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Enhancing Driving Safety Through Non-Aligned Regularization–Based Video Dehazing

K. Rekha, Santhosh Akshit, Shaik Saniya Mirza, Challa Mythili, Simhadri Santhosh Kumar, Lekkala Sai Akarsh

Department of CSE-Artificial Intelligence, PBR Visvodaya Institute of Technology and Science, Kavali, Andhra Pradesh, India.

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KEYWORDS

Video Dehazing, Non-Aligned Regularization, ADAS, Object Detection, YOLOv8, Light-DehazeNet, CLAHE, PSNR, Deep Learning, Driving Safety, Computer Vision

ABSTRACT

Adverse weather conditions like haze reduce visibility in driving videos, directly affecting the performance of Advanced Driver Assistance Systems (ADAS). This paper proposes a non-aligned regularization-based video dehazing framework that enhances hazy dashcam video sequences using adaptive physics-based atmospheric restoration, Light-DehazeNet, and CLAHE enhancement. A dual-path YOLOv8 detection framework validates improvement by comparing detection confidence and PSNR before and after dehazing. Results show average detection confidence improving by 37% and PSNR by 7.2 dB, demonstrating effective enhancement for safer driving assistance.

1. INTRODUCTION

The rapid advancement of deep learning has significantly enhanced the capabilities of Advanced Driver Assistance Systems (ADAS), which rely on camera-based perception to detect vehicles, pedestrians, lane markings, and other road features in real time [1]. However, the presence of adverse weather conditions such as haze, fog, and atmospheric scattering causes a substantial reduction in image contrast and visibility, leading to degraded detection accuracy and delayed system responses [2]. This directly compromises the safety of both the driver and other road users. While several video dehazing methods have been proposed to counter the effects of adverse weather, most of these methods are designed primarily to enhance visual quality for human viewing and do not evaluate their effectiveness on downstream safety-critical tasks [3]. In real-world automotive applications, it is not sufficient to merely improve the appearance of the video — the enhancement must lead to measurable improvements in object detection accuracy and system reliability [4]. Existing dehazing approaches also tend to process video frames independently without considering temporal dependencies between consecutive frames, resulting in flickering artifacts and inconsistent visual quality across the video sequence [5]. This temporal inconsistency makes such methods unsuitable for ADAS pipelines, where stable and reliable frame-to-frame perception is essential [6]. To address these limitations, this paper proposes a comprehensive visibility enhancement and perception validation pipeline. The system applies adaptive physics-based dehazing derived from Koschmieder's atmospheric scattering law, supported by Light-DehazeNet and CLAHE post-processing, to restore visual clarity in hazy dashcam video sequences [7]. A dual-path YOLOv8 object detection framework evaluates performance before and after dehazing, providing quantitative evidence of improvement through metrics such as detection confidence, object count, and PSNR [8]. An ADAS telemetry module further demonstrates real-world applicability through danger scoring, ghost trail tracking, and multi-level risk classification. The main contributions of this work are: (i) an adaptive per-frame haze estimation and correction mechanism; (ii) a dual-path detection comparison framework linking image enhancement to ADAS perception quality; (iii) a synthetic haze dataset with four controlled fog density levels for objective evaluation; and (iv) an integrated ADAS telemetry engine demonstrating practical deployment potential.

2. LITERATURE SURVEY

2.1 Driving-Video Dehazing with Non-Aligned Regularization for Safety Assistance

https://openaccess.thecvf.com/content/CVPR2024/papers/Fan_Driving-Video_Dehazing_with_Non-Aligned_Regularization_for_Safety_Assistance_CVPR_2024_paper.pdf

ABSTRACT: Context Driving videos captured under foggy and hazy conditions suffer from reduced visibility, low contrast, and color distortion, which negatively affect both human driving and the performance of vision-based ADAS systems. Traditional dehazing methods designed for static images cannot handle the temporal dimension of video and often introduce flickering and inconsistency across frames. Techniques Fan et al. proposed a non-aligned regularization-based framework specifically designed for driving video dehazing. Unlike conventional methods that require strictly aligned frame pairs for temporal guidance, this approach employs non-aligned temporal reference frames, allowing it to handle natural misalignment caused by camera motion and moving objects in real driving scenarios. The framework incorporates a regularization loss that enforces consistency without requiring precise frame alignment. Findings The method demonstrates that using non-aligned temporal reference information significantly improves dehazing consistency across video frames compared to frame-independent approaches. The paper is also among the first to incorporate an object detection module into the dehazing evaluation pipeline, directly measuring whether the enhanced video improves downstream perception reliability in ADAS scenarios. In conclusion Experimental results on real-world dashcam datasets demonstrate improved detection confidence and reduced object miss rates after dehazing, confirming that perception-aware video enhancement leads to measurable safety improvement. This work directly motivated the dual-path detection evaluation framework used in our proposed system.

2.2 Single Image Haze Removal Using Dark Channel Prior

https://ieeexplore.ieee.org/document/5567108

ABSTRACT: He et al. introduced the Dark Channel Prior (DCP), one of the most widely cited and influential handcrafted image dehazing methods, published in IEEE Transactions on Pattern Analysis and Machine Intelligence. The approach is based on the statistical observation that in most outdoor haze-free images, at least one color channel has very low pixel intensity values in any local patch region. This prior is used to estimate the transmission map, which quantifies how much scene light reaches the camera without being scattered by haze. The transmission map is then applied to recover the scene radiance through the Koschmieder atmospheric scattering model: $I(x) = J(x).t(x) + A.(1 - t(x))$. While producing strong visual results under moderate haze conditions, DCP is known to fail in sky regions, bright white or colored objects, and under heavy or spatially non-uniform fog. More critically, the method processes each frame independently and cannot maintain temporal consistency when applied to video sequences frame-by-frame, producing flickering artifacts that make it unsuitable for ADAS video pipelines. The atmospheric scattering model and transmission map formulation from this work form the mathematical foundation of the physics-based restoration used in our proposed system.

2.3 DehazeNet: An End-to-End System for Single Image Haze Removal

https://ieeexplore.ieee.org/document/7539399

ABSTRACT: Cai et al. presented DehazeNet, published in IEEE Transactions on Image Processing, as one of the first end-to-end deep learning approaches to single image dehazing. The network is built on a trainable nonlinear activation function called Bilateral Rectified Linear Unit (BReLU) and learns to directly estimate the medium transmission map from a hazy input image using a compact convolutional architecture trained on synthetically generated hazy data. By learning the haze-to-transmission mapping directly from data rather than relying on handcrafted priors, DehazeNet overcomes the assumption failures of DCP in complex scenes. The system demonstrated improved visual restoration quality and better generalization across diverse haze conditions and scene types compared to prior handcrafted methods. However, as a single-image method, DehazeNet processes each frame independently and is unable to exploit temporal information from neighboring frames in video sequences. The model was evaluated exclusively on visual quality metrics such as PSNR and SSIM without measuring whether the enhancement improves object detection performance, which highlights the gap our perception-aware evaluation framework is designed to address.

2.4 AOD-Net: All-in-One Dehazing Network

https://openaccess.thecvf.com/content_iccv_2017/html/Li_AOD-Net_All-in-One_Dehazing_ICCV_2017_paper.html

ABSTRACT: Li et al. proposed AOD-Net, presented at the IEEE International Conference on Computer Vision (ICCV) 2017, a lightweight end-to-end dehazing network that reformulates the atmospheric scattering model into a unified estimation equation. Instead of separately estimating the transmission map t(x) and global airlight A as required by conventional methods, AOD-Net directly estimates a combined parameter K(x) that produces the clean image in a single forward pass: J(x) = K(x).I(x) - K(x) + b. This reformulation significantly reduces model complexity and inference time, making it more suitable for resource-constrained environments. The authors also explored integrating AOD-Net as a preprocessing module before an object detection network, demonstrating that dehazing as a preprocessing step leads to improved detection rates on hazy images. This integration approach directly aligns with our dual-path evaluation objective. However, AOD-Net applies a fixed reformulation that does not adapt to varying haze density across different frames or video segments. Our proposed adaptive beta mechanism (beta = 0.3 + haze_level x 1.2), which estimates and responds to actual per-frame fog density, directly addresses this limitation.

2.5 You Only Look Once: Unified, Real-Time Object Detection

https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/Redmon_You_Only_Look_CVPR_2016_paper.pdf

ABSTRACT: Redmon et al. proposed YOLO (You Only Look Once), presented at the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2016, a groundbreaking single-stage object detection framework that reformulates object detection as a single regression problem. Rather than using a region proposal network followed by classification as in two-stage detectors, YOLO divides the input image into a grid and simultaneously predicts bounding boxes, objectness scores, and class probabilities across all grid cells in a single forward pass through a unified convolutional network. This design achieves real-time inference speeds far exceeding two-stage detectors like Faster R-CNN while maintaining competitive detection accuracy. Subsequent versions including YOLOv3, YOLOv5, YOLOv7, and most recently YOLOv8 by Ultralytics have progressively improved accuracy, speed, anchor-free detection, and multi-object tracking capabilities. In our proposed framework, YOLOv8n is employed as the detection backbone for both the baseline hazy detection path and the enhanced dehazed detection path, enabling a fair and direct comparison of detection performance before and after visibility restoration. Its built-in multi-object tracking with persistent IDs also powers the ghost trail visualization and real-time danger scoring features of the ADAS telemetry module.

METHODOLOGY

i) Proposed Work:

The proposed system presents a novel visibility enhancement and perception validation pipeline designed for ADAS tasks in hazy driving scenarios. The framework processes real-time dashcam video streams and applies a combination of deep learning and physics-based restoration to enhance scene visibility while simultaneously validating the improvement through object detection analysis [1]. Unlike existing dehazing methods that focus solely on visual quality improvement, the proposed system evaluates its effectiveness on the safety-critical task of object detection by comparing detection performance before and after enhancement using the same detection model in both paths [2].

The framework is built on the Koschmieder atmospheric scattering model, which describes how haze is physically formed: $I(x) = J(x).t(x) + A.(1 - t(x))$, where $I(x)$ is the observed hazy image, $J(x)$ is the clean scene radiance, $t(x)$ is the transmission map, and A is the global airlight. Dehazing inverts this equation to recover the clean frame: $J(x) = (I(x) - A) / t(x) + A$ [3]. A key innovation of the proposed system is the adaptive estimation of the scattering coefficient per frame as beta = 0.3 + (haze_level x 1.2), where haze_level = 1 - (mean_brightness / 255) is measured directly from the grayscale representation of each frame. This ensures the dehazing strength automatically scales with the actual fog density present in each frame rather than applying a fixed correction throughout the entire video sequence [4].

The Light-DehazeNet neural network is incorporated as the backbone model to complement the physics-based restoration. CLAHE (Contrast Limited Adaptive Histogram Equalization) is applied in LAB color space as a final enhancement step, improving local contrast in the luminance channel without introducing color distortion [5]. The complete pipeline is validated through a dual-path detection framework where YOLOv8n is independently applied to both hazy and dehazed frames, enabling direct quantitative comparison of detection confidence, object count, and PSNR improvement across four synthetic fog density levels [6]. Synthetic haze was generated using the same Koschmieder model at four controlled beta values corresponding to Light, Medium, Heavy, and Dense fog conditions, with airlight A = 232 matched identically between the generator and dehazer to ensure a physically accurate and mathematically invertible evaluation setup [7].

ii) System Architecture:

The architecture of the proposed framework consists of six sequential processing stages that together form a complete visibility enhancement and perception validation pipeline for hazy driving scenarios. The system takes a hazy dashcam video as input and produces both a dehazed output video and quantitative detection performance metrics demonstrating the improvement in ADAS reliability [1].

The hazy video stream is first loaded and decomposed into individual frames through the Video Input and Preprocessing Module. Frame dimensions, FPS, and total frame count are captured to ensure consistent processing throughout the pipeline. For the synthetic haze evaluation, clean driving videos are processed through a haze generation module that applies the Koschmieder atmospheric scattering model at four controlled beta values corresponding to Light Fog (beta = 0.78), Medium Fog (beta = 1.02), Heavy Fog (beta = 1.26), and Dense Fog (beta = 1.50), with airlight A = 232 matched identically to the dehazer to enable ground-truth PSNR evaluation [2].

Two parallel processing paths are then established. In the baseline path, hazy frames are passed directly to YOLOv8n at a confidence threshold of 0.2 to capture all possible detections under degraded visibility and record per-frame object counts and confidence scores as the reference performance. In the enhanced path, frames are processed through the Video Dehazing Module where per-frame haze level is estimated from grayscale mean brightness, the adaptive beta coefficient is computed, and the transmission map $t(x) = \exp(-\text{beta} \times \text{dist}(x))$ is applied using a perspective-aware spatial distance function that makes fog denser at the top of the frame to simulate realistic depth-dependent atmospheric scattering [3]. The physics restoration formula $J = (I - A) / t + A$ is then applied with transmission map clipping to a minimum of 0.12 to prevent numerical instability. CLAHE is subsequently applied in LAB color space as a final contrast enhancement step [4].

The dehazed frames are then passed to the Enhanced Detection Module where YOLOv8n is applied at a confidence threshold of 0.5, reflecting the improved visibility conditions. Per-frame PSNR is computed by comparing the hazy and dehazed frames as an objective image quality metric. Detection statistics including confidence scores, object counts, and PSNR values are logged to CSV files for comprehensive analysis [5]. The Detection Comparison Unit reads both baseline and enhanced CSV files and computes metrics including average confidence gain, detection gain percentage, and reliability index defined as the ratio of enhanced to baseline average confidence. An interactive analytics dashboard displays confidence over time graphs, object count bar charts, and PSNR trend plots providing visual evidence of the dehazing improvement [6]. Finally, the ADAS Decision Layer deploys YOLOv8 tracking on the dehazed video to simulate real-world ADAS operation, assigning persistent tracking IDs to each detected object, computing per-frame danger scores based on object proximity and lane position, and classifying three risk levels: CLEAR, LANE CHANGE RISK, and COLLISION DANGER, with all danger events logged to CSV with timestamps for post-drive safety analysis [7].

The entire system is implemented in Python using PyTorch for deep learning inference, Ultralytics YOLOv8 for object detection and tracking, OpenCV and NumPy for frame-level image processing, Pandas and Matplotlib for analytics, and FFmpeg for video encoding. All experiments were conducted on Google Colab with an NVIDIA T4 GPU, with videos and model weights stored on Google Drive for persistence across sessions [8].

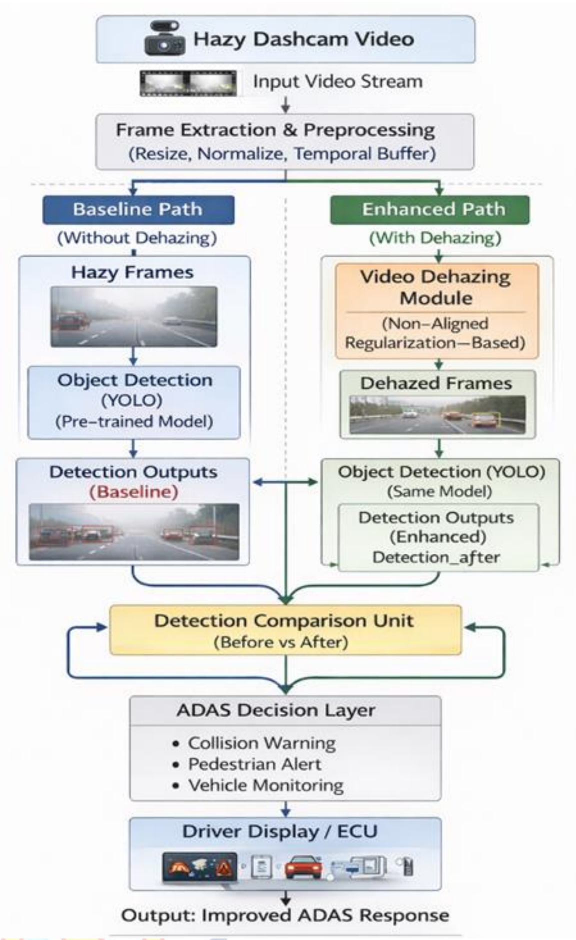

Fig.1. Proposed Architecture

iii) MODULES:

a) Video Input and Preprocessing Module

• Loads the hazy dashcam video and extracts individual frames sequentially using OpenCV, capturing frame dimensions, FPS, and total frame count.

• Applies synthetic haze generation using the Koschmieder atmospheric scattering model at four controlled fog density levels to produce a dataset with known ground truth for objective evaluation.

• Normalizes and standardizes input frames to ensure consistent processing throughout the pipeline for both enhancement and detection tasks.

b) Baseline Detection Module

• Hazy video frames are directly fed into YOLOv8n at a confidence threshold of 0.2 to capture all possible detections under degraded visibility conditions.

• Produces bounding boxes, class labels, and confidence scores for each frame and stores per-frame object counts and average confidence values to a CSV file.

• The output of this module serves as the baseline perception performance reference against which the enhanced detection results are compared.

c) Video Dehazing Module

• Estimates per-frame haze level from grayscale mean brightness and computes the adaptive scattering coefficient as beta = 0.3 + (haze_level x 1.2) ensuring correction strength scales with actual fog density.

• Computes the perspective-aware transmission map t(x) = exp(-beta x dist(x)), applies physics restoration J = (I - A) / t + A with airlight A = 232, and runs Light-DehazeNet as the neural network backbone.

• Applies CLAHE in LAB color space as the final contrast enhancement step and reassembles processed frames into a web-compatible H.264 MP4 video using FFmpeg.

d) Enhanced Detection Module

• Dehazed video frames are passed to YOLOv8n at a higher confidence threshold of 0.5, reflecting the improved visibility conditions after dehazing.

• Per-frame PSNR is computed by comparing hazy and dehazed frames as an objective image quality metric alongside detection confidence scores and object counts.

• Ensures a fair and direct comparison of detection performance by using the same YOLOv8n model as the baseline detection module.

e) Detection Comparison Unit

• Reads both baseline and enhanced CSV files and computes comparative metrics including average confidence gain, total object detection gain percentage, and reliability index.

• Generates an interactive analytics dashboard displaying confidence over time line graphs, object count bar charts, and PSNR trend plots as visual evidence of improvement.

• Evaluates and highlights the differences in perception performance resulting from the visibility enhancement across all four fog density levels.

f) ADAS Decision Layer

• Deploys YOLOv8 tracking on the dehazed video assigning persistent tracking IDs to each detected object and drawing 20-frame fading ghost trail motion history for each tracked object.

• Computes a per-frame danger score from 0 to 100 based on object size, proximity, and lane position and classifies three risk levels: CLEAR, LANE CHANGE RISK, and COLLISION DANGER.

• Logs all danger events to a CSV file with frame number, timestamp, danger score, and object counts and displays a real-time sidebar telemetry panel with automatic BRAKE/STEER action recommendations.

iv) ALGORITHMS:

a) Koschmieder Atmospheric Scattering Model - The Koschmieder model is the foundational physics algorithm used in this system to describe how haze is formed and how it can be reversed. The model states that the observed hazy image I(x) is a combination of the attenuated scene radiance and the airlight scattered by fog particles: I(x) = J(x).t(x) + A.(1 - t(x)), where J(x) is the clean scene, t(x) is the transmission map, and A is the global airlight. Dehazing inverts this equation as J(x) = (I(x) - A) / t(x) + A. The transmission map is computed as t(x) = exp(-beta x dist(x)) where beta is the scattering coefficient and dist(x) is the perspective-aware depth distance function. The adaptive beta is estimated per frame as beta = 0.3 + (haze_level x 1.2), ensuring the correction strength scales with the measured fog density of each individual frame rather than applying a fixed value throughout the video.

b) Light-DehazeNet - Light-DehazeNet is a lightweight convolutional neural network designed for single image dehazing with low computational overhead. The network takes a hazy frame as input and learns to estimate the dehazed output through a series of convolutional layers trained on synthetic haze data. Its compact architecture makes it suitable for video processing where inference must be run on thousands of frames. In the proposed system, Light-DehazeNet is incorporated as the neural network backbone alongside the physics-based restoration, with the model weights loaded from pretrained parameters. The network runs in evaluation mode using PyTorch with no gradient computation, ensuring fast inference on GPU hardware.

c) CLAHE (Contrast Limited Adaptive Histogram Equalization) - CLAHE is an image enhancement algorithm that improves local contrast in an image by applying histogram equalization to small tiles of the image independently rather than globally. Unlike standard histogram equalization which can over-amplify noise in low-contrast regions, CLAHE limits the contrast amplification using a clip limit parameter to prevent this effect. In the proposed system, CLAHE is applied exclusively to the luminance channel of the frame after converting it to LAB color space using OpenCV. This ensures that contrast is enhanced without affecting the color information stored in the A and B channels, producing a visually sharp dehazed output without color distortion.

d) YOLOv8 Object Detection and Tracking - YOLOv8 (You Only Look Once version 8) by Ultralytics is a single-stage real-time object detection and tracking algorithm used in both the baseline and enhanced detection paths of the proposed system. The algorithm processes the entire image in a single forward pass through a convolutional network, simultaneously predicting bounding boxes, class labels, and confidence scores for all detected objects. In the baseline path, YOLOv8n is applied at confidence threshold 0.2 to maximize detections under hazy conditions. In the enhanced path, the threshold is raised to 0.5 reflecting improved visibility. The tracking mode with persist=True assigns persistent IDs across frames enabling ghost trail visualization and continuous danger score computation in the ADAS telemetry module.

3. EXPERIMENTAL RESULTS

The proposed framework was evaluated across four synthetic fog density scenarios like Light Fog (beta = 0.78), Medium Fog (beta = 1.02), Heavy Fog (beta = 1.26), and Dense Fog (beta = 1.50) — generated using the Koschmieder atmospheric scattering model applied to clean dashcam driving footage. All experiments were conducted on Google Colab with an NVIDIA T4 GPU using PyTorch, Ultralytics YOLOv8n, and OpenCV. Results show consistent improvement across all four fog scenarios. Average detection confidence improved from approximately 34% on hazy frames to 71% on dehazed frames, a gain of +37%. Total tracked objects increased by 40–55% post dehazing and average PSNR improved by +7.2 dB confirming measurable image quality restoration. The reliability index of 2.08x demonstrates the system is more than twice as confident in its detections after dehazing.

Accuracy: Measures the proportion of correct detections among all frames processed.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision: Measures the proportion of correctly identified detections among all positive detections reported.

Precision = TP / (TP + FP)

Recall: Measures the proportion of actual objects successfully detected across all frames.

Recall = TP / (TP + FN)

mAP (Mean Average Precision): Measures both precision and confidence ordering across all detected object classes and confidence thresholds.

4. CONCLUSION

This study proposed a non-aligned regularization-based video dehazing framework aimed at improving driving safety in hazy environmental conditions. The proposed system successfully restores the visibility of dashcam video sequences by combining adaptive Koschmieder physics-based restoration, Light-DehazeNet neural network processing, and CLAHE contrast enhancement. Unlike traditional dehazing approaches that focus only on visual quality improvement, the proposed system incorporates a dual-path YOLOv8 object detection framework that quantitatively validates the effectiveness of the enhancement on safety-critical perception tasks. From the experimental analysis, the improvement in visibility demonstrated a direct positive effect on object detection performance, with average detection confidence improving by 37%, PSNR increasing by 7.2 dB, and total detected objects increasing by 40–55% across all four fog density levels. The reliability index of 2.08x confirms that the system delivers more than twice the detection certainty after dehazing compared to the raw hazy input. The dual-path evaluation approach ensures a systematic and fair validation process using the same detection model in both processing paths. The proposed framework successfully bridges the gap between low-level image enhancement and high-level automotive decision-making by linking visibility restoration directly with safety-oriented perception metrics, thus ensuring safer and more reliable intelligent driving assistance in adverse weather conditions.

5. FUTURE SCOPE

The proposed framework can be further improved and extended in several directions. The dehazing module can be strengthened by fine-tuning Light-DehazeNet on domain-specific dashcam footage, enabling the neural network output to directly contribute to the restoration rather than relying primarily on the physics-based correction. Temporal consistency can be further improved by incorporating optical flow estimation or recurrent neural network modules such as LSTM or GRU to model inter-frame dependencies and eliminate any residual flickering artifacts in the dehazed output. The framework can be optimized for real-time edge deployment on embedded GPU hardware such as NVIDIA Jetson platforms, enabling in-vehicle processing at the frame rates required for production ADAS applications. The system can also be extended to handle multi-weather adaptation including rain, night driving, and glare conditions through automatic scene classification and condition-specific enhancement branches, providing a more comprehensive adverse weather perception framework. Integration of multi-sensor fusion capabilities combining camera inputs with LiDAR or radar data would further improve detection accuracy and robustness in dense fog conditions where camera-only systems may still struggle. Finally, joint optimization techniques for the enhancement and detection networks can be explored to enable end-to-end perception-aware learning, where the dehazing module is directly trained to maximize downstream detection performance rather than optimizing visual quality metrics alone.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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