International Journal of Robotics and Autonomous Systems
Volume 1, Issue 2, July-December, 2016

Sensor Fusion for Real-Time SLAM in Mobile Robotics: Enhancing Accuracy and Robustness

Dr. Ravi Bansal,
Assistant Professor
, Department of Robotics,
Indian Institute of Technology, Kanpur
Email: ravibansal@iitk.ac.in

Ananya Ghosh,
M.Tech Scholar,
Department of Electronics,
National Institute of Technology, Rourkela
Email: ananyagh@nitrkl.ac.in

Abstract

Sensor fusion has become a cornerstone in the advancement of mobile robotic systems, particularly in achieving real-time localization and mapping. Simultaneous Localization and Mapping (SLAM) has emerged as a critical task in autonomous robotics, relying on the integration of various sensors such as LiDAR, GPS, IMU, and vision systems. This paper explores modern techniques in sensor fusion that enable robust SLAM in dynamic and unstructured environments. The work delves into Kalman Filters, Particle Filters, and deep learning-based fusion approaches. A comparative analysis of these techniques is presented, highlighting their effectiveness in indoor and outdoor navigation. Emphasis is laid on accuracy, computational efficiency, and adaptability. Real-world applications in autonomous vehicles, drones, and service robots are discussed to showcase practical relevance. The study concludes with insights into the challenges, limitations, and future research directions of sensor fusion for SLAM.

Keywords: *Sensor Fusion, SLAM, Mobile Robots, Localization, Mapping, Kalman Filter, Deep Learning.*

INTRODUCTION

Autonomous mobile robots have gained immense traction across various industries, ranging from manufacturing to healthcare and agriculture. A foundational capability for these systems is the ability to accurately localize themselves within an environment while simultaneously constructing a map of it—a process known as Simultaneous Localization and Mapping (SLAM). Accurate SLAM enables robots to navigate, avoid obstacles, and execute complex tasks with minimal human intervention.

However, no single sensor can provide all the necessary information with the required precision and reliability. For instance, LiDAR provides accurate distance measurements but lacks semantic understanding; GPS offers global positioning but suffers indoors; cameras offer rich visual cues but are sensitive to lighting conditions. Sensor fusion addresses these limitations by combining data from multiple sensors, enhancing the reliability and robustness of localization and mapping. This paper investigates various sensor fusion methodologies used in real-time SLAM applications for mobile robots.

LITERATURE REVIEW

Recent studies have focused on improving SLAM through sensor fusion frameworks. Mur-Artal and Tardós (2017) developed ORB-SLAM2, a visual SLAM system with inertial sensor integration, demonstrating significant accuracy in monocular and stereo setups. Li et al. (2020) presented a multi-sensor fusion approach combining GPS, IMU, and LiDAR data using Extended Kalman Filters (EKF) for autonomous vehicle navigation.

Other approaches involve deep learning for sensor fusion, where Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) are employed to learn sensor correlations. While traditional methods like Particle Filters and EKFs are computationally efficient, learning-based methods provide adaptability in dynamic environments but often require extensive training data.

METHODOLOGIES

Sensor fusion for SLAM can be broadly categorized into model-based and learning-based techniques. Model-based approaches rely on statistical models like the Extended Kalman Filter (EKF) and Particle Filter. The EKF is widely used due to its ability to estimate nonlinear systems efficiently, but it assumes Gaussian noise and can diverge under high uncertainty. Particle Filters offer better accuracy in non-Gaussian noise scenarios but are computationally expensive.

Learning-based methods use deep neural networks to model the complex relationship between multiple sensor inputs. End-to-end frameworks like DeepVO and VINet integrate camera, IMU, and LiDAR data to predict robot poses. These methods benefit from flexibility and scalability but face challenges in generalization and interpretability.

COMPARISON OF SENSOR FUSION TECHNIQUES

Technique	Sensors Used	Advantages	Limitations
Extended Kalman Filter	LiDAR, IMU, GPS	Low computation, real-time	Limited non-linear modeling
Particle Filter	Camera, IMU	Robust to non-Gaussian noise	High computation
Deep Learning (CNN)	Camera, LiDAR	Adaptive, scalable	Data intensive
Hybrid SLAM	LiDAR, Camera, IMU	High accuracy	Complex integration

APPLICATIONS

Sensor fusion in SLAM finds applications in various domains. Autonomous vehicles utilize GPS, IMU, LiDAR, and camera fusion to navigate urban environments. In warehouse robotics, sensor fusion enables AGVs to move safely and efficiently in cluttered settings. Drones leverage visual-inertial SLAM for stable flight and navigation in GPS-denied environments.

Furthermore, service robots in healthcare and hospitality sectors rely on SLAM for safe human-robot interaction. These applications demand real-time performance, low latency, and robustness to sensor failures—goals effectively met through advanced sensor fusion.

CHALLENGES AND FUTURE WORK

Despite significant progress, sensor fusion for SLAM still faces challenges such as sensor calibration errors, synchronization issues, and drift over long durations. Moreover, computational overhead remains a concern for real-time embedded platforms.

Future work should focus on adaptive fusion techniques that dynamically weigh sensor reliability, use of edge AI for faster inference, and self-supervised learning to reduce dependency on labeled data. Standardizing datasets and benchmarks will also aid in consistent evaluation of new methods.

CONCLUSION

Sensor fusion is critical to achieving robust, real-time SLAM in mobile robotics. By combining the strengths of multiple sensors, fusion techniques enable autonomous systems to perceive and navigate complex environments effectively. This paper reviewed classical and modern fusion methodologies, their applications, and associated challenges. It is evident that while model-based approaches offer efficiency, learning-based methods provide adaptability and accuracy. The future lies in hybrid systems that leverage the best of both worlds, paving the way for safer and more efficient mobile robots.

REFERENCES

1. 1. H. Durrant-Whyte and T. Bailey, “Simultaneous localization and mapping: part I,” IEEE Robotics & Automation Magazine, vol. 13, no. 2, pp. 99–110, 2006.
2. 2. 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.
3. 3. Y. Li, K. Yu, and B. Liu, “A sensor fusion method using Kalman Filter for SLAM,” Sensors, vol. 20, no. 5, p. 1350, 2020.
4. 4. J. Engel, V. Koltun, and D. Cremers, “Direct sparse odometry,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 40, no. 3, pp. 611–625, 2018.
5. 5. H. Cho, Y. Kim, and B. Song, “Real-time multi-sensor fusion and SLAM for autonomous driving,” Sensors, vol. 19, no. 20, p. 4575, 2019.
6. 6. S. Leutenegger et al., “Keyframe-based visual–inertial odometry using nonlinear optimization,” International Journal of Robotics Research, vol. 34, no. 3, pp. 314–334, 2015.
7. 7. J. Zhang and S. Singh, “LOAM: Lidar Odometry and Mapping in real-time,” in Robotics: Science and Systems, 2014.
8. 8. C. Cadena et al., “Past, present, and future of SLAM,” IEEE Transactions on Robotics, vol. 32, no. 6, pp. 1309–1332, 2016.