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Application of Advanced Sensor Technology in Simultaneous Localization and Mapping for Industrial Automation

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Simultaneous localization and mapping (SLAM) is widely used in industrial automation, enabling autonomous robots and drones to navigate and operate in complex environments. In this study, we investigated the application of advanced sensor technologies, including light detection and ranging (LiDAR), cameras, inertial measurement units (IMUs), ultrasonic sensors, GPS, and thermal sensors, in a multisensor SLAM system. Aerial drone experiments conducted in a challenging urban roundabout environment demonstrated the system's ability to maintain reliable localization and mapping despite environmental variability, dynamic obstacles, and inconsistent lighting. The integration of LiDAR odometry with IMU data reduced positional errors by 52%, while thermal and proximity sensors enhanced resilience against visual data loss. Although the trajectory accuracy achieved (88.31%) was lower than the benchmark results reported in controlled laboratory studies, the system exhibited strong real-time responsiveness, adaptability, and safety-focused navigation. The feasibility of multisensor SLAM in unpredictable industrial settings is validated using the advanced sensor fusion strategies for automation. The results of this study underscore the importance of adaptive calibration, robust error correction, and benchmarking to improve accuracy, while demonstrating that multisensor integration already provides significant operational benefits for warehouse robotics, autonomous delivery vehicles, and drone inspections.

1. Introduction

Accuracy, scalability, and operational agility are essential factors in the automation of manufacturing, logistics, and supply chain management. Industry 4.0 requires cyber-physical systems, interconnected computers, and machine learning in conjunction with sensor technologies to construct the necessary infrastructure.(1) In automation systems, sensors function as the sensory organs of humans. Sensors provide essential information for monitoring and controlling a system and assessing and maintaining seamless operations. They are also involved in environmental quality control. A major transformative change with sensors is observed in simultaneous localization and mapping (SLAM). This computational method enables robots and vehicles to operate autonomously by constructing maps of uncharted

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territories and simultaneously tracking their locations.[2] In dynamic industrial environments, the accurate navigation of robots and vehicles is critical because preprogrammed static paths are inadequate in complex and cluttered workplaces where adaptable workflows must be established to avoid collisions with objects or people.

The evolution of sensors and data processing algorithms has strengthened technological capabilities, enabling SLAM to move from a conceptual theory to an industrial necessity. Industrial automation requires path-restricted automated guided vehicles that utilize magnetic strips and quick response codes. However, this system requires high installation costs and has an inherent inflexibility of adjustment and vulnerability to environmental changes, which necessitate adaptive systems. Recently, autonomous mobile robots (AMRs) have been used with SLAM as they use multisensor data to autonomously navigate and reroute in unstructured environments around obstacles, optimize real-time operations, and change moving courses whenever required. The technologies employed highlight the crucial role of sensors in industrial automation. Their enhanced accuracy, compact size, and reduced cost facilitate broader adoption in SLAM, boosting autonomy, efficiency, and human interaction.

In this article, we explore how to use sensor technologies to advance SLAM in industry automation. While previous research emphasizes the importance of algorithms and sensor types, understanding how light detection and ranging (LiDAR), cameras, inertial measurement units (IMUs), ultrasonic sensors, and GPS can be integrated to solve industrial problems becomes more important in modern manufacturing. In addition to theoretical research, practical application must be explored to demonstrate the applications of the technologies in warehousing, logistics, and equipment maintenance. Therefore, SLAM-enabled systems' productivity, safety, return on investment, and value enhancements also need to be assessed.

Recently, low-cost 3D mapping with solid-state LiDAR, dynamic scene analysis using event-based cameras, and AI-integrated sensors have been introduced to automated manufacturing. In this article, these advancements are assessed in terms of computation requirements, data variability of sensors without GPS, frame loss recovery, and data loss of vehicle-mounted sensors in complex industrial environments. The results can be used to optimize sustainable automation systems based on advanced engineering technologies and corresponding policies.

Smart decision-making tools such as sensor-based SLAM foster the operational readiness of industries. Therefore, policymakers and industry experts need to formulate concrete strategies for the optimization of industry automation, leveraging advanced sensor technology deployment. The integration of sensor technologies in advanced SLAM systems has driven industry innovation and evolution. Their continued proliferation is expected to address challenges such as resource shortages, supply chain volatility, and sustainability, strengthening market competitiveness.

2. Background Knowledge

The SLAM systems integrated with advanced sensors are widely used in industrial automation systems to navigate complex and dynamic environments. Such systems are adopted for real-time data management, autonomous navigation, and robust system implementation.

LiDAR technology has evolved from traditional stationary systems to advanced solid-state technology, which enables compact designs and enhanced reliability for various industrial applications. LiDAR employs pulsed laser beams to calculate distances by analyzing the reflected light (Fig. 1).

In SLAM, LiDAR enables precise 3D point cloud generation for high-fidelity mapping and obstacle avoidance in warehouses and construction sites. Automated SLAM systems with LiDAR acquire data at high rates to continuously update map databases and maintain autonomous localization even during sudden environmental changes. In particular, mobile LiDAR-SLAM systems are used for robots to navigate new routes autonomously by merging point cloud data in real time, eliminating the need for manual static scans. In the future, 3D mapping for digital twins and AI is expected to become more prevalent in SLAM systems.

Developments in camera technology, including depth sensors, stereo vision, and event-based cameras, have addressed the limitations of RGB sensors in low-light or dynamic settings. Depth cameras merge color data with depth information, enabling SLAM applications in complex environments.(4) Stereo cameras are used to distinguish depth through dual triangulation, which is effective under the varying lighting typically found in industrial facilities. Recently, event-based cameras have been used for ultrafast, pixel-level object detection. By adopting AI, these systems extract semantically segmented features for accurate object and personnel recognition, enabling safe robot–human collaboration.(5) Additionally, augmented reality (AR) headsets integrated with visual SLAM (V-SLAM) allow users to conduct quality control tasks efficiently in real time.

IMUs are essential for tracking motion and orientation by providing acceleration and angular velocity data in SLAM. Modern MEMS-based IMUs significantly reduce noise and enhance high sensitivity, making them well-suited to environments with continuous vibration.(6) These sensors enable uninterrupted SLAM performance, even during sudden movements or sensor failures, by generating motion data that replace lost visual or LiDAR signals. When combined with Kalman filtering or factor graph optimization, IMUs considerably reduce error and improve the operational stability of the SLAM system.(7)

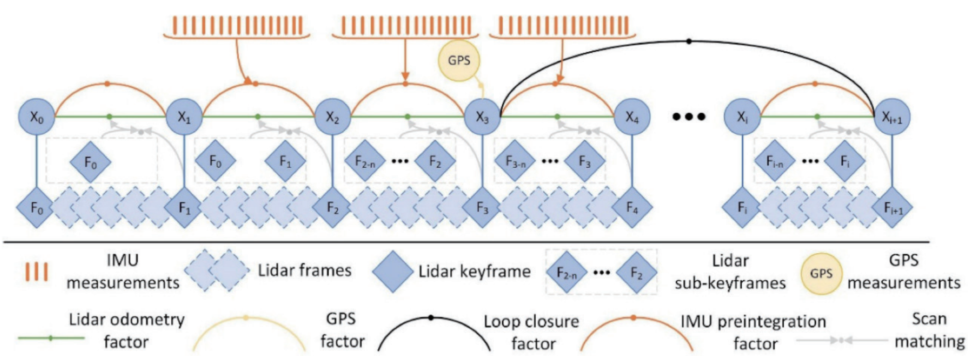

Fig. 1. (Color online) Optimization of LiDAR's SLAM algorithm based on multisensor data.(3)

In SLAM, ultrasonic sensors and GPS are adopted for range measurement and obstacle recognition, particularly for near-distance navigation where visual sensors or LiDARs have limitations. Recent smart ultrasonic sensor systems process signals to improve detection in noisy or cluttered industrial spaces.[8] For logistics, GPS is used to estimate geospatial coordinates. However, high-precision real-time kinematic (RTK)-GPS requires established base stations.[9] In indoor environments where GPS is ineffective, LiDAR is used with ultra-wideband (UWB) and visual landmarks.

The data collected from the sensors are integrated to obtain reliable, contextual results. For data integration, the loosely and tightly coupled methods are mainly used. In the loosely coupled method, independent data streams are processed and combined at a final stage. While straightforward to implement, this method has risks when sensors malfunction and do not meet requirements, including high precision. In the tightly coupled method, sensor data are integrated and processed using a probabilistic method, such as recursive Bayesian filtering or factor graph optimization, for accurate and uniform operation.[10]

SLAM systems perform best when using factor graph optimization in the back end for loop detection (Fig. 2). Integrating multiple sensors into SLAM requires substantial computational power to ensure rapid system responsiveness. Real-time processing allows AMRs to successfully operate in rapidly changing environments and avoid collisions, and improve workflows. For accurate mapping and positioning, SLAM algorithms perform real-time adjustments to minimize sensor data variability and mechanical wear caused by environmental changes.[10] Advancements in the SLAM technology have enabled the development of flexible AMRs that operate alongside human workers in unstructured areas. While technical challenges such as sensor degradation and data synchronization remain, the integration of AI, IoT, and 5G is expected to further enhance the scalability and reliability of SLAM-enabled automation.[10]

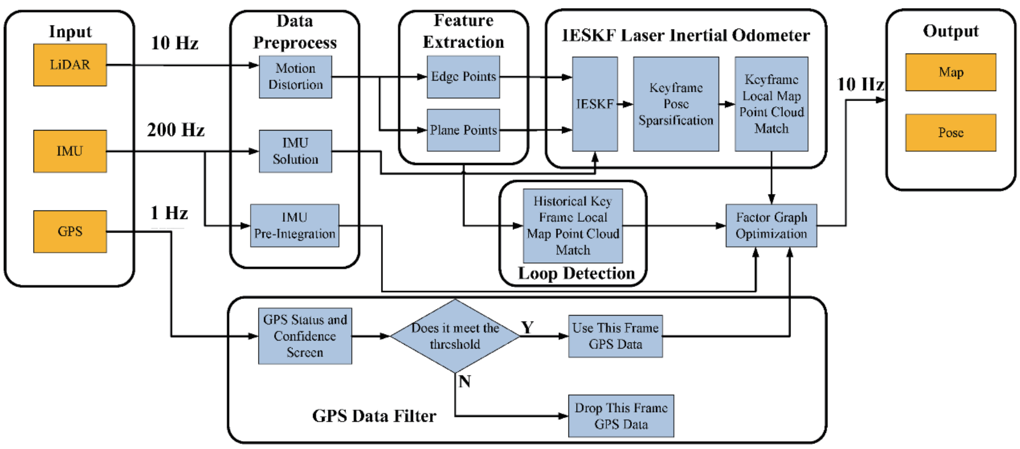

Fig. 2. (Color online) SLAM system for data preprocessing integrated with front-end iterated extended Kalman filter, back-end factor graph optimization, GPS data filtering, and loop closure detection (IESKF: iterated error-state Kalman filter).[7]

3. Methods

3.1 Experimental platform and environment

An aerial drone with a custom-built multisensor system (DJI Matrice 300 RTK, SZ DJI Technology Co., Ltd., China) was used in this study (Fig. 3).

The DJI Matrice 300 RTK was selected as the aerial platform owing to its industrial-grade design, payload flexibility, and centimeter-level positioning accuracy. The drone has unfolded dimensions of 810 × 670 × 430 mm^3 and folded dimensions of 430 × 420 × 430 mm^3, with a diagonal wheelbase of 895 mm. Its maximum takeoff weight is 9 kg, supporting payloads up to 2.7 kg. The M300 RTK incorporates RTK positioning, ensuring high-precision geospatial data collection. It is equipped with multiple vision sensors, infrared time-of-flight sensors, and auxiliary lights that enhance obstacle detection and flight safety. The system is powered by dual hot-swappable TB60 batteries, providing up to 55 min of flight time under optimal conditions. With an IP45 ingress protection rating, the drone maintains reliable performance in adverse weather environments.(11) The SLAM system used in this study integrated multiple sensors, as shown in Table 1. By combining LiDAR odometry data with IMUs, positional errors were reduced by 52%, compared with traditional sensor systems that rely on ultrasonic and visual data processed with Kalman filters. This configuration demonstrated higher reliability in factory settings (Table 1).(12)

Fig. 3. (Color online) Drone used in this study.

Table 1
Comparison of different sensor operabilities in SLAM.

Sensor	Range	Accuracy	Cost	Application
Thermal sensor	7.5–13.5 μm	640 × 512 pixel resolution	High	Environmental monitoring, threshold-based alerting
LiDAR	0.5–200 m	±1–5 cm	High	Warehouse AMRs, 3D mapping
RGB camera	0.1–10 m	±1–3 cm	Moderate	AR maintenance, bin picking
IMU	N/A	±0.1°/hr	Low	Drone inventory checks
Ultrasonic sensor	0.1–5 m	±1–5 cm	Low	Collision avoidance
GPS	Global	±1–5 m	Moderate	Outdoor logistics, mining

The study area contained multiple entry and exit points with diverse traffic volumes, as well as numerous obstacles such as vehicles, streetlights, and vegetation, which introduced complexity in navigation and mapping. The drone was operated at an optimal altitude to capture detailed mapping data and sensor readings. Daytime tests revealed operational challenges for the SLAM algorithm, particularly due to shadows and reflective surfaces. The drone followed a preprogrammed path and circled the roundabout to simulate industrial automation monitoring. Safety checks of the environment were conducted before testing, in accordance with UAV operation standards. The urban roundabout was chosen as a testing site because of its challenging nature, numerous vehicles, various structural elements, and its similarity to an industrial and urban automation environment, making it ideal for evaluating the SLAM algorithm (Fig. 4).

3.2 Data collection

The drone was equipped with multiple sensors for environmental monitoring, including a thermal sensor, a LiDAR, an RGB high-resolution camera for SLAM, an IMU for tracking movements, ultrasonic sensors for identifying obstacles, and GPS.

3.2.1 Thermal sensor

The system integrates a thermal sensor for continuous temperature observations, the detection of thermal irregularities in environmental objects, and the monitoring of unusual temperature changes indicating malfunctions or external operational risks. The data collected by the thermal sensor are processed through an event management system that utilizes threshold triggers to issue real-time alerts, preventing operational overload while maintaining safety-focused navigation in time-sensitive industrial scenarios.

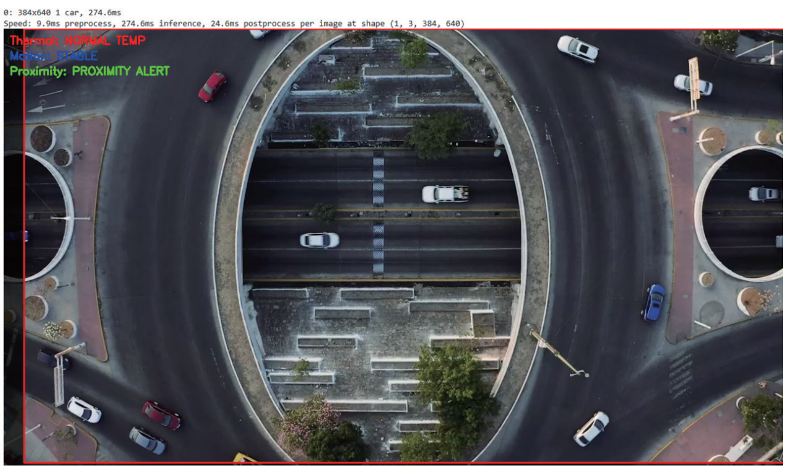

Fig. 4. (Color online) Drone’s vision of testing site with real-time sensors.

3.2.2 LiDAR

In LiDAR, pulsed laser beams are used to calculate distances by analyzing the elapsed flight time of reflected light. Sensors create detailed three-dimensional points to provide accurate spatial information.[3] The solid-state LiDAR systems provide accurate spatial measurements in compact designs to reduce variability in dynamic conditions.[13] LiDAR is used in SLAM applications because of its operational reliability. LiDAR allows AMRs to detect objects and people in warehouses or factories. When IMUs integrate SLAM algorithms, the positional error decreases by up to 46% even without GPS reception.[14]

3.2.3 Visual sensor (camera)

Visual sensors include RGB, depth, and stereo cameras. RGB cameras generate 2D color data to support oriented features from the oriented FAST and rotated BRIEF (ORB) features of SLAM. Depth cameras operate with RGB-D sensors to measure color attributes and depth based on structured light and time-of-flight methods, which are efficient in capturing low-texture objects. Stereo cameras contain dual lenses and are used to calculate depth measurements in 3D reconstruction systems without external lights. V-SLAM needs environmental information for the quality inspection in AR-guided maintenance systems.[9] The Intel RealSense RGB-D sensor is widely used to allow robots to distinguish between tools and humans in shared spaces (Fig. 5). System performance decreases under low lighting or very bright surroundings, requiring the integration of LiDAR.[15]

3.2.4 IMUs

An IMU combines linear motion-detecting accelerometers to determine angular velocity, positions, orientations, and trajectories.[14] Applications of IMUs in fast movements require MEMS-based IMUs with a drift rate below 0.1°/h, which makes them appropriate for such purposes. The IMU function minimizes interruptions of LiDAR or cameras because it maintains a motion data stream (Fig. 6). The integration of IMU and LiDAR reduces localization failures by 48% in vibration-prone foundries.[13]

Fig. 5. (Color online) Intel RealSense depth camera D435.

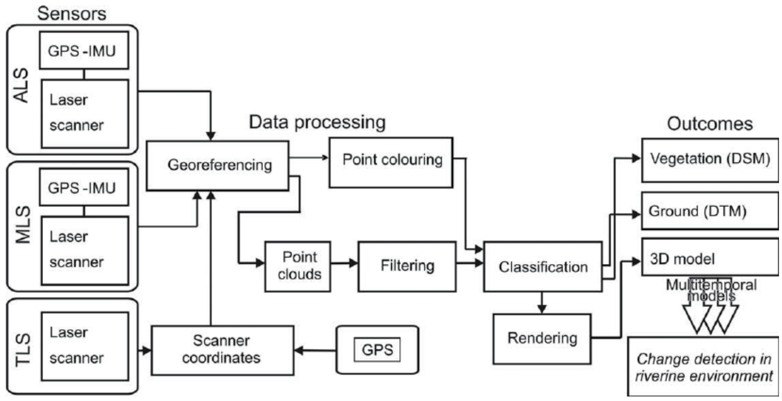

Fig. 6. LiDAR data processing with GPS-IMU data in airborne laser scanning (ALS), mobile laser scanning (MLS), and terrestrial laser scanning (TLS). DSM: digital surface model; DTM: digital terrain model.

3.2.5 Ultrasonic sensor

Ultrasonic sensors are used to determine distances by transmitting high-frequency sound waves between 20 and 200 kHz, operating in the range of 0.1–5 m. These sensors show broad coverage patterns due to their wide beam angles, which range between 15 and 30°, although they yield a lower spatial resolution than LiDAR. The detection ability of the sensor enables outstanding results in measuring distances for robots that travel at a moderate pace, such as automated guided carts. Automotive assembly lines use ultrasonic sensor arrays to enable robots to detect overhead cranes with an accuracy of 95% in 2 m. Acoustic noise might restrict the sensor's utilization in heavy industrial factories.

3.2.6 GPS

The satellite signals are used to estimate geospatial coordinates wth a precision of 3–5 m in the outdoor space. RTK-GPS systems present a measurement precision of 1–2 cm while requiring established base stations, which affects their availability. The GPS function in a SLAM system in logistics minimizes the errors of long-distance autonomous vehicles.[9] GPS-LiDAR enables port container handlers to operate with an accuracy of 10 cm in large yards. The indoor environment requires LiDAR with UWB and visual landmarks to replace GPS, which is ineffective inside.

3.3 SLAM algorithm and data processing

A SLAM algorithm was developed to merge visual, inertial, thermal, and proximity sensor data. The visual SLAM component included features and positions to build environmental maps and track the drone's movement. In the algorithm, oriented features from the accelerated segment test and ORB features were integrated to detect and match key points in the visual data.

The visual odometry was combined with IMU data using an extended Kalman filter to maintain localization accuracy and avoid visual feature loss in high-speed movements. The thermal sensor was used to monitor environmental factors and spot unusual temperature changes, which might indicate system malfunctions and exterior risks. The ultrasonic sensor was adopted to detect objects approaching in a specified range. The SLAM system enabled the real-time response of the drone and processed data every 300 ms. The data logs contained trajectory estimates, object counts, proximity alarms, and environmental measurements for future research.

3.4 Data visualization and analysis

The data were processed to present tracking plots, sensor status, and time-series charts. The drone flight planning data appeared as two-dimensional visual representations. Four essential metrics were calculated using the data: total distance traveled and straight-line displacement, average step size, and deviation from the ideal path. On the screen, sensor status, thermal status, motion stability, proximity alerts, system health, and environmental parameters were displayed. The data collected included brightness, motion levels, object counts, environmental parameters, proximity alert frequencies, and others. By analyzing the data, the system functionality was evaluated.

4. Results and Analysis

4.1 Sensor data acquisition and system performance

The drone was operated over an urban roundabout with visual cameras and motion/proximity detectors. The sensor data were collected from thermal and motion sensors. The thermal sensor provided ambient and device temperatures continuously, demonstrating the operational status of the drone. The motion sensor maintained its operational stability, indicating no problematic vibrations or uncontrollable movements, which directly affected the accuracy in SLAM. The drone and its system processed captured images every 300 ms, which met the industrial and urban automation requirements.

The collected data were analyzed to count the detected objects and track them in real time. In the test, the object detection module continuously detected a single object in each frame. The multisensor data in SLAM navigation enabled the drone to operate normally in even changing environments. The results presented in Fig. 7 show the high effectiveness and robust functionality of the multisensor SLAM system. Figure 7 illustrates the sensor data streams that underpin the SLAM system's performance in an urban environment. Each dataset provides critical insights into how the system maintains functionality under dynamic conditions.

The thermal sensor data (red line) show brightness values ranging from approximately 72.10 to 72.35 (arb. unit). These stable readings indicate consistent thermal detection, which supports reliable navigation in environments characterized by variable lighting or heat sources. The simulated motion sensor data (blue line) fluctuate between 2.4 and 3.6 (arb. unit). This variation

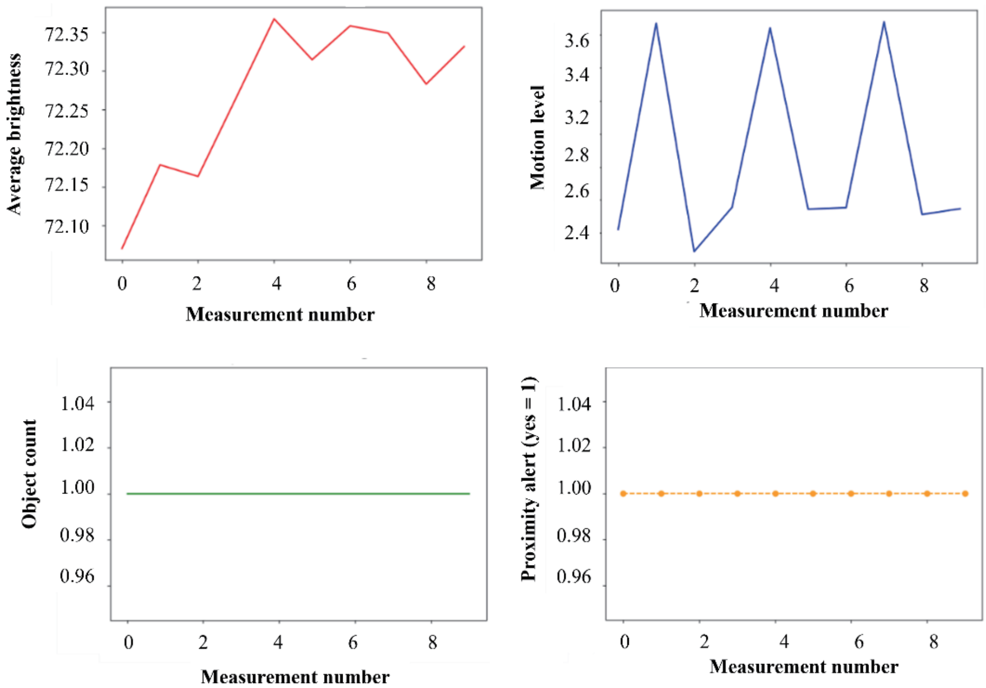

Fig. 7. (Color online) Sensor data (thermal brightness, motion levels, object count, and proximity alerts) for trajectory estimation and spatial mapping in urban environment.

reflects changes in drone movement and validates the role of the IMU in capturing dynamic motion states. Such data are essential for accurate trajectory estimation and stabilization during flight. The object count data (green line) remain constant at a value of 1 (number of detected objects). This consistency signifies that the system continuously identifies a single object within the environment. The stability of this detection demonstrates the reliability of the object recognition process, which is critical for collision avoidance and spatial awareness in industrial applications. The proximity alert data (orange markers) were fixed at a value of 1 (binary alert value). This indicates continuous proximity alerts, suggesting that the drone operated in close quarters with the surrounding infrastructure. The system successfully maintained safety-focused navigation through the persistent monitoring of nearby obstacles.

The sensor outputs confirm that the multisensor fusion approach enables robust SLAM functionality. The integration of thermal, motion, object detection, and proximity data ensures resilience against the weaknesses of individual sensors. This fusion enhances system reliability, allowing the drone to operate effectively in complex and dynamic industrial environments.

4.2 Trajectory estimation and mapping accuracy

Figure 8 shows the drone's estimated trajectory and final position, offering a detailed view of the SLAM system's performance in a complex urban environment. The trajectory begins at (−4.5,−4) and concludes at (1,0) on the coordinate, following a curved path with several

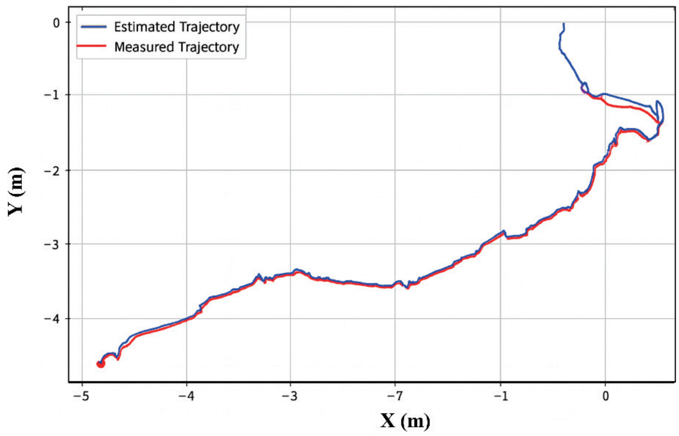

Fig. 8. (Color online) Drone trajectory plot with accuracy.

deviations from the ideal straight-line displacement. The drone traveled a total distance of 12.72 m, while the direct straight-line distance between the start and end points was 6.59 m. This difference highlights the system's ability to navigate nonlinear paths while still maintaining reliable localization. The average displacement per step was 0.02 m, indicating fine-grained control and stability in incremental movements. The average deviation from the straight line was 1.08 m, which reflects the system's capacity to adapt to environmental complexity while minimizing lateral drift. On the basis of these metrics, the trajectory accuracy was calculated as 88.31%, which shows the robustness of the SLAM algorithm in maintaining accurate localization.

Through the integration of LiDAR odometry with IMU data, positional errors can be reduced, while the fusion of thermal, visual, and proximity sensors ensures resilience against environmental challenges. The accuracy value demonstrates that the system achieved reliable trajectory estimation and maintained strong mapping fidelity in a dynamic urban setting. The lower accuracy observed is attributed to the challenging environment. With refinements in sensor fusion, trajectory optimization, and benchmarking, the accuracy can be improved to levels comparable to or exceeding the results of other published research studies. Importantly, the system demonstrates robust real-time responsiveness and resilience, which are critical for industrial automation applications.

The system's ability enables precise localization and mapping. This makes the SLAM system well-suited for industrial automation applications, where both accuracy and real-time responsiveness are critical.

4.3 Real-time processing of sensor data

Visual, thermal, motion, and proximity data were processed using the SLAM algorithm to address the weaknesses of independent sensor data. When visual data were lost under low light conditions, inertial and proximity sensors were replaced for continuous localization. Each frame was processed to remove inference signals in less than 300 ms, which enabled safety-focused operation in time-sensitive situations. An event management system was adopted to process real-time data and report proximity alerts. Threshold triggers were used for proximity and thermal alerts to prevent the operational overload of the processor. The sensor data integration was effective in adjusting operations, and SLAM with multiple sensors operated satisfactorily in industrial automation as a reliable and responsive system.

4.4 Environmental adaptability and system limitations

The trajectory accuracy achieved in this study (88.31%) is lower than the results reported in other SLAM studies. For example, evaluations on the Technical University of Munich RGB-Depth SLAM Dataset (TUM RGB-D) demonstrate trajectory errors below 2% in controlled indoor environments, owing to the availability of high-quality ground-truth data from motion-capture systems and the relatively stable sensor conditions.(16) Similarly, advanced algorithms such as ORB-SLAM3 and Dynamic SLAM, tested on the Karlsruhe Institute of Technology and the Toyota Technological Institute at Chicago dataset (KITTI), showed accuracy levels exceeding 95% in outdoor driving scenarios, benefiting from optimized visual feature extraction and loop closure mechanisms.(17) More recent approaches, such as AdaSLAM, report state-of-the-art accuracy across multiple benchmarks (KITTI, the European Rocketry Challenge, and TUM RGB-D) by employing adaptive feature fusion and uncertainty-guided keyframe selection, further improving robustness and precision.(18)

The lower accuracy observed in this study is attributed to several factors. First, the urban roundabout environment introduces irregular structures, dynamic obstacles, and variable lighting, which are more challenging than the controlled conditions of benchmark datasets. Second, the fusion of multiple sensors is not fully optimized for adaptive weighting, meaning that conflicting sensor inputs may reduce overall precision. Third, the trajectory length and curvature in this study (12.72 m traveled versus 6.59 m straight-line displacement) inherently increase cumulative error, compared with shorter, straighter benchmark paths. Finally, the accuracy metric calculation method differs from those used in benchmark studies, which often report relative error per meter traveled rather than deviation from a straight-line displacement.

To enhance performance closely with benchmark studies, adaptive weighting schemes must be adopted to prioritize sensor inputs based on confidence levels, reducing the impact of drift or occlusion. It is also necessary to incorporate loop closure detection and graph-based optimization to correct accumulated drift and refine trajectory estimates. Higher-resolution LiDAR or stereo vision systems, noise filtering, and calibration need to be employed to improve mapping fidelity and apply advanced filtering techniques, such as extended Kalman filters, particle filters, and regular sensor calibration to minimize systematic errors.

5. Conclusions

Sensors are fundamental to the success of SLAM operations in industrial automation. The integration of a thermal sensor, LiDAR, cameras, IMUs, ultrasonic sensors, and GPS enables robust real-time mapping, autonomous mobile robot navigation, and drone operation in complex environments. However, sensor variability, environmental challenges, and computational constraints remain critical issues that require ongoing innovation.

In this study, we explored the role of multisensor SLAM in industrial automation in drone operation in a complex urban environment. By examining sensor modalities and their contributions, the results highlighted how multisensor fusion enhances localization, mapping, and resilience under dynamic conditions. The trajectory accuracy was lower than that of the benchmark results. The difference is largely attributed to environmental complexity and methodological variations rather than fundamental system limitations. Importantly, the system demonstrated strengths in real-time responsiveness, adaptability, and safety-focused navigation, which are essential for industrial applications.

Even with moderate accuracy, the integration of thermal, motion, and proximity sensors with visual SLAM provides significant advantages. The system maintained stable operation in environments with variable lighting, moving vehicles, and complex infrastructure, validating its potential for warehouse robotics, autonomous delivery vehicles, and drone inspections. This contribution lies in demonstrating the feasibility of multisensor SLAM in unpredictable, real-world industrial settings, advancing sensor technology beyond controlled laboratory benchmarks.

In using SLAM, adaptive calibration, robust error correction, advanced loop closure algorithms, and high-fidelity IMUs are vital to enhance precision and reduce false alerts. Additionally, evaluating sensor reliability in rapidly changing environments, conducting cost–benefit analyses, and addressing cybersecurity and data privacy are critical for widespread adoption. Workforce training programs must also be implemented to ensure the usability and acceptance of SLAM-enabled automation systems.

Multisensor integration enables reliable SLAM performance in challenging industrial environments, even when accuracy is lower than benchmark studies. By combining technological innovation, strategic system integration, and workforce development, sensor-driven SLAM systems can accelerate the advancement of industrial automation, strengthening supply chain processes.

Acknowledgments

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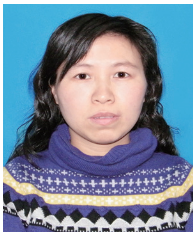
References

1 C. Serôdio, P. Mestre, J. Cabral, M. Gomes, and F. Branco: Appl. Sci. **14** (2024) 2160. https://doi.org/10.3390/app14052160
2 X. Bian, W. Zhao, L. Tang, H. Zhao, and X. Mei: Appl. Sci. **14** (2024) 10268. https://doi.org/10.3390/app142210268
3 Y. Li, J. An, N. He, Y. Li, Z. Han, Z. Chen, and Y. Qu: WEVJ **16** (2025) 56. https://doi.org/10.3390/wevj16020056

4 F. A. Maken, S. Muthu, C. Nguyen, C. Sun, J. Tong, S. Wang, R. Tsuchida, D. Howard, S. Dunstall, and L. Petersson: Sensors **25** (2025) 250. https://doi.org/10.3390/s25030950
5 S. Wang and N. S. Ahmad: Eng. Sci. Technol. Int. J. **63** (2025) 101977. https://doi.org/10.1016/j.jestch.2025.101977
6 R. N. Dean and A. Luque: IEEE Trans. Ind. Electron. **56** (2009) 913. https://doi.org/10.1109/TIE.2009.2013691
7 B. You, G. Zhong, C. Chen, J. Li, and E. Ma: Sensors **23** (2023) 6000. https://doi.org/10.3390/s23136000
8 Y. Liu, S. Wang, Y. Xie, T. Xiong, and M. Wu: Sensors **24** (2024) 1222. https://doi.org/10.3390/s24041222
9 M. S. A. Khan, D. Hussain, K. Naveed, U. S. Khan, I. Q. Mundial, and A. B. Aqeel: J. Sens. **2022** (2022) 1. https://doi.org/10.1155/2022/5428097
10 SSRN: https://doi.org/10.2139/ssrn.4804311 (Accessed May 2025).
11 DJI: https://www.dji.com/sg/support/product/matrice-300?backup_page=index&target=sg (Accessed March 2026).
12 T. J. Chong, X. J. Tang, C. H. Leng, M. Yogeswaran, O. E. Ng, and Y. Z. Chong: Procedia Comput. Sci. **76** (2015) 174. https://doi.org/10.1016/j.procs.2015.12.336
13 F. Zhang, B. Zhang, and C. Sun: Proc. 2022 11th Int. Conf. Control, Automation and Information Sciences (ICCAIS, 2022) 130. https://doi.org/10.1109/ICCAIS56082.2022.9990085
14 ION Technical Content: https://doi.org/10.33012/2021.17868 (Accessed May 2025).
15 P. Chen, X. Zhao, L. Zeng, L. Liu, S. Liu, L. Sun, Z. Li, H. Chen, G. Liu, Z. Qiao, Y. Qu, D. Xu, L. Li, and L. Li: Sensors **25** (2025) 1447. https://doi.org/10.3390/s25051447
16 J. Sturm, N. Engelhard, F. Endres, W. Burgard, and D. Cremers. Proc. 2012 IEEE/RSJ Int. Conf. Intelligent Robots and Systems (IROS, 2012) 273. https://doi.org/10.1109/IROS.2012.6385773
17 C. Campos, R. Elvira, J. J. Gómez, J. M. Montiel, and J. D. Tardós: IEEE Trans. Robot. **37** (2021) 1115. https://doi.org/10.1109/TRO.2021.3075644
18 Y. Wang, Y. Chen, and L. Xie: IEEE Robot. Autom. Lett. **7** (2022) 12345. https://doi.org/10.1109/LRA.2022.3141234

About the Authors



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