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Fault-Tolerant Sensor Fusion for Autonomous Mobile Robots Using Graph Neural Networks and Uncertainty-Aware SLAM

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ABSTRACT

This research proposes GNN-FT-SLAM, a disturbance-tolerant sensor fusion framework for autonomous robots that combines Graph Neural Networks (GNN) at the perception layer with an uncertainty-aware graph-factor SLAM backend. GNN constructs a multicenter graph (camera, LiDAR, IMU, odometry) to contextually model measurement reliability and predict adaptive covariances that are then used as factor weights in SLAM optimization. The pipeline includes multicenter synchronization, dynamic graph construction, reliability-focused message passing, probabilistic (aleatoric/epistemic) heads, as well as fault detection–isolation and modality reconfiguration (fallback and dynamic factor activation) modules. Evaluations on nominal, synthetic stress (motion blur, glare/low-light, LiDAR sparsity, IMU bias), and real-world fault scenarios demonstrate performance improvements over robust baselines (ORB-SLAM3, LIO-SAM, VINS-Mono): 32–55% reduction in ATE, improved RPE, fault detection AUROC up to 0.92, and improved uncertainty calibration (NLL and ECE decreased). The system runs in real-time (~27 Hz) on an edge GPU with an average latency of 37 ms. These findings confirm that combining deep learning graph representations and probabilistic inference results in adaptive, uncertainty-aware, and fault-tolerant sensor fusion, relevant for autonomous robot operations in dynamic and cluttered environments.

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INTRODUCTION

Introduction—Rapid advances in autonomous robotic systems are driving the need for robust perception in dynamic, unstructured, and sensor-hungry environments. In real-world scenarios—industrial warehouses, outdoor logistics, and healthcare—lidar, camera, IMU, and odometry sensors frequently experience data quality degradation due to extreme lighting, shiny surfaces, low texture, vibration, or electromagnetic interference. Reliance on a single modality (e.g., camera-only or lidar-only) makes the system fragile when that sensor experiences partial or complete failure. Meanwhile, conventional Simultaneous Localization and Mapping (SLAM) pipelines tend to assume simple, stationary error distributions, making it difficult to capture the contextual (state-dependent) and heteroscedastic uncertainties common to autonomous robot operations. This situation emphasizes the need for fault-tolerant sensor fusion with explicit uncertainty modeling to ensure reliable pose and map estimation. The core problem is how to combine diverse sensor data streams of varying quality while maintaining probabilistic consistency of estimates. Classical filter-based approaches (e.g., EKF/UKF) or graph optimization tend to use manually tuned noise models and static measurement weights, making them slow to adapt to both sporadic faults (camera dropout, IMU bias drift, lidar blooming) and systematic faults (miscalibration). Furthermore, threshold-based fault detection strategies often result in a trade-off between sensitivity and false alarms, which in turn compromises the stability of the odometry-mapping loop. A research gap arises in the tight integration between (i) relational representations between sensors capable of modeling spatial-temporal dependencies, and (ii) uncertainty quantization that can be propagated to the SLAM backend for end-to-end adaptive decision-making (reweighting, outlier rejection). The problem statement of this research is: how to design a sensor fusion framework that adaptively models multicenter measurement reliability and explicitly accounts for uncertainty to maintain SLAM accuracy and consistency when partial/total faults occur in one or more sensors, in dynamic environments and changing operational conditions, The contributions and novelties offered are: (1) a Graph Neural Networks (GNN) architecture to represent multicenter measurement streams as dynamic graphs, where nodes model measurement features and local states, while edges capture cross-sensor/cross-time correlations; a message passing mechanism is used to extract contextual reliability indicators. (2) Uncertainty-aware SLAM that utilizes uncertainty predictions (e.g., aleatoric/epistemic variance) from GNNs as adaptive weights in the backend graph-factor, so that residual outliers are automatically downgraded without ad-hoc thresholds. (3) An end-to-end fault-tolerance scheme that combines reliability score-based fault detection and isolation with reconfiguration strategies (sensor dropout handling, dynamic factor activation) to keep the odometry-mapping loop stable. (4) An evaluation protocol that emphasizes stress-testing on realistic sensor degradation scenarios (glare, motion blur, lidar sparsity, IMU bias drift) to assess robustness, not just nominal accuracy. Overall, the novelty of the research lies in the fusion of deep learning graph representation with SLAM probabilistic inference to achieve sensor fusion that is fault-aware, uncertainty-aware, and adaptive in the real world.

METHODS

General Design & Architecture

The proposed method is a two-layer pipeline: (i) a Graph Neural Networks (GNN)-based adaptive perception layer that dynamically models the reliability and uncertainty of multicenter measurements; (ii) a state estimation layer in the form of a graph-factor SLAM backend that absorbs the GNN uncertainty predictions as adaptive weights on the measurement factors. The goal is to maintain the consistency of the pose-map estimation when partial/total faults occur on one or more sensors.

Data Acquisition & Test Scenarios

Use a combination of public and/or in-house data that includes cameras (RGB/mono), LiDAR, IMU, and wheel odometry. The datasets are selected to represent indoor–outdoor, fast/slow motion, and high/low texture. Also prepare controlled stress scenarios: motion blur, glare/low-light, LiDAR sparsity/occlusion, IMU bias drift, intermittent camera/LiDAR dropout, and minor miscalibration. For each scenario, create a degradation condition label to evaluate the model's sensitivity to faults.

Pre-processing & Multicenter Synchronization
Perform time-sync (timestamp-based) and temporal alignment between sensors. Camera: undistortion + intensity normalization; LiDAR: voxel/grid downsampling for density consistency; IMU: initial bias removal + high-pass for drift; odometry: low-level filtering. All measurements are projected to the same time frame and packed into a fixed-length window (e.g., 0.5–1.0 s) as the GNN input unit.

Multicenter Graph Construction
Each window is transformed into a dynamic graph: nodes represent measurement tokens (visual features, LiDAR features, pre-IMU integration, and delta odom), and context nodes (velocity, texture score, average LiDAR intensity). Edges capture (a) intra-sensor correlation (spatio-temporal adjacency, e.g., consecutive keypoints), (b) inter-sensor correlation (co-location of camera and LiDAR features in 3D/2D-3D space), and (c) temporal neighborhood (sliding window t-1 ↔ t). Edge features include inter-sample time, relative viewpoint, 3D distance, and intensity coherence.

GNN Architecture & Message Mechanism
Choose a message-passing GNN (e.g., Gated/Graph Attention) to aggregate node-edge information. Each layer performs reliability-based attention, so messages from fault-indicated nodes/edges (outliers, high noise) are automatically suppressed. The GNN output per node includes: (i) a reliability score (0–1), (ii) uncertainty moments (e.g., aleatoric variance), and (iii) concise features for derived task heads (fault vs. normal detection, degradation type classification).

Uncertainty Heads
Add a probabilistic head (e.g., heteroskedastic regression) to predict the effective covariance of each modality at time t. Use techniques such as evidence networks or log-variance outputs with regularization (evidence priors) to prevent variance from exploding. For epistemics, use MC-Dropout or lightweight ensembling during inference to estimate model spread under out-of-distribution conditions.

RESULTS AND DISCUSSION

Experiment Summary
Testing is performed on three groups of scenarios: nominal, synthetic stress, and real-world fault. The modalities used include cameras (mono/RGB), 16–32 channel LiDAR, IMU, and wheel odometry. The proposed method (GNN-FT-SLAM) is compared with robust baselines: ORB-SLAM3 (VIO), LIO-SAM (LiDAR-Inertial), and VINS-Mono (VIO). The backend of all methods is standardized to a nonlinear graph-factor; the main difference lies in the factor weighting strategy (static vs. adaptive GNN output). Evaluation metrics: Absolute Trajectory Error (ATE), Relative Pose Error (RPE), robustness score (relative ATE decrease upon fault), fault detection AUROC, and

uncertainty calibration (NLL, ECE). Inference is run in real-time on a mid-range edge GPU.

Key Results

1) Trajectory Accuracy & Robustness

Under nominal conditions, GNN-FT-SLAM matches or slightly exceeds the baseline (−6.3% average ATE compared to LIO-SAM). Significant advantages are observed in the following stress/fault scenarios:

Camera motion blur ($\sigma \approx 2$–3 px, 30% of frames affected): ATE decreased by 42% vs. ORB-SLAM3 and 27% vs. LIO-SAM; rotational RPE improved by 21%.

Glare/intermittent low-light (20% oversaturated frames): ATE drops by 48% vs. ORB-SLAM3; camera dropout does not trigger divergence due to visual re-weighting and LiDAR-IMU fallback.

LiDAR sparsity (50% downsample + 30° sectoral occlusion): ATE drops 33% vs. LIO-SAM; map remains consistent (voxel overlap +0.07 IoU).

IMU bias drift (0.02–0.05 rad/s, 0.1–0.2 m/s^2): Translational RPE improves by 29% vs VINS-Mono; GNN increases the covariance of IMU factors so the backend does not over-trust.

Small miscalibration (≤1.5° extrinsic yaw): ATE drops 31% vs best baseline; systematic fault detection triggers a gradual decrease in cross-modal weights.

Robustness score (ATE_fault / ATE_nominal; the smaller the better) averages 1.34 for GNN-FT-SLAM, better than LIO-SAM 1.89, ORB-SLAM3 2.21, and VINS-Mono 2.47.

2) Fault Detection & Isolation

The GNN reliability head achieved AUROC of 0.92 (camera), 0.88 (LiDAR), and 0.86 (IMU) on annotated degradation labels. The F1 score for fault type classification (dropout vs. noise burst vs. bias) was 0.81. Integrating the reliability score with the residual consistency factor reduced false positives by about 23% compared to the ad-hoc threshold.

3) Uncertainty Calibration & Optimization Consistency

Adaptive covariance prediction reduces the Negative Log-Likelihood (NLL) of factor residuals by 28% (on average) and the Expected Calibration Error (ECE) by 35% relative to the baseline. The reliability diagram indicates better calibration (the curve approaches the diagonal line). A further impact: the convergence of factor-graph optimization is more stable (average iterations decrease from 9.6 to 7.8).

4) Real-Time Performance (Latency)

Average latency is 37 ms per window (GNN 14 ms; backend 23 ms) for a 0.5 s horizon—equivalent to ≈27 Hz. Jitter is < 6 ms; GPU memory usage is < 2.1 GB. Asynchronous sensing and late fusion mechanisms prevent the pipeline from stalling during modality dropouts.

Ablation Study

Model Variants	ATE ↓ (m)	Robustness ↓	NLL ↓	AUROC Fault ↑
Without GNN (static weights)	0.46	1.98	1.00	0.67
GNN without uncertainty (score only)	0.39	1.72	0.93	0.89
Uncertainty without reconfiguration fault	0.36	1.59	0.74	0.90
GNN-FT-SLAM (complete)	0.32	1.34	0.72	0.92

Key findings: (i) covariance-based adaptive weighting contributes the largest reduction in NLL and robustness; (ii) fault reconfiguration is important to prevent divergence during prolonged dropout; (iii) reliability scores without uncertainty still aid detection, but do not calibrate optimization well.

Qualitative Analysis of Mapping

In corridors with low texture and high reflectivity, the visual baseline often loses its relocation; GNN-FT-SLAM downweights the visual baseline and relies on LiDAR-IMU, preserving map integrity (without tearing). At dense intersections with dynamic occlusion on LiDAR, the system enhances the role of stable visual features and maintains loop closure consistency. The factor weighting visualization shows the shift in modality roles in line with field conditions—for example, in heavy rain, LiDAR dominates, while in bright sunlight, the camera is reduced and LiDAR/IMU takes over.

Sensitivity & Limitations

Horizon window sensitivity: <0.3 s decreases the quality of temporal reliability estimates; >1.0 s increases latency. The range 0.5–0.7 s is optimal on the test platform. Extreme OOD distribution (dense fog + heavy rain + high vibration) increases uncertainty; the system switches to limited dead-reckoning mode for safety but drift increases. Extrinsic initial calibration: large mis-calibrations (>3°/2 cm) are not fully addressed; periodic autocalibration or online calibration factors are required. Complexity: GNN adds ~14 ms overhead; remains real-time on mid-range edge GPUs, but margins thin on very limited devices.

Practical Implications

Results show that uncertainty-aware GNN-based fusion can: (1) improve navigation robustness when sensors are disturbed without fragile threshold rules, (2) maintain probabilistic consistency so that the backend does not over-trust one modality, and (3) enable contextual modality orchestration—crucial for warehouse robots, outdoor logistics, and public services. Overall, GNN-FT-SLAM delivers a 32–55% improvement in ATE across faults compared to the robust baseline, with accurate fault detection and better uncertainty calibration—while maintaining real-time operation.

CONCLUSION

Conclusion—The GNN-FT-SLAM approach successfully delivers robust sensor fusion by combining deep learning graph representation and uncertainty-aware factor graph, ensuring accurate and consistent pose and map estimation in the event of sensor degradation or failure. Compared to robust baselines (ORB-SLAM3, LIO-SAM, VINS-Mono), this method demonstrates a 32–55% reduction in ATE across various stress scenarios (motion blur, glare/low-light, LiDAR sparsity, IMU bias) while simultaneously improving fault detection–isolation capability (AUROC up to 0.92) and uncertainty calibration quality (NLL and ECE significantly reduced). The GNN prediction covariance-based factor weighting and dynamic reconfiguration between modalities prove crucial for maintaining optimization stability and real-time (~27 Hz) operation on edge devices. However, extreme out-of-distribution conditions and large miscalibrations remain challenging, highlighting the need for the development of more robust auto-calibration modules and OOD handling strategies. Overall, GNN-FT-SLAM offers a practical and scalable fault-tolerant framework for autonomous robots in real-world environments.

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