IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 28 May 2024, accepted 11 July 2024, date of publication 15 July 2024, date of current version 25 July 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3428568

RESEARCH ARTICLE

Image Dehaze Algorithm Based on Improved Atmospheric Scattering Models

WENQIANG YAN AND LEI CUI, (Member, IEEE)
School of Intelligent Intelligence and Control Engineering, Shanghai Polytechnic University, Shanghai 201209, China
Corresponding author: Lei Cui (cuilei@sspu.edu.cn)

ABSTRACT Due to the influence of rainy and foggy weather, obtaining clear images becomes more challenging, often resulting in low visibility, poor contrast, and missing detail information. To address these issues, a robust image defogging algorithm is proposed. Firstly, the input image undergoes conversion into a detailed image, with attenuation and redefinition of its three color channels. Color compensation and balance are then applied based on the principle of minimizing color loss. Secondly, the problem of image darkening is tackled through an improved atmospheric scattering model (EASM) and the dark channel a priori algorithm. The defogging results exhibit noticeable enhancements in terms of bright colors and clear details. In the natural images showcased in the paper, the proposed algorithm achieves improvements in information entropy, the fog density evaluator (FADE), and the natural image quality evaluator (NIQE) by 0.46%, 9.7%, and 12.0%, respectively, compared to the suboptimal algorithm. In the synthetic image datasets I-HAZE and O-HAZE, there are enhancements in information entropy by 0.19% and 0.76%, respectively, and in NIQE by 1.05% each, albeit slightly lower than the sub-optimal results. The structural similarity (SSIM) also sees improvements of 6.3% and 10.9% compared to the suboptimal results in FADE. These findings demonstrate the superior performance of the proposed algorithm over the latest defogging algorithms in terms of information entropy, FADE, NIQE, and SSIM, underscoring its high robustness and promising application prospects.

INDEX TERMS Image processing, haze removal, atmospheric scattering model, color correction, gray world assumption.

I. INTRODUCTION

with the rapid development of computer vision, addressing the issue of clarity in blurred images acquired in adverse weather conditions such as haze, rain, fog, snow, sandstorms, etc., is becoming increasingly urgent. The presence of numerous haze particles in such conditions significantly diminishes image visibility and alters the inherent color. Hence, robust image dehazing techniques are indispensable for eliminating detrimental factors and reconstructing blurred information [1]. Compared to low-level vision tasks like image denoising, enhancement, and super-resolution, the unique challenge of image de-fogging lies in managing image distortions induced by atmospheric haze. This necessitates simultaneous consideration of complex factors such as haze scattering models, restoration of lost details, and color aberrations to achieve clear, realistic image reconstruction. Overcoming these challenges entails accurate modeling of haze scattering behavior and precise estimation of depth information.

To restore the quality of hazy images, image dehazing and enhancement techniques have been widely used [2]. Current image dehazing algorithms are primarily divided into a priori-based and deep learning-based approaches. Most a priori-based algorithms rely on the Atmospheric Scattering Model (ASM) [3], wherein the transmittance and atmospheric light parameters are computed to derive the haze-free image. He et al. proposed the dark channel prior (DCP) algorithm [4] to estimate the distribution of hazy images. Despite its ability to produce haze-free images, DCP may introduce color distortion in sky regions and overall darkening in the image. Xiao et al. refined atmospheric light estimation using

The associate editor coordinating the review of this manuscript and approving it for publication was You Yang.

a multi-channel quadtree algorithm, enhancing image quality but still suffering from color distortion at sky boundaries. Ling et al. [5] revealed an end-to-end dehazing framework based on the linear distribution of local pixels, yet struggled to restore details in images with uneven haze distribution. Zhu et al. [6] adjusted transmittance and compensated images to improve clarity and color restoration based on saturation and brightness differences in hazy images. The application of deep learning in image dehazing is increasingly prominent [7], typically leveraging convolutional neural networks (CNNs) as the base model. Cai et al. [8] proposed the DehazeNet neural network dehazing algorithm, estimating transmittance using DehazeNet and combining it with image a priori information to estimate global atmospheric illumination, ultimately generating clear images via ASM. Li et al. [9] introduced AOD-Net, comprising a K estimation module and a clear image generation module, which estimates the final output using the input K values. Lang's small sample image segmentation [10], [11] [12], [13] and similar methods aid in segmenting foggy images to obtain locally optimal transmittance and atmospheric light. While these deep learning-based algorithms have shown superior performance in image dehazing, they are heavily reliant on datasets comprising clear and hazy images. Consequently, their performance can vary significantly across different test sets [14]. For instance, networks trained on synthetic fuzzy image datasets may not generalize well to real-world fog scenarios.

In this paper, addressing the issues of color distortion and darkness in the resultant clear image post-dehazing operation, we propose an enhancement to the atmospheric scattering model. This enhancement involves introducing a light absorption coefficient alongside the traditional atmospheric scattering model. Additionally, prior to the dehazing process, the foggy image undergoes pre-processing for color correction. These measures ensure that the final clear image exhibits authentic color representation, optimal brightness, and improved contrast.

In this paper, we address the issue of image darkening post-defogging by introducing an improved atmospheric scattering model. Through derivation and MATLAB fitting, we transform the transcendental equation governing the transmittance map into a solution of a simple quadratic equation. Furthermore, to tackle color aberration in the sky region post-processing by the DCP algorithm, we introduce a local adaptive color correction method based on the fusion of minimum color loss and maximum attenuation mapping. This approach effectively inhibits the occurrence of color distortion phenomena in the input fog map after defogging. While the IDE algorithm demonstrates superior performance in the defogging process, its robustness is limited, resulting in color distortion in processing certain natural images. In contrast, our proposed algorithm exhibits higher color reproduction fidelity and preserves more detailed information compared to the IDE algorithm [12]. Moreover, it demonstrates superior values in information entropy, FADE, SSIM, and NIQE, presenting a significant advantage in enhancing visual effects and overall quality improvement.

II. IMPROVED DARK CHANNEL DEFOGGING ALGORITHM

A. IMPROVED ATMOSPHERIC SCATTERING MODEL

In the realm of computer vision, the majority of algorithms and vision systems are designed for scenarios with favorable weather conditions and high visibility. However, the reality is that adverse weather conditions such as rain and fog occur intermittently. For instance, in the case of fog, haze particles in the air disrupt the refraction of atmospheric light [15], consequently impacting the integrity of information captured by cameras. In the 1990s, Nayar et al. introduced the Atmospheric Scattering Model (ASM), represented by the following equation:

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

where x denotes the pixel position; I(x) denotes the input hazy image; J(x) denotes the output haze-free image; t(x) denotes the transmittance of atmospheric light propagation; and A denotes the global atmospheric light in the image. When the distribution of haze particles in the atmosphere is uniform, the transmittance t can be expressed as follows:

$$t(x) = e^{-\beta \cdot d(x,y)}. \tag{2}$$

where d and β denote the scene depth and scattering coefficient, respectively. The first term on the right side of Eq.1 represents the attenuation of the light, also known as direct attenuation, which decays exponentially with scene depth [16], the second term represents the imaging of atmospheric light.

In the process of defogging through atmospheric scattering modeling, although the atmospheric light is treated as a globally constant value [17], the dimness of the image varies across different locations. Ju et al. proposed that this phenomenon arises from the partial absorption of light by the scene's texture during propagation, with greater absorption occurring in regions of higher texture density [18]. Assuming the absorption coefficient is $\varepsilon \in (0, 1]$, the reflected light is $(1 - \varepsilon) \cdot A \cdot \sigma$. The scene reflectance of the fog-free image produced by ASM is lower than the scene reflectance of the real image without considering the absorbed light $\sigma_{ASM} < \sigma_{real}$. Since traditional ASM models do not account for light absorption, this leads to the final image appearing dark.

To minimize this problem, the absorption coefficient ε is introduced into the ASM model, and the improved atmosphere is modeled as:

$$I(x) = A \cdot (1 - \varepsilon(x)) \cdot \sigma(x) \cdot t(x) + A[1 - t(x)] \tag{3}$$

where $\varepsilon \in (0, 1]$, and the light absorption coefficient increases as the depth of field decreases, so the absorption coefficient expression is defined as:

$$\varepsilon(x) = 1 - \frac{d(x)}{\max(d)} \tag{4}$$

The expression for the depth of field is obtained from Eq. 2 and brought into Eq. 4 to further obtain the expression for the absorption coefficient, which is then brought into Eq. 1 to obtain the improved ASM model:

$$I(x) = A \cdot \frac{\ln(t(x))}{\ln(t_{\min})} \cdot \sigma(x) \cdot t(x) + A \cdot (1 - t(x)) \tag{5}$$

According to the grey world assumption [19], it is assumed that the average reflectance of the scene in the image is similar in different color channels, and the overall tone presented by the image is close to the neutral color, so the reflectance can be approximated as 0.5 [20], and then the ASM model is rewritten as:

$$I(x) = A \cdot \frac{\ln(t(x))}{2 \cdot \ln(t_{\min})} \cdot t(x) + A \cdot (1 - t(x)) \tag{6}$$

Since Eq. 6 contains logarithmic functions belonging to transcendental equations that cannot be solved directly, for this problem, the logarithmic function is fitted to a simple function by MATLAB, where $h_1 = -0.397$, $h_2 = 0.7774$.

$$ln(t) \approx \frac{h_1}{h_2 + t} \tag{7}$$

The quadratic equation for the transmittance t is obtained by taking Eq. 7 into Eq. 6. The transmittance t of the input image can be obtained by a simple root formula. At this time t_{min} is the only unknown quantity, in this paper, the input image is downsampled and converted to a one-dimensional array, and then the golden section search algorithm is used to obtain the final.

He observed that in most non-sky images of natural landscapes, some pixels in at least one color channel exhibit very low brightness values close to zero, a phenomenon termed the "dark channel prior". The DCP algorithm first computes the dark channel of a foggy image by selecting the smallest value among all pixels in the three color channels within a local window for each pixel. Then, it identifies the brightest pixels at corresponding positions in the original image as the dark channel values. For each pixel, the minimum value across all pixels in its local window in the three color channels is chosen as the dark channel value, and the brightest pixels are identified at the corresponding locations in the original image by analyzing the dark channel map. The first few pixels with the highest brightness are selected as an estimate of the global atmospheric light.

Following the above algorithm to obtain the atmospheric light A and transmittance t, these values are substituted into Equation 3 to derive the scene reflectance, resulting in a clear image after recovery. However, during the processing of natural images, color aberration may occur. To address this issue, the next section introduces a color correction algorithm.

B. COLOR CORRECTION

For the problem of color distortion that still exists in the clear image after recovery, color correction [21] is introduced and optimized in this paper. In local adaptive color correction, the color transfer image is firstly obtained by using the principle of minimum color loss, and the fusion method is guided by the maximum attenuation image to adjust the color and details of the input image while using the color transfer image.

In this paper, the input image is redefined based on the average of the color channels as red, green and blue channels, which are denoted as:

$$\begin{aligned} \bar{I}_R &= \frac{1}{h \cdot w} \sum_{i=1}^{h} \sum_{j=1}^{w} I_R(i,j) \\ \bar{I}_G &= \frac{1}{h \cdot w} \sum_{i=1}^{h} \sum_{j=1}^{w} I_G(i,j) \\ \bar{I}_B &= \frac{1}{h \cdot w} \sum_{i=1}^{h} \sum_{j=1}^{w} I_B(i,j) \end{aligned} \tag{8}$$

where I_R, I_G, I_B are the average values of the three channels respectively, h, w are the height and width of the image and I is the input image. Then the channel with the largest, medium, and smallest values is defined as $I_{max}, I_{medin}, I_{min}$.

$$\begin{aligned} I_{\max} &= \max(\bar{I}_R, \bar{I}_G, \bar{I}_B) \\ I_{medin} &= median(\bar{I}_R, \bar{I}_G, \bar{I}_B) \\ I_{\min} &= \min(\bar{I}_R, \bar{I}_G, \bar{I}_B) \end{aligned} \tag{9}$$

According to the grayscale world assumption, the color channels of a natural image have similar mean values, so the color loss L of the three channels $I_{max}, I_{medin}, I_{min}$ are defined as:

$$\begin{aligned} &L = J + k \\ &J = I_{\max} - I_{medin}, k = I_{\max} - I_{\min} \end{aligned} \tag{10}$$

For the color channels corresponding to the I_{medin} and I_{min} channels, correction is performed by Eq.11 and Eq.12:

$$I_{medin}^{R} = I_{medin} + (I_{\max} - I_{medin}) \cdot I_{\max} \tag{11}$$

$$I_{min}^{R} = I_{min} + (I_{\max} - I_{min}) \cdot I_{\max} \tag{12}$$

To make the mean values of each color channel similar, the loss function is satisfied by iterating Eqs. 11,12 until it is satisfied:

$$\min_{I_{\max}, I_{medin}, I_{\min}} \|L_{color}\| = \min(J, k) \tag{13}$$

where, in this paper, we set the threshold value of L_{color} as 0.2, and after iteration continuously optimize the loss function to finally obtain the color transfer image I^{CT}. The fusion using the maximally attenuated image Q as a guide image can be expressed as:

$$Q_{\max} = \max\{1 - I_R^{\alpha}, 1 - I_G^{\alpha}, 1 - I_B^{\alpha}\} \tag{14}$$

$$I_{CR} = Q_{\max} \cdot I^{CT} + (1 - Q_{\max}) \cdot I_c \tag{15}$$

The final color corrected image I_{CR} can be derived from Eq.15.

FIGURE 1. From left to right, haze image, DCP, IDE, SLP, Our.

III. EXPERIMENTAL RESULTS AND ANALYSIS

In this paper, experiments are carried out on real image datasets and publicly available datasets I-HAZE and O-HAZE, and the proposed algorithm is compared with the three algorithms in terms of three performance metrics, and finally ablation experiments are carried out on the proposed algorithm to evaluate the impact of the parameters.

A. SUBJECTIVE EVALUATION

When selecting real image datasets, it's crucial to consider the diversity and representation of the images. This ensures coverage of various scenes, weather conditions, and degrees of haze, thereby facilitating a more comprehensive evaluation of algorithm performance and robustness. In this section, several images with varying degrees of haze from real image datasets are chosen to test the proposed algorithm alongside DCP [3], IDE [12], and SLP [4] algorithms. A comparative validation is then conducted.

As depicted in Figure 1, the clear images recovered by the DCP algorithm generally appear dark and exhibit severe color distortion in E2 and E4. While the IDE algorithm improves image darkness to some extent, careful observation of the sky region reveals a fuzzy texture leading to loss of detailed information and a slight color aberration phenomenon persists. The SLP algorithm demonstrates better defogging effects, albeit the inaccurate estimation of atmospheric light contributes to overall image darkness. The proposed algorithm in this paper, based on IDE, not only achieves superior fog removal effects but also enhances image details, reducing information loss. Both the DCP and SLP algorithms notably darken during the processing of E1. Comparing IDE with the proposed algorithm, the effects of color correction are evident post-correction, with no overall yellowing observed in the image. Additionally, E5 showcases clearer building details compared to the IDE algorithm, with colors more aligned with human visual perception.

TABLE 1. Comparison of natural image dehazing index.

Metrics	image	DCP	IDE	SLP	Our
Entropy	E1	7.3843	7.5225	7.5917	7.5934
	E2	6.7954	7.7060	7.0682	7.7418
	E3	7.2859	7.3649	7.7759	7.5127
	E4	7.3048	7.5626	7.4688	7.5964
	E5	7.2676	7.6329	7.5883	7.0955
FADE	E1	0.3611	0.5456	0.5880	0.3261
	E2	0.1587	0.1401	0.2016	0.1265
	E3	0.3412	0.4645	0.4933	0.3349
	E4	0.2265	0.2383	0.2250	0.2167
	E5	0.3028	0.3077	0.2274	0.2631
NIQE	E1	2.8209	2.9221	2.9309	2.9998
	E2	4.6822	5.2826	4.8674	5.0201
	E3	2.1084	1.9268	1.8493	2.6664
	E4	2.5296	3.1033	2.7823	3.1856
	E5	2.9340	2.8230	2.7152	2.3900

B. OBJECTIVE EVALUATION

Due to the subjective nature of individual perceptions, achieving a fair comparison of clear images recovered by different algorithms is inherently challenging. In this paper, the robustness of the proposed algorithm is evaluated using both a natural image dataset and a synthetic image dataset obtained from the internet. The synthetic dataset consists of the I-HAZE [22] and O-HAZE public datasets. The I-HAZE dataset comprises 35 pairs of foggy images along with corresponding haze-free (ground truth) indoor images. Unlike most existing dehazing databases, the haze images in I-HAZE are generated using real haze produced by specialized haze machines. To simplify color calibration and enhance dehaze algorithm evaluation, a MacBeth color checker is included in each scene. Furthermore, since the images were captured in a controlled environment, both haze-free and haze images were obtained under identical lighting conditions. The O-HAZE dataset comprises 45 images captured under various weather conditions in outdoor scenes. In this paper, four metrics are utilized to quantitatively analyze the clear images recovered by the proposed algorithm. These metrics include structural similarity (SSIM) [23], information entropy, referenceless fog-aware image dehazing (FADE) [24], and natural image quality evaluator (NIQE) [25]. SSIM measures the similarity between two images, with values closer to 1 indicating a smaller gap between the recovered clear image and the real image, thus signifying better image quality. Information entropy estimates the richness and distribution uniformity of image information, with higher-quality images generally exhibiting higher information entropy. FADE evaluates visual quality, dehazing effects, and color fidelity, while NIQE measures image quality, with smaller values indicating higher image quality.

Table 1 presents the evaluation indices of clear images recovered by different algorithms using the natural image dataset. A smaller value of information entropy (Entropy) indicates better performance, while larger values of FADE and NIQE signify higher image quality. It is evident from the table that the clear images recovered by the algorithm proposed in this paper either rank as the best or the second best in terms of information entropy and FADE. Although the numerical value of NIQE may not be as favorable as other algorithms, notably the SLP algorithm, which exhibits the best performance, it is apparent that the proposed algorithm surpasses others in terms of visual quality. To further strengthen the comparison, this paper conducts additional testing of the proposed algorithm and other comparative algorithms on the public datasets I-HAZE and O-HAZE. Specifically, 34 images are randomly selected for evaluation, with SSIM serving as a reference index. Real images are required to participate in the evaluation of image quality. The indices of the test dataset are presented in Table 2, highlighting the excellent performance of the proposed algorithm across multiple performance indices, thereby asserting its superiority.

TABLE 2. Comparison of dehazing metrics for synthetic images.

Dataset	Technique	Entropy	SSIM	FADE	NIQE
I-HAZE	DCP	6.3896	0.4162	0.8487	3.2588
	IDE	7.2130	0.3722	0.6157	3.2691
	SLP	6.7807	0.5188	0.7418	3.3067
	Our	7.2266	0.4390	0.5486	3.2245
O-HAZE	DCP	7.0646	0.2596	0.4734	2.7930
	IDE	7.4551	0.2985	0.3408	3.1943
	SLP	7.1132	0.3206	0.4034	2.9253
	Our	7.5117	0.3407	0.3648	2.9510

TABLE 3. Comparison of ablation experiment indicators.

Ablated models	image	Entropy	FADE	NIQE
a	E1	7.3843	0.3611	2.8209
	E2	6.7954	0.1587	4.6822
	E3	7.2859	0.3412	2.1084
b	E1	7.5244	0.5405	2.8907
	E2	7.6361	0.1599	5.1789
	E3	7.2418	0.6011	1.9061
c	E1	7.5934	0.3261	2.9998
	E2	7.7418	0.1265	5.0201
	E3	7.5127	0.3349	2.6664

IV. ABLATION EXPERIMENT

To illustrate the effectiveness of each component of this paper's method, ablation experiments are performed on natural images, including (a) ASM model + dark channel prior, (b) improved ASM model + dark channel prior, and (c) improved ASM model + improved color correction dark channel prior. Table 3 quantitatively shows the results for different components in natural images, indicating that each component of the proposed algorithm contributes to the performance of the algorithm.

V. CONCLUSION

In this paper, we introduce a novel unsupervised single image dehazing algorithm comprising a color correction model and a dehazing model, yielding superior results. Through testing the algorithm on both real and synthetic image datasets, we demonstrate its superiority and robustness across varying degrees of haze. The integration of the color correction model effectively enhances color fidelity, resulting in clearer and more natural processed images. Simultaneously, the dehazing model efficiently removes haze from images and restores scene information, with the added benefit of the proposed algorithm not requiring training data, ensuring its high efficiency. By improving the visual quality and information transfer effect of images, our algorithm exhibits commendable performance and robustness, showcasing its potential value and wide-ranging applications. Experimental results affirm that in defogging based on the improved atmospheric scattering model, preprocessing foggy images with the color correction model significantly reduces the occurrence of color aberration and restores detailed information from the original image, leading to superior processing outcomes and visual appeal.

REFERENCES

[1] M. Ju, D. Zhang, and X. Wang, "Single image dehazing via an improved atmospheric scattering model," *Vis. Comput.*, vol. 33, no. 12, pp. 1613–1625, Dec. 2017.
[2] S. Santra, R. Mondal, P. Panda, N. Mohanty, and S. Bhuyan, "Image dehazing via joint estimation of transmittance map and environmental illumination," in *Proc. 9th Int. Conf. Adv. Pattern Recognit. (ICAPR)*, Dec. 2017, pp. 1–6.
[3] S. G. Narasimhan and S. K. Nayar, "Contrast restoration of weather degraded images," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 6, pp. 713–724, Jun. 2003.
[4] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 12, pp. 2341–2353, Dec. 2011.
[5] P. Ling, H. Chen, X. Tan, Y. Jin, and E. Chen, "Single image dehazing using saturation line prior," *IEEE Trans. Image Process.*, vol. 32, pp. 3238–3253, 2023.
[6] Q. Zhu, J. Mai, and L. Shao, "A fast single image haze removal algorithm using color attenuation prior," *IEEE Trans. Image Process.*, vol. 24, no. 11, pp. 3522–3533, Nov. 2015.
[7] R. R. Choudhary, K. K. Jisnu, and G. Meena, "Image DeHazing using deep learning techniques," *Proc. Comput. Sci.*, vol. 167, pp. 1110–1119, Jan. 2020.
[8] B. Cai, X. Xu, K. Jia, C. Qing, and D. Tao, "DehazeNet: An end-to-end system for single image haze removal," *IEEE Trans. Image Process.*, vol. 25, no. 11, pp. 5187–5198, Nov. 2016.
[9] B. Li, X. Peng, Z. Wang, J. Xu, and D. Feng, "AOD-Net: All-in-one dehazing network," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Oct. 2017, pp. 4780–4788.
[10] C. Lang, G. Cheng, B. Tu, C. Li, and J. Han, "Base and meta: A new perspective on few-shot segmentation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 45, no. 9, pp. 10669–10686, Sep. 2023.
[11] C. Lang, J. Wang, G. Cheng, B. Tu, and J. Han, "Progressive parsing and commonality distillation for few-shot remote sensing segmentation," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, 2023, Art. no. 5613610, doi: 10.1109/TGRS.2023.3286183.
[12] C. Lang, G. Cheng, B. Tu, and J. Han, "Few-shot segmentation via divide-and-conquer proxies," *Int. J. Comput. Vis.*, vol. 132, no. 1, pp. 261–283, Jan. 2024.
[13] G. Cheng, C. Lang, and J. Han, "Holistic prototype activation for few-shot segmentation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 45, no. 4, pp. 4650–4666, Apr. 2023.
[14] M. K. Othman and A. A. Abdulla, "Enhanced single image dehazing technique based on HSV color space," *UHD J. Sci. Technol.*, vol. 6, no. 2, pp. 135–146, Dec. 2022.
[15] S. Lee, S. Yun, J.-H. Nam, C. S. Won, and S.-W. Jung, "A review on dark channel prior based image dehazing algorithms," *EURASIP J. Image Video Process.*, vol. 2016, no. 1, pp. 1–23, Dec. 2016.
[16] M. Ju, C. Ding, Y. J. Guo, and D. Zhang, "IDGCP: Image dehazing based on gamma correction prior," *IEEE Trans. Image Process.*, vol. 29, pp. 3104–3118, 2020.
[17] H. Tang, Z. Li, R. Zhong, J. Zhang, and X. Fang, "Sky-preserved image dehazing and enhancement for outdoor scenes," in *Proc. IEEE 4th Int. Conf. Electron. Technol. (ICET)*, May 2021, pp. 1266–1271.
[18] M. Ju, C. Ding, W. Ren, Y. Yang, D. Zhang, and Y. J. Guo, "IDE: Image dehazing and exposure using an enhanced atmospheric scattering model," *IEEE Trans. Image Process.*, vol. 30, pp. 2180–2192, 2021.
[19] G. Buchsbaum, "A spatial processor model for object colour perception," *J. Franklin Inst.*, vol. 310, no. 1, pp. 1–26, Jul. 1980.
[20] C. O. Ancuti and C. Ancuti, "Single image dehazing by multi-scale fusion," *IEEE Trans. Image Process.*, vol. 22, no. 8, pp. 3271–3282, Aug. 2013.
[21] W. Zhang, P. Zhuang, H.-H. Sun, G. Li, S. Kwong, and C. Li, "Underwater image enhancement via minimal color loss and locally adaptive contrast enhancement," *IEEE Trans. Image Process.*, vol. 31, pp. 3997–4010, 2022.
[22] C. Ancuti, C. O. Ancuti, R. Timofte, and C. De Vleeschouwer, "I-HAZE: A dehazing benchmark with real hazy and haze-free indoor images," in *Proc. Int. Conf. Adv. Concepts Intell. Vis. Syst.*, Poitiers, France, Sep. 2018, pp. 620–631.
[23] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *IEEE Trans. Image Process.*, vol. 13, no. 4, pp. 600–612, Apr. 2004.
[24] L. K. Choi, J. You, and A. C. Bovik, "Referenceless prediction of perceptual fog density and perceptual image defogging," *IEEE Trans. Image Process.*, vol. 24, no. 11, pp. 3888–3901, Nov. 2015.
[25] A. Mittal, R. Soundararajan, and A. C. Bovik, "Making a 'completely blind' image quality analyzer," *IEEE Signal Process. Lett.*, vol. 20, no. 3, pp. 209–212, Mar. 2013.

WENQIANG YAN is currently pursuing the M.S. degree with the School of Intelligent Manufacturing and Control Engineering, Shanghai Polytechnic University, Shanghai, China. His current research interests include computer vision, image processing, machine learning, and deep learning.

LEI CUI (Member, IEEE) received the M.S. degree in control theory and control engineering from Shandong University, Shandong, China, in 2007, and the Ph.D. degree in control theory and control engineering from Shanghai Jiao Tong University, in 2012. She was with Shanghai Aircraft Manufacturing Company Ltd., from 2012 to 2014. Since 2014, she has been a Teacher of automation with Shanghai Polytechnic University. She was appointed as an Associate Professor, in 2019. She is engaged in the intelligent control of the production process, state monitoring, and fault early warning. She has presided over and participated in a number of projects, published more than 20 articles, and has been authorized with three patents for invention, and has authored three books.