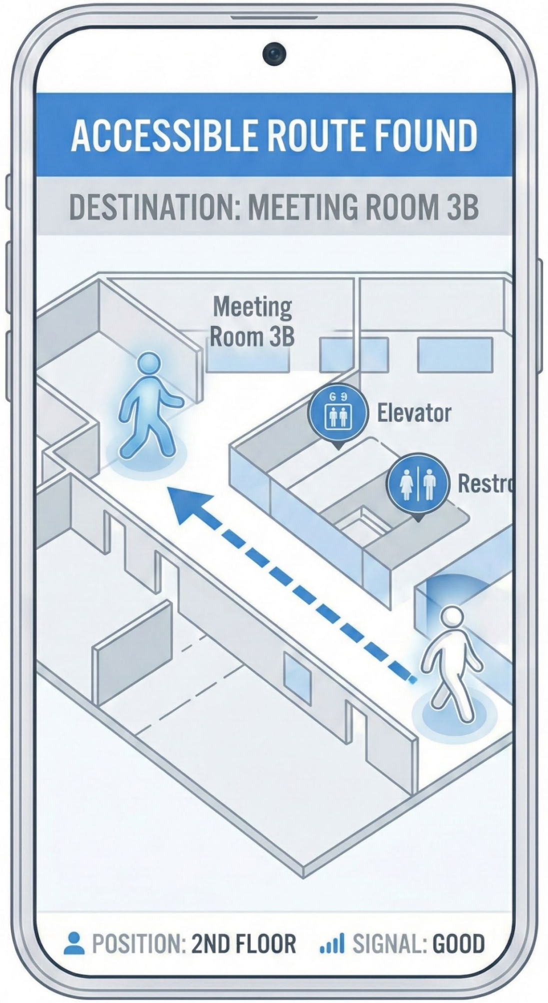
Conclusions & Future work

Conclusions

The migration to ROS2 Humble on the Jetson Orin NX is a strategic response to the limitations of DIY architectures.

Successfully distributed the workload across 18 active ROS2 nodes, eliminating computational bottlenecks.

Demonstrated that lightweight autonomous navigation is viable using only LiDAR and RF2O, without wheel odometry.



Future work

Semantic map processing: Investigate advanced AI techniques (e.g., computer vision, image-based RAG) to automatically extract, classify, and label architectural barriers from the generated 3D data.

Mobile app integration: Deploy this semantically optimized map into a future indoor positioning mobile application, enabling accessible and barrier-aware navigation for end-users.

Acknowledgements

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References

[1] C. M. Mesa-Cantillo, I. Alonso-González, D. Sánchez Rodríguez, M. A. Quintana-Suárez, and K. D. García Mederos, “A Methodology Based on Lidar, Time-Of-Flight Camera and Odometry for a Real-Time 3D Model Generation,” Preprints 2023, 2023060303, 2023. [Online]. Available: https://doi.org/10.20944/preprints202306.0303.v1 [retrieved: January, 2026].

[2] X. Xu et al., “A Review of Multi-Sensor Fusion SLAM Systems Based on 3D LIDAR,” Remote Sens., vol. 14, no. 12, p. 2835, 2022. https://doi.org/10.3390/rs14122835

[3] P. Zhou, X. Guo, X. Pei, and C. Chen, “T-LOAM: Truncated Least Squares LiDAR-Only Odometry and Mapping in Real Time,” IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1–13, https://doi.org/10.1109/TGRS.2021.3083606 2022.

[4] A. Macario Barros, M. Michel, Y. Moline, G. Corre, and F. Carrel, “A Comprehensive Survey of Visual SLAM Algorithms,” Robotics, vol. 11, no. 1, p. 24, 2022. https://doi.org/10.3390/robotics11010024

[5] C. Campos, R. Elvira, J. J. Gómez, J. M. M. Montiel, and J. D. Tardós, “ORB-SLAM3: An Accurate Open-Source Library for Visual, Visual-Inertial and Multi-Map SLAM,” IEEE Transactions on Robotics, vol. 37, no. 6, pp. 1874–1890, 2021. https://doi.org/10.1109/TRO.2021.3070826

[6] R. Mur-Artal and J. D. Tardós, “ORB-SLAM2: An Open Source SLAM System for Monocular, Stereo, and RGB-D Cameras,” IEEE Transactions on Robotics, vol. 33, no. 5, pp. 1255–1262, 2017. https://doi.org/10.1109/TRO.2017.2705103

[7] R. A. Newcombe et al., “KinectFusion: Real-time dense surface mapping and tracking,” in 2011 10th IEEE International Symposium on Mixed and Augmented Reality, Basel, Switzerland, 2011, pp. https://doi.org/10.1109/ISMAR.2011.6092378 127–136.

[8] T. Gupta and H. Li, “Indoor mapping for smart cities — An affordable approach: Using Kinect Sensor and ZED stereo camera,” in Proceedings of the 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN), 2017, pp. 1–8. https://doi.org/10.1109/IPIN.2017.8115909

References

[9] Y. K. Tee and Y. C. Han, “Lidar-Based 2D SLAM for Mobile Robot in an Indoor Environment: A Review,” in Proceedings of the 2021 International Conference on Green Energy, Computing and Sustainable Technology (GECOST), 2021, pp. 1–7. https://doi.org/10.1109/GECOST52368.2021.9538731

[10] K. Takaya, T. Asai, V. Kroumov, and F. Smarandache,

[11] R. Raveendran, S. Ariram, A. Tikanmäki, and J. Röning, “Development of task-oriented ROS-based Autonomous UGV with 3D Object Detection,” in Proceedings of the 2020 IEEE International Conference on Real-time Computing and Robotics (RCAR), 2020, pp. 427–432. https://doi.org/10.1109/RCAR49640.2020.9303034

[12] Z. Yin, M. Fu, and K. Shen, “A Novel Robust Kalman Filter for Unmanned Ground Vehicles Positioning under GNSS Abnormal Measurements,” in 2020 39th Chinese Control Conference (CCC), Shenyang, China, 2020, pp. 3427–3432. https://doi.org/10.23919/CCC50068.2020.9189178

[13] X. Xia et al., “Estimation on IMU yaw misalignment by fusing information of automotive onboard sensors,” Mechanical Systems and Signal Processing, vol. 162, p. 107993, 2022. https://doi.org/10.1016/j.ymssp.2021.107993

[14] X. Zhang, Y. Li, H. Yin, and R. Xiong, “3D LiDAR Map Compression Using Deep Neural Network,” in Proceedings of the 2019 IEEE International Conference on Robotics and Biomimetics (ROBIO), 2019, pp. 1430–1434. https://doi.org/10.1109/ROBIO49542.2019.8961606

[15] J. Petershans, J. Herbst, E. Mittag, M. Rueb, and H. D. Schotten, “Advancing Telerobotics: Evaluating ROS2 in a Real-World Communication Test Environment,” in Mobilkommunikation; 29. ITG-Fachtagung, Osnabrück, 2025, pp. 97–102. “Nav2CAN: Achieving Context Aware Navigation in ROS2 Using Nav2 and RGB-D sensing,” in 2023 IEEE International Conference on Imaging Systems and Techniques (IST), Copenhagen, Denmark, 2023, pp. 1–6. https://doi.org/10.1109/IST59124.2023.10355731

References

[16] T. Schwörer, J. E. Schmidt, and D. Chrysostomou, “Simulation environment for mobile robots testing using ROS and Gazebo,” in Proceedings of the 2016 20th International Conference on System Theory, Control and Computing (ICSTCC), 2016, pp. 96–101. https://doi.org/10.1109/ICSTCC.2016.7790647

[17] L. Kästner et al., “Arena-Rosnav 2.0: A Development and Benchmarking Platform for Robot Navigation in Highly Dynamic Environments,” arXiv preprint arXiv:2302.10023, 2023. [Online]. Available: https://arxiv.org/abs/2302.10023 [retrieved: January, 2026].

[18] G. M. C. van den Hoven, “Introducing a Performance Observation Framework to ROS2,” Master’s thesis, Eindhoven University of Technology, 2024. [Online]. Available: https://research.tue.nl/en/studentTheses/introducing-a performance-observation-framework-to-ros2 [retrieved: January, 2026].

[19] M. Ryalat, G. Al-refai, N. Almtireen, and H. ElMoaqet, “Design of a ROS2-Based Hybrid Aerial-Ground Robot for Autonomous Inspection Applications,” IEEE Access, vol. 13, pp. 1–1, 2025. https://doi.org/10.1109/ACCESS.2025.3582653

[20] D. D. Yanyachi et al., “Laser_RobMap: An open source ROS2 compatible tool for 3D mapping using a Mobile Robot and 2D LiDAR,” SoftwareX, vol. 30, p. 102142, May 2025. https://doi.org/10.1016/j.softx.2025.102142

[21] Ultralytics, “Discover YOLO models | Cutting-Edge Computer Vision,” 2025. [Online]. Available: https://www.ultralytics.com/yolo [retrieved: January, 2026]