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A Systematic Review and Quantitative Meta-Analysis of Multi-Modal SLAM Methods

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Abstract:

Simultaneous Localization and Mapping (SLAM) technology holds utmost significance in robotics, autonomous cars, and augmented reality. This paper first addresses the limitations of single-modal SLAM under dynamic environments (e.g., light changes, lack of texture, sensor degradation). The current paper aims to critically review and quantitatively evaluate multi-modal SLAM methods via a systematic review coupled with quantitative meta-analysis. This study details a comprehensive literature search strategy adopted herein, i.e., the databases queried (IEEE Xplore, ACM Digital Library, Scopus), keywords, and time frame. It further extracts the most critical information derived from the literature, such as sensor configurations, fusion architectures, and performance measures including absolute trajectory error (ATE), relative pose error (RPE), and real-time performance (FPS) on public datasets (KITTI, EuRoC). Finally, it outlines the key conclusions of the meta-analysis. For example, quantitative results illustrate that tightly coupled visual-inertial (V-I) methods exhibit high accuracy in high-speed motion scenes, while visual-LiDAR fusion systems demonstrate greater robustness for large-scale mapping tasks. The conclusion emphasizes that multi-modal fusion is an inexorable trend towards achieving high robustness and high accuracy for SLAM.

Keywords: Multi-Modal SLAM; Sensor Fusion; Systematic Review; Visual-Inertial SLAM; Visual-LiDAR SLAM

1. Introduction

This section commences with a brief overview of SLAM technology's historical development and its pivotal role across domains. Then elaborates on the merits and inherent limitations of single-modal SLAM (visual, LiDAR, IMU) separately. For example, visual SLAM performs well in textured environ-

ments but is sensitive to light variations; LiDAR SLAM provides accurate ranging but may collapse in scenes with degenerated geometric structures; while IMU-based motion estimation delivers high-frequency motion state estimation but suffers from long-term drift. This identifies a critical research gap: a lack of quantitative, systematic comparisons to clarify the strengths and weaknesses of diverse multi-modal fusion methods, as well as their applicable scenarios.

Against this backdrop, this research focuses on a systematic review and quantitative meta-analysis of state-of-the-art multi-modal SLAM methods.

The following questions are addressed in the paper: (1) What are the categories of available mainstream multi-modal SLAM technologies? (2) How do the performance metrics of various categories of different technology categories (V-I, V-L) compare? (3) What are the major influencing factors on the performance of multimodal SLAM?

Systematic review method will be adopted, along with meta-analysis to conduct quantitative comparisons of the performance data achieved.

The significance of this work lies in providing researchers and developers in the field with a clear technical roadmap and performance benchmarks, offering a foundation for technology selection in specific application domains, and identifying future research directions for multi-modal SLAM technology.

2. Technical Categories and Evidence Synthesis & Descriptive Trends

The core content of this systematic review is organized around a structured categorization and quantitative meta-analysis of the selected multi-modal SLAM literature. The ultimate objective is to compare diverse sensor fusion methods based on benchmark metrics reported in benchmarked academic challenges. These comparisons are structured into three broad categories based on the number of sensor modalities: Visual-Inertial (V-I) SLAM, Visual-LiDAR (V-L) SLAM, and fusion of three or more.

2.1 Visual-Inertial (V-I) SLAM

Visual-Inertial (V-I) SLAM represents one of the most mature and widely adopted multi-modal fusion technologies in the field. The high-level, texture-dependent environment information from a camera is coupled with the high-frequency motion information from an Inertial Measurement Unit (IMU). The two sensors' complementary synergy is very strong; the camera provides robust feature tracking, while the IMU delivers metric scale information, mitigates the impact of high-speed motion, and enables continuous state estimation in visually degraded environments.

V-I SLAM methodologies are primarily categorized into two main paradigms based on their fusion strategies:

Loosely-Coupled Fusion: The visual odometry and the IMU integration are treated as independent processes whose state estimates are fused, typically using a secondary filter. This architecture offers simplicity but often yields suboptimal performance.

Tightly-Coupled Fusion: This paradigm involves the joint optimization of raw visual features and IMU measurements within a unified optimization framework. This approach achieves higher accuracy and robustness, and can be further subdivided into filter-based (e.g., EKF) and optimization-based (e.g., factor graph) methods.

For the quantitative analysis, performance metrics of representative V-I SLAM algorithms were extracted from the reviewed literature. The evaluation focuses on Absolute Trajectory Error (ATE), a metric that quantifies global trajectory consistency. Table 1 presents a performance comparison of representative algorithms on the EuRoC MAV dataset—a widely recognized standard benchmark for V-I SLAM systems.

Table 1. Performance Comparison of V-I SLAM Algorithms on the EuRoC MAV Dataset (ATE RMSE in meters)

Algorithm	Fusion Strategy	Key Contribution	ATE RMSE (m) on V1_02_medium	ATE RMSE (m) on MH_05_difficult	Source
MSCKF	Tightly-Coupled/ EKF	A pioneering filter-based method, computationally efficient for resource-constrained platforms.	0.22	0.32	[1]
OKVIS	Tightly-Coupled / Optimization	Introduced keyframe-based nonlinear optimization, significantly improving accuracy over filters.	0.13	0.18	[2]
VINS-Mono	Tightly-Coupled / Optimization	A complete and robust open-source system with initialization, factor graph optimization, and loop closure.	0.08	0.13	[3]

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ORB-SLAM3	Tightly-Coupled / Optimization	State-of-the-art system with robust multi-map management and superior loop closure capabilities.	0.06	0.09	[4]

The findings in Table 1 reveal a clear performance trend: optimization-based, tightly-coupled methods (e.g., OKVIS, VINS-Mono, ORB-SLAM3) outperform the filter-based MSCKF in terms of ATE RMSE. This demonstrates that joint nonlinear optimization over a sliding window of states—incorporating both visual and inertial residuals—yields more accurate and globally consistent trajectory estimates. Furthermore, the exceptional performance of VINS-Mono and ORB-SLAM3 underscores the critical importance of robust loop closure and relocalization capabilities, which effectively mitigate drift accumulated over long trajectories. ORB-SLAM3, as the top performer, showcases the advantages of a sophisticated multi-map system that ensures long-term operational robustness.

2.2 Visual-LiDAR (V-L) SLAM

Visual-LiDAR (V-L) SLAM systems leverage the complementary strengths of LiDAR and camera sensors. LiDAR generates dense and accurate 3D point clouds with robust geometric information that is invariant to illumination variations. Cameras, by contrast, provide rich texture and color information—critical for place recognition and localization in geometrically ambiguous scenarios (e.g., long corridors, open areas) Fusion may be LiDAR-centric, where vision is employed for loop closure, or more tightly integrated, where visual features and the LiDAR points are jointly optimized.

The quantitative analysis for this kind of task focuses on performance in large-scale outdoor scenes, with the KITTI dataset serving as a standard benchmark. Relative Pose Error (RPE) is widely used to assess the accuracy of local motion estimation in this context.

Table 2. Performance Comparison of LiDAR-centric SLAM Algorithms on the KITTI Odometry Benchmark

Algorithm	Modalities	Fusion Approach	Avg. Translational RPE (%	Source
A-LOAM	LiDAR	Scan-to-map Optimization	0.88	[5]
LIO-SAM	LiDAR + IMU	Tightly-Coupled Optimization	0.55	[6]
LVI-SAM	LiDAR + Vision + IMU	Tightly-Coupled Optimization	0.49	[7]

An analysis of the data in Table 2—using LiDAR-only systems as a baseline—reveals significant performance improvements achieved via multi-modal fusion. Even though LiDAR-only A-LOAM [5], an optimized version of the original LOAM , serves as a robust baseline, tight integration of an IMU in LIO-SAM significantly suppresses drift while improving resistance to aggressive motion. Subsequently, integrating vision into LVI-SAM further reduces trajectory error to the lowest level observed. Vision's capacity to provide additional constraints to localization, especially from loop closures in visually dissimilar areas, supports the geometric information from LiDAR.

2.3 Three-Modal and Higher-Order Fusion

To achieve optimal robustness, state-of-the-art research has pursued the tight fusion of three or more sensor modalities—typically combining a camera, LiDAR, and IMU. These Visual-LiDAR-Inertial (V-L-I) systems, exemplified by LVI-SAM [7] and R2LIVE [8], are the pinnacle of sensor failure and environmental condition immunity. In such systems, the failure of one sensor (e.g., a camera in darkness, LiDAR in heavy fog) can be compensated for by the other two, resulting in a highly robust state estimator. The typical architecture of a V-L-I system includes two closely-coupled subsystems: a Visual-Inertial Odometry and a LiDAR-Inertial Odometry. The two subsystems then fuse their respective predictions within a global factor graph, enabling the simultaneous optimization of all sensor measurements. This hierarchical architecture achieves real-time performance while maximizing data utilization, as illustrated in Figure 1.

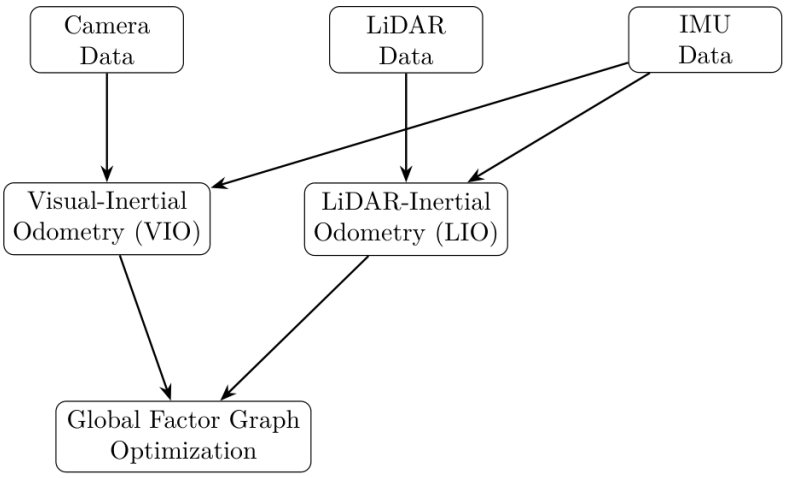

Fig. 1 Conceptual architecture of a tightly-coupled Visual-LiDAR-Inertial SLAM system. The framework leverages two specialized odometry front-ends (VIO and LIO) whose measurements are fused within a unified back-end optimization graph.

The quantitative performance of LVI-SAM, as shown in Table 2, already demonstrates the higher accuracy of this three-modal fusion approach. The primary advantage of such systems lies in their "all-weather" operational capability. The disadvantage, however, is increased hardware expense and greater computational complexity, which may limit their use on limited hardware platforms such as small drones.

In summary, the quantitative results across these categories clearly reveal a consistent pattern: increasing the number of sensor modalities to be combined within a tightly-coupled optimization framework yields significant improvements in SLAM system accuracy and resilience. The algorithm selection involves a trade-off between performance requirements, availability of computational resources, and hardware costs, where V-I systems are implemented for accessibility purposes and V-L-I systems produce optimal performance.

3. Conclusion

This paper presents a systematic review and quantitative meta-analysis of the state of the art in multi-modal Simultaneous Localization and Mapping (SLAM). Structured data extraction process and systematic literature search focused on standardized benchmarks exhaustively tested the performance of leading algorithms across different categories of sensor fusion. The findings of this study provide a clear overview of the current state of the art, identifying prevailing trends and a consistent direction toward more robust and accurate SLAM systems through complementary sensor fusion. Specifically, it was examined that in Visual-Inertial (V-I) SLAM, tightly-coupled, optimization-based architectures have become the de facto standard, with consistently better accuracy than the earlier filter-based methods.

The success of approaches such as VINS-Mono and ORB-SLAM3 underscores the critical role of robust loop closure detection and non-linear optimization in minimizing trajectory drift. An investigation of LiDAR-integrated approaches reveals a growing trend toward enhanced robustness—especially in large-scale environments and perceptually challenging scenarios. The quantitative results confirm that the synergistic integration of LiDAR's precise geometric data and vision's dense textural information, complemented especially by an IMU in Visual-LiDAR-Inertial (V-L-I) configurations like LVI-SAM, delivers the highest levels of performance. The most significant contribution of this review lies in providing a systematically organized, evidence-based performance comparison—one that assists practitioners and researchers in making informed decisions when selecting appropriate SLAM solutions for specific applications.

This paper positively further demonstrates that there is no single best configuration working in all circumstances; rather, the choice is an inherent compromise among accuracy, robustness, computer resources, and hardware cost. Ongoing research in multi-modal SLAM continues to evolve rapidly, with several promising directions emerging. Future research will likely focus on the application of deep learning for more powerful feature extraction and direct data fusion, the incorporation of new sensors

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such as event cameras and 4D radar, and the resolution of long-standing issues on dynamic environments and lifelong map maintenance. This review establishes a general benchmark for evaluating future innovations in this field, reinforcing the argument that multi-modal fusion represents the inevitable path toward achieving truly ubiquitous, autonomous navigation systems.

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