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LIDAR DEGRADATION IN ROBOTIC PERCEPTION: PROBLEM ANALYSIS, COMPARISON OF MITIGATION APPROACHES AND RESEARCH DIRECTIONS

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Abstract. *LiDAR measurements in mobile robotics frequently degrade due to hardware, environmental, and algorithmic factors. This paper systematizes degradation sources, compares five mitigation paradigms (geometric estimation, point-cloud learning, LiDAR imagery, multi-sensor fusion, and simulation), and outlines open challenges, providing practical guidelines for designing resilient robotic perception systems.*
Keywords: *LiDAR; sensor degradation; SLAM; LiDAR imagery; sensor fusion.*

Introduction. Light Detection and Ranging (LiDAR) is a primary modality for localization, mapping, and obstacle detection in mobile robotics [1,4]. Alongside mechanical spinning sensors, solid-state and dome-shaped LiDARs with distinct scanning patterns, fields of view (FoV), and point densities are increasingly deployed [1]. As robots operate in unstructured outdoor environments, perception reliability has become a critical operational requirement [3,6].

Here, LiDAR degradation denotes any loss of measurement quality, coverage, or geometric information relative to downstream algorithmic assumptions [6]. Because this topic is typically studied in isolation – within simultaneous localization and mapping (SLAM) failure analysis [2], adverse-weather detection [3], or hardware benchmarking [1] – shared root causes and cross-task remedies are often overlooked. **The purpose** of this paper is to systematize degradation sources, compares five mitigation approaches, and identifies future research priorities.

Problem analysis and failure scenarios. Degradation stems from three interrelated domains:

• **Sensor-related causes.** Variations in scanning patterns (repetitive vs. non-repetitive), FoV, range, and intensity calibration impede cross-device generalization, causing pipelines tuned for dense spinning units to fail on sparse solid-state or dome-shaped sensors [1].

• **Environment-related causes.** Precipitation, fog, and dust cause beam attenuation and backscatter, reducing effective range and generating volumetric noise [3]. Structurally featureless scenes (e.g., long corridors or tunnels) lack geometric constraints, rendering scan registration ill-conditioned [2].

• **Data- and algorithm-related causes.** Dense point clouds from modern sensors often exceed embedded real-time budgets, requiring aggressive down-sampling [4,5]. Naive uniform or voxel sampling frequently discards critical geometric features while retaining noise, inducing odometry drift [5].

In deployment, these factors compound. In long corridors, insufficient geometric constraints cause pose estimates to slide along the corridor axis [2]. In rain or fog, spurious returns corrupt surface normals and trigger false obstacle detections [3]. On resource-constrained platforms, aggressive down-sampling strips away fine geometry [5], while mixed-sensor fleets face severe calibration and transferability bottlenecks [1].

Comparison of mitigation approaches. Table 1 summarizes five methodological paradigms developed to counteract LiDAR degradation.

Table 1

Qualitative comparison of mitigation approaches

Approach	Core Mechanism	Strengths	Limitations	Refs
Geometric / robust estimation	Hessian eigenvalue analysis; tightly coupled IMU integration	Low computational cost; interpretable; IMU coupling limits drift	Empirical thresholds; vulnerable to heavy volumetric noise	[2, 4]
Learning-based point-cloud processing	3D CNNs/Transformers; physics-based weather augmentation	Adapts to complex non-linear noise; strong object-level filtering	High onboard compute; cross-sensor domain gap	[1, 3]
Lidar-image representation	2D range/intensity projection; image super-resolution	Reuses fast 2D vision models; reduces points for registration	Loses 3D topology; tied to vertical sensor resolution	[1, 5]
Multi-sensor fusion	Tight/loose coupling with IMUs, cameras or radar	Complementary failure modes; high resilience in extreme scenes	Complex calibration, synchronization, and hardware cost	[2, 4]
Degradation simulation	Phenomenological noise, dropout, and weather injection	Repeatable, controlled benchmarking and stress-testing	Residual realism gap between synthetic and field data	[3, 6]

• **Geometric and robust estimation.** This approach addresses degradation within the state-estimation back-end by evaluating optimization observability [2]. Degeneracy-aware methods analyze Hessian or Jacobian eigenvalues during scan matching to detect ill-conditioned directions and constrain pose updates along unobservable axes [2]. Tightly coupled LiDAR-inertial odometry (LIO), such as FAST-LIO2 [4], fuses high-frequency IMU pre-integration with direct point-to-plane registration via incremental k-d trees. While offering low latency, interpretability, and short-term resilience to geometric sparsity, these methods rely on empirical degeneracy thresholds and degrade under heavy volumetric weather noise [2,4].

• **Learning-based point-cloud processing.** Deep neural networks operating on 3D points or voxels filter non-linear noise distributions that defeat classical heuristics [3]. Physics-based data augmentation – such as simulating realistic fog scatter and attenuation on clear-weather scans – enables detectors to generalize to adverse weather without costly field collection [3]. However, 3D networks incur high onboard compute costs and suffer from domain gaps across different sensor architectures [1,3].

• **LiDAR-image representations.** Many modern sensors output 360° panoramic range, reflectivity, and near-infrared images alongside 3D point clouds [5]. Projecting perception into the 2D domain allows reusing efficient computer-vision backbones without external cameras [5]. Applying deep colorization and super-resolution to low-resolution LiDAR imagery enhances keypoint extraction, guiding intelligent down-sampling that reduces odometry errors while processing significantly fewer points [5]. Trade-offs include the loss of explicit 3D topology and sensitivity to vertical sensor resolution [1,5].

• **Multi-sensor fusion.** Combining LiDAR with IMUs, RGB, radar, or event cameras provides physical redundancy [2,4]. When LiDAR geometry fails in featureless tunnels or smoke, complementary modalities preserve trajectory stability [4], though at the expense of hardware cost, power draw, and strict spatiotemporal calibration.

• **Degradation simulation.** Sensor-aware phenomenological frameworks inject controlled, physically grounded corruptions – such as beam dropout, FoV reduction, and weather clutter – directly onto real scans [3,6]. This enables repeatable SLAM stress-testing across continuous degradation levels [6], despite a residual realism gap relative to complex real-world physics [3,6].

Evaluation criteria and selection guidelines. Mitigation strategies should be evaluated across four axes: accuracy (pose error or detection precision) [4,5], robustness (performance decay rate under escalating degradation) [6], cross-sensor generality [1], and system cost (compute, memory, and calibration effort) [4,5]. Because benchmarks vary in hardware and metrics, direct numerical comparison is limited, motivating practical selection rules:

• **Geometric sparsity (corridors, tunnels):** Prioritize degeneracy-aware LIO, adding visual or event cameras only for prolonged featureless motion [2,4].

• **Adverse weather (fog, rain):** Use denoising or detection models trained with physics-based weather augmentation aligned with target sensor specs [3].

• **Strict compute limits:** Apply LiDAR-image super-resolution and guided sampling to reduce point cloud cardinality before registration [5].

• **Heterogeneous fleets:** Use cross-sensor datasets and degradation simulation early in development to verify cross-platform stability [1,6].

Limitations and Open Research Directions. As a qualitative synthesis across varied experimental setups, these comparisons require unified empirical validation [1,6]. Six open research directions emerge (mapped in Table 2):

• **Cross-sensor generalization:** Designing models invariant to scanning patterns across spinning, solid-state, and dome-shaped LiDARs [1].

• **Online degradation awareness:** Developing real-time self-assessment modules to quantify measurement reliability and dynamically re-weight sensors [2,6].

• **Hybrid image-geometric pipelines:** Pairing lightweight LiDAR-image keypoint selection with LIO back-ends for embedded efficiency [4,5].

• **Edge-efficient deep learning:** Compressing 3D models via pruning, quantization, or 2D range-view projections for real-time onboard execution [3,5].

• **Standardized stress-testing:** Establishing unified benchmarks combining real multi-sensor data with phenomenological degradation models [1,6].

• **Vision foundation models:** Evaluating whether pretrained 2D foundation models generalize to non-RGB range and reflectivity channels under degradation [5].

Table 2

Mapping of degradation causes to mitigation strategies and research gaps

Cause of degradation	Primary mitigation strategies	Remaining research gap	Refs
Sensor heterogeneity	Cross-sensor datasets; lidar-image processing; simulation	Lack of architectures validated across all LiDAR designs	[1, 5, 6]
Adverse weather	Point-cloud denoising networks; physics-based augmentation	Domain gap between simulated and real atmospheric scatter	[3, 6]
Geometric sparsity	Degeneracy-aware optimization; LiDAR-inertial coupling	Limited integration of learned online degeneracy prediction	[2, 4]
Excess density / low compute	LiDAR-image guided sampling; lightweight back-ends	Balancing aggressive point reduction against registration accuracy	[4, 5]

Conclusions. LiDAR degradation in robotic perception stems from interacting sensor, environmental, and algorithmic factors that require targeted yet complementary remedies. No single paradigm is universally optimal: geometric methods are computationally efficient but rigid under severe noise; deep learning adapts to complex corruptions but incurs high computational and domain-transfer costs; LiDAR-image pipelines offer speed at the expense of 3D structural fidelity; and multi-sensor fusion maximizes resilience while increasing system complexity. Future progress lies in hybrid, degradation-aware perception architectures systematically validated across diverse LiDAR hardware.

Use of AI tools. Claude (Sonnet 5.5) was used for selecting and analyzing references, as well as structuring the text according to the template. The authors reviewed and verified all content and bear full responsibility for the publication.

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