A Review of Simultaneous Localization and Mapping Methods for Off-Road Mobile Robots

Nuralem Abizov
International Engineering Technological University, Kazakhstan
abizov94@gmail.com (corresponding author)

Received: 9 August 2025 | Revised: 8 September 2025 and 21 September 2025 | Accepted: 24 September 2025

 DOI: https://doi.org/10.48084/etasr.13976

ABSTRACT

Simultaneous Localization and Mapping (SLAM) enable autonomous mobile robots to build a map of an unknown environment while estimating their own position within it. Unstructured terrain, dynamic environmental conditions, and sensor limitations, often encountered in off-road areas can limit the effectiveness of SLAM. This review analyzes SLAM methodologies applicable to off-road mobile robots, categorizing them into LiDAR-based, visual, multi-sensor fusion, and learning-based or semantic approaches. Each category is examined in terms of algorithmic principles, performance characteristics, and suitability for varying terrain and environmental conditions. Furthermore, to assess the performance of these categories evaluation metrics are utilized, including accuracy, drift rate, robustness, computational efficiency, and benchmarking datasets. The comparative analysis highlights trade-offs between geometric precision, adaptability, and computational demands, with multi-sensor fusion and semantic integration. Real-time operation under limited onboard computation, scalability to large unstructured terrains, resilience in GPS-denied and feature-scarce environments, and integration with autonomous navigation systems are some of the identified research gaps. The findings emphasize the need for hybrid, computation-aware SLAM frameworks and standardized off-road benchmarks to accelerate the deployment of reliable autonomous systems in challenging outdoor environments.

Keywords-simultaneous localization and mapping; SLAM; off-road mobile robots; LiDAR-based SLAM; visual SLAM; multi-sensor fusion; semantic mapping; terrain adaptability; autonomous navigation

I. INTRODUCTION

SLAM integrates environmental mapping and self-positioning, allowing autonomous robots to navigate effectively in new environments [1]. Despite SLAM algorithms being efficient in structured indoors and urban settings, their application to off-road environments is limited. This limitation is attributed to unstructured terrain, dynamic environmental conditions, and sensor limitations [2]. Off-road SLAM must operate with irregular ground surfaces, vegetation occlusions, dust, and variable lighting conditions, which can impair feature detection, data association, and loop closure processes [3].

The development of SLAM algorithms for off-road robotics is critical for advancing autonomous capabilities in sectors, such as agriculture, forestry, mining, environmental monitoring, and military reconnaissance [4]. The successful application of SLAM in these domains requires navigation with limited GPS availability [5]. Sensor technologies, including LiDAR, stereo vision, and multi-sensor fusion, can improve the effectiveness of SLAM to off-road scenarios. However, computational efficiency, accuracy, and robustness remain a central research concern [6].

A comprehensive review of off-road SLAM methodologies is essential to consolidate current knowledge, compare algorithmic approaches, and identify unresolved challenges. This study aims to systematically classify SLAM methods relevant to off-road robotics, analyze their performance in various terrain types, and highlight key innovations in sensor integration and algorithm design. The ultimate objective is to provide a knowledge base that guides future research and facilitates the development of SLAM systems capable of reliable operation in complex, unstructured environments.

II. FUNDAMENTALS OF SLAM

SLAM refers to the computational problem of constructing a consistent map of an unknown environment while simultaneously estimating the robot's position within that map [7]. As illustrated in Figure 1, SLAM operates through iterative cycles of prediction, data acquisition, matching, and update. Proprioceptive sensors provide motion data for the prediction step, while exteroceptive sensors supply environmental measurements for feature matching. The update refines both the robot state x_t and map m_t, often using probabilistic formulations such as the Bayes filter, as described by:

$$p(x_t, m_t|z_{1:t}, u_{1:t}) \subset P(z_t\!: x_t, m_t) \int p(x_t|u_t, x_{t-1}) p(x_{t-1}, m_{t-1}) dx_{t-1} \quad (1)$$

This recursive process continues until a complete, accurate map is built.

SLAM techniques are classified based on their sensing process in visual, LiDAR-based, and multi-Sensor fusion SLAM. To begin with, visual SLAM utilizes monocular, stereo, or RGB-D cameras to extract image features and track them over time [8]. Subsequently, it offers low-cost and lightweight solutions, though performance can degrade in low-light or texture-sparse environments. Moreover, LiDAR-based SLAM leverages high-precision range measurements to construct accurate 3D maps [9]. Consequently, it can be employed in environments with poor lighting but at the expense of higher cost and sensor weight. Finally, multi-sensor fusion SLAM combines data from complementary sensors, such as cameras, LiDAR, IMU, and GNSS, to improve robustness, accuracy, and adaptability, particularly in challenging off-road terrains, where single-sensor approaches may fail [10]. The categorization of SLAM approaches and their core pipeline components are illustrated in Figure 2.

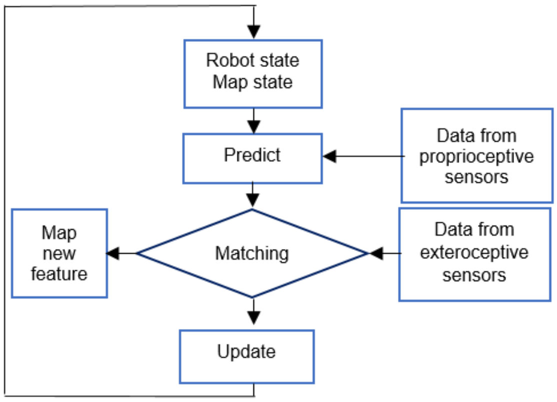

Fig. 1. Generalized SLAM process flow integrating prediction, sensor data fusion, feature matching, and map updating.

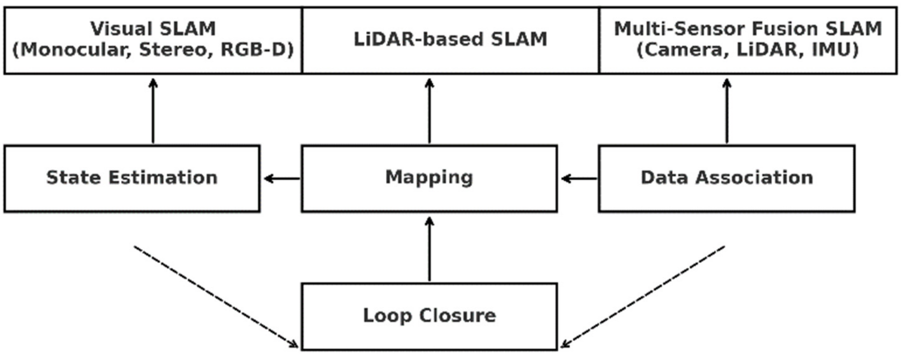

Fig. 2. Classification of SLAM methods and core pipeline components for off-road mobile robots.

The SLAM pipeline integrates several components that operate in a continuous loop. State estimation determines the robot's pose over time using motion and observation models. It relies on probabilistic frameworks like the extended Kalman or particle filters [11]. The mapping process involves building and refining the representation of the environment, which may be metric, topological, or semantic. Furthermore, data association identifies the relationship between current sensor observations and existing map features, a critical step to maintain map consistency. Loop closure detects revisited locations to correct accumulated drift and improve global accuracy. These components form the main computational framework of SLAM, thus enabling reliable navigation and mapping even in unstructured and dynamic environments.

III. OFF-ROAD ENVIRONMENTAL AND OPERATIONAL CHALLENGES

Off-road environments are typically compromised due to highly irregular and unpredictable terrain with uneven ground, steep slope gradients, and deformable surfaces such as mud or sand. These factors significantly affect vehicle stability and traction, introducing additional uncertainty in motion modeling and complicated path planning [12]. Robot speed and maneuverability are also restricted by such factors, suggesting the need for robust localization and mapping methods [13].

Additionally, dynamic environmental factors, such as varying weather conditions, dense vegetation, airborne dust, and fluctuating lighting, further impair off-road SLAM performance [14]. For instance, rain or snow can obscure sensors. Bright sunlight or deep shadows affect visual feature detection. Moreover, vegetation and dust particles may produce false measurements in LiDAR scans or obstruct camera observations, leading to lower map quality and reduced localization accuracy [15]. The adaptation process of SLAM in these conditions involves sensor fusion strategies, dynamic filtering techniques, and semantic scene understanding to distinguish between transient and static environmental features.

Localization in off-road is further complicated by the GPS signals' unreliability, especially in forested, mountainous, or canyon-like environments [16]. GPS drift along long trajectories introduces position estimate errors [17]. Therefore, other localization techniques must be implemented, such as LiDAR or vision-based odometry. The methods should be integrated into the SLAM framework for consistent mapping and navigation.

An additional challenge of off-road SLAM is sensor limitations. Noise from vibration, terrain features' temporary occlusions, and calibration drift due to mechanical stress can impair sensor accuracy and consistency. Dust and mud deposits can physically obstruct lenses or LiDAR emitters, reducing measurement reliability. To address these limitations, SLAM implementations often incorporate real-time calibration, redundancy in sensing modalities, and error modeling to mitigate the impact of degraded data.

IV. SLAM METHODOLOGIES FOR OFF-ROAD MOBILE ROBOTS

To implement SLAM in off-road mobile robots requires terrain adaptability, sensor availability, and computational constraints. As depicted in Figure 3, these approaches can be broadly classified into four categories: LiDAR-based SLAM, visual SLAM, multi-sensor fusion SLAM, and learning-based or semantic SLAM.

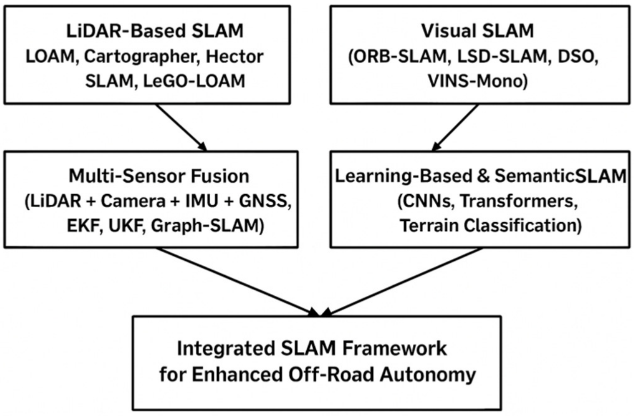

Fig. 3. SLAM methodologies that contribute to the framework of off-road mobile robots.

The mathematical foundation of SLAM can be expressed through the probabilistic estimation of the joint posterior, as depicted in:

$$p(x_{1:t}, m|z_{1:t}, u_{1:t}) \subset \mathrm{P}(z_t: x_t, \mathrm{m}) \int p(x_t|u_t, x_{t-1}) p\binom{x_{1:t}, m}{z_{1:t-1}, u_{1:t-1}} dx_t \quad (2)$$

State estimation often employs recursive filtering, such as the Extended Kalman Filter (EKF), shown in:

$$\hat{x_t} = \hat{x}_{t-1} + K_t(z_t - h(\hat{x}_{t-1})) \quad (3)$$

where K_t is the Kalman gain. Alternatively, optimization-based formulations minimize a cost function over the SLAM graph, as depicted in:

$$\min_{x,m} \sum_i \left\| z_i - h_i(x, m) \right\|^2_{\Sigma_i^{-1}} \quad (4)$$

These formulations serve as the computational backbone for the diverse SLAM methodologies displayed in Figure 3.

A. LiDAR-Based SLAM Approaches

LiDAR-based SLAM methods can generate precise 3D point clouds that are less sensitive to lighting variations compared to vision-based systems [18]. Lidar Odometry and Mapping (LOAM) algorithms offer high-accuracy motion estimation by separating odometry and mapping tasks, thus enabling real-time performance even in complex terrain [19]. Google's cartographer provides robust 2D and 3D mapping with loop closure optimization enhancing global consistency [20]. Robots with minimal onboard motion sensing can utilize hector SLAM, which relies on scan matching without definite odometry [21]. The LeGO-LOAM algorithm adapts LOAM principles for ground vehicles, incorporating ground segmentation to improve feature extraction in uneven environments [22].

In off-road mapping, LiDAR captures detailed terrain geometry, detects obstacles, and operates effectively in low-light or night conditions. However, environments with sparse geometric features and limited scan matching accuracy, such as open fields or snow-covered areas, decrease the performance of LiDAR. Additionally, LiDAR sensors are sensitive to dust, rain, and reflective surfaces, which can introduce noise or erroneous measurements. To address these limitations, hybrid approaches often integrate LiDAR with complementary sensing techniques to enhance robustness.

B. Visual SLAM Approaches

Visual SLAM techniques utilize camera imagery to extract and track visual features over time. Accelerated Segment Test (FAST) and Rotated Binary Robust Independent Elementary Features (BRIEF) SLAM (ORB-SLAM) utilizes ORB components for efficient feature matching and loop closure. Furthermore, Large-Scale Direct SLAM (LSD-SLAM) utilizes pixel intensity information without explicit feature extraction to create a dense map from monocular input [23]. Visual-Inertial Odometry for Monocular SLAM (VINS-Mono SLAM) integrates monocular visual odometry with inertial measurements to enhance pose estimation stability during rapid movements or temporary visual degradation [24].

Visual SLAM systems in off-road environments address issues related to lighting variation, texture deficiency, and environmental occlusions. Uneven illumination, caused by shadows, sunlight glare, or changing weather conditions, restricts feature detection. Poor-texture surfaces, such as sand or snow, reduce the number of trackable points. Adaptive selection, exposure control, and photometric calibration techniques are employed to mitigate such issues. Additionally, combining visual data with inertial or depth information leads to improved robustness.

C. Multi-Sensor Fusion Approaches

Multi-sensor fusion SLAM approaches integrate sensing methods, such as LiDAR, cameras, Inertial Measurement Units (IMU), and Global Navigation Satellite Systems (GNSS) to enhance localization accuracy and mapping robustness in off-road environments [25]. LiDAR collects precise geometric information, cameras provide rich visual context, IMUs offer high-frequency motion data for short-term pose estimation, and GNSS delivers absolute position measurements. Fusion-based systems combine such sensors to compensate for the individual limitations of each sensor.

Sensor fusion frameworks typically employ probabilistic estimation techniques to integrate multi-modal data. The EKF and Unscented Kalman Filter (UKF) are widely employed for continuous position estimation to manage noise and uncertainty [26]. Graph-SLAM formulations model the SLAM problem as a graph optimization task [27]. Specifically, nodes represent poses and landmarks while edges correspond to sensor constraints, thus allows for efficient loop closure handling and drift correction. In off-road applications, such frameworks enable consistent mapping despite GPS outages, LiDAR occlusions, or visual feature scarcity. Moreover, they operate in real time, dynamically weighting sensor contributions based on their reliability. Consequently, they ensure robust and adaptive SLAM performance across diverse and challenging unstructured environments.

D. Learning-Based and Semantic SLAM

Deep neural network architectures, such as Convolutional Neural Networks (CNNs) and transformer architectures are utilized in learning-based SLAM approaches to enhance feature extraction, place recognition, and data association in challenging environments [28]. CNN-based models can learn robust, task-specific features directly from raw sensor data, outperforming traditional handcrafted descriptors under lighting variation, texture sparsity, and partial occlusion conditions [29]. These learning-based pipelines can be directly employed as standalone SLAM modules or augment classical systems through learned front-ends.

In addition to this concept, semantic SLAM incorporates scene understanding into the mapping process, also assigning class labels to environmental elements [30]. Semantic mapping for off-road mobile robots, enables terrain classification of traversable ground, vegetation, water bodies, rocks, and man-made structures to enhance navigation safety and efficiency. This semantic layer allows planners to integrate high-level contextual information into path planning. Semantically informative maps that are also metrically correct can be produced by learning-based models of semantic segmentation, typically trained on labeled off-road datasets, combined with geometric mapping approaches. Such hybrid systems have great potential for robust, context-sensitive autonomy over unstructured difficult terrain.

V. EVALUATION METRICS AND BENCHMARKING

The accuracy and drift rate are fundamental quantitative measures for SLAM evaluation. They indicate how well estimated trajectories align with the ground truth. The Root Mean Square Error (RMSE) is calculated through [31]:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\|\widehat{p_i} - p_i\|^2} \quad (5)$$

where $\widehat{p_i}$ is the estimated position and p_i is the ground truth. The drift rate is expressed by:

$$Drift\ Rate = \frac{\|\widehat{p_f} - p_f\|}{L} \times 100\% \quad (6)$$

where L refers to the traveled distance. Robustness to environmental changes evaluates SLAM stability under lighting variations, weather interference, and terrain irregularities [32]. Algorithms are often tested using perturbation models that introduce noise into sensor measurements, as described by:

$$z_t' = z_t + N(0, \sigma^2) \quad (7)$$

where σ denotes the noise severity. Performance is measured by degradation in RMSE or successful loop closures under such perturbations.

Real-time performance and computational load are critical in off-road SLAM. Metrics, such as average processing time per frame T_f and computational efficiency E_c, are used and calculated as depicted in:

$$E_c = \frac{Frames\ Processed}{Total\ Computation\ Time} \quad (8)$$

Ensuring T_f remains below the sensor acquisition rate is essential for seamless navigation.

Public datasets and benchmarks provide standardized test environments. While KITTI [33] and EuRoC MAV [34] serve structured settings, off-road evaluations increasingly use the RELLIS-3D [35] and Newer College [36] Datasets. These datasets contain the ground truth and heterogeneous sensor data, enabling consistent algorithm comparison across accuracy, robustness, and efficiency metrics.

VI. COMPARATIVE ANALYSIS OF SLAM METHODS

The comparison of SLAM methods based on sensor modality differs across LiDAR, vision, multi-sensor, and learning-based systems. LiDAR-based methods offer superior geometric accuracy in 3D mapping. However, they require heavier and more expensive hardware. Visual SLAM provides lightweight and low-cost solutions at the expense of susceptibility to lighting variations. Multi-sensor fusion approaches utilize complementary modalities to enhance resilience in diverse conditions. Learning-based frameworks facilitate semantic understanding, therefore improving navigation in complex and unstructured terrain.

Terrain adaptability is a critical factor for off-road applications. Relevant methods are evaluated according to their capacity to reliably operate across uneven, deformable, and vegetation-rich surfaces. Furthermore, LiDAR-based methods excel in environments with a high number of features. Visual methods are successful on high-textured terrains in contrast to uniform landscapes such as snow or sand. Fusion-based and learning-augmented SLAM often exhibit superior adaptability by integrating geometric and semantic cues in traversability assessment.

Computational requirements vary across the different SLAM methods, affecting their performance. Optimization-heavy, graph-based methods may yield high accuracy but at increased computational cost. On the other hand, filter-based approaches provide faster updates with potential compromises in global consistency [37]. The optimization of efficient learning-based pipelines, supported by hardware acceleration, can close this gap.

Factors, such as sensor occlusions, dust, variable lighting, and GNSS outages, are used to evaluate stability. The field results consistently show that hybrid SLAM architecture combining multi-sensor fusion with learning-based components achieves the most robust navigation performance, sustaining mapping accuracy and localization stability over extended missions. The comparative analysis highlights distinct strengths and limitations of the under-study SLAM methods and is summarized in Table I.

TABLE I. COMPARATIVE ANALYSIS OF SLAM METHODS

SLAM method	Sensor modality	Terrain adaptability	Computational requirements	Robustness in field trials	Reference
LiDAR-Based	LiDAR	High in feature-rich terrains; reduced in open fields	Moderate to high	High in stable conditions; affected by dust/reflections	[18-22]
Visual	Monocular/Stereo/RGB-D Cameras	Good in textured terrains; poor in low-texture/low-light	Low to moderate	Variable; sensitive to lighting/occlusions	[23, 24]
Multi-Sensor Fusion	LiDAR + Camera + IMU + GNSS	High adaptability across varied terrains	High	Very high; resilient to sensor failures	[25, 26]
Learning-Based and Semantic	Camera/LiDAR + Deep Learning Models	High adaptability with semantic understanding	High (requires GPU)	Very high; context-aware and robust	[28-30]

VII. OPEN CHALLENGES AND RESEARCH DIRECTIONS

Real-time implementation of SLAM with high performance in off-road environments is still considered a challenge. Embedded platforms in mobile robots limit the complexity of applied algorithms without reducing processing speed. Lightweight algorithmic designs, efficient data structures, and hardware-aware optimizations are required to achieve low-latency performance along with high mapping accuracy. Processes including model compression, parallel computing, and dedicated AI accelerators can address these limitations but are not yet validated.

An additional concern in large, unstructured terrains is scalability. Off-road missions are frequently performed in vast areas with irregular topography. Consequently, the required SLAM systems must be able to handle long-term mapping without drift or map degradation. Graph-based optimization and hierarchical mapping structures have been proposed to address scalability. However, maintaining consistent accuracy over extensive and heterogeneous terrains remains difficult. Additionally, storage and memory management are crucial as map size and complexity grow during prolonged deployments.

Dense vegetation, tunnels, and open fields lack distinguishable landmarks and interfere with both LiDAR and vision-based SLAM. Research into adaptive feature selection, sensor fusion with inertial and proprioceptive data, and semantic scene understanding can enhance resilience under such conditions. Moreover, improved performance techniques that integrate preceding structural or learning-based perception can be utilized.

To create fully operational off-road robotic systems, their integration with autonomous navigation and obstacle avoidance is essential. SLAM outputs must communicate uninterrupted with path planning and control modules, providing accurate, low-latency localization and updated maps to support safe maneuvering. In summary, mapping and navigation must operate without overloading computational resources.

VIII. CONCLUSION

This review analyzed Simultaneous Localization and Mapping (SLAM) methodologies for off-road mobile robots. It is not limited to a general overview but expands to a structured comparative framework. This framework distinguishes sensor modalities, terrain adaptability, computational requirements, and robustness in field trials.

Specifically, LiDAR, visual, multi-sensor fusion, and learning-based approaches are compared. The review accumulates fragmented research into a single taxonomy that focuses on practical applicability in unstructured terrain. In contrast, previous research concentrates on indoor or urban environments. This study presents novel insights into off-road challenges, such as GPS-denied localization, feature-scarce environments, and sensor degradation under dust, rain, and vegetation occlusions. During the comparison, evaluation metrics are utilized, including drift rate, robustness quantification under perturbation models, and benchmarking with off-road datasets such as RELLIS-3D and Newer College.

The novelty of this review lies in linking algorithmic categories to real-world deployment domains. Sectors, such as agriculture, forestry, mining, and defense, can benefit through academic development with industrial implementation. The current work also identifies hybrid, computation-aware SLAM frameworks as the most promising research direction. By combining classical optimization with learning-based semantic understanding robust autonomy can be achieved. In summary, this integrated perspective: the current limitations are classified, evaluation strategies are consolidated, and a concrete roadmap for developing reliable, field-ready SLAM systems for off-road conditions is described.

ACKNOWLEDGMENT

This work was supported by the Science Committee of the Ministry of Higher Education and Science of the Republic of Kazakhstan within the framework of grant AP19679910 "Development of an experimental model of an autonomous unmanned mobile robot with off-road capability", International Engineering Technological University, Almaty.

REFERENCES

[1] R. B. Sousa, H. M. Sobreira, and A. P. Moreira, "A Systematic Literature Review on Long-Term Localization and Mapping for Mobile Robots," *Journal of Field Robotics*, vol. 40, no. 5, pp. 1245–1322, Apr. 2023, https://doi.org/10.1002/rob.22170.

[2] W. Hess, D. Kohler, H. Rapp, and D. Andor, "Real-Time Loop Closure in 2D LiDar SLAM," presented at the IEEE International Conference on Robotics and Automation, Stockholm, Sweden, Feb. 2016, pp. 1271–1278, https://doi.org/10.1109/ICRA.2016.7487258.

[3] J. Zhang and S. Singh, "LOAM: Lidar Odometry and Mapping in Real-time," *Robotics: Science and systems*, vol. 2, no. 9, pp. 1–9, July 2014, https://doi.org/10.15607/RSS.2014.X.007.

[4] R. Mur-Artal, J. M. M. Montiel, and J. D. Tardós, "ORB-SLAM: A Versatile and Accurate Monocular SLAM System," *IEEE Transactions on Robotics*, vol. 31, no. 5, pp. 1147–1163, Oct. 2015, https://doi.org/10.1109/TRO.2015.2463671.

[5] Md. A. A. Noman *et al.*, "A Computer Vision-Based Lane Detection Technique Using Gradient Threshold and Hue-Lightness-Saturation Value for an Autonomous Vehicle," *International Journal of Electrical and Computer Engineering*, vol. 13, no. 1, pp. 347–357, Feb. 2023, https://doi.org/10.11591/ijece.v13i1.

[6] C. Forster, Z. Zhang, M. Gassner, M. Werlberger, and D. Scaramuzza, "SVO: Semidirect Visual Odometry for Monocular and Multicamera Systems," *IEEE Transactions on Robotics*, vol. 33, no. 2, pp. 249–265, Apr. 2017, https://doi.org/10.1109/TRO.2016.2623335.

[7] C. Campos, R. Elvira, J. J. G. Rodríguez, J. M. M. Montiel, and J. D. Tardós, "ORB-SLAM3: An Accurate Open-Source Library for Visual, Visual–Inertial, and Multimap SLAM," *IEEE Transactions on Robotics*, vol. 37, no. 6, pp. 1874–1890, Sept. 2021, https://doi.org/10.1109/TRO.2021.3075644.

[8] A. Tourani, H. Bavle, J. L. Sanchez-Lopez, and H. Voos, "Visual SLAM: What Are the Current Trends and What to Expect?," *Sensors*, vol. 22, no. 23, Nov. 2022, Art. no. 9297, https://doi.org/10.3390/s22239297.

[9] D. T. Fasiolo, L. Scalera, and E. Maset, "Comparing LiDAR and IMU-Based SLAM Approaches for 3D Robotic Mapping," *Robotica*, vol. 41, no. 9, pp. 2588–2604, Nov. 2023, https://doi.org/10.1017/S026357472300053X.

[10] Z. Shen, J. Wang, C. Pang, Z. Lan, and Z. Fang, "A LiDAR-IMU-GNSS fused mapping method for large-scale and high-speed scenarios," *Measurement*, vol. 225, Dec. 2023, Art. no. 113961, https://doi.org/10.1016/j.measurement.2023.113961.

[11] M. Dorvash, A. Eslamian, and M. R. Ahmadzadeh, "Enhanced Unscented Kalman Filter-Based SLAM in Dynamic Environments: Euclidean Approach." arXiv, Dec. 19, 2023, https://doi.org/10.48550/arXiv.2312.12204.

[12] Y. Zhao, Z. Xiong, S. Zhou, J. Wang, L. Zhang, and P. Campoy, "Perception-Aware Planning for Active SLAM in Dynamic Environments," *Remote Sensing*, vol. 14, no. 11, May 2022, Art. no. 2584, https://doi.org/10.3390/rs14112584.

[13] S. Siva, M. Wigness, J. G. Rogers, L. Quang, and H. Zhang, "Self-reflective terrain-aware robot adaptation for consistent off-road ground navigation," *The International Journal of Robotics Research*, vol. 43, no. 7, pp. 1003–1023, Jan. 2024, https://doi.org/10.1177/02783649231225243.

[14] V.-H. Le, H.-S. Do, V.-N. Phan, and T.-H. Te, "TQU-SLAM Benchmark Feature-based Dataset for Building Monocular VO," *Engineering, Technology & Applied Science Research*, vol. 14, no. 4, pp. 15330–15337, Aug. 2024, https://doi.org/10.48084/etasr.7611.

[15] S. Zhao *et al.*, "SubT-MRS Dataset: Pushing SLAM Towards All-weather Environments," presented at the 2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Seattle, WA, USA, June 2024, pp. 22647–22657, https://doi.org/10.1109/CVPR52733.2024.02137.

[16] M. Rybansky *et al.*, "GNSS Signal Quality in Forest Stands for Off-Road Vehicle Navigation," *Applied Sciences*, vol. 13, no. 10, May 2023, Art. no. 6142, https://doi.org/10.3390/app13106142.

[17] S. Boche, X. Zuo, S. Schaefer, and S. Leutenegger, "Visual-Inertial SLAM with Tightly-Coupled Dropout-Tolerant GPS Fusion," presented at the 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Kyoto, Japan, July 2022, pp. 7020–7027, https://doi.org/10.1109/IROS47612.2022.9981134.

[18] D. Zhu, Q. Wang, F. Wang, and X. Gong, "Research on 3D LiDAR Outdoor SLAM Algorithm Based on LiDAR/IMU Tight Coupling," *Scientific Reports*, vol. 15, no. 1, Apr. 2025, Art. no. 11175, https://doi.org/10.1038/s41598-025-95730-3.

[19] S. Li, B. Tian, X. Zhu, J. Gui, W. Yao, and G. Li, "InTEn-LOAM: Intensity and Temporal Enhanced LiDAR Odometry and Mapping," *Remote Sensing*, vol. 15, no. 1, Dec. 2022, Art. no. 242, https://doi.org/10.3390/rs15010242.

[20] J. Lin, C. Zheng, W. Xu, and F. Zhang, "R 2 LIVE: A Robust, Real-Time, LiDAR-Inertial-Visual Tightly-Coupled State Estimator and Mapping," *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 7469–7476, Oct. 2021, https://doi.org/10.1109/LRA.2021.3095515.

[21] S. Kawaguchi, R. Nomoto, H. Sato, T. Takarada, Y. H. Chang, and H. Kawarada, "pH Measurement at Elevated Temperature with Vessel Gate and Oxygen-Terminated Diamond Solution Gate Field Effect Transistors," *Sensors*, vol. 22, no. 5, Feb. 2022, Art. no. 1807, https://doi.org/10.3390/s22051807.

[22] G. Xue, J. Wei, R. Li, and J. Cheng, "LeGO-LOAM-SC: An Improved Simultaneous Localization and Mapping Method Fusing LeGO-LOAM and Scan Context for Underground Coalmine," *Sensors*, vol. 22, no. 2, Dec. 2021, Art. no. 520, https://doi.org/10.3390/s22020520.

[23] Q. Zang, K. Zhang, L. Wang, and L. Wu, "An Adaptive ORB-SLAM3 System for Outdoor Dynamic Environments," *Sensors*, vol. 23, no. 3, Jan. 2023, Art. no. 1359, https://doi.org/10.3390/s23031359.

[24] J. Huang, S. Zhao, and L. Zhang, "E2-VINS: An Event-Enhanced Visual–Inertial SLAM Scheme for Dynamic Environments," *Applied Sciences*, vol. 15, no. 3, Jan. 2025, Art. no. 1314, https://doi.org/10.3390/app15031314.

[25] Z. Fan, L. Zhang, X. Wang, Y. Shen, and F. Deng, "LiDAR, IMU, and camera fusion for simultaneous localization and mapping: a systematic review," *Artificial Intelligence Review*, vol. 58, no. 6, Mar. 2025, Art. no. 174, https://doi.org/10.1007/s10462-025-11187-w.

[26] C.-C. Wong, H.-M. Feng, and K.-L. Kuo, "Multi-Sensor Fusion Simultaneous Localization Mapping Based on Deep Reinforcement Learning and Multi-Model Adaptive Estimation," *Sensors*, vol. 24, no. 1, Dec. 2023, Art. no. 48, https://doi.org/10.3390/s24010048.

[27] M. Hoshi, Y. Hara, and S. Nakamura, "Graph-based SLAM using wall detection and floor plan constraints without loop closure," *ROBOMECH Journal*, vol. 11, no. 1, Dec. 2024, Art. no. 18, https://doi.org/10.1186/s40648-024-00285-z.

[28] M. Chen, H. Guo, R. Qian, G. Gong, and H. Cheng, "Visual simultaneous localization and mapping (vSLAM) algorithm based on improved Vision Transformer semantic segmentation in dynamic scenes," *Mechanical Sciences*, vol. 15, no. 1, pp. 1–16, Jan. 2024, https://doi.org/10.5194/ms-15-1-2024.

[29] C. Deng, Z. Deng, S. Lu, M. He, J. Miao, and Y. Peng, "Fault Diagnosis Method for Imbalanced Data Based on Multi-Signal Fusion and Improved Deep Convolution Generative Adversarial Network," *Sensors*, vol. 23, no. 5, Feb. 2023, Art. no. 2542, https://doi.org/10.3390/s23052542.

[30] L. Li, L. Zhang, Z. Wang, and Y. Shen, "GS3LAM: Gaussian Semantic Splatting SLAM," in *Proceedings of the 32nd ACM International Conference on Multimedia*, New York, NY, USA, July 2024, pp. 3019–3027, https://doi.org/10.1145/3664647.368073.

[31] T. O. Hodson, "Root-Mean-Square Error (RMSE) or Mean Absolute Error (MAE): When To Use Them or Not," *Geoscientific Model Development*, vol. 15, no. 14, pp. 5481–5487, July 2022, https://doi.org/10.5194/gmd-15-5481-2022.

[32] F. Schmidt, C. Blessing, M. Enzweiler, and A. Valada, "Visual-Inertial SLAM for Unstructured Outdoor Environments: Benchmarking the Benefits and Computational Costs of Loop Closing," *Journal of Field Robotics*, vol. 42, no. 7, pp. 3726–3747, May 2025, https://doi.org/10.1002/rob.22581.

[33] A. Geiger, P. Lenz, C. Stiller, and R. Urtasun, "Vision meets robotics: The KITTI dataset," *The International Journal of Robotics Research*, vol. 32, no. 11, pp. 1231–1237, Aug. 2013, https://doi.org/10.1177/0278364913491297.

[34] M. Burri *et al.*, "The EuRoC Micro Aerial Vehicle Datasets," *The International Journal of Robotics Research*, vol. 35, no. 10, pp. 1157–1163, Jan. 2016, https://doi.org/10.1177/0278364915620033.

[35] P. Jiang, P. Osteen, M. Wigness, and S. Saripalli, "RELLIS-3D Dataset: Data, Benchmarks and Analysis," presented at the 2021 IEEE International Conference on Robotics and Automation (ICRA), Xi'an, China, Feb. 2021, pp. 1110–1116, https://doi.org/10.1109/ICRA48506.2021.9561251.

[36] M. Ramezani, Y. Wang, M. Camurri, D. Wisth, M. Mattamala, and M. Fallon, "The Newer College Dataset: Handheld LiDAR, Inertial and Vision with Ground Truth," presented at the 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems, A, July 2020, pp. 4353–4360, https://doi.org/10.1109/IROS45743.2020.9340849.

[37] A. Miller and A. Rak, "A Measurement System for the Environmental Load Assessment of a Scale Ship Model—Part II," *Sensors*, vol. 23, no. 7, Mar. 2023, Art. no.. 3415, https://doi.org/10.3390/s23073415.