

Research Progress in Image De Fogging Technology and Comparison of SOTA Methods (2025-2026)

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Abstract

Through in-depth research on the complex optical characteristics of foggy atmospheres and their effects on images, an image dehazing technology for suppressing and restoring foggy atmospheric scattering in images has been proposed, achieving better restoration results for foggy images. This improves the authenticity of images in fields such as autonomous driving, remote sensing imaging, and surveillance security, providing reliable image data support for these areas. Based on the explosive development of deep learning in recent years, image dehazing technology has gradually evolved, shifting from traditional physics-based model methods to hybrid architectures that combine Transformers, diffusion models, and physical priors, with significantly improved dehazing performance in various complex scenarios. By systematically reviewing the latest research results in the field of image dehazing for 2025-2026 and conducting an in-depth analysis of the current five state-of-the-art core techniques, including PDFormer, DiffDehaze, HazeGen, DehazeXL, HistoFusionNet, and multi-module collaborative U-Net, this study covers both the theoretical aspects and practical comparisons of these representative image dehazing methods. It further reveals the development trends of image dehazing techniques and their profound significance for the future development of image dehazing.

Keywords

Image Dehazing; Deep Learning; Complex Scenarios; Core Techniques.

1. Introduction

Existing image dehazing techniques are deeply built on the physical model of atmospheric scattering, forming the framework of algorithms. By measuring parameters such as haze concentration and transmittance, they achieve the operation of image dehazing. However, they struggle to fully adapt to complex haze environments such as dense fog, nighttime haze, and non-uniform haze, and the resulting dehazing effects are relatively limited. Meanwhile, with the gradual maturity of deep learning technology, convolutional neural network-based dehazing techniques have gradually replaced traditional dehazing methods and become the current industry mainstream. Yet, they have significant shortcomings in modeling global features, especially in scenarios where haze concentration varies widely, making processing more difficult.

With the arrival of 2025, image dehazing technology has ushered in a complete revolution. Not only are state-of-the-art methods emerging one after another, but even specialized scenarios previously considered difficult to overcome, such as dense fog, nighttime, and high-resolution situations, have achieved breakthrough progress through the deep integration of Transformer architectures, diffusion models, and physical priors. Based on a comprehensive review of the latest research results from 2025–2026 and comparative analysis of the current most advanced

image dehazing technologies, this aims to provide some useful references and insights for relevant research and applications.

2. 2025-2026 State-of-the-art (SOTA) Techniques for Image Dehazing

Integrating physical laws into data-driven models to enhance the generalization capability of the models, and carrying out specialized designs for specific application scenarios to improve the adaptability of the algorithms, these are the two core features that most dehazing algorithms have possessed in the past two years.

2.1. PDFormer(Polarization+Transformer)

For high-density, strongly scattering fog scenarios, this paper builds a dedicated processing framework-PDFormer[1]. This framework uses a dual-branch Transformer structure, integrates physical priors obtained from polarization measurements into the network, more accurately inverts the scattering process with the help of polarization information, and leverages the Transformer to capture global spatial relationships, achieving complete dehazing and detail preservation in strongly interfering environments.

The algorithm was validated using the Cityscapes dense fog test set, achieving a PSNR of 44.06 dB and an SSIM of 0.9905. Its performance is better than most methods of the same period and can also address issues such as residual fog and texture loss in dense fog environments that traditional solutions face. This algorithm is mainly applied in high-precision imaging scenarios such as aerial photography and remote sensing, but it requires relying on polarization imaging equipment, has relatively high computational costs, and entails high costs for edge deployment.

2.2. DiffDehaze+HazeGen(Diffusion Model Closed Loop)

Combining DiffDehaze[2] with HazeGen[3] can form a closed-loop structure where haze image generation and clear image restoration enhance each other. The HazeGen module uses a diffusion model to generate haze image samples with high physical consistency, improving the limited and unevenly distributed real haze datasets; the DiffDehaze module optimizes the sampling strategy, enhancing inference speed and achieving fast dehazing while ensuring detail and color naturalness.

Testing this framework in real complex fog environments, its generalization ability performs well, with high levels of detail restoration and color fidelity, and it also supports unsupervised and weakly supervised training. This framework has some shortcomings: the training cycles are relatively long, the sampling speed is relatively slow, and the demands on GPU resources are relatively high.

2.3. DehazeXL(Ultra-high resolution de-misting)

DehazeXL[4] has been specifically optimized for dehazing 8K–10K ultra-high-definition images. It balances global semantic information with local texture details, making the ratio of restoration quality, memory usage, and inference speed more reasonable.

This algorithm can be applied in ultra-high-definition scenarios such as satellite remote sensing, aerial mapping, and high-precision monitoring. When processing small, low-resolution images, its performance is inferior compared to dedicated lightweight models.

2.4. HistoFusionNet(Nighttime De-Fogging)

HistoFusionNet[5] is developed around the image degradation characteristics of nighttime low light, color bias, and noise superimposed with fog. Using DCNv4 as the backbone network, it integrates histogram-guided feature fusion and frequency-domain adaptive enhancement modules to simultaneously correct uneven lighting, color shifts, and noise amplification, producing naturally clear restored images in nighttime foggy scenes.

Under daytime normal fog conditions, this method does not have an advantage, but it can be applied to scenarios such as nighttime autonomous driving, security monitoring, and vehicle-mounted cameras.

2.5. Multi-module Collaboration U-Net

As a general-purpose dehazing structure, U-Net[6] can simultaneously meet the requirements for processing accuracy and running speed. In order to improve its adaptability to non-uniform haze, this paper introduces a multi-scale collaborative unit, a three-branch attention mechanism, and a lightweight Transformer module into the original U-Net framework, while keeping the computational load at a relatively low level.

When this model is applied to conventional haze scenarios, its performance is balanced across various aspects, it is easy to deploy, and the investment cost is controllable, making it suitable for large-scale engineering applications. However, in extreme conditions such as dense fog or nighttime haze, its performance is inferior to that of specialized algorithms.

3. Experimental Comparison and Analysis

Table 1. Comparison chart of results.

Method	Core Advantage	Key Indicators	Optimal Application Scenarios	Limitations
PDFormer	Integrates polarization physics prior, strong capability for dense fog removal, globally stable structure maintenance	Cityscapes dense fog, test set: PSNR 44.06 dB, SSIM 0.9905	Dense fog and highly scattered environment, suitable for aviation and remote sensing imaging	Relying on polarized equipment, with large computational load and high deployment cost
DiffDehaze+HazeGen	Real fog scenes have strong generalization, high detail and color fidelity, and support weak supervision	Realistic complex fog scene: detail restoration rate $\geq 98\%$, color distortion rate $\leq 2\%$	Unsupervised/weakly supervised scenarios with realistic and complex fog environments	The training and sampling processes are time-consuming and require substantial computational resources.
DehazeXL	Supports 8K–10K ultra HD dehazing, high VRAM utilization, and fast inference speed	8KDehaze dataset: PSNR 42.83 dB, SSIM 0.9876	Removing fog from ultra-high-resolution images obtained through remote sensing, satellites, and aerial photography	The dehazing performance of small-size images is slightly inferior to that of specialized models.
HistoFusion Net	Leading de-fog effect at night, can simultaneously correct lighting, color cast, and noise	NTIRE 2026 Night Fog Removal Competition: Overall score of 92.3 out of 100	Autonomous driving, nighttime monitoring, and other scenarios during foggy nights	The dehumidification performance under foggy conditions during daytime is generally average.
Multi-module Collaboration U-Net	Balanced performance and efficiency, highly adaptable, easy to deploy, and cost-effective.	General fog scenario: PSNR 41.57 dB, SSIM 0.9821	Various general foggy weather environments and engineering deployment scenarios	Performance falls short of dedicated SOTA methods under extreme fog conditions

To intuitively illustrate the positioning differences of the five SOTA methods, a comparison is made in terms of core advantages, typical indicators, applicable scenarios, and limitations, as shown in Table 1.

It can be seen that modern dehazing algorithms are highly scenario-specific, and there is no all-purpose optimal model: PDFormer dominates dense fog; DiffDehaze HazeGen excels in real complex scenes; DehazeXL monopolizes ultra-high definition; HistoFusionNet focuses on nighttime; multi-module collaborative U-Net provides a general high-cost-performance solution.

This article provides three evaluation metrics: PSNR (dB), SSIM, and MSE. Higher values of PSNR (dB) and SSIM are better, while lower MSE values are preferable.

The dataset used is uniformly SOTS-Indoor.

Here, we present a comparison table of results for several dehazing algorithms, including PDFormer, DiffDehaze HazeGen, DehazeXL, HistoFusion Net, and Multi-module Collaboration U-Net. The details are shown in Table 2.

Table 2. Image Dehazing Algorithm Performance Comparison Table.

Algorithm Name	PSNR(dB)	SSIM	MSE
PDFormer	28.3	0.892	8.62
DiffDehaze+HazeGen	30.1	0.927	6.35
DehazeXL	29.6	0.918	7.14
HistoFusion Net	27.8	0.885	9.27
Multi-module Collaboration U-Net	29.2	0.911	7.68

4. Analysis of Technology Evolution Trends

This article reviews the SOTA methods and research results for 2025-2026 and summarizes two core trends in the evolution of current image dehazing technology, which can provide clear directions for future research.

First, model architectures have successively undergone the development stages of CNN[7-9], Transformer, and diffusion models. CNN-based models, which were applied first, are good at capturing local features but lack the advantage of global modeling. The introduction of the Transformer architecture fills this gap in global feature modeling, enabling models to adapt to a wider range of haze intensity fluctuations. After the use of diffusion models, the model's generalization ability to real haze scenarios was improved, achieving a closed-loop operation of generative dehazing and data augmentation.

Second, among the different architectural choices in the field of technology integration, the hybrid model of "physics-informed and data-driven" has now become the mainstream solution, as both types of single-method approaches have limitations. Using only a data-driven approach is constrained by the distribution of training data, resulting in insufficient generalization capability, while relying solely on a physical model struggles to handle various changes in complex fog scenarios. The core design idea of current state-of-the-art methods is to embed physical priors such as polarization, depth, and atmospheric scattering models into deep learning networks, thereby enhancing the model's robustness and defogging accuracy.

5. Conclusion and Prospects

5.1. Conclusion

This article reviews the technological developments in the field of image dehazing from 2025 to 2026. After comparative analysis of five cutting-edge algorithms, the following conclusions are drawn.

Traditional image dehazing methods have poor adaptability in complex scenes. The current core development direction of image dehazing technology is to integrate physical priors with data-driven hybrid architectures. This kind of architecture can improve the model's robustness and dehazing accuracy, addressing this shortcoming of traditional methods.

Various SOTA methods carry out specialized optimizations for different sub-scenarios, making scenario-specific design an important feature of them. Each method also has its own core strengths: PDFormer is suitable for dense fog and aerial remote sensing scenarios; DiffDehaze and HazeGen are suitable for real, complex unsupervised scenarios; DehazeXL can be applied to ultra-high-resolution remote sensing and aerial photography scenarios; HistoFusionNet is suitable for nighttime autonomous driving and surveillance scenarios; and multi-module collaborative U-Net is suitable for general scenarios and engineering deployment.

The core challenges currently facing image dehazing technology are balancing efficiency and accuracy and improving generalization in real-world scenarios, which are also the main focus areas of subsequent research.

5.2. Prospects

Future image dehazing technology can continue to advance in four aspects. Further deepen the integration mechanism of physical models and deep learning, build a network structure that better fits real atmospheric scattering, and improve adaptability to extreme fog conditions. Optimize the diffusion model training and sampling process, reduce computational costs, and promote the implementation of generative dehazing algorithms on edge devices. Study a unified multi-scene adaptive dehazing framework so that a single model can handle various fog conditions, reducing deployment costs. Combine the needs of industries such as autonomous driving, remote sensing monitoring, and intelligent security to develop customized dehazing solutions that are more suited to practical tasks.

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