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Nighttime Image Dehazing: A Review

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Abstract: Nighttime image dehazing is a core technology for improving the performance of all-weather visual systems, and its key challenge lies in overcoming the degradation of image quality caused by the coupling of multiple factors including haze degradation, inhomogeneous illumination, multi-light source interference and low signal-to-noise ratio (SNR). Traditional physics-based methods have inherent limitations under the complex illumination conditions of nighttime, while deep learning and multimodal fusion technologies have brought new breakthroughs to this field. The integration of data-driven approaches and physical constraints has significantly improved dehazing performance and scene adaptability. This paper systematically reviews the recent research advances in this field: firstly, it elaborates on the particularity of nighttime image degradation; secondly, it classifies and analyzes the mechanisms of existing methods; furthermore, it compares the performance of typical algorithms through subjective and objective experiments. Current research still faces challenges such as the scarcity of real-world data, insufficient model generalization ability and low computational efficiency. In the future, developing efficient, robust and physically interpretable algorithms, constructing high-quality datasets, and promoting end-to-end optimization with high-level vision tasks will become important research directions in this field. This paper aims to provide a systematic reference and technical outlook for subsequent research in this area.

Keywords: Nighttime Image Dehazing, Traditional Methods, Deep Learning.

1. Introduction

Image dehazing technology is a cutting-edge interdisciplinary research topic at the intersection of computer vision and atmospheric optics, which holds important theoretical research value and broad application prospects. Under severe weather conditions such as fog and haze, images captured by devices like outdoor surveillance and intelligent transportation systems suffer from severe degradation, manifested as reduced contrast, color distortion and detail loss. This problem is particularly pronounced in nighttime environments: insufficient and inhomogeneous illumination, coupled with the complex scattering and absorption of artificial light by airborne suspended particles, leads to low image SNR and color shift, which seriously impairs subsequent target recognition and analysis tasks. This makes nighttime dehazing technology a key to ensuring the reliability of fields such as autonomous driving, aerospace and all-weather traffic surveillance, and also a major focus and difficult problem in dehazing research.

Current research on nighttime dehazing at home and abroad is mainly divided into two categories: traditional physics-based methods and modern deep learning-based methods. In foreign research fields, scholars initially focused on the improvement of atmospheric scattering models. Narasimhan and Nayar first introduced the Atmospheric Point Spread Function (APSF), laying a theoretical foundation for nighttime glow modeling. Subsequently, Metari et al. further optimized the APSF kernel modeling in an attempt to enhance glow suppression performance. In recent years, deep learning-based methods have become the mainstream. Zhang et al. [1] conducted fully supervised training by synthesizing nighttime hazy images, yet the synthetic data failed to fully account for the glow effect, resulting in limited dehazing performance. The semi-supervised method proposed by Yan et al. [2] suffers from underexposed output images and detail loss, while the unpaired dehazing method based on CycleGAN addresses the scarcity of real paired data but neglects the physical characteristics of haze environments, making it prone to image distortion. In addition, most foreign related studies focus on the optimization of a single problem and fail to balance the collaborative processing of multi-light source scattering, low-light enhancement and glow suppression.

In domestic research, on the basis of drawing on advanced foreign technologies, scholars have carried out targeted research combined with the requirements of practical scenarios and developed numerous improved schemes. Some studies attempt to integrate multi-light source models with the dark channel prior algorithm, achieving dehazing by analyzing the contribution of different light sources, yet such methods suffer from incomplete dehazing and poor stability in complex haze scenarios. Other studies focus on the optimization of synthetic data and the improvement of network structures; for example, the CoA compression adaptation algorithm enhances the model's adaptability to real-world scenarios through a divide-and-conquer strategy, but it fails to balance light source compensation and dehazing performance in nighttime multi-light source scenarios and is prone to excessive light source suppression or residual glow. Overall, although domestic research has made breakthroughs in specific scenarios, there is still a lack of collaborative solutions that balance data authenticity and the accuracy of light compensation in the face of complex light source/glow problems caused by nighttime multi-light source scattering and the core pain point of excessive suppression of light source regions by pre-trained models.

In summary, the current research on nighttime dehazing at home and abroad still faces two prominent bottlenecks. First, the scarcity of high-quality training data: most existing synthetic data fail to fully integrate the real haze scattering laws with the illumination effects of nighttime multi-light sources and deviate from the degradation mechanisms of real-world scenarios, resulting in insufficient model generalization ability. Second, the low processing accuracy of light source regions: existing methods struggle to accurately locate light source/haze regions and achieve differentiated optimization; pre-trained models tend to excessively suppress light source regions, causing image brightness imbalance and color distortion, which in turn impairs the effectiveness of subsequent vision tasks.

2. Nighttime Image Degradation Model and Research Status

2.1. Imaging Principle of Nighttime Hazy Images

The imaging process in nighttime foggy conditions is jointly affected by the illumination environment, atmospheric scattering and imaging systems, and its degradation mechanism is significantly different from that in daytime foggy conditions. Daytime scenes take uniform sunlight as the main light source, and atmospheric light can be approximated as a global constant, while nighttime scenes mainly rely on artificial point light sources such as street lamps and car lights, with extremely inhomogeneous illumination distribution and obvious spatially varying characteristics of atmospheric light. Atmospheric suspended particles such as fog and haze absorb and scatter light, with Mie scattering dominating, which causes the exponential attenuation of target reflected light during propagation. At the same time, ambient light enters the imaging sensor after multiple scattering, forming a hazy background superimposed on the image. Near point light sources, the forward scattering effect is particularly significant, forming a large range of glow, which further reduces image contrast and obscures target details.

Based on atmospheric scattering theory, the degradation process of nighttime foggy images can be described by an improved imaging model. The reflected light of scene targets reaches the imaging end after transmittance attenuation, and is superimposed with a spatially varying ambient light component formed by atmospheric scattering and a glow component generated by point light source scattering. Transmittance is closely related to scene depth and atmospheric scattering coefficient, following the law of exponential attenuation. The atmospheric scattering coefficient is jointly determined by particle concentration, particle size distribution and wavelength: the higher the fog concentration, the stronger the scattering effect and the more severe the image degradation. Due to the low nighttime illuminance and limited dynamic range, the noise of the imaging system is amplified, resulting in multiple degradation problems of the image such as low illumination, low contrast, color shift, glow diffusion and noise amplification. The schematic diagram of the atmospheric scattering model is shown in Figure 1:

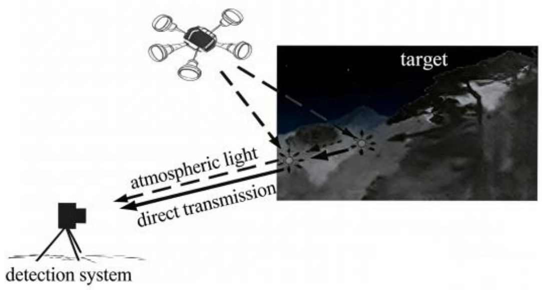


Figure 1. Schematic diagram of nighttime haze imaging

The degradation process of nighttime foggy images con structed based on the atmospheric scattering model is sho wn in Formula (1).

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

Where $I(x)$ is the observed hazy image, $J(x)$ is the fog-free clear image, $t(x) = \exp(-\beta d(x))$ is the transmittance varying with scene depth and scattering coefficient, $A(x)$ is the spatially varying atmospheric light at nighttime, and $G(x)$ is the glow term formed by the forward Mie scattering of point light sources. Compared with the daytime model, nighttime imaging has uneven light source distribution, stronger multiple scattering, and obvious spatial differences in atmospheric light and glow, leading to typical degradation characteristics of images such as low illumination, low contrast, strong glow and color shift.

2.2. Research Status of Nighttime Dehazing

(1) Traditional Nighttime Dehazing Algorithms

Traditional nighttime dehazing algorithms mainly follow the framework of physics-based models [3] and dark channel prior [4]. However, the core challenge for nighttime image dehazing is the existence of inhomogeneous multi-color light sources in nighttime scenes, which makes the assumption of global atmospheric light in the classic atmospheric scattering model invalid. Therefore, the research focus has shifted to modifying or establishing new models to adapt to nighttime conditions and restoring images using tools such as the dark channel prior.

Early attempts focused on preprocessing the input image to make it more in line with the assumptions of existing models. For example, Pei et al. [5]adopted color transfer technology: according to the color transfer method proposed by Reinhard et al. [6], the color statistical properties of nighttime images are adjusted before dehazing to approximate the illumination and tone characteristics of daytime, thus creating conditions for the subsequent application of the dark channel prior (DCP). The process is shown in Figure 2.

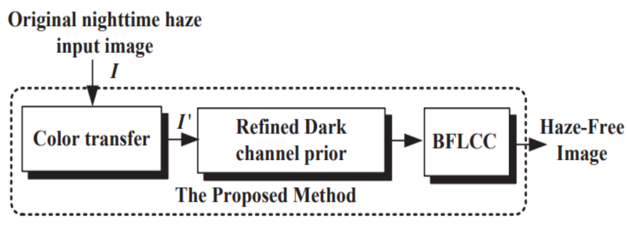


Figure 2. The color transfer preprocessing process for nighttime images

First, the human visual model is used to convert the RGB space to the LMS space, as shown in Formula (2)

$$\begin{bmatrix} L \\ M \\ S \end{bmatrix} = \underbrace{\begin{bmatrix} 0.3811 & 0.5783 & 0.0402 \\ 0.1967 & 0.7244 & 0.0782 \\ 0.0241 & 0.1288 & 0.8444 \end{bmatrix}}_{M_{RGB2LMS}} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{2}$$

Then, the logarithmic transformation is applied to the LMS channels to compress the dynamic range and weaken multiplicative noise, as shown in Formula (3):

$$L' = \log_{10} L, \quad M' = \log_{10} M, \quad S' = \log_{10} S \tag{3}$$

Next, the logarithmic LMS is converted to an uncorrelated space through an orthogonal matrix, as shown in Formula (4):

$$\begin{bmatrix} l \\ \alpha \\ \beta \end{bmatrix} = \underbrace{\begin{bmatrix} \frac{1}{\sqrt{3}} & 0 & 0 \\ 0 & \frac{1}{\sqrt{6}} & 0 \\ 0 & 0 & \frac{1}{\sqrt{2}} \end{bmatrix}}_{M_{norm}} \underbrace{\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & -2 \\ 1 & -1 & 0 \end{bmatrix}}_{M_{basis}} \begin{bmatrix} L' \\ M' \\ S' \end{bmatrix} \quad (4)$$

Let the mean and standard deviation of the l, α, β channels of the nighttime image (source) be $\mu_l, \mu_\alpha, \mu_\beta$ and $\sigma_l, \sigma_\alpha, \sigma_\beta$ respectively; the mean and standard deviation of the daytime image (target) be $\mu_{l'}, \mu_{\alpha'}, \mu_{\beta'}$ and $\sigma_{l'}, \sigma_{\alpha'}, \sigma_{\beta'}$ respectively. The correction formula is Formula (5):

$$\begin{cases} l' = \frac{\sigma_l'}{\sigma_l} \cdot (l - \mu_l) + \mu_l' \\ \alpha' = \frac{\sigma_\alpha'}{\sigma_\alpha} \cdot (\alpha - \mu_\alpha) + \mu_\alpha' \\ \beta' = \frac{\sigma_\beta'}{\sigma_\beta} \cdot (\beta - \mu_\beta) + \mu_\beta' \end{cases} \quad (5)$$

Then the corrected $\sigma_{l'}, \sigma_{\alpha'}, \sigma_{\beta'}$ are converted back to logarithmic LMS, and the antilogarithm is taken to obtain LMS, and finally converted back to RGB, as shown in Formula (6)

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \underbrace{\begin{bmatrix} 4.4679 & -3.5873 & 0.1193 \\ -1.2186 & 2.3809 & -0.1624 \\ 0.0497 & -0.2439 & 1.2045 \end{bmatrix}}_{M_{LMS2RGB}} \begin{bmatrix} L \\ M \\ S \end{bmatrix} \quad (6)$$

Based on the foggy image degradation model, Zhang et al. [7] first constructed a new nighttime imaging model considering the inhomogeneous ambient illumination and light source color characteristics:

$$I_i^\lambda = L_i \eta_i^\lambda R_i^\lambda t_i + B_i^\lambda (1 - t_i) \triangleq L_i \eta_i^\lambda R_i^\lambda t_i + L_i \sigma_i^\lambda (1 - t_i) \quad (7)$$

Where I_i^λ is the intensity value of the observed nighttime foggy image at position x in the RGB channel c, L_i is the local illumination intensity of the scene point, R_i^λ is the color characteristic of the incident light, t_i is the transmittance, σ_i^λ is the ambient light.

Li et al. [8] went a step further on this basis and first considered the glow effect caused by multiple scattering of visible light sources. By introducing the Atmospheric Point Spread Function (APSF [9]) into the classic atmospheric scattering model to simulate the luminous effect of visible light sources, the foggy image degradation model was modified to:

$$I^\lambda(i) = J^\lambda(i) t(i) + A^\lambda(i)(1 - t(i)) + A_a(i) \cdot APSF \quad (8)$$

Where $A_a(i)$ represents the visible light source, and its intensity is convolved with the APSF function to generate a glow effect in the image, thus separating this interference term. To solve the problems of illumination estimation and color distortion, existing studies integrate a variety of image processing theories. For example, based on the nighttime foggy imaging model constructed in [5], Zhang et al. [7] first convert the nighttime foggy image to the HSV color space, taking the V-channel image as the initial estimated value of the incident light intensity; then combine the Retinex theory to accurately solve the incident light intensity, calculate the corresponding intermediate parameters after guided filtering processing, and complete the solution of core variables through exponential operation; subsequently, the image is subjected to gamma correction enhancement and color correction processing in turn, and finally the foggy image dehazing is realized by combining the dark channel prior (DCP) theory and guided filtering. The same team, Zhang et al. [10], based on the nighttime blurring imaging model in [9], first introduced the maximum reflectance prior to realize the direct estimation of the ambient light color varying with spatial position.

Yu Shunyuan et al. [11] started from the optimization of the imaging model and reconstructed the formula of the nighttime foggy imaging model. Also based on the Retinex theory, the Gaussian surround function is used to iteratively optimize the estimated results of ambient light and transmittance:

$$I(x, y) = J(x, y) \cdot t(x, y) + A(x, y) \cdot (1 - t(x, y)) \quad (9)$$

Where $I(x,y)$ is the observed nighttime foggy image, $J(x,y)$ is the restored clear image, $t(x,y)$ is the transmittance, and $A(x,y)$ is the ambient light. At the same time, drawing on the design idea based on information loss constraint in [12], it is assumed that the ambient light intensity and depth of field change in the local image block have local smoothness and no abrupt changes. Non-overlapping translation operations are performed on the ambient light and transmittance estimated from the local block, and the global ambient light and transmittance are optimally solved through iterative calculation. Finally, the clear restored image is obtained after the refinement processing of the guided filter.

Shi et al. [13] proposed a nighttime foggy image enhancement method based on image negative. First, the nighttime hazy image is inverted to obtain a negative image. Utilizing its imaging characteristics highly similar to daytime foggy images, dehazing processing is directly completed based on the DCP theory. Finally, the corrected negative image is inverted again to obtain the enhanced clear image. The team later proposed a dehazing algorithm fusing dark channel prior and bright channel prior [14]: first, the atmospheric light value is estimated through the DCP theory, and the mean value of the top 10% brightest pixels in the bright channel is selected as the ambient light estimated value; then the initial transmittance map is solved based on the bright channel prior, and after refinement by the guided filter, the clear restoration of the foggy image is completed.

Based on the classic foggy image degradation model and DCP dehazing theory, Ancuti et al. [15] first proposed a nighttime hazy image restoration algorithm based on multi-scale fusion. Aiming at the problem of inhomogeneous illumination distribution in nighttime scenes, Fang Shuai et al. [16] proposed to eliminate the interference of inhomogeneous illumination on dehazing effect through accurate estimation of the illumination map.

Based on [19], Yang Aiping et al. [17] and Tang Chunming et al. [18] divided the foggy image into a structural layer and a textural layer, restored the structural layer, and then superimposed it with the textural layer to form the final restored image. On the basis of layered processing, Tang Chunming et al. [18] further decomposed the structural layer into an illumination component and a reflectance component based on the Retinex theory: first, the illumination is estimated and optimized, the ratio of the structural layer to the optimized illumination is taken as the reflectance component to suppress strong light and noise, and the structural layer after strong light suppression is obtained; then the optimized illumination is inverted as the estimated value of transmittance to realize the dehazing processing of the structural layer; finally, the post-processed textural layer is fused with the dehazed structural layer to obtain the final dehazed image.

On the basis of previous research, Yang Aiping et al. [6] carried out in-depth optimization of the nighttime dehazing algorithm and proposed an ambient light estimation method based on low-pass filtering. This method first performs low-pass filtering on the hazy image to complete the estimation of local ambient light; then solves the initial transmittance map through the dark channel prior, optimizes the transmittance map through the guided filter, and finally realizes the color correction of the image through histogram matching. In another study [20], three types of features including image contrast, saturation and information entropy are fused to construct a multi-feature joint optimization function to complete the estimation and optimization of transmittance. Finally, the Shade of Gray algorithm [21] based on non-overlapping local image blocks is used for color correction.

These traditional methods have laid an important foundation for nighttime dehazing, but they all attempt to use mathematical models designed for uniform illumination to repair or fit highly inhomogeneous and complex optical phenomena with multi-light sources. This results in algorithms that are often complex in structure, have numerous parameters and limited generalization ability.

(2) Deep Learning-based Nighttime Dehazing Algorithms

Compared with traditional methods relying on physical models and physical priors, deep learning-based algorithms can more effectively learn various complex degradations of nighttime haze images through data-driven approaches, and also show greater potential in the field of nighttime image dehazing. Although relevant research started late and the number of literatures is relatively small, many researchers have proposed many innovative technical approaches.

Early deep learning methods focused on designing model structures. For example, Kuanar et al. [22] proposed an iterative deep learning framework for glow and haze removal. The framework first uses a dilated convolutional network to eliminate the glare effect generated by light sources, then estimates the ambient light from the transmittance map through a subnetwork based on a recursive structure, and finally realizes image restoration. The iterative architecture for haze and glare removal based on deep learning is shown in Figure 3. The structure is divided into two parts: one is a CNN-based glare removal model, which extracts features through dilated convolution and can significantly eliminate the glare effect; the other is an independent dehazing network, which includes a recursive structure based on the context expansion framework [23] and can estimate ambient light from transmittance to obtain the restored image. Constructing high-quality dedicated datasets is the key to promoting the development of this field.

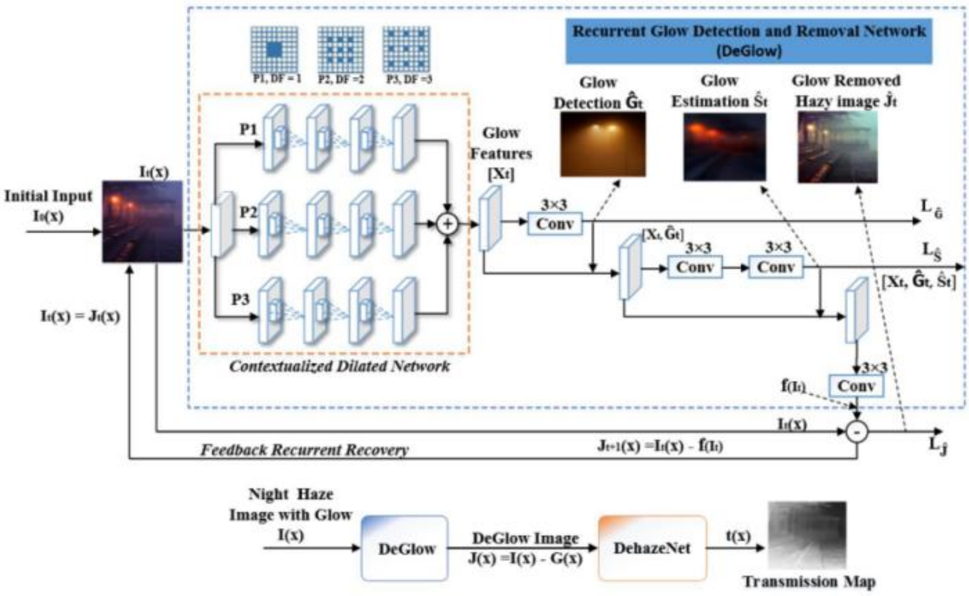


Figure 3. Iterative deep learning framework for nighttime haze and glare removal

Tang et al. [24] synthesized NTHAZE, the first dehazing dataset for nighttime traffic scenes, and on this basis proposed an end-to-end network NDPCNet, which bypasses the ill-posed problem of solving the atmospheric scattering model in traditional methods.

Yang et al. [25] proposed a weakly supervised image translation method, combining the imaging mechanism of haze weather with the Generative Adversarial Network (GAN), and using a semi-supervised training method to construct a deep learning nighttime image restoration framework to realize image translation from the haze domain to the clear domain.As shown in the Figure 4.

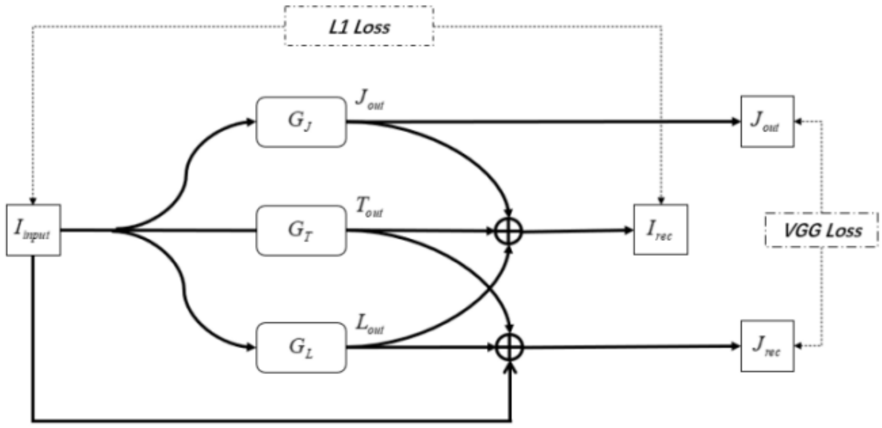


Figure 4. The Overview of NightDNet

The work of Kis et al. [26] shows that by adopting a color correction strategy to preprocess nighttime images, the Deep Multi-Patch Hierarchical Network (DMPHN) trained on real daytime dehazing datasets can be effectively transferred to nighttime scenes. Kis et al. [27] adopted a new strategy that uses a deep learning model trained on daytime image dehazing datasets. The model uses a DMPHN trained on a real daytime image dehazing dataset, and takes an effective color correction strategy as a preprocessing step to extend this method to nighttime hazy scenes.

Wang et al. [28] proposed a simple and efficient Gray Haze-Line Prior (GHLP) method as shown in the Figure 5, which can realize the accurate identification of haze feature regions, and based on this, construct a brand-new unified nighttime dehazing framework.

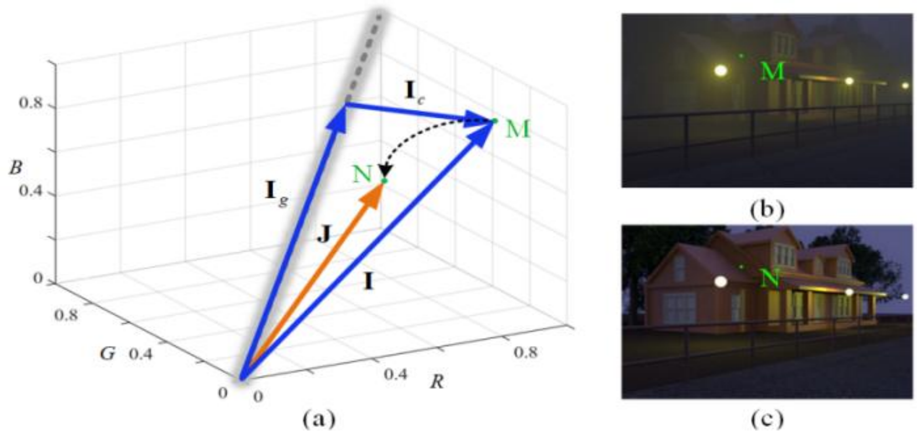


Figure 5. Demonstration of the GHLP. (a) Vector decomposition with the GHLP in the RGB color space. (b), (c) A nighttime hazy scene and the corresponding nighttime clear scene from

This framework first decomposes the nighttime haze image into chrominance and luminance components in the YUV color space; then completes glare elimination of the chrominance component and illuminance enhancement of the luminance component through the luminous color correction step; finally, for the preprocessed image, a structure-aware variational framework is designed to simultaneously estimate the reciprocal scene brightness and the transmittance in the luminance component, while restoring high-quality night scene images, it completely retains the structural information and inherent color attributes of the scene. As shown in the Figure 6.

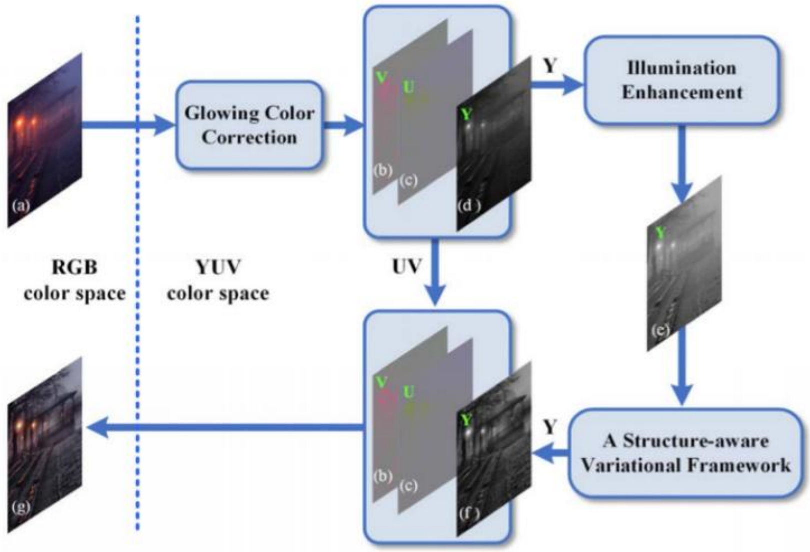


Figure 6. Overall flowchart of the proposed method in the YUV color space

Yan et al. [29] designed dual grayscale and color processing modules, and at the same time decomposed the input image into high-frequency and low-frequency layers: the high-frequency layer mainly carries scene texture information and is less affected by haze degradation; the low-frequency layer contains scene layout and structural information, and at the same time concentrates haze and luminous degradation features. On this basis, the grayscale module realizes the texture visibility enhancement of the high-frequency layer and the elimination of luminous and haze of the low-frequency layer respectively, and finally fuses the processing results of high and low frequencies to obtain the grayscale domain dehazed image. As shown in the Figure 7.

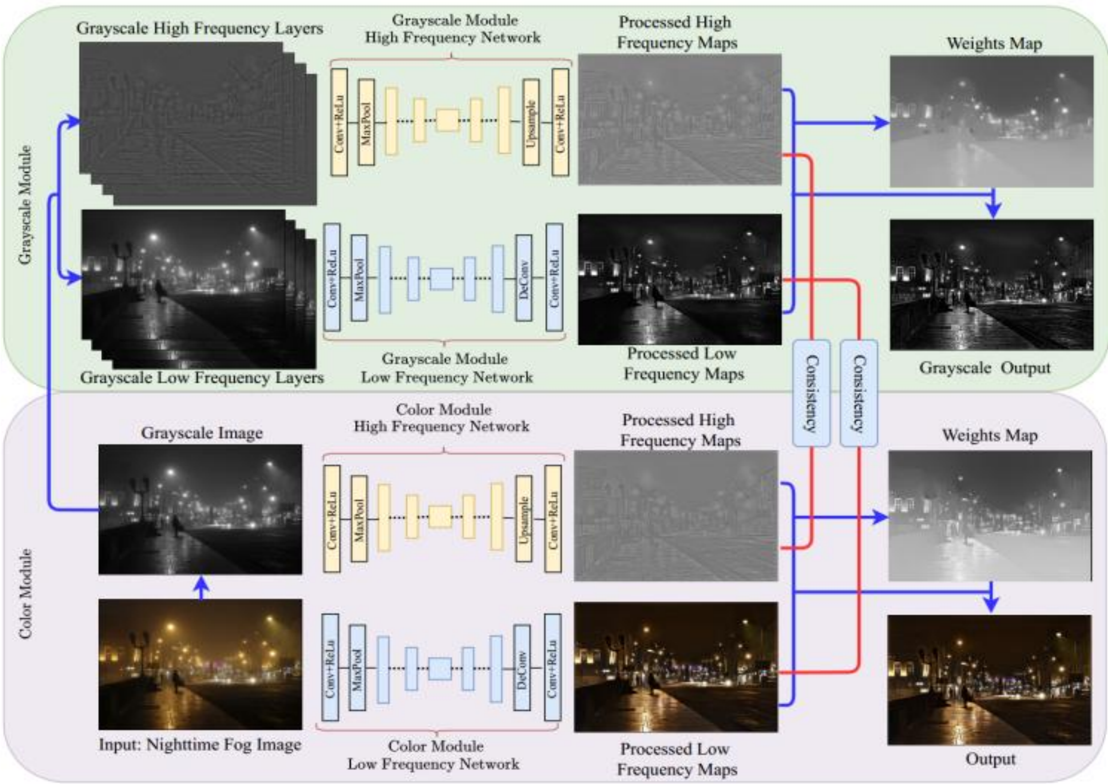


Figure 7. The flowchart of the NightDefog framework, consisting of two main modules: the grayscale module (top) and the color module (bottom)

Li et al. [30] proposed an end-to-end nighttime dehazing framework NightHazeFormer based on Transformer, which adopts a two-stage training strategy of supervised pre-training and semi-supervised fine-tuning. In the pre-training stage, two types of strong prior information are introduced into the Transformer decoder to generate non-learnable prior queries to guide the model to accurately extract specific degradation features; in the fine-tuning stage, the generated pseudo ground truth and the input real-world nighttime haze images form paired data to complete the fine-tuning optimization of the pre-trained model in the synthetic domain. As shown in the Figure 8.

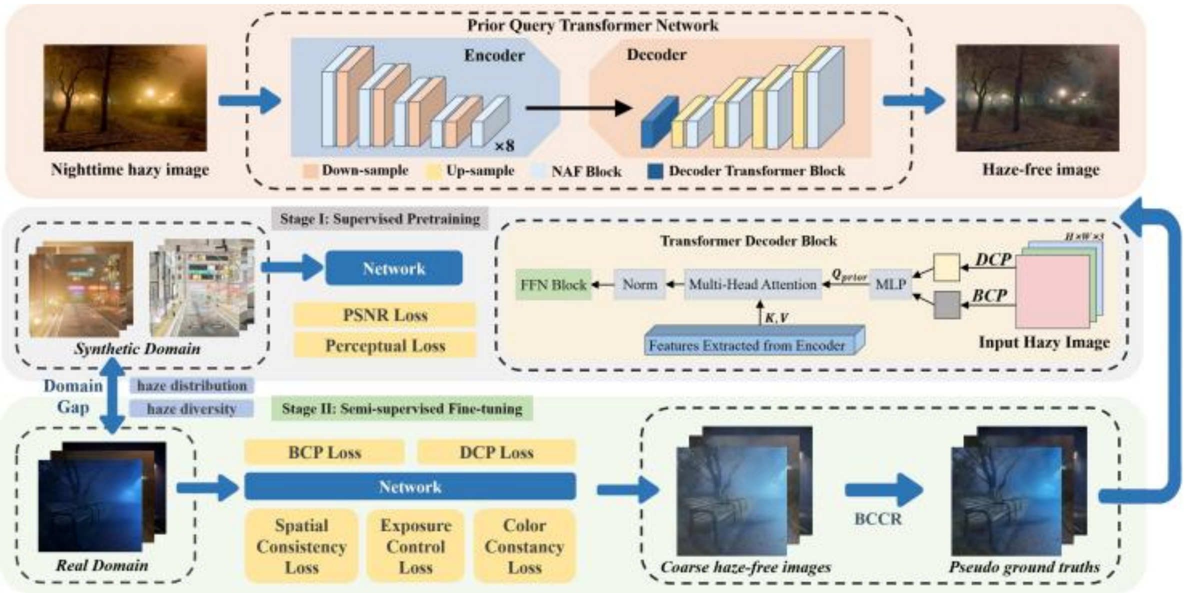


Figure 8. The architecture of NightHazeFormer

Jin et al. [31] realized the visibility improvement of single nighttime haze images by simultaneously suppressing image glare and enhancing the brightness of low-light regions. As shown in the Figure 9, a nighttime dehazing and enhancement framework is constructed by fusing physical priors and deep learning. This study locates light source regions through a light source-aware network, realizes guided glow rendering relying on the Atmospheric Point Spread Function (APSF), generates highly realistic paired training data to solve the problem of lack of annotated data for nighttime dehazing, and proposes a gradient-adaptive convolution module that dynamically adjusts convolution kernel weights according to local gradient information of the image to accurately enhance edge texture and suppress noise amplification in smooth regions. The network adopts an encoder-decoder architecture and integrates a spatial attention mechanism, and completes joint optimization combined with pixel loss, perceptual loss, glow suppression loss and gradient loss. Experiments verify that this method achieves better objective evaluation indicators on both synthetic and real datasets, can collaboratively complete glow suppression and low-light enhancement, and relying on the advantages of both physical interpretability and detail recovery ability, it provides a new technical idea for image visualization enhancement in scenarios such as nighttime surveillance and autonomous driving.

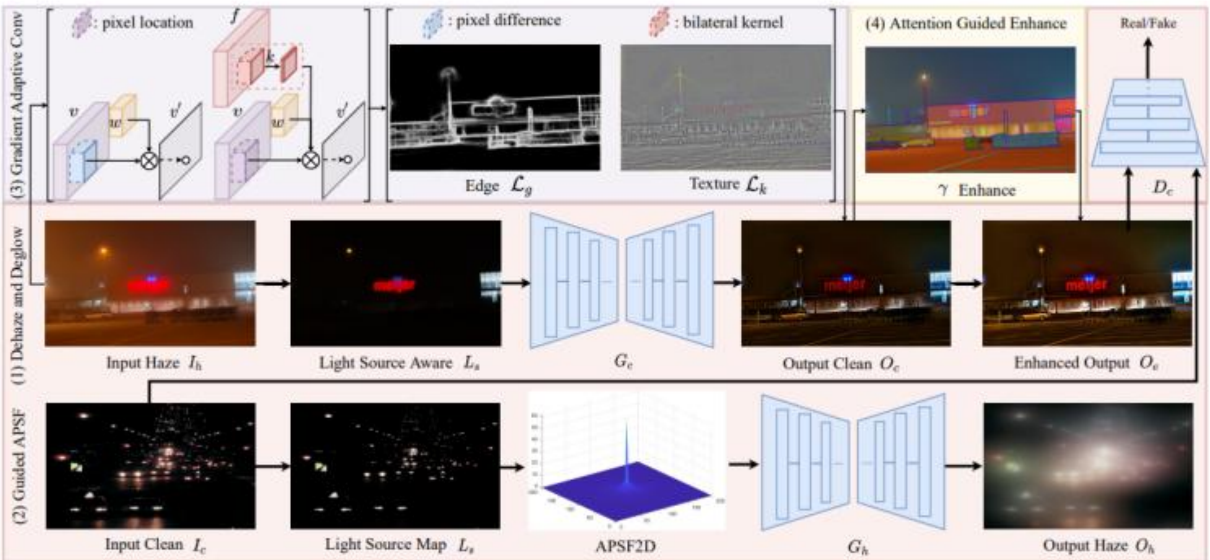


Figure 9. Overview of nighttime dehazing framework

Aiming at the real nighttime scene dehazing task, Cong et al. [32] proposed a semi-supervised learning model. As shown in Figure 10. The model first designs a spatial-frequency domain information interaction module, fusing spatial attention and spectral filtering capabilities to solve the degradation problem of coupling between glare and noise; at the same time, for the semi-supervised training process, it designs a pseudo label-based retraining strategy and a local window-based brightness loss function, which realizes the simultaneous suppression of haze and glare while restoring the real brightness of the scene.

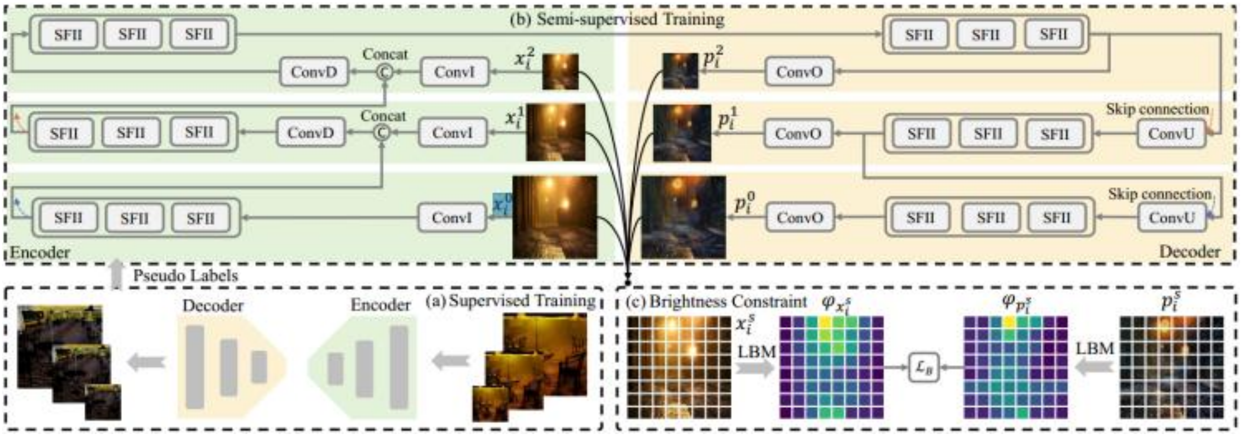


Figure 10. The overall pipeline of the proposed SFSNiD

Lin et al. [33] proposed a nighttime dehazing framework based on self-prior learning, innovatively introducing the MAE-based severe augmentation strategy into the field of nighttime image enhancement. As shown in Figure 11. This method generates diverse training samples through extreme data augmentation such as strong light effect and noise, enabling the model to learn robust strong prior knowledge for real nighttime haze; constructs a self-optimization module of a semi-supervised teacher-student framework, where the teacher model generates pseudo ground truth based on confidence scores, and the student model is trained on high-confidence prediction results, effectively solving the over-suppression problem that may be caused by self-prior learning; designs a brightness-aware loss function to balance glow suppression and brightness fidelity, avoiding the underexposure or overexposure defects of traditional methods.

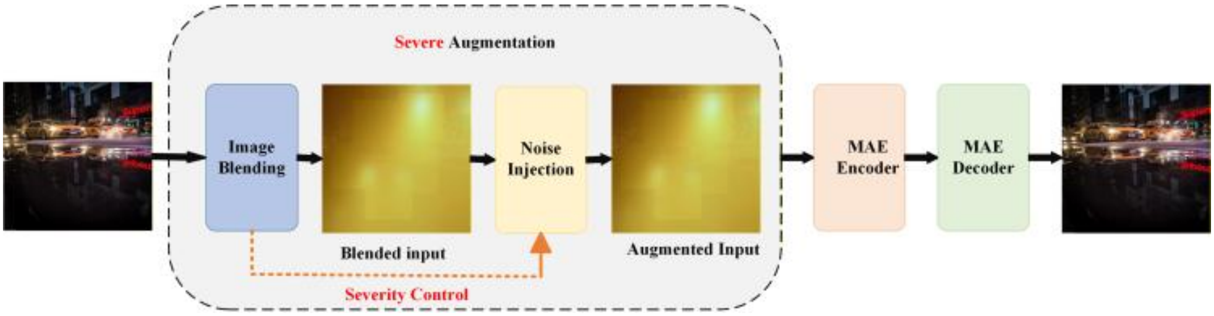


Figure 11. Overview of self-prior learning

3. The application value of traditional embroidery in modern fashion design

3.1. Experimental Setup

The performance of nighttime image dehazing algorithms largely depends on the quality and scale of image datasets used in the training and evaluation process. Such datasets are usually divided into training set, validation set and test set according to their purposes. The training set is used for the model training process, enabling the model to learn the mapping law from nighttime foggy images to fog-free images and realize haze removal and detail recovery; in the training stage, the algorithm adjusts the model parameters by optimizing the loss function combined with the validation set, making the dehazing output results as close as possible to the real fog-free images; after the model training is completed, the generalization ability of the algorithm on unseen nighttime foggy images is evaluated through the test set to quantify the practical application performance of the algorithm. Supervised nighttime image dehazing methods usually require paired nighttime foggy images and corresponding fog-free images as training samples. Such annotated datasets can provide clear learning objectives for the model, help the model accurately grasp the feature mapping relationship between nighttime foggy and fog-free images, adjust the internal weights of the model through iterative training, and finally achieve high-quality dehazing output. The following focuses on the various datasets commonly used in nighttime image dehazing research to support the training and evaluation of algorithms.

Datasets commonly used for nighttime image dehazing can be divided into two categories: paired datasets and unpaired datasets. Among them, GTA5 [34], NHC [1], NHM [1], NHR [1], NHRW [1] and UNREAL_NH [30] datasets are mainly composed of paired samples, which are mainly used for the training and comprehensive performance evaluation of supervised nighttime dehazing models; DCRW [1] and RWNH [35] datasets contain both paired and unpaired samples, which can be adapted to the training and testing of both supervised and no-reference algorithms. The comparison of commonly used datasets is shown in Table 1.

Table 1. Comparison of commonly used nighttime dehazing image datasets

Dataset	Number	Real/ Synthetic	Paired/ Unpaired
GTA5	864	Synthetic	Paired
NHC	2750	Synthetic	Paired
NHM	350	Synthetic	Paired
NHR	897	Synthetic	Paired
UNREAL_NH	10080	Synthetic	Paired
NHRW	150	Real	Unpaired
DCRW	1500	Real	Unpaired
RWNH	443	Real	Unpaired

3.2. Evaluation Metrics

The core goal of nighttime image dehazing algorithms is to eliminate image degradation caused by the superposition of nighttime low illumination and haze, restore clear scene details and reasonable brightness distribution, and ultimately improve the visual recognizability and practical value of nighttime dehazed images. In nighttime scenes, haze scattering will aggravate light attenuation, and low illumination environments are prone to noise and detail blurring, making the evaluation of dehazing effect more complex. How to construct a scientific and objective evaluation system has become a key link in nighttime image dehazing research. To comprehensively and accurately quantify the performance of dehazing algorithms, researchers have proposed a variety of evaluation metrics, which can be divided into full-reference evaluation metrics and no-reference evaluation metrics according to whether they rely on clear reference images. This section focuses on the most commonly used PSNR and SSIM metrics in the two types of metrics for the quantitative evaluation of nighttime image dehazing effects.

(1) Peak Signal-to-Noise Ratio (PSNR) [36]: Peak Signal-to-Noise Ratio (PSNR) is one of the most widely used traditional metrics in the field of image quality assessment, and is also suitable for the quantitative evaluation of nighttime image dehazing effects. Its core principle is to measure the recovery accuracy of the dehazing algorithm by calculating the pixel-level error between the dehazed image and the fog-free reference image. The calculation of PSNR is based on the Mean Squared Error (MSE), a classic quantitative method for measuring the difference in pixel grayscale values between two images. From a physical perspective, PSNR represents the maximum possible signal-to-noise ratio of the dehazed image relative to the fog-free reference image, with the unit of decibels (dB). Its calculation formula is as follows:

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{R^2}{\mathrm{MSE}}\right) \tag{10}$$

In Formula (10) R represents the maximum pixel grayscale value of the image. For 8-bit grayscale images or 24-bit color images (each channel is calculated independently), $R = 255$; MSE is the mean squared error between the dehazed image and the fog-free reference image, and its specific calculation formula is:

$$\mathrm{MSE} = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[I(i,j) - K(i,j)\right]^2 \tag{11}$$

In Formula (11) M and N represent the height and width of the image respectively; $I(i,j)$ represents the grayscale value of the nighttime dehazed image at pixel position (i,j); $K(i,j)$ represents the grayscale value of the corresponding nighttime fog-free reference image at the same pixel position (i,j). The core advantages of the PSNR metric are simple calculation logic and strong interpretability, which can directly reflect the pixel difference between the dehazed image and the reference image. For the nighttime image dehazing task, a higher PSNR value indicates a smaller pixel deviation between the dehazed image and the fog-free reference image, meaning that the algorithm better retains the detailed information of the original scene while eliminating haze, and the dehazing effect is better.

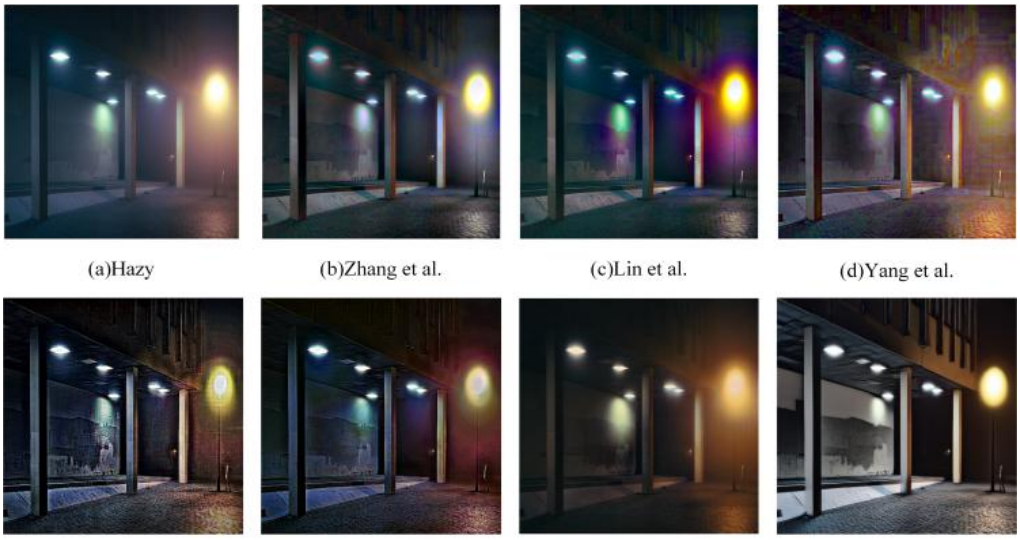
(2) Structural Similarity Index Measure (SSIM) [37]: Different from PSNR which only focuses on pixel-level errors, the Structural Similarity Index Measure (SSIM) pays more attention to the integrity of image structural information. Its design concept is in line with the perceptual characteristics of the human visual system—human judgment of image quality relies more on scene structure, edges, textures and other information rather than simple pixel grayscale differences. This characteristic makes it more suitable for evaluating the visual quality of nighttime dehazed images (nighttime scenes pay more attention to the restoration of details and edges). SSIM quantifies the structural similarity between the dehazed image and the fog-free reference image by comprehensively considering three core dimensions of the image: luminance, contrast and structure. Its calculation formula is as follows:

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{12}$$

In Formula (12) x represents the nighttime dehazed image and y represents the corresponding nighttime fog-free reference image; μ_x and μ_y are the mean grayscale values of images x and y respectively, used to characterize the luminance characteristics of the images; σ_x^2 and σ_y^2 are the grayscale variances of images x and y respectively, reflecting the contrast information of the images; σ_{xy} is the grayscale covariance of images x and y, used to measure the structural correlation between the two images; C_1 and C_2 are tiny constants set to avoid the denominator being zero, usually taking values of $C_1 = (0.01R)^2$ and $C_2 = (0.03R)^2 (R = 255)$. The value range of SSIM is [0, 1]. A value closer to 1 indicates a higher structural similarity between the dehazed image and the fog-free reference image, meaning that the algorithm effectively retains key structural information such as scene edges and textures while removing nighttime haze, and the dehazing effect is more in line with the needs of human visual perception. Compared with PSNR, SSIM can more accurately capture the detail recovery degree of nighttime dehazed images, and the evaluation results are more consistent with the actual visual experience.

3.3. Result Comparison and Analysis

Representative nighttime dehazing algorithms are tested and compared. Commonly used evaluation methods include subjective and objective methods. The subjective method is to make subjective evaluation and analysis through the observation of images by testers, which is the most direct and commonly used method. The comparison of dehazing effects of several typical nighttime dehazing algorithms (Zhang et al. [7], Lin et al. [6], Yang et al. [8], Yan et al. [29], Jin et al. [31], Cong et al. [32], Lin et al. [33]) is shown in the figure (12).



(a)Hazy (b)Zhang et al. (c)Lin et al. (d)Yang et al.

(e)Yan et al. (f)Jin et al. (g)Cong et al. (h)Lin et al.

Figure 12. Dehazed results of different methods

Since the subjective method is susceptible to the personal factors of observers, the evaluation is inaccurate. Therefore, Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) are used as objective evaluation metrics to evaluate the above typical algorithms, as shown in the Table 2.

Table 2. The average PSNR and SSIM in dehazing results

	PSNR	SSIM
Zhang et al.	19.82	0.8209
Lin et al.	21.136	0.739
Yang et al.	19.82	0.8209
Yan et al.	26.997	0.850
Jin et al.	32.642	0.923
Cong et al.	33.7	0.935

4. Conclusion

In summary, as an important research topic in the field of computer vision, nighttime image dehazing has currently formed two core research directions among researchers: traditional algorithm-based and deep learning-based methods. Both methods have their own focuses and advantages, and together promote the continuous development and improvement of nighttime dehazing technology.

Research based on traditional algorithms focuses on the optimization of the nighttime atmospheric scattering model. By continuously improving the imaging model and combining key technologies such as image fusion, glow removal and layered processing, the clarity of nighttime foggy images has been effectively improved, achieving relatively ideal dehazing effects and laying a solid theoretical and practical foundation for nighttime dehazing technology. Deep learning-based nighttime dehazing algorithms, relying on their strong feature extraction capabilities, perform better in both subjective visual effects and objective evaluation metrics. Especially with the support of high-quality datasets, they can show stronger robustness and generalization ability. They have become the mainstream research direction in the current nighttime dehazing field and the core trend of future technological development.

At the same time, existing research still has obvious room for improvement. Among them, deep learning-based methods face the prominent problem of consuming a lot of computational resources and time in the training process, which also points out a clear direction for subsequent research. Future research on nighttime dehazing can focus on three aspects: first, relying on novel models in the field of deep learning, explore their application in nighttime dehazing tasks and strive to improve the model training speed; second, in view of the complexity of nighttime scenes, further explore a more complete imaging model that is more in line with the actual nighttime foggy environment to break through the limitations of existing models; third, expand research scenarios, focus on the real-time requirements of nighttime hazy video dehazing, conduct in-depth research on efficient video dehazing algorithms, and fill the weak links in current research.

Overall, the research on nighttime dehazing technology has achieved phased results, but it is still necessary to combine practical application requirements, continuously break through technical bottlenecks, and promote the continuous improvement of the practicality, efficiency and generalization of algorithms, so as to provide stronger technical support for the development of related fields such as nighttime transportation and surveillance and security.

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