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A Lightweight Image Denoising and Adverse Weather Enhancement Method for Real-Time Visual Perception Services in Autonomous Driving Systems

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Abstract. Real-time visual perception is a critical informatics service in autonomous driving systems, directly supporting downstream decision-making, control, and safety assurance. Under adverse weather conditions such as rain, fog, snow, and low-light environments, images captured by onboard cameras suffer from severe noise, contrast degradation, and detail loss, which significantly reduce the reliability of perception services. Moreover, perception algorithms are typically deployed on vehicle-grade embedded platforms with limited computational resources, making heavyweight denoising and enhancement models unsuitable for real-time operation. To address these challenges, this paper proposes a lightweight image denoising and adverse weather enhancement method designed for real-time autonomous driving perception services. A low-complexity denoising network is developed based on shallow architecture, lightweight convolutional operators, and residual learning. On this basis, targeted enhancement strategies are introduced for rainy, foggy, and low-light scenes, enabling joint optimization of noise suppression and visual enhancement under strict resource constraints. Experimental results on multiple autonomous driving datasets demonstrate that the proposed method improves image quality, reduces inference latency, and enhances the performance of downstream perception tasks such as object detection and semantic segmentation. The results indicate that the proposed approach provides an effective and deployable informatics solution for robust real-time perception services in autonomous driving systems.

Keywords: autonomous driving; real-time perception; lightweight algorithm; image denoising; adverse weather enhancement

1. Introduction

With the rapid development of artificial intelligence and intelligent transportation, autonomous driving has become an important research topic in smart vehicles. In an autonomous driving system, the environment perception module plays a key role in decision making and vehicle control, and its performance is closely related to driving safety and overall system reliability, especially in complex traffic environments. At present, most autonomous vehicles rely on onboard cameras to capture road images, which are then processed by visual perception algorithms for tasks such as object detection, lane detection, and semantic segmentation.

In real-world driving environments, autonomous vehicles inevitably operate under adverse weather conditions such as rain, fog, snow, and night-time low-light scenes. These conditions significantly interfere with the imaging process of onboard cameras, leading to increased noise, reduced contrast, and loss of structural details. As illustrated in Figure 1, different weather conditions introduce distinct degradation patterns, including rain streaks and strong reflections in rainy scenes, contrast attenuation and detail loss in foggy environments, as well as severe sensor noise and low signal-to-noise ratios under low-light conditions. Although the physical causes of degradation vary, these adverse conditions share common negative effects on visual perception reliability, particularly for object detection and semantic segmentation tasks. If such degraded images are directly used by perception algorithms, the stability and accuracy of downstream perception services are significantly compromised.

Fig.1: Impact of Adverse Weather Conditions on Autonomous Driving Visual Perception

To address image degradation caused by adverse weather, various approaches have been proposed. Traditional denoising methods are mainly based on filtering or transform-domain techniques. While these methods are computationally efficient, they often remove important image details when noise characteristics become complex (Zheng et al., 2025). In recent years, deep learning‑based methods have demonstrated strong performance in image denoising and enhancement, as deep networks are capable of modeling complex degradation patterns. However, these methods usually rely on deep architectures with large model sizes and high computational demands, which makes them difficult to deploy in real-time autonomous driving systems. Moreover, many existing weather enhancement approaches are designed for a single type of adverse condition and employ complex model structures, further limiting their practical applicability.

In real-world applications, visual perception algorithms are typically deployed on vehicle-grade or embedded computing platforms with limited computational resources. This imposes strict constraints on model size, computational complexity, and inference latency. Based on this background, this paper investigates lightweight image denoising and adverse weather enhancement for real-time perception in autonomous driving systems. In this study, the term “lightweight” does not merely refer to a small model size, but is defined from a practical deployment perspective. Specifically, a lightweight method is characterized by a shallow network architecture, a limited number of parameters, and low computational complexity, enabling low-latency inference and stable performance on vehicle-grade embedded platforms with constrained resources. This definition emphasizes deployability and real-time service reliability rather than pursuing maximal numerical performance. By analyzing image degradation mechanisms under different adverse weather conditions, a low-complexity denoising network and corresponding weather-aware enhancement strategies are designed. The proposed method improves image quality while maintaining strict real-time constraints, providing a practical solution for stable visual perception in complex driving environments.

From a service science perspective, this work treats visual perception as a real-time informatics service within autonomous driving systems. The proposed lightweight preprocessing approach enhances the reliability, responsiveness, and deployability of this service under adverse environmental conditions, thereby supporting robust and continuous perception for downstream autonomous driving tasks.

2. Real-Time Perception System Requirements for Autonomous Driving

In an autonomous driving system, the visual perception system is a core component for acquiring information about the surrounding environment. Its main function is to understand and model road scenes based on data collected from multiple sensors. Among these sensors, cameras are the most important and information-rich, as they provide detailed visual data for road object recognition, traffic element perception, and scene semantic understanding. A typical architecture of an autonomous driving visual perception system is illustrated in Figure 2. The overall processing pipeline generally includes image acquisition, image preprocessing, feature extraction, and high-level perception tasks, with clear data dependencies between each stage (Wang et al., 2023).

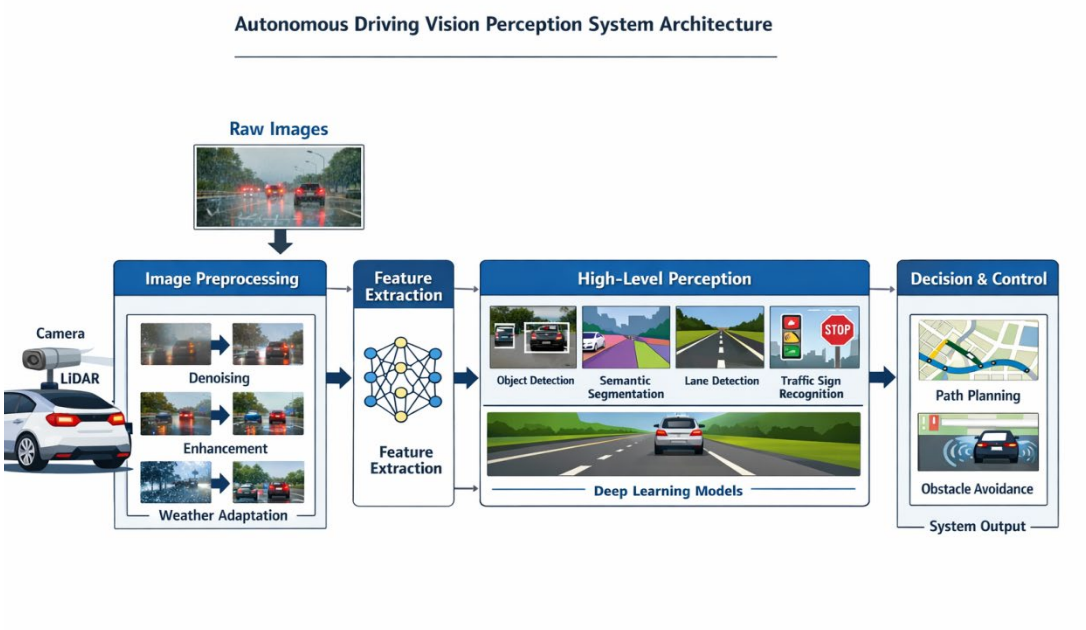

Fig.2: Architecture of the Autonomous Driving Visual Perception System

At the front end of the system, onboard cameras continuously capture road scene images and transmit raw image data to the perception processing unit. In real driving environments, these raw images are often affected by various factors, such as sensor noise, motion blur, and adverse weather conditions including rain, fog, and low-light scenes. These factors can significantly degrade image quality and directly influence the stability and accuracy of subsequent perception algorithms. As a result, image preprocessing is an essential step before high-level perception tasks are executed. This stage typically includes image denoising, contrast enhancement, brightness correction, and image recovery under adverse weather conditions (Aloufi et al., 2024). The main objective of preprocessing is to improve overall image quality and visibility while preserving important structural information as much as possible. After preprocessing, the processed images are input into perception algorithm modules to perform tasks such as object detection, semantic segmentation, lane detection, and traffic sign recognition. The high-level perception tasks usually rely on deep learning models to extract and represent image features. Their performance is highly sensitive to input image quality. If noise is not effectively suppressed or weather-related degradation is not properly addressed during preprocessing, feature extraction may become incomplete, leading to higher error rates. This can ultimately affect the safety of decision making and vehicle control in autonomous driving systems. It is important to note that in real-time autonomous driving applications, the entire visual perception pipeline typically runs on vehicle-grade embedded computing platforms (Choi & Jeong, 2022). These platforms impose strict constraints on algorithm latency, computation cost, and resource usage. Therefore, as reflected in the system architecture, the image preprocessing module must not only achieve effective denoising and enhancement, but also satisfy lightweight and real-time requirements (Zhang et al., 2025). Based on these system characteristics, this paper treats image denoising and adverse weather enhancement as key foundational components of the visual perception pipeline, aiming to provide stable, reliable, and high-quality image input for subsequent perception tasks.

3. Lightweight Image Denoising Algorithm Design

3.1. Overall Design Idea of the Denoising Model

In real-time autonomous driving perception systems, image denoising is an early and important step in the visual pipeline. The denoising module must not only reduce noise and recover useful image details, but also satisfy strict constraints on latency and resource usage on vehicle-grade embedded platforms. For this reason, the proposed denoising model follows a “lightweight-first” design principle. While maintaining effective denoising performance, the model aims to minimize parameter size and computation cost so that it can run stably on platforms with limited computing power (Zheng et al., 2025).

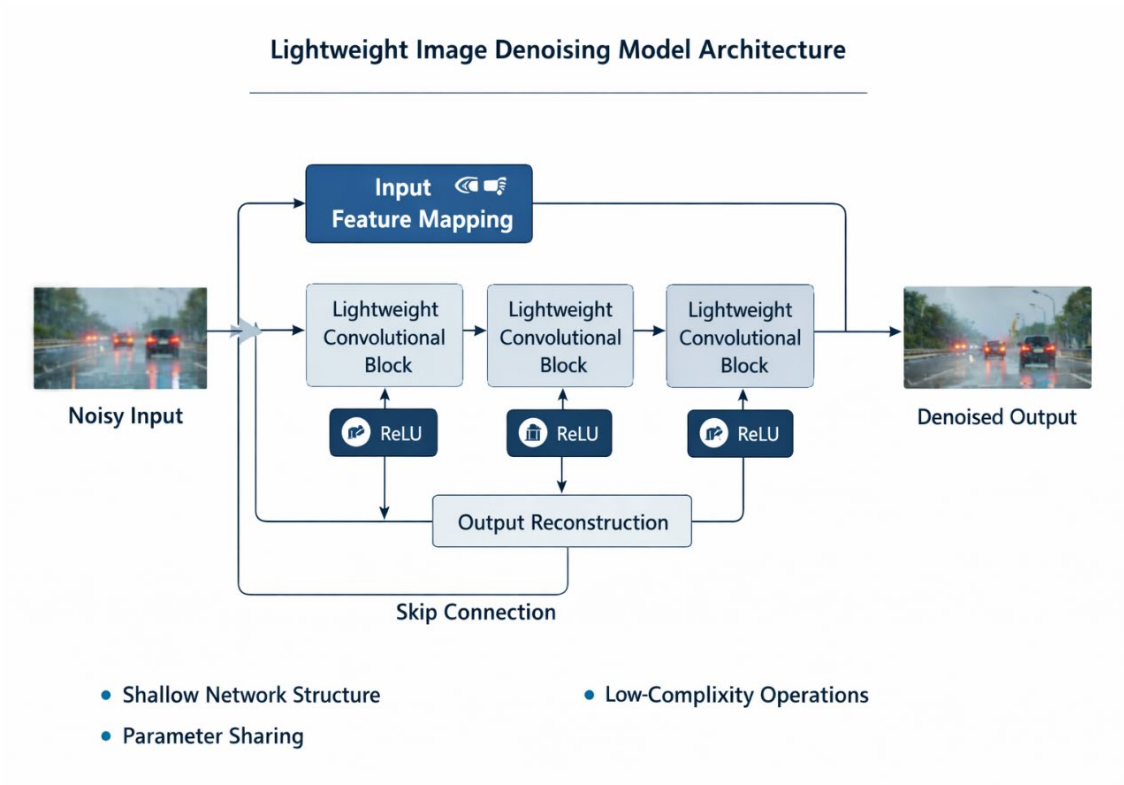

Fig.3: Architecture of the Proposed Lightweight Image Denoising Model

As shown in Figure 3, the proposed lightweight image denoising model adopts a shallow network structure. The overall model size is controlled by reducing network depth and the number of feature channels. Unlike traditional deep denoising networks that rely on many stacked layers, this model focuses on efficient modeling of key low-level visual features. This helps avoid redundant feature extraction and unnecessary computation (Bradley et al., 2021). Structurally, the network is composed of an input feature mapping stage, lightweight feature extraction modules, and an output reconstruction stage. The data flow is simple and clear, which supports fast inference on embedded platforms. To further reduce resource consumption, parameter sharing and module reuse are applied. The lightweight convolution blocks with the same structure are reused at different stages, allowing the model to maintain representation ability while reducing the number of trainable parameters. In addition, low-complexity operators such as small convolution kernels and depthwise separable convolutions are used. These operators reduce FLOPs and lower hardware load, which shortens per-frame processing time. To handle diverse and time-varying noise in driving scenes, residual learning is introduced. As shown in Figure 3, residual connections pass the input image directly to the output, helping preserve structural information and avoid over-smoothing. Overall, the proposed lightweight denoising model is optimized at structural, parameter, and operator levels, providing an efficient and practical solution for real-time image preprocessing in autonomous driving systems (Walambe et al., 2021).

3.2. Construction of the Lightweight Network Structure

The denoising network in this paper is designed with a clear strategy: focusing on low-level details, using lightweight operators as the core, and applying residual learning as the main structure. The goal is to achieve real-time denoising that can be stably deployed on vehicle-grade embedded platforms (Anoop & Deivanathan,2025). The network consists of four parts: shallow input mapping, a lightweight feature extraction backbone, lightweight attention enhancement, and output reconstruction. A global residual path is introduced to keep structural information and brightness consistency. This design helps the model mainly learn noise components instead of repeatedly learning the original image content. The overall data flow, shown in Figure 3-1, follows “Noisy Input → Input Feature Mapping → Lightweight Blocks → Output Reconstruction → Denoised Output”, with skip connections running through the network. In the input feature mapping stage, one or two small convolution layers, such as 3×3 kernels, are used to encode shallow texture and edge information from the RGB image. Spatial resolution is kept unchanged to avoid early detail loss, which is important for later detection and segmentation tasks. Channel numbers are kept small to reduce computation and memory access cost. The main feature extraction backbone is built from repeated lightweight convolution blocks. Each block mainly uses depthwise separable convolution, which greatly reduces parameters and computation. A typical block includes a depthwise 3×3 convolution, a pointwise 1×1 convolution, and a nonlinear activation. This design preserves edge and texture information while lowering hardware load. Residual learning is applied at both local and global levels. Local residuals help information flow across layers, while the global residual adds the input image to the predicted noise, making the task focus on noise estimation. Lightweight attention modules are also used to enhance important features without heavy computation. Finally, a small number of convolution layers reconstruct the output image, which can be directly used by later perception modules.

3.3. Loss Function and Training Strategy

In real-time perception for autonomous driving, image denoising algorithms should not only achieve good numerical results, but also keep important structure and semantic information for later perception tasks. Based on this goal, the loss function in this paper considers both pixel-level error and structure consistency. This design guides the lightweight denoising network to remove noise while keeping key visual information, such as lane markings and object boundaries. The basic goal of image denoising is to reduce the difference between the denoised image and the clean reference image. Therefore, mean squared error (MSE) loss is first used as the basic constraint to measure pixel-level reconstruction error. This loss is simple and stable, and it is easy to train efficiently on embedded platforms. The MSE loss is defined as shown in Formula 1:

$$L_{MSE}=\frac{1}{N}\sum_{i=1}^{N}\left\|\hat{I}_i-I_i\right\|_2^2 \quad (1)$$

where $\hat{I}_i$ is the denoised output image, I_i is the corresponding clean reference image, and N is the number of training samples. This loss can effectively control overall brightness and color distribution. However, under complex weather conditions, it may cause over-smoothing of local structures. To better keep structural information, a structure-aware constraint is added during training and combined with the MSE loss using weighted summation. The structure constraint mainly focuses on edges and texture regions. It helps the model recover key areas in rainy, foggy, and low-light scenes. The final loss function is expressed as a linear combination of multiple loss terms. This design balances numerical accuracy and visual structure quality. For training strategy, supervised learning is adopted. Paired noisy images and clean images are used as training data. Mini-batch stochastic gradient descent is applied, together with an adaptive learning rate optimizer, to improve training stability. Since noise distributions are different under various adverse weather conditions, the training dataset includes samples with different noise levels and weather types. This helps improve model generalization. In the later training stage, the learning rate is gradually reduced to avoid instability or overfitting caused by the lightweight network structure. With this loss design and training strategy, the proposed denoising model can achieve stable performance while meeting real-time requirements. It also provides reliable input for later image enhancement and perception tasks (Appiah & Mensah,2025).

4. Adverse Weather Image Enhancement Algorithm Design

In real-time perception systems for autonomous driving, adverse weather often causes reduced contrast, blurred details, and color distortion in images. Denoising alone is not enough to fully recover image quality. Therefore, after basic denoising, it is necessary to apply image enhancement for typical complex scenes such as rain, fog, and low-light conditions. This helps improve image clarity and stability. Based on the proposed lightweight denoising model, this chapter designs an image enhancement framework that considers both enhancement performance and real-time deployability. In foggy and low-contrast scenes, image degradation mainly comes from atmospheric scattering. This causes gray appearance and loss of distant details. According to a classical imaging model, a foggy image can be expressed as shown in Formula 2:

$$I(x)=J(x)t(x)+A(1-t(x)) \tag{2}$$

where $I(x)$ is the observed foggy image, $J(x)$ is the clean scene image, A is the atmospheric light, and $t(x)$ is the transmission map. To meet real-time requirements, this paper does not directly solve complex physical inversion. Instead, a lightweight network is used to implicitly model transmission-related features. This improves contrast and depth perception while keeping low computation cost. In rainy and snowy scenes, image degradation often appears as streak-like or point-like high-frequency noise, together with local brightness changes. To avoid noise amplification during enhancement, a guided enhancement strategy is applied after denoising. Low-frequency structures and high-frequency details are processed differently. The enhanced image is expressed as shown in Formula 3:

$$I_{enh}(x)=I_{den}(x)+\alpha \cdot G(x) \tag{3}$$

where I_{den} is the denoised image, $G(x)$ is the enhancement guidance extracted by lightweight feature modules, and α controls enhancement strength. This form allows targeted enhancement of important structures, such as lane lines and vehicle contours, without greatly increasing model complexity. In night-time or low-light conditions, image signal-to-noise ratio is usually very low. Simple linear stretching often causes noise amplification and color imbalance. To solve this problem, an adaptive brightness remapping strategy is used. Pixel values are adjusted based on local brightness distribution as shown in Formula 4:

$$I_{out}(x)=\left(\frac{I_{in}(x)}{L(x)+\varepsilon}\right)^{\gamma} \tag{4}$$

where $I_{in}(x)$ is the input brightness component, $L(x)$ is the local brightness estimation, γ is an adjustment factor, and ε is a small constant for numerical stability. This method improves visibility in dark regions while suppressing noise growth. It works well with lightweight network structures. Overall, the proposed adverse weather image enhancement algorithm is not designed for a single weather condition. Instead, a unified lightweight enhancement framework is used to model and adjust different degradation mechanisms. While keeping good enhancement quality, computation cost and inference delay are effectively controlled. This allows smooth integration into real-time autonomous driving perception systems and provides clearer and more stable visual input for later object detection and semantic segmentation tasks (Shafiee et al.,2021).

5. Experimental Design and Results Analysis

5.1. Experimental Environment and Dataset Description

To fully evaluate the effectiveness and deployability of the proposed lightweight image denoising and adverse weather enhancement algorithm in real-time autonomous driving scenarios, experiments are designed from two aspects: dataset coverage and experimental platform configuration. On the data side, several representative public autonomous driving vision datasets are selected (Tasnim et al.,2025). These datasets are further filtered and extended according to adverse weather conditions. This ensures that the experimental results can reflect real image degradation in complex road environments. On the platform side, vehicle-grade embedded deployment conditions are considered, and the real-time performance and resource consumption of the algorithm are evaluated. For dataset selection, public datasets that are widely used in autonomous driving research are preferred. These datasets have clear advantages in scene diversity, annotation quality, and academic comparability. At the same time, to improve coverage of adverse weather scenes, special attention is given to images captured under rain, fog, snow, and low-light conditions. In addition, synthetic degradation is applied in some cases to build a self-collected adverse weather dataset. This helps compensate for the lack of extreme weather samples in real data. Different datasets focus on different scene types, weather conditions, and data scales. Their basic information is summarized in Table 1.

Table 1. Overview of Autonomous Driving Adverse Weather Image Datasets Used in Experiments

Dataset	Scene Type	Weather Conditions	Number of Images	Main Purpose
Cityscapes	Urban roads	Clear, cloudy	5,000	Baseline denoising and enhancement
BDD100K	Urban & highway	Rain, fog, night	10,000	Multi-weather evaluation
ACDC	Urban roads	Rain, fog, snow, night	4,000	Adverse weather testing
Self-built dataset	Urban roads	Heavy rain, dense fog, low light	3,500	Robustness validation

As shown in Table 1 public datasets provide standardized evaluation benchmarks, while the self-built dataset extends the sample distribution under adverse weather. This makes the experimental results closer to real autonomous driving applications. Cross-dataset evaluation allows a more comprehensive analysis of model adaptability under different weather types and degradation levels. For experimental platform configuration, model training is conducted on a workstation with GPU acceleration to ensure training efficiency and stability. For inference and performance testing, embedded and vehicle-grade deployment conditions are emphasized. An ARM-based embedded computing platform is used together with a lightweight inference framework. Single-frame processing latency, memory usage, and power consumption are measured. With this setup, the proposed method can be evaluated both in image quality improvement and engineering feasibility (Wang et al.,2022).

5.2. Quantitative Analysis of Denoising and Enhancement Performance

To objectively evaluate the performance of the proposed lightweight image denoising and adverse weather enhancement algorithm, peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) are selected as main quantitative metrics. PSNR measures pixel-level reconstruction accuracy between the processed image and the reference image. SSIM evaluates structural similarity from brightness, contrast, and texture perspectives. Together, these two metrics provide a balanced evaluation of numerical accuracy and structural preservation, which is important for autonomous driving scenarios. First, from an overall performance comparison perspective, the proposed method is compared with several typical denoising and enhancement algorithms on the same adverse weather test datasets. The comparison methods include traditional filtering-based approaches and representative deep learning models. Figure 4 reports the average PSNR and SSIM results.

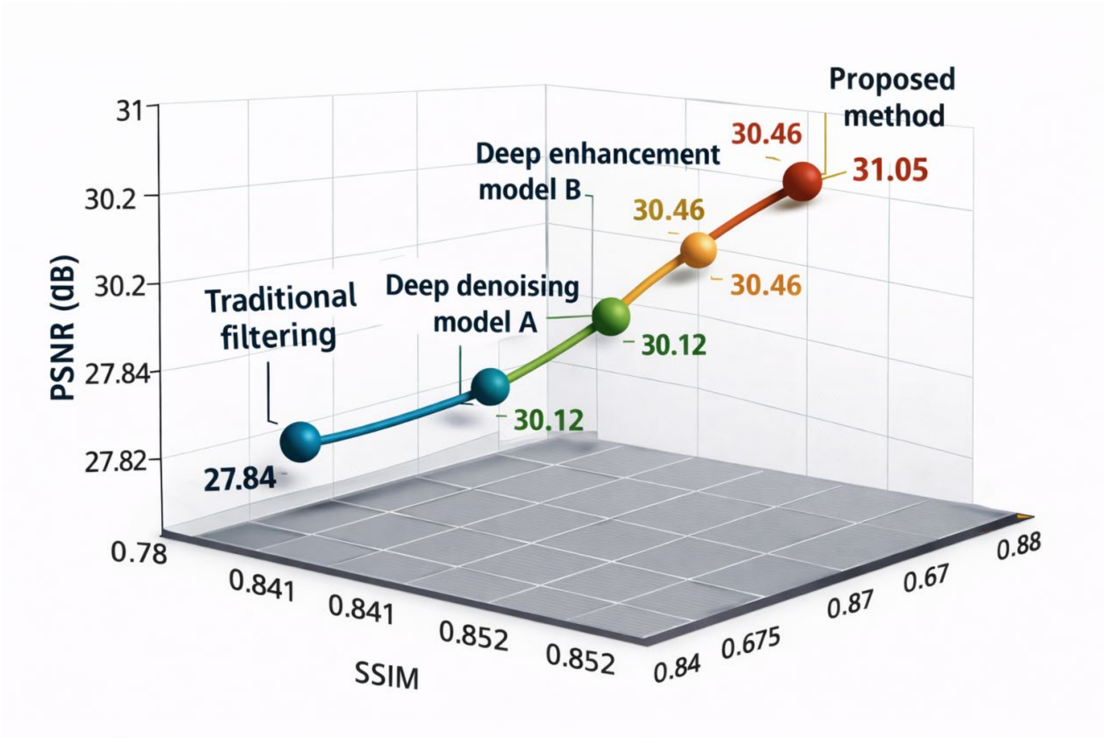

Fig.4: Performance Comparison on Adverse Weather Datasets

The results show that traditional methods have low computation cost but poor recovery of image details. Some deep models achieve higher PSNR but show limited SSIM improvement due to over-smoothing. In contrast, the proposed method achieves balanced improvement in both PSNR and SSIM, indicating good trade-off between noise removal and structure preservation. To further analyze adaptability under different weather conditions, experiments are conducted separately on rainy, foggy, and low-light scenes. The results are shown in Figure 5.

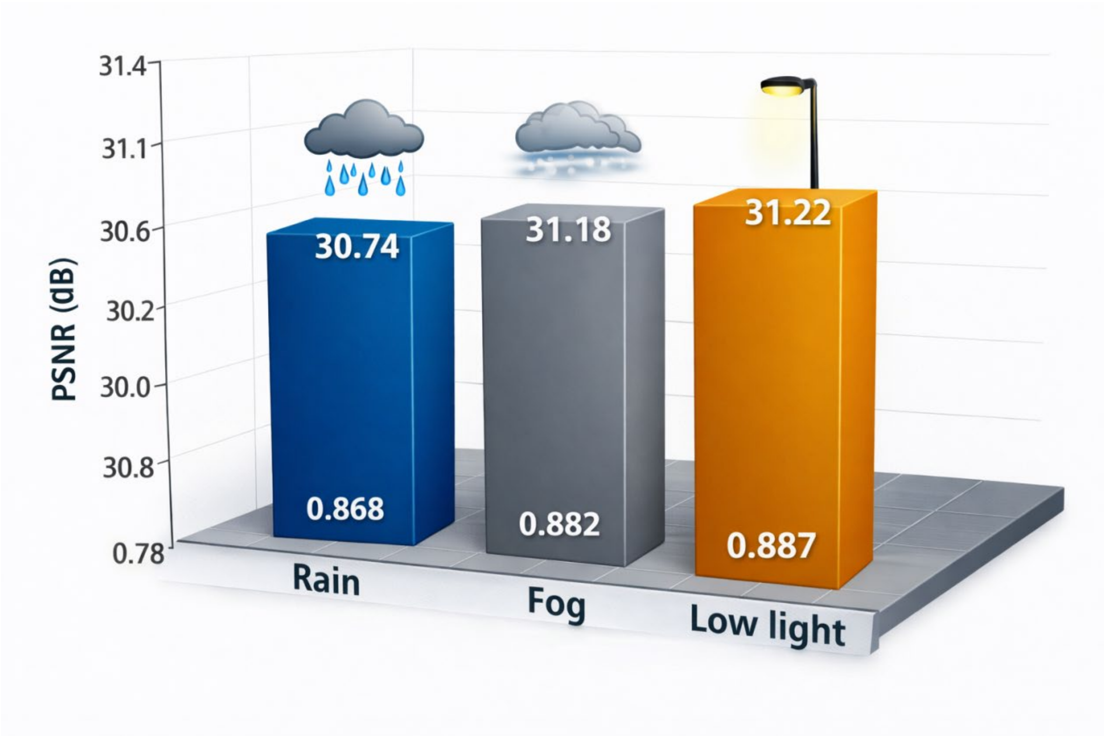

Fig.5: Performance of the Proposed Method under Different Weather Conditions

The proposed method shows stable performance across different weather conditions. The SSIM improvement is especially clear in fog and low-light scenes, which confirms the effectiveness of the targeted enhancement strategies.

5.3. Impact on Autonomous Driving Perception Tasks

The final goal of image denoising and enhancement in autonomous driving is not only to improve image quality metrics, but also to provide better input for high-level perception tasks. Therefore, this section evaluates the impact of image enhancement on object detection and semantic segmentation performance.For object detection, common autonomous driving targets such as vehicles, pedestrians, and cyclists are selected. The same detection model is applied to original adverse weather images and enhanced images. Mean average precision (mAP) is used as the evaluation metric. The results are shown in Figure 6.

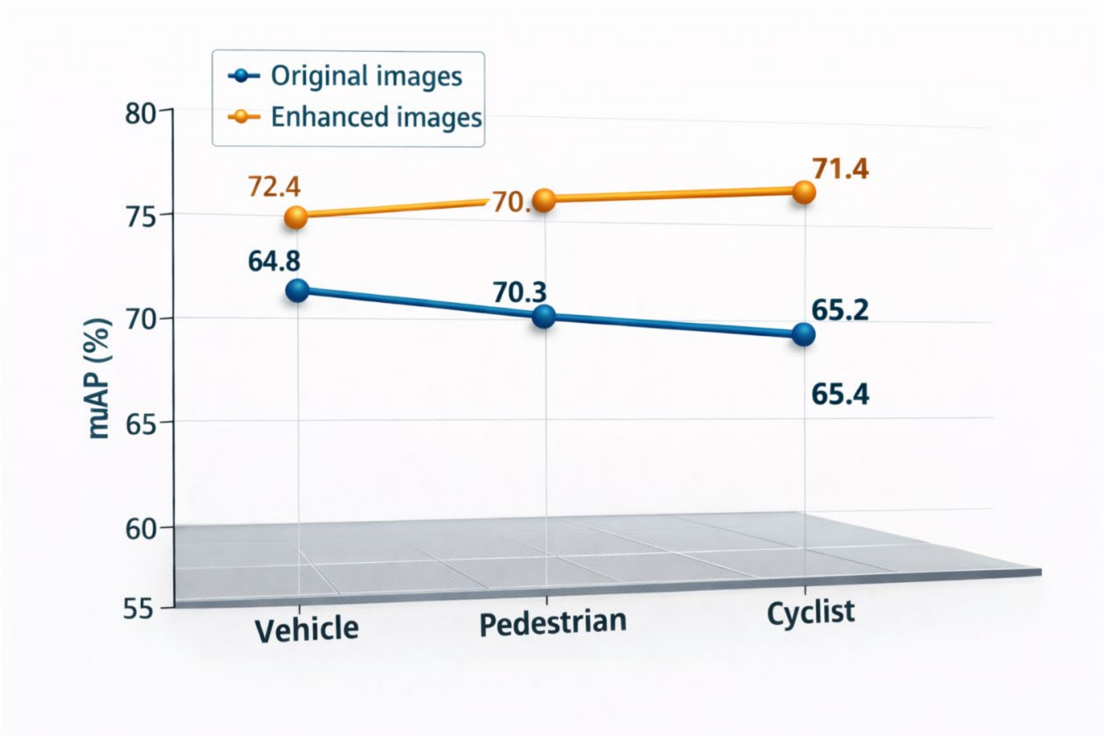

Fig.6: Object Detection Performance before and after Enhancement (mAP, %)

Without enhancement, adverse weather clearly reduces detection accuracy. After applying the proposed method, detection performance improves across all target categories.For semantic segmentation, the influence of image enhancement on pixel-level scene understanding is analyzed. Mean intersection over union (mIoU) is used as the evaluation metric. The results are shown in Figure 7.

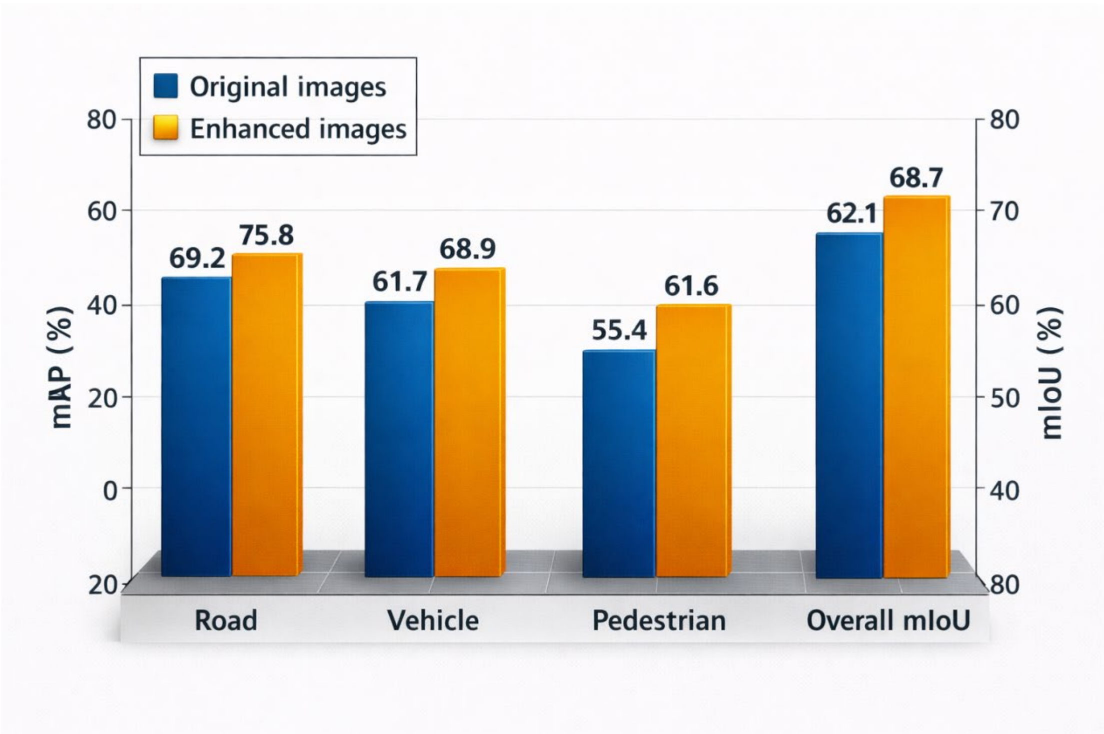

Fig.7: Semantic Segmentation Performance before and after Enhancement (mIoU, %)

The enhanced images lead to clearer boundaries and better segmentation accuracy, especially for road regions and object edges. These results show that the proposed method improves perception performance at the system level. From a system-level perspective, the observed improvements in object detection and semantic segmentation performance can be interpreted through a clear causal chain. Lightweight image denoising and adverse weather enhancement act as a foundational preprocessing step that directly improves the quality and stability of visual inputs. Clearer and less noisy images facilitate more reliable feature extraction, which enhances the robustness of perception results and reduces uncertainty in downstream perception outputs. As a consequence, improved preprocessing quality contributes to higher perception reliability and ultimately supports safer and more stable decision-making and control processes in autonomous driving systems.

Moreover, under adverse weather conditions, image quality should be regarded not only as a performance factor but also as a key determinant of perception service continuity. Severe noise, low contrast, and visibility degradation can lead to intermittent or unreliable perception outputs, effectively disrupting real-time perception services. By suppressing noise and enhancing visibility while maintaining low inference latency, the proposed lightweight preprocessing method helps sustain continuous and reliable visual perception services even in challenging environmental conditions. From a service science perspective, this capability is critical for autonomous driving systems that are required to operate without interruption across diverse and dynamic weather scenarios.

6. Conclusion

This paper addresses the problem of image degradation and computational constraints in real-time autonomous driving perception services operating under adverse weather conditions. A lightweight image denoising and adverse weather enhancement method is proposed to improve the reliability and efficiency of visual perception as a core informatics service. By combining a shallow denoising network with lightweight operators and weather-adaptive enhancement strategies, the proposed method effectively suppresses noise, enhances visual clarity, and preserves key structural information while maintaining low computational complexity. Experimental evaluations demonstrate consistent improvements in image quality metrics as well as measurable gains in downstream perception tasks, including object detection and semantic segmentation, under multiple adverse weather scenarios. At the same time, inference latency and model size remain compatible with vehicle-grade embedded deployment. Overall, this study provides a practical and service-oriented image preprocessing solution that enhances the robustness, stability, and real-time performance of autonomous driving perception systems, offering valuable insights for the design of reliable intelligent transportation and perception service architectures.

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