Visibility Enhancement and Intelligent Sensing in Foggy Environments

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***Abstract*—**Fog is one of the most pervasive atmospheric phenomena adversely affecting transportation safety, optical imaging, wireless communication, and autonomous navigation. The Mie scattering and absorption of electromagnetic radiation by suspended water droplets substantially reduce visibility and impair the performance of conventional optical sensing systems. This paper presents a systematic review of state-of-the-art techniques for sensing through fog, encompassing infrared imaging, LiDAR, radar, computational image dehazing, and AI-driven multimodal sensor fusion. The underlying physical mechanisms of fog-induced optical attenuation are examined, and the capabilities and limitations of each sensing modality are critically assessed. Key application domains—including autonomous ground vehicles, civil aviation, marine navigation, and free-space optical (FSO) communication—are discussed in detail. The review concludes that adaptive multimodal sensor fusion, guided by intelligent decision algorithms, constitutes the most promising approach for ensuring reliable system operation in foggy environments.

***Keywords*—**Fog Sensing; LiDAR; Radar; Visibility Enhancement; Multimodal Sensor Fusion; Artificial Intelligence; Autonomous Vehicles; Image Dehazing; Free-Space Optical Communication.

I. INTRODUCTION

Fog is a meteorological phenomenon comprising microscopic water droplets suspended near the Earth's surface, reducing horizontal visibility to below 1 km [1]. Dense fog imposes serious operational constraints on transportation networks, surveillance infrastructure, and autonomous navigation systems. Conventional RGB camera-based sensors are fundamentally vulnerable to Mie scattering and optical attenuation under such conditions, leading to precipitous drops in perception reliability.

The rapid proliferation of intelligent transportation systems and fully autonomous vehicles has intensified research interest in fog-penetrating sensing technologies. Contemporary approaches to mitigating visibility degradation include infrared (IR) imaging, millimeter-wave radar, LiDAR, and AI-based signal processing, each offering distinct trade-offs between penetration capability, spatial resolution, and computational complexity [2]–[5].

This paper reviews the physical principles governing fog-induced signal attenuation and systematically evaluates modern sensing and computational technologies deployed to restore or maintain operational visibility under adverse foggy conditions. The primary contributions are: (1) a unified treatment of fog attenuation physics across optical, infrared, and microwave bands; (2) a comparative analysis of active and passive sensing modalities; (3) a discussion of AI-enabled sensor fusion strategies with architectural taxonomy; and (4) identification of emerging research directions and open challenges.

II. PHYSICS OF FOG AND VISIBILITY REDUCTION

Fog is composed of microscopic water droplets with diameters typically in the range of 1–20 µm, suspended in the lower atmosphere at liquid water contents (LWC) generally between 0.01 and 0.5 g/m³. These droplets interact with incident electromagnetic radiation primarily through Mie scattering—a regime applicable when the droplet circumference is comparable to the illuminating wavelength—resulting in strong, spectrally dependent attenuation that degrades image contrast and reduces effective visibility [1], [9].

Koschmieder's law relates the meteorological optical range (MOR), commonly referred to as the visibility distance, to the atmospheric extinction coefficient [9]:

$$V = 3.912 / \beta \qquad (1)$$

where V is the meteorological optical range (km) and β is the volumetric extinction coefficient (km^{-1}). As fog density increases, β rises accordingly, leading to rapid exponential attenuation of transmitted optical power (see Fig. 1). Empirical studies by Nebuloni [9] have established strong correlations between β and liquid water content across advection, radiation, and freezing fog types.

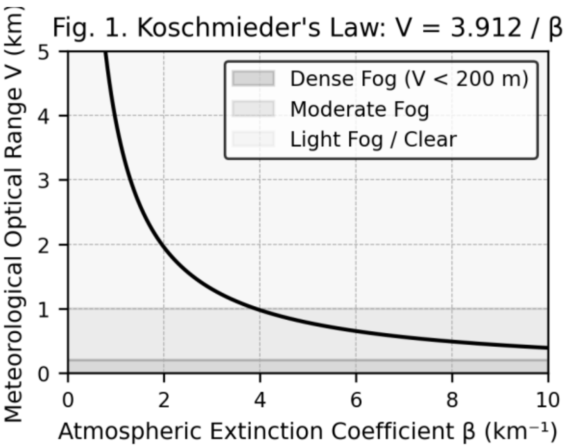

Fig. 1. Koschmieder's Law: Meteorological optical range versus atmospheric extinction coefficient, showing the three operational visibility zones relevant to transport and sensing systems.

Atmospheric fog exhibits strongly wavelength-dependent attenuation behavior. Visible wavelengths (400–700 nm) experience pronounced Mie scattering. Near- and mid-infrared wavelengths (1–14 µm) exhibit comparatively lower scattering cross-sections, affording improved penetration depth. Millimeter-wave and microwave frequencies (1–300 GHz) are largely unaffected by fog droplets (Fig. 2).

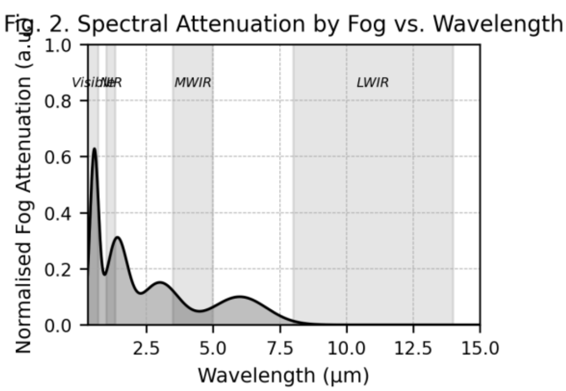

Fig. 2. Normalised fog attenuation as a function of wavelength, illustrating the principal atmospheric transmission windows (shaded) exploited by IR and thermal sensing modalities.

III. LIMITATIONS OF CONVENTIONAL IMAGING

Conventional RGB camera systems rely entirely on reflected visible-band radiation and are therefore highly susceptible to fog-induced degradation. Principal performance deficiencies observed under foggy conditions include:

- Severe reduction in scene contrast, caused by multiply-scattered background luminance,
- Loss of spatial resolution and boundary definition at object edges,
- Erroneous depth and disparity estimates from stereo and monocular depth algorithms,
- Substantial degradation in object detection and classification accuracy in deep learning-based perception pipelines.

These limitations are particularly critical in autonomous vehicles, where real-time lane boundary detection, pedestrian identification, and obstacle avoidance are essential safety functions that cannot tolerate significant degradation [3], [4]. Table I summarises comparative visibility thresholds at which each sensor type experiences critical performance degradation.

TABLE I. VISIBILITY THRESHOLDS FOR CRITICAL SENSOR DEGRADATION

Sensor Type	Critical Visibility Threshold (m)	Primary Degradation Mechanism	Reference
RGB Camera	< 500	Mie scattering / contrast loss	[3], [4]
Stereo Camera	< 300	Disparity noise / depth error	[3]
LiDAR (905 nm)	< 100	Backscatter / beam attenuation	[2], [5]
LWIR Thermal	< 80	Dense fog absorption (emissivity)	[4]
Radar (77 GHz)	< 20	Heavy rain / extreme LWC only	—

IV. FOG PENETRATION TECHNIQUES

A. Infrared Imaging

Infrared imaging systems exploit wavelengths beyond the visible spectrum to achieve reduced Mie scattering in fog. Long-wave infrared (LWIR) thermal cameras, operating in the 8–14 µm atmospheric transmission window, detect thermal radiation passively emitted by objects, enabling target discrimination under both foggy and low-illumination nighttime conditions without requiring active illumination [4]. Key advantages include improved detection probability, passive night vision, and inherent robustness to illumination changes and glare. Drawbacks include lower spatial resolution and substantially higher procurement costs compared to visible-band cameras.

B. LiDAR Systems

LiDAR (Light Detection and Ranging) systems emit collimated laser pulses—typically at 905 nm or 1550 nm—and measure the time-of-flight of backscattered returns to reconstruct high-resolution three-dimensional point clouds [2]. The range equation is:

$$d = ct / 2 \qquad (2)$$

where d is the target range (m), $c \approx 3 \times 10^8$ m/s, and t is the measured round-trip pulse travel time. In foggy environments, water droplets cause both backscatter from the fog layer and forward attenuation of the beam (Fig. 4), degrading point cloud density and range accuracy. Recent deep learning architectures, including fog-noise filtering networks and domain-adaptive point cloud processors, have demonstrated promising capability in separating genuine object returns from fog clutter [5].

Fig. 4. LiDAR Time-of-Flight Principle in Foggy Conditions

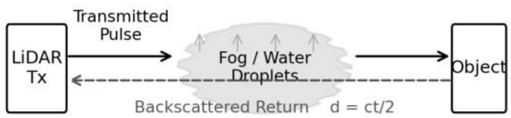

Fig. 4. LiDAR time-of-flight principle under foggy conditions, illustrating the transmitted pulse, fog backscatter noise (vertical arrows), and the attenuated return from the target object.

C. Radar and Microwave Sensing

Radar systems operating at millimeter-wave frequencies (typically 24, 77, or 79 GHz for automotive applications) are minimally attenuated by fog droplets, given that droplet diameters are far smaller than the illuminating wavelength. This physical property enables reliable long-range obstacle detection and velocity estimation under all-weather conditions, making radar an indispensable sensor in current autonomous vehicle architectures. Principal advantages include near-transparent fog propagation, operational ranges exceeding 200 m, and robustness under heavy precipitation. Notable limitations are inferior angular resolution compared to camera or LiDAR, and limited object classification capability for small or geometrically similar targets.

D. Polarization and Modulated Imaging

Polarized and intensity-modulated imaging systems selectively suppress diffusely scattered fog radiation by exploiting the polarimetric and temporal signatures that distinguish ballistic photons from scattered photons. Quadrature lock-in detection, as demonstrated by Kumar et al. [6], employs phase-sensitive demodulation to isolate the coherent signal component while rejecting incoherent fog scatter, yielding measurable improvements in image contrast under dense fog conditions. These techniques are particularly attractive for short-to-medium range applications where active illumination is feasible, such as forward-looking automotive cameras and surveillance systems.

E. Image Dehazing Algorithms

Computational image dehazing algorithms recover perceptually clear images from fog-degraded observations by inverting the physical scattering model. The widely adopted atmospheric scattering model expresses the observed intensity I(x) as:

$$I(x) = J(x) \cdot T(x) + A \cdot [1 - T(x)] \qquad (3)$$

where J(x) is the scene radiance, T(x) is the medium transmission map, and A is the global atmospheric light. Recovering J(x) requires estimating T(x) and A. Key algorithmic approaches, illustrated in Fig. 7, include the dark channel prior (DCP) [3], contrast-limited adaptive histogram equalization (CLAHE), Retinex-based reflectance separation, and end-to-end deep learning dehazing networks. CNN- and GAN-based dehazing architectures have achieved state-of-the-art performance on the RESIDE and HSTS benchmark datasets, with some achieving real-time throughput suitable for embedded automotive deployment [5].

Fig. 7. Dark Channel Prior / CNN-Based Image Dehazing Pipeline

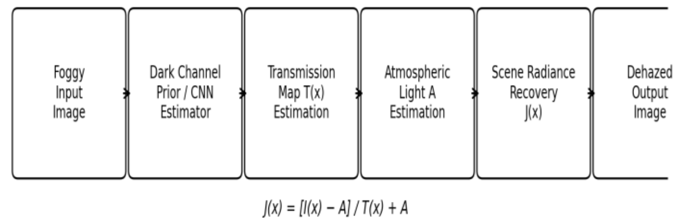

Fig. 7. Image dehazing pipeline: from fog-degraded input to scene radiance recovery via transmission map and atmospheric light estimation (Eq. 3). Based on He et al., IEEE Trans. PAMI, 2011 [3].

V. ARTIFICIAL INTELLIGENCE AND SENSOR FUSION

No single sensing modality provides satisfactory performance across the full range of environmental conditions encountered in real-world deployment. Multimodal sensor fusion addresses this limitation by combining complementary data sources within a unified perception framework, as shown in the system architecture of Fig. 3. Typical configurations integrate RGB cameras, LWIR thermal imagers, LiDAR, millimeter-wave radar, and ultrasonic sensors.

Fig. 3. Multimodal Sensor Fusion Architecture for Fog-Degraded Environments

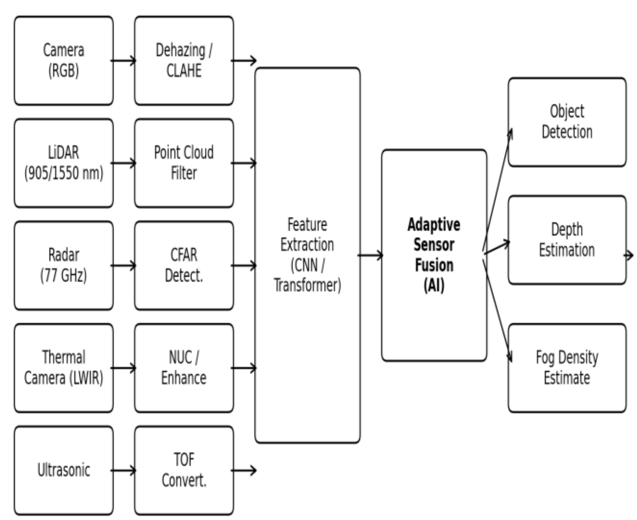

Fig. 3. End-to-end multimodal sensor fusion architecture for fog-degraded environments, illustrating the data flow from heterogeneous sensor inputs through pre-processing, feature extraction, adaptive AI fusion, and task-specific outputs. Architecture based on Bijelic et al. [5].

Fusion architectures range from early-fusion (raw data concatenation), through mid-fusion (feature-level combination), to late-fusion (decision-level aggregation), with hybrid schemes increasingly favored in learning-based systems [5]. AI-driven fusion modules dynamically weight and arbitrate among sensor modalities based on real-time estimates of environmental quality and sensor reliability. In clear conditions, camera-centric perception dominates; during dense fog, radar becomes primary; thermal imaging serves as a primary or supplementary source during nighttime operation. Deep learning models have also been applied to real-time fog density estimation and collision risk prediction [5].

TABLE II. COMPARISON OF SENSOR FUSION ARCHITECTURES

Fusion Level	Method	Fog Robustness	Computational Cost
Early Fusion	Raw data concat. (CNN input)	Moderate	Low
Mid Fusion	Feature-level concat./attention	High	Medium
Late Fusion	Decision-level weighting	Moderate	Low
Hybrid Fusion	Adaptive multi-level fusion (AI)	Very High	High

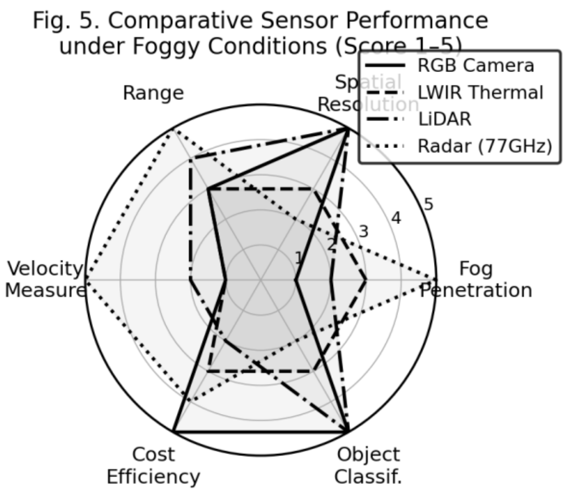

Fig. 5. Multi-attribute comparison of key sensing modalities under foggy conditions (score 1–5 per attribute). Data synthesised from [2]–[5].

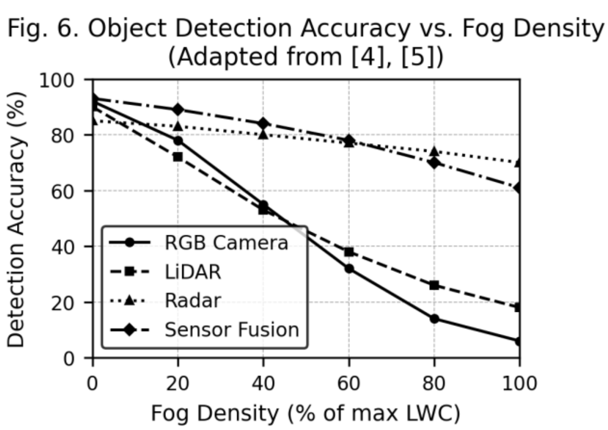

Fig. 6. Object detection accuracy versus fog density for individual sensors and multimodal sensor fusion (adapted from Kim & Sumi [4] and Bijelic et al. [5]).

VI. APPLICATIONS

A. Autonomous Vehicles

Fog poses a critical threat to the perception stack of Advanced Driver Assistance Systems (ADAS) and fully autonomous vehicles, as it simultaneously degrades the primary sensors relied upon for environment understanding. Modern production vehicles and research platforms address this challenge through adaptive front-lighting systems, automatic emergency braking (AEB), on-board fog detection and density classification algorithms, and heterogeneous sensor fusion architectures that maintain reliable obstacle maps even when individual modalities are degraded. Studies have demonstrated that camera-radar fusion can sustain near-nominal pedestrian detection rates at fog densities where camera-only systems suffer greater than 80% accuracy loss [4].

B. Aviation Systems

Civil aviation is particularly sensitive to low-visibility events. Airports deploy Instrument Landing Systems (ILS), Microwave Landing Systems (MLS), surface movement radar (SMR), transmissometer-based runway visual range (RVR) sensors, and AI-assisted nowcasting systems for fog onset prediction. Emerging interventional approaches include UAV-assisted fog dispersal using hygroscopic seeding agents and ultraviolet photolysis systems designed to accelerate droplet evaporation along critical runway corridors [10].

C. Marine Navigation

Sea fog constitutes one of the most dangerous navigational hazards for maritime operations, frequently causing collisions and grounding incidents in high-traffic coastal waters [7]. Modern vessels rely on radar, Automatic Identification Systems (AIS), thermal imaging, and satellite-based meteorological forecasting. Recurrent neural network and convolutional architectures trained on satellite imagery and reanalysis weather data have shown encouraging accuracy in predicting fog onset over coastal regions several hours in advance [7].

D. Free-Space Optical Communication

Free-space optical (FSO) communication links exploit narrow, high-bandwidth laser beams propagating through the atmosphere to deliver fiber-equivalent data rates without physical cabling. Fog represents the dominant impairment mechanism, causing signal attenuation frequently exceeding 100 dB/km under dense conditions [8] (Fig. 8). Active research directions include adaptive wavelength multiplexing across the 780–1550 nm range, intelligent automatic gain control, spatial diversity schemes using multiple apertures, and hybrid RF/FSO architectures that activate a radio-frequency backup link during severe optical attenuation [8].

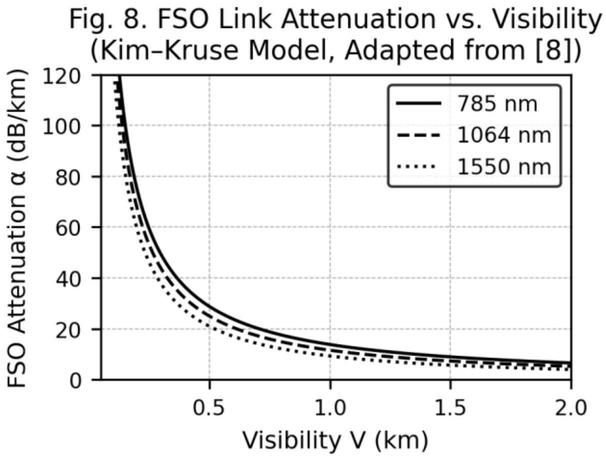

Fig. 8. FSO link attenuation versus visibility for three wavelengths, computed using the Kim–Kruse model (adapted from Ijaz et al. [8]). Dense fog (V < 200 m) can cause attenuation exceeding 100 dB/km.

TABLE III. SUMMARY OF FOG-MITIGATION TECHNOLOGIES ACROSS APPLICATION DOMAINS

Application Domain	Primary Sensors	AI/Algorithm Method	Key Reference
Autonomous Vehicles	Camera, LiDAR, Radar, Thermal	Sensor fusion CNN, Fog density estimator	[4], [5]
Aviation	ILS/MLS, SMR, RVR Sensors	AI nowcasting, UAV fog dispersal	[10]
Marine	Radar, AIS, Satellite Imaging	LSTM sea-fog prediction	[7]
FSO Comm.	Multi-aperture Photodetectors	Adaptive wavelength multiplexing	[8]
Surveillance	LWIR Thermal, LiDAR	GAN dehazing, DCP, CLAHE	[3], [5]

VII. FUTURE DIRECTIONS

Several emerging sensing paradigms are expected to substantially advance fog-penetrating capability in the coming decade:

- Quantum illumination and ghost imaging techniques leveraging photon-pair entanglement to detect object signatures below the classical noise floor,
- Single-photon avalanche diode (SPAD) LiDAR arrays capable of detecting individual backscattered photons, enabling ranging through extremely dense fog at reduced laser power,
- Neuromorphic event-driven vision sensors that encode temporal contrast rather than absolute intensity, inherently suppressing slowly varying fog-induced illumination bias,
- AI-driven adaptive sensing architectures that dynamically reconfigure sensor parameters, fusion weights, and transmission modes in real time,
- Non-line-of-sight (NLOS) computational imaging using multiply-scattered photons to reconstruct hidden scene geometry.

The convergence of these technologies with edge AI accelerators, high-bandwidth V2X networking, and cooperative multi-agent perception is expected to enable fundamentally new approaches to situational awareness under adverse atmospheric conditions. Standardised fog-condition test protocols, publicly available annotated multimodal fog datasets (e.g., STF [5]), and regulatory performance certification frameworks are critical enabling factors currently under active development by the research community and standardisation bodies.

VIII. CONCLUSION

Fog remains among the most operationally challenging atmospheric conditions for optical and electro-optical sensing systems. Conventional visible-band cameras are fundamentally constrained by Mie scattering from suspended water droplets, leading to severe contrast loss, blurred boundaries, and failure of downstream perception algorithms. However, substantial advances across a broad front—encompassing infrared thermal imaging, LiDAR, millimeter-wave radar, polarimetric sensing, computational dehazing, and AI-driven sensor fusion—have collectively improved the robustness of perception systems operating under adverse atmospheric conditions.

The most capable and resilient solutions require tightly integrated multimodal sensor fusion architectures driven by adaptive AI-based processing pipelines. Such systems will be central to achieving the safety and reliability targets of autonomous ground transportation, aerospace operations, maritime navigation, and high-availability FSO communication networks. Persistent challenges—including high sensor costs, demanding real-time computational requirements, limited annotated fog-condition datasets, and absence of standardised performance benchmarks—represent important areas for continued research investment. Future work should focus on hardware-efficient neural architectures for embedded deployment, physics-informed generative models for synthetic fog data augmentation, and cooperative multi-agent sensing strategies that leverage shared environmental awareness across networked platforms.

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