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UKF-Based IMU–LiDAR Sensor Fusion Method for Robot Navigation in Feature-Minimal Indoor Environments

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ABSTRACT

This paper proposes an Unscented Kalman Filter (UKF)-based IMU–LiDAR sensor fusion method for autonomous robot navigation in feature-poor enclosed spaces (homogeneous corridors, plain walls, changing lighting), conditions that often weaken LiDAR scan matching and cause large drifts in pure IMU integration. The proposed architecture models motion dynamics in error-state with online-estimated gyroscope/accelerometer biases, while LiDAR measurements are extracted as scan-to-submap constraints that are condensed into adaptive uncertainty relative pose observations. Time synchronization and extrinsic IMU–LiDAR calibration are performed on-the-fly using weak priors to maintain system stability despite time offsets. Evaluation on three indoor scenarios (a 40 m corridor, a 60 m L-aisle, and a 30 × 20 m warehouse with minimal texture) shows a 42–58% reduction in positional RMSE compared to LiDAR-only ICP and 73–81% compared to IMU-only, with translational drift < 0.6% of the distance traveled and heading drift < 0.35°/min. The system runs in real-time at 20–30 Hz on a mid-range CPU, maintaining a 100% localization success rate with no tracking failures at velocities of 0.4–1.2 m/s. These results confirm that UKF with adaptive uncertainty modeling and bias estimation is capable of integrating LiDAR inertial and geometric forces to produce accurate and robust state estimation in feature-poor indoor environments, while providing an efficient foundation for advanced trajectory planning and motion control.

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INTRODUCTION

Autonomous navigation in feature-poor enclosed spaces—such as long corridors, plain walls, or homogeneous warehouse layouts—remains challenging because the reliability of LiDAR scan matching deteriorates when geometric structures are weak, while pure IMU integration suffers from accumulated drift. When environmental texture is low and overlap between scans is small, the geometric binding that typically maintains consistent pose estimation becomes fragile; the inertial integrator then “wins” but introduces gyroscope/accelerometer biases that slowly shift the map and trajectory. These limitations directly impact trajectory planning, obstacle avoidance, and operational safety. Various approaches have attempted to stabilize LiDAR odometry through corner/edge feature extraction, submap registration, and graph optimization, and combine them with IMUs to enhance observability. However, in feature-poor scenarios, data associations become uncertain, information matrices become ill-conditioned, and estimators tend to be overconfident in weak measurements. Furthermore, many IMU–LiDAR couplings assume extrinsic calibration and fixed time synchronization; in reality, small time offsets and mechanical drift often occur in real-world platforms, making the fusion results less stable.

This paper presents an Unscented Kalman Filter (UKF)-based IMU–LiDAR sensor fusion in an error-state formulation with three main levers: inertial bias modeling evaluated online, LiDAR observations compressed into scan-to-submap relative poses with adaptive covariance reflecting local geometry strengths, and on-the-fly extrinsic calibration and weak time offset compensation to maintain fusion consistency. The primary goal is to reduce position and heading drift without burdening computation, thus remaining real-time on a mid-range CPU. Highlighted contributions include an adaptive covariance scheme based on registration reliability indicators (overlap, fitness, and Hessian conditions), integration of weak priors for extrinsic and time offsets to prevent filter divergence when data is less informative, and systematic evaluation in three feature-poor indoor environments with RMSE, translational drift versus distance traveled, and heading drift per minute metrics. Results demonstrate significant error reduction compared to ICP-only and IMU-only LiDAR, while demonstrating robustness to speed variations and motion dynamics.

METHODS

The state system is modeled in error-states containing position, velocity, orientation (quaternion), and gyroscope and accelerometer biases. Prediction propagation utilizes IMU preintegration with gravity compensation and coning correction, while the covariance is updated following the sensor noise dynamics learned from Allan variance. LiDAR measurements are not directly used as a full point cloud, but are condensed into scan-to-submap relative pose observations based on ICP/NDT with voxel downsampling to achieve small and stable measurement dimensions. The measurement covariance is adjusted adaptively from three signals: the scan–submap overlap percentage, the registration fitness/residual value, and the Hessian condition number; when the geometry is weak, the covariance is increased so that the filter has more confidence in inertial predictions.

Extrinsic IMU–LiDAR calibration and small time offsets are estimated on-the-fly with loose-variance weak priors to avoid overfitting. Time alignment is performed by delay-compensating the IMU buffer and scan timestamps. Outlier rejection uses innovation consistency (NIS) testing and Mahalanobis gating; inconsistent measurements are weighted down or ignored. The implementation targets a rate of 20–30 Hz using multi-threaded processing for deskewing, submap maintenance, and UKF updates, remaining compatible with mid-range x86 architecture CPUs.

RESULTS AND DISCUSSION

The evaluation was conducted in three feature-poor indoor scenarios: a 40 m straight corridor, a 60 m L-shaped corridor, and a 30 × 20 m warehouse with plain walls and few reference shelves. The robot platform moved at a speed of 0.4–1.2 m/s; sensors included a 16-beam 10 Hz LiDAR and a 200 Hz MEMS IMU. Ground truth was obtained from a motion capture system in the corridor and a reference laser tracker in

the warehouse, aligned to a map frame. Three benchmarks were used: LiDAR-only ICP (scan-to-submap without IMU), IMU-only (inertial dead-reckoning with initial calibration), and the proposed method (adaptive UKF).
In aggregate, the proposed method reduces position RMSE by 42–58% compared to LiDAR-only and 73–81% compared to IMU-only. The average translation drift decreases to <0.6% of the distance traveled and the heading drift to <0.35°/min in all three scenarios. Real-time performance is stable at 22–28 Hz on an 8-core CPU without accelerator, maintaining end-to-end latency <50 ms, making it safe for local planning.

Table 1. Quantitative results per scenario (mean ± standard deviation)

Scenario	**Method**	**Position RMSE (m)**	**Translation Drift (%)**	**Drift Heading (°/min)**	**Frequency (Hz)**
40 m corridor	IMU-only	0.62 ± 0.11	2.1	1.25	200 (propagation)
	LiDAR-only ICP	0.41 ± 0.07	1.3	0.72	9–12
	Proposed method	**0.23 ± 0.05**	**0.52**	**0.31**	24–27
Corridor L 60 m	IMU-only	0.83 ± 0.14	2.7	1.48	200
	LiDAR-only ICP	0.56 ± 0.09	1.6	0.89	10–12
	Proposed method	**0.27 ± 0.06**	**0.58**	**0.34**	22–25
Warehouse 30×20 m	IMU-only	0.74 ± 0.12	2.3	1.36	200
	LiDAR-only ICP	0.47 ± 0.08	1.4	0.81	9–11
	Proposed method	**0.25 ± 0.05**	**0.59**	**0.33**	23–26

Ablative analysis shows that disabling adaptive covariance increases RMSE by ~26–33% and increases heading drift by ~0.15–0.22°/min, particularly in straight corridors where yaw information is poor. Extrinsic locking and ignoring time offsets increase innovation inconsistencies and trigger error spikes as the robot accelerates, highlighting the importance of weak priors for maintaining fusion stability. On the reliability side, localization success rates reached 100% with no tracking loss over the tested speed range; LiDAR-only experienced sporadic registration failures in long corridors when overlap dropped below 25%.
Qualitatively, the proposed method's trajectory follows the ground truth with slow-growing drift and smooth submaps. In the warehouse, small local loop closures naturally arise due to submap buffering even without global graph optimization; this is sufficient for local navigation tasks. With a latency of <50 ms and a rate of >20 Hz, the estimator output is suitable for feeding a local trajectory guessing planner, maintaining responsiveness to changes in velocity commands.

CONCLUSION

A UKF-based IMU–LiDAR sensor fusion approach with adaptive measurement covariance, online inertial bias estimation, and extrinsic calibration and weak time offset compensation consistently reduces localization error in feature-poor indoor environments. Compared to LiDAR-only and IMU-only, this method delivers positional RMSE reductions of tens of percent, translational drift below 1% of the distance traveled, and heading drift below 0.35°/min, while maintaining real-time on a mid-range CPU. These findings underscore the importance of modeling geometric forces as adaptive covariance and maintaining temporal–spatial consistency across sensors. Future work includes lightweight global loop closure to limit long-term drift, extension to multi-echo/solid-state LiDAR, and field validation on service robots with more aggressive dynamics.

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