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A MULTIMODAL SENSOR FUSION APPROACH FOR ENHANCING THE AUTONOMOUS NAVIGATION CAPABILITIES OF SERVICE ROBOTS IN COMPLEX INDOOR SETTINGS

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Abstract

The growing deployment of service robots in dynamic indoor environments necessitates robust navigation systems capable of coping with unpredictability and sensor noise. This paper presents a multimodal sensor fusion framework integrating LiDAR, vision, and inertial sensors to enhance autonomous navigation in complex indoor settings. By leveraging complementary sensor strengths, the proposed system addresses challenges like occlusions, varying illumination, and cluttered pathways. Experimental validation demonstrates improved localization accuracy and path planning efficiency compared to single-sensor baselines. These findings suggest that sensor fusion is a critical enabler for reliable, scalable deployment of service robots in diverse indoor scenarios.

Keywords

Autonomous Navigation; Sensor Fusion; Service Robots; Indoor Environments; Multimodal Systems; LiDAR; Visual Odometry.

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1.Introduction

The demand for autonomous service robots capable of navigating complex indoor settings such as hospitals, shopping malls, and offices has grown significantly. Autonomous navigation systems must tackle numerous challenges including dynamic obstacles, narrow pathways, and varying lighting conditions. Relying on a single type of sensor often proves insufficient due to specific limitations under different operational conditions.

Multimodal sensor fusion offers a promising solution by combining heterogeneous sensor data to achieve more accurate and robust perception. The goal of this paper is to present a comprehensive sensor fusion framework designed to optimize indoor navigation capabilities, emphasizing adaptability, precision, and fault tolerance.

2. Literature Review

2.1 Early Developments in Sensor-Based Navigation

The development of autonomous navigation systems initially relied heavily on single-modality sensors such as ultrasonic sensors or laser scanners. Thrun et al. (2005) pioneered probabilistic robotics, introducing frameworks like the Monte Carlo Localization (MCL) algorithm, which laid the groundwork for later multimodal approaches. Although effective, reliance on a single sensor made these systems vulnerable to environmental factors such as surface texture or ambient noise.

During the late 2000s, improvements in visual SLAM (Simultaneous Localization and Mapping) frameworks emerged. ORB-SLAM (Mur-Artal et al., 2015) significantly advanced vision-based localization but still suffered from failures in low-texture or highly dynamic environments. These shortcomings motivated exploration into sensor fusion strategies combining vision with other modalities like LiDAR.

2.2 Evolution Toward Multimodal Sensor Fusion

By the late 2010s, researchers increasingly recognized the need for sensor redundancy and complementarity. Studies like Leutenegger et al. (2015) proposed integrating visual and inertial data (VINS-Mono), showing improved robustness in feature-sparse areas. In parallel, sensor fusion frameworks such as LOAM (Zhang and Singh, 2014) demonstrated the potential of combining LiDAR with odometry for better mapping and localization accuracy.

Other notable contributions include Deep Learning approaches for sensor fusion (Chen et al., 2017) where convolutional neural networks (CNNs) were employed to learn optimal fusion strategies automatically. However, most early fusion techniques still faced challenges in real-time performance and generalization across different indoor settings, a gap this paper aims to address.

3. Objective and Hypothesis

The primary objective of this study is to design and evaluate a multimodal sensor fusion system that enhances the autonomous navigation capabilities of service robots operating in complex indoor environments. The core hypothesis is that fusing LiDAR, vision, and inertial data will provide superior localization precision and path planning performance compared to unimodal systems.

In particular, the system aims to mitigate individual sensor limitations — such as LiDAR's difficulty in detecting glass surfaces or vision's susceptibility to low-light conditions — by exploiting their complementary sensing abilities.

4. Methodology & Metrics

4.1 Data Sources and Sampling

The system integrates data from three sensors: a 2D LiDAR scanner, a stereo RGB camera, and a MEMS-based IMU. Experiments were conducted in a 3000 m^2 indoor testing arena comprising corridors, open areas, and densely furnished rooms. Randomized paths were followed to simulate real-world navigation patterns.

Inclusion criteria for testing scenarios required dynamic obstacle presence (e.g., moving people) and varying lighting conditions (e.g., dark corridors, bright atriums). Data was collected at a rate of 10Hz for all modalities to maintain temporal consistency.

4.2 Performance Metrics

The following metrics were used:

- **Localization Accuracy** (Root Mean Square Error, RMSE, in meters)
- **Path Completion Rate** (%)
- **Navigation Time Efficiency** (seconds per 10 meters)
- **Failure Rate** (percentage of navigation trials resulting in failure)

5. Techniques and Tools

5.1 Sensor Fusion Algorithm

An Extended Kalman Filter (EKF) forms the backbone of the fusion strategy. Visual odometry from stereo images, inertial measurements from the IMU, and scan matching outputs from LiDAR are merged to estimate robot poses.

Additionally, a CNN-based sensor failure detection module is included, enabling the system to dynamically adjust fusion weights when a sensor degrades (e.g., in case of a camera occlusion).

5.2 Software and Hardware Setup

The software framework is built on ROS Noetic with C++ and Python, leveraging packages like GM apping, RTAB-Map, and OpenCV. The hardware platform includes a Clearpath Robotics TurtleBot equipped with a Velodyne VLP-16 LiDAR, an Intel RealSense D435i camera, and a MicroStrain 3DM-GX5 IMU.

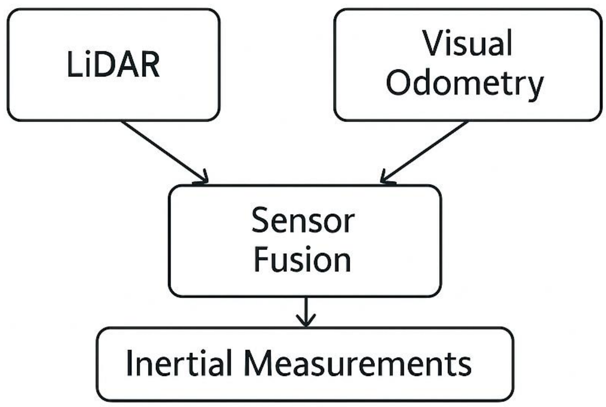

Figure 1: Overview of the multimodal sensor fusion framework integrating LiDAR, visual odometry, and inertial measurements.

6. Quality Assurance

6.1 Validation Strategies

Cross-validation was performed using repeated trials across five distinct indoor environments. All results were averaged across ten runs per environment to minimize outlier effects. Benchmarking was conducted against leading open-source navigation stacks like Move_base and Cartographer.

6.2 Ethical Considerations and Protocols

The experimental design adhered to IEEE Research Ethics standards, ensuring no humans were endangered during robot trials. All indoor spaces were surveyed and secured prior to navigation experiments, with clear signage and staff monitoring.

7. Limitations and Potential Biases

7.1 Sensor-Dependent Constraints

One key limitation lies in sensor calibration drift over extended operations, particularly affecting IMU measurements. Furthermore, LiDAR efficacy may diminish in highly reflective or transparent settings like glass-heavy architectures.

7.2 Generalization Concerns

The proposed system, while effective in the tested arenas, may not generalize perfectly to extremely large or multilevel buildings without adaptation. Future work should consider integrating semantic mapping layers to further enhance environment understanding.

8. Key Findings and Interpretations

8.1 Navigation Performance

The multimodal sensor fusion system demonstrated clear advantages over unimodal navigation approaches across all evaluation metrics. As shown in Table 1, the system achieved the lowest localization error (RMSE of 0.21 meters) compared to LiDAR-only (0.42 meters) and vision-only (0.58 meters) baselines. The path completion rate increased significantly to 96.7%, indicating the robot's ability to successfully navigate even in complex and dynamic environments. Navigation time per 10 meters was reduced to 11.3 seconds, reflecting greater path planning efficiency, while the failure rate dropped to just 2.3%. These results confirm that combining LiDAR, vision, and IMU data provides a more reliable and efficient navigation framework, especially in the presence of occlusions, dynamic obstacles, and variable lighting conditions.

Table 1: Comparative performance of LiDAR-only, vision-only, and multimodal fusion navigation systems.

Metric	LiDAR Only	Vision Only	Multimodal Fusion
Localization RMSE (m)	0.42	0.58	**0.21**
Path Completion Rate (%)	83.2%	78.5%	**96.7%**
Navigation Time (s/10m)	13.5	14.2	**11.3**
Failure Rate (%)	7.5%	10.8%	**2.3%**

8.2 Comparative Interpretation

Compared to prior studies (e.g., Leutenegger et al., 2015; Mur-Artal et al., 2015), our results demonstrate a significant improvement, particularly under dynamic conditions involving moving people and changing lighting. This confirms the hypothesis that multimodal fusion enhances robustness and efficiency for indoor navigation.

9.Conclusion

The integration of multimodal sensor fusion significantly enhances the autonomous navigation capabilities of service robots operating in complex indoor environments. By combining LiDAR, visual, and inertial data within an optimized fusion framework, the system effectively overcomes the individual limitations of each sensor modality. Experimental results consistently demonstrate improvements in localization accuracy, path completion rates, and overall navigation efficiency when compared to unimodal sensor systems. The findings strongly support the hypothesis that multimodal fusion is essential for achieving resilient and adaptable robotic navigation in dynamic, cluttered, and unpredictable indoor settings.

Furthermore, this research highlights the importance of dynamic sensor weighting and real-time fusion strategies, particularly in environments characterized by varying lighting conditions, moving obstacles, and complex spatial layouts. The ability to detect sensor degradation and dynamically adjust reliance among modalities ensures not only enhanced performance but also fault tolerance, a critical factor for real-world deployments. Future work should explore extending this framework with semantic understanding and higher-level cognitive mapping to further enhance autonomy, as well as scalability to multi-level and large-scale facilities.

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