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Integrating Haze Density Features for Fast Nighttime Image Dehazing

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ABSTRACT To date, much progress has been achieved on daytime image dehazing, yet the nighttime dehazing problem is still not well addressed. Different from the imaging conditions in the daytime, the ambient illumination in the nighttime hazy scene is usually not globally isotropic due to the non-uniform incident lights from multiple artificial light sources. Currently, almost all the existing nighttime dehazing methods use a certain kind of image priors, whereby these spatial filtering based priors are not widely applicable in nighttime hazy scenes. For example, the maximum reflectance prior (MRP) cannot handle the dark regions well and the dark channel prior (DCP) is not valid in the light source regions. In this paper, we propose an efficient and fast method for nighttime image dehazing. By exploring the visual properties of hazy images, we construct an effective linear model to build the connection between the transmission and multiple haze-relevant features. Towards solving this model, a data-driven approach is adopted to learn the unknown coefficients. Operating on the pixel level, this novel approach requires no further refinement of transmission map as used in those prior-based methods. In addition, aiming at solving the problem of halo effect around the light sources caused by MRP, we introduce a color-dependant MRP method for color correction. We demonstrate the effectiveness of our method on a number of experiments compared to the state-of-the-art nighttime dehazing methods.

INDEX TERMS Image dehazing, image restoration, color correction.

I. INTRODUCTION

The presence of daze can change color and degrade the quality of captured images. There are two main reasons for the degradation of hazy images. Firstly, the reflected light of an object is absorbed and scattered by the suspended particles in the atmosphere, resulting in the attenuation of reflected light energy, which leads to the reduction of image brightness and contrast; secondly, the ambient light such as sunlight is scattered by the scattering medium in the atmosphere to form the bright background. Usually, the intensity of the background light is greater than that of the reflected light, which results in blurred images. For applications such as computer vision systems [8]–[11], [27], [46], the input hazy images may lead to the incorrect output.

Recently, the issue of image dehazing has received considerable attention. Many single image dehazing methods have been developed based on the atmospheric scattering model [18]. The key idea that most methods share is the employment of various image priors, such as color attenuation prior [32], dark channel prior [16], and so on. These methods are effective when dealing with daytime hazy images, but they are not quite useful to recover nighttime hazy scenes. This is not surprising, as the imaging conditions of nighttime scenes are more complicated than that of daytime scenes. The daytime model assumes the ambient illumination is globally consistent, as sunlight is usually the only and primary light source in the daytime scenes. However, nighttime

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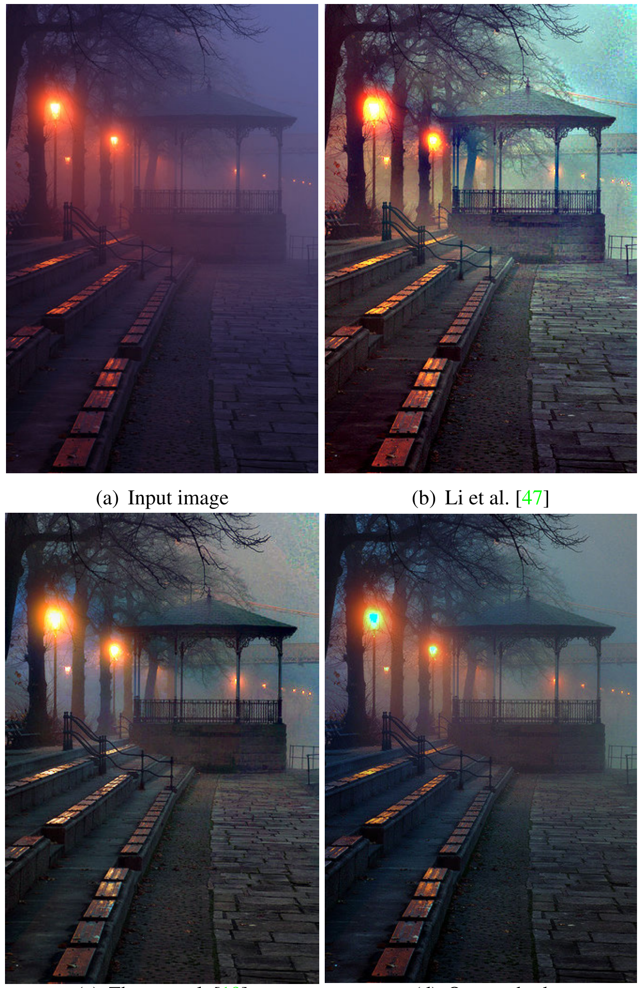
scenes generally have multiple active light sources, such as street lights, car lights, building lights, etc. These lights contribute to the scattering-in process and make the ambient illumination spatially variant, which make the atmospheric light cannot be simply obtained from the brightest region of the input image. Moreover, the traditional image priors are invalid in many nighttime scenes. For example, the dark channel prior is not able to handle the light source regions due to the high intensity values in all color channels.

To overcome the above difficulties, many new techniques have been developed, such as color transfer [31], glow removal [47], multi-scale fusion [2], maximum reflectance prior [19], pixel-wise blending [49], and so on. In this paper, we propose a novel and effective method for nighttime image dehazing. Considering the instinct nature of the night scene, we first introduce the nighttime haze imaging model [20]. Compared with the traditional model, this model replaces the constant atmospheric light with point-wise variables, which can explain the inhomogeneity of incident light intensity and color characteristics from different active light sources. According to [19], estimation of transmission, ambient illumination, and color factor are the key steps for nighttime haze removal. State-of-the-art nighttime image dehazing methods mostly adopt the prior-based methods which are frequently invalid in nighttime hazy scenes. By observing that hazy images at night are usually with low contrast, high brightness, and under-saturated, we propose to combine gradient, brightness, and saturation features into a linear model to estimate the transmission map. Since it is hard to manually decide the contribution of these three features, we adopt a data-driven approach to learn the weight of each component. For the color factor estimation, we propose a modified MRP method that operates each channel individually for color correction, which can reduce the halo effect around the light source areas caused by the original MRP. Based on the retinex theory, a self-guided filtering method is adopted to extract the low-frequency component as the estimation of the ambient illumination. This method is more theoretically convincing than the traditional local maxima method for the nighttime case. Experimental results demonstrate that our method can effectively restore the haze-free image from the input nighttime hazy images, as an example shown in Fig. 1. In addition, it has the benefit of alleviating the halo artifacts.

The contributions of our paper can be summarized as follows:

1) We introduce a novel color-dependant MRP for color correction, which can recover a halo-free hazy image with balanced colors and preserved edges.

2) Towards dealing with the nighttime dehazing model, a novel approach for estimating the transmission is proposed based on the inverse correlation between the transmission and haze density. It extracts haze-relevant features and integrates them in a linear learning model. This method operates on pixel-level without any non-linear spatial filtering, thus no further refinement step for the transmission map is required.



(a) Input image (b) Li et al. [47] (c) Zhang et al. [19] (d) Our method

FIGURE 1. The method of Yu *et al.* [47] and Jing *et al.* [19] produce artifacts at the light source and exhibit excessive noise in the sky areas. Our result shows reduced halos and looks more natural.

3) Instead of using the traditional local maxima, we introduce a self-guided filtering method for estimating the spatially-variant ambient lights.

II. RELATED WORKS

Currently, there have a variety of approaches to handle haze removal from a single daytime image. Most of these methods rely on the traditional atmospheric scattering model [18]. They have made remarkable achievements on processing of hazy images in the daytime. Those methods can be divided into two catagories. They either use traditional image enhancement techniques or prior-based computational models [6], [7], [12]–[14], [16], [24], [29], [30], [32], [36]–[44], [48], or learn a deep neural network for recovering the haze-free images [7], [23], [25], [26], [33], [50]. These methods cannot be directly applied to the nighttime dehazing problem due to its complex imaging conditions and the ineffective use of daytime image priors.

In recent years, more and more scholars have started to pay attention to the haze removal of nighttime images.

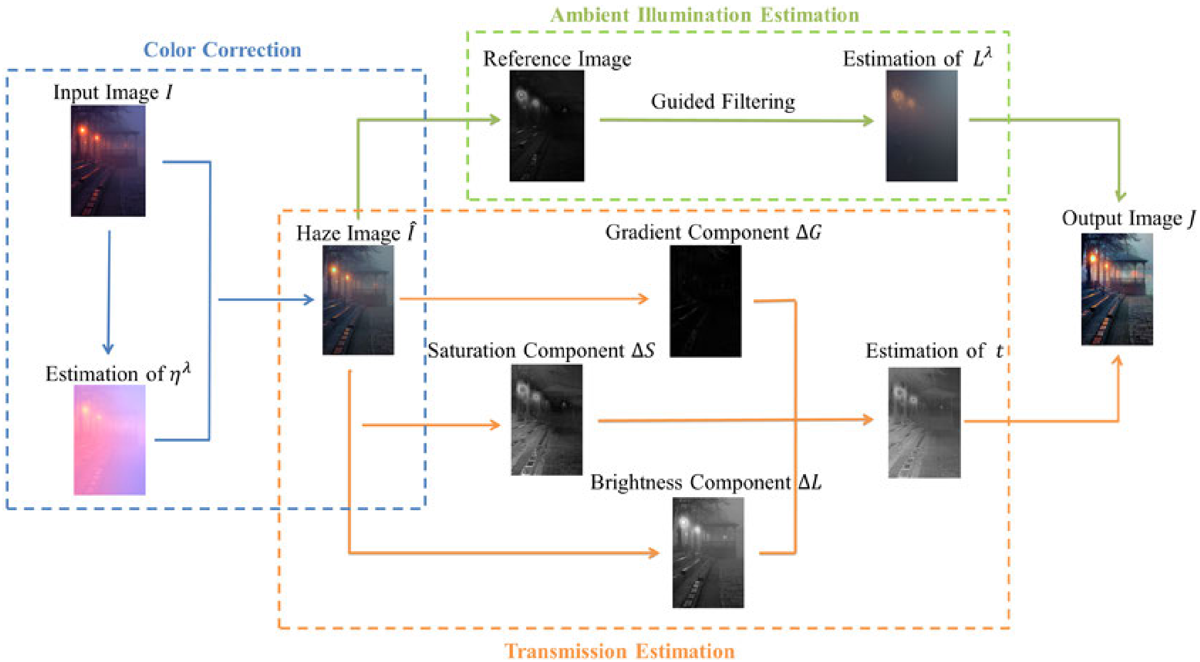


FIGURE 2. Flow chart of the proposed nighttime dehazing method.

Pei and Lee [31] propose a color transfer method to transform the colors of a nighttime hazy image into those of a daytime hazy image before applying the dark channel prior. While this approach improves the visibility of the image, the overall color of the output does not seem realistic. Jing *et al.* [20] propose a new nighttime haze imaging model for light compensation, color correction and haze removal. Since this method involves post-processing technique, some halo effects and glow often occur. Yu *et al.* [47] update the nighttime image model by adding the atmospheric point spread function to simulate the glow from the light source, and then use a layered algorithm to break down the glow contained in the input image. Their method produces fewer halo artifacts, but tends to produce excessive enhancement in the light source area. Ancuti *et al.* [2] estimate the airlight component on the patch of the image, and then use the multi-scale fusion method to recover the haze-free image. Jing *et al.* [19] propose to use the maximum reflectance prior to estimate the ambient illumination, which is based on an assumption that for the daytime haze-free image patches, the maximum intensity value of each color channel is 1. Very recently, Yu *et al.* [49] adopt the method of pixel-wise alpha blending for estimating the transmission maps by estimating the light source area and the non-light source area respectively, and then blend them effectively.

Recently, more and more attention has been paid to the application of deep learning in image dehazing and low illumination image enhancement. An image enhancement method for low light image is proposed by Guo *et al.* [15], which is a simple yet effective method. First, they estimate the illumination of each pixel individually by finding the maximum value in three channels, and then refine the initial illumination image by adding a structure as the final illumination image. Kuanar *et al.* [21] propose a CNN based DeGlow model, which is able to remove the glow effect significantly and a separate DeHaze network is included to remove the haze effect. Shi *et al.* [35] develop a rainy image model to describe rainy scenes at night with low illumination and propose a joint deep neural network-based method. Wei *et al.* [45] collect a Low-Light dataset (LOL) containing low/normal-light image pairs and propose a deep Retinex-Net learned on this dataset, including a Decom-Net for decomposition and an Enhance-Net for illumination adjustment. Based on the decomposition, subsequent lightness enhancement is conducted on illumination by an enhancement network called Enhance-Net.

Most of those mentioned nighttime dehazing methods rely on certain image priors such as DCP and MRP, whereby these image priors are not always valid in nighttime images. In our method, instead of applying image priors, we propose to remove the haze effect by exploring the nature of hazy images and adopt a data-driven approach by learning haze density relevant features for transmission estimation.

III. NIGHTTIME DEHAZING

The flow chart of our proposed nighttime dehazing method is illustrated in Fig. 2. Details for each step are presented in the following subsections.

A. ATMOSPHERIC SCATTERING MODEL FOR NIGHTTIME HAZE ENVIRONMENT

For daytime hazy scenes, the most commonly used optical model is the atmospheric scattering model. The model is

(a) Hazy Image (b) Zhang et al. [19] (c) Our method

FIGURE 3. An example for color correction. (a) Input nighttime image. (b) Zhang's color-corrected haze image. (c) Our result.

expressed as

$$I(x) = J(x)t(x) + L_\infty(1 - t(x)). \tag{1}$$

The first term is the light that the reflected light of the object reaches the camera after passing through the attenuation of particles and the second term is the atmospheric light from the light source (illumination) scattered by the particles. $I(x)$ is the hazy image captured by the camera and $J(x)$ is the haze-free image to be recovered. L_∞ is the value of atmospheric light at infinity, which is assumed to be globally uniform. The transmission $t(x) = e^{-\beta d(x)}$ denotes the proportion of light that can reach the camera after attenuation. β is the scattering coefficient and $d(x)$ is the distance from the scene point to the camera. The parameter x represents the position of the pixel in the image.

Most researchers take the above atmospheric scattering model as the theoretical model for daytime image dehazing. This model shows its effectiveness for daytime image dehazing, especially when coupled with the dark channel prior (DCP) [16]. However, the light sources of the night image are mainly various artificial lights and the moonlight, which are different from that of the the day image illuminated by the single source (sunlight).

According to retinex theory [22], the image of an object seen by the observer is acquired through the reflected incident light from the object surface, and the reflectivity is determined by the object itself, which is invariant to the incident light. Mathematically, it can be expressed as $J(x) = A(x)R(x)$, in which $A(x)$ is the ambient illumination map and $R(x)$ is the scene reflectance. Based on the above analysis, we can rewrite (1) as

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

B. COLOR CORRECTION

Haze usually blurs the image and makes the color of the image distorted. The color correction for nighttime hazy images is a critical step. Eq. (2) can be expressed as

$$I(x)^\lambda = L^\lambda \eta^\lambda R(x)t(x) + L^\lambda \eta^\lambda (1 - t(x)), \tag{3}$$

where $A(x) = L^\lambda \eta^\lambda$ is the ambient illumination. L^λ is the intensity of ambient illumination, and η^λ is the color map of the ambient illumination. λ represents one of the RGB channels. Since for most images, $R(x)$ lies in the range of [0,1] [20] and according to the statistics of a large number of outdoor haze-free images, the maximum intensity in a local patch is close to 1 for each color channel [19]. Mathematically, it is expressed as

$$R(x) = \max_{i \in \omega(x)} R^\lambda(i) \to 1, \quad \lambda \in \{r, g, b\}. \tag{4}$$

Based on these observations, Jing *et al.* [19] propose a method using the maximum reflectance prior (MRP) to remove the color effect from the input nighttime images. However, Zhang's method does not deal with the light source area well and frequently produces halos in the light source area. Therefore, we propose a novel color correction method based on the MRP named color-dependant MRP. We first obtain the maximum channel of an input image, i.e., applying a max-operator on both side of Eq. (3) within each local patch $\omega(x)$. In particular, after filtering the image with haze to its maximum channel map, we refine each color channel by using the guided filtering [17]. This ensures that the edge of the image is well preserved during local maximum filtering. The intensity L^λ is fixed to the maximum of the image after guided filtering in all color channels. It is worth noticing that this approach differs from MRP in that the method we propose here is color dependent. Fig. 3 shows that for the input image after color balance operation, the method of Jing *et al.* [19] enlarges the light source area, which is alleviated by our method.

After obtaining the estimate of η^λ, we can remove the color effect from the input image and rewrite Eq. (3) as

$$\widehat{I(x)} \triangleq I(x)^\lambda / \eta^\lambda = J(x)^\lambda t(x) + L^\lambda (1 - t(x)). \tag{5}$$

(a) (b) (c) (d)

FIGURE 4. (a) The color-corrected haze image. (b) The gradient component map. (c) The brightness component map. (d) The saturation component map.

where $\widehat{I(x)}$ denotes the haze image with color balanced. $J(x)^{\lambda} = L^{\lambda}R(x)$ is the nighttime haze-free image that ultimately needs to be recovered.

C. TRANSMISSION ESTIMATION

After the color correction, the key steps to remove haze from a single hazy image are estimating the ambient illumination map and the transmission map.

Unlike the hazy images captured at daytime, there are often multiple light sources in the hazy images at nighttime. Previous methods have been attempted to handle using one image prior, such as the DCP. With this prior, the transmission map can be directly estimated, and further restore the haze-free image via the atmospheric scattering model. Although the DCP is effective in most cases, it is not valid in the light source regions.

In this work, instead of using image priors, we propose a novel method to estimate the transmission map. Based on the characteristics of hazy images, our method extracts three image features related to the haze density. Theoretically, haze has the property of high brightness, low saturation, and flatness. Hence, for an input hazy image, we can describe it by the brightness component ΔL, the saturation component ΔS, and the gradient component ΔG, as shown in Fig. 4. We define the haze density as

$$H(x) = e^{-\alpha(\Delta G(x))^2} \times e^{-\gamma(1-\Delta L(x))^2} \times e^{-\mu(\Delta S(x))^2}. \quad (6)$$

Considering the fact that the transmission is inversely proportional to the haze intensity, we construct a linear model between the transmission and the haze-aware density feature as

$$t(x) = a - \varphi H(x). \quad (7)$$

In Eq. (6) and Eq. (7), there are many unknown coefficients to be solved.

As a step towards solution, we adopt a learning method to learn the unknown coefficients precisely, in which we collect a large number of images of nighttime haze from D-HAZY dataset [1]. Since this database is all about daytime images, we change it to night images by reducing the brightness and contrast. Considering that the transmission is only related to depth, it does not need to be changed. Fig. 5 shows a sample of a nighttime hazy image using the D-HAZY dataset. According to Marquardt [28], our training model can be described using quadratic loss function as

$$E = \sum_{i=1}^{n}\sum_{x=1}^{|l_i|}\sum_{y=1}^{|w_i|}(a - \varphi H_i(x, y)). \quad (8)$$

where n is the number of training samples, and $|l_i|$, $|w_i|$ denote the height and the width of the ith sample. After training, the final learning results are that $\alpha = 2.7563$, $\gamma = 0.6567$, $\mu = 3.3801$, $a = 0.84$, and $\varphi = 0.6342$. Once these unknown coefficients have been determined, they can be used to estimate the transmission map by Eq. (6) and Eq. (7). Fig. 6 shows the transmission map estimated by our algorithm. More importantly, since our estimation of the transmission is processed in a pixel-wise way, the subsequent refinement processing of quadratic optimization can be eliminated, which greatly saves the running time. Therefore, our method is computationally efficient.

It is noteworthy that Eq. (6) in our paper uses a similar fusion form as the one used in Ancuti *et al.*'s underwater image enhancement method [5], and they all contain a saturation component. However, our other two components (gradient and brightness components) are different from what they use (laplacian and saliency components), since we choose our features based on the fact that hazy images are usually under-saturated, low contrast, high brightness. The gradient component we use is the first derivative whereas they emphasize on the edge information by applying a second

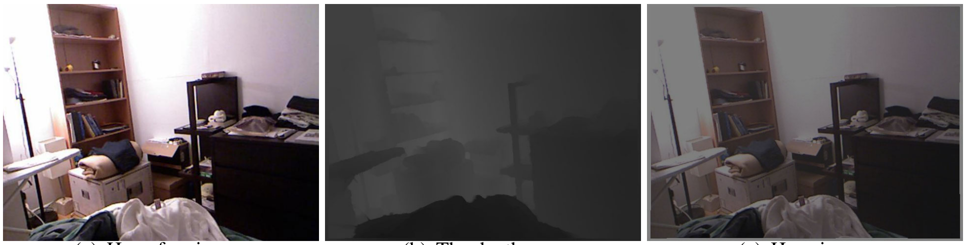


FIGURE 5. An example from the D-HAZY dataset.

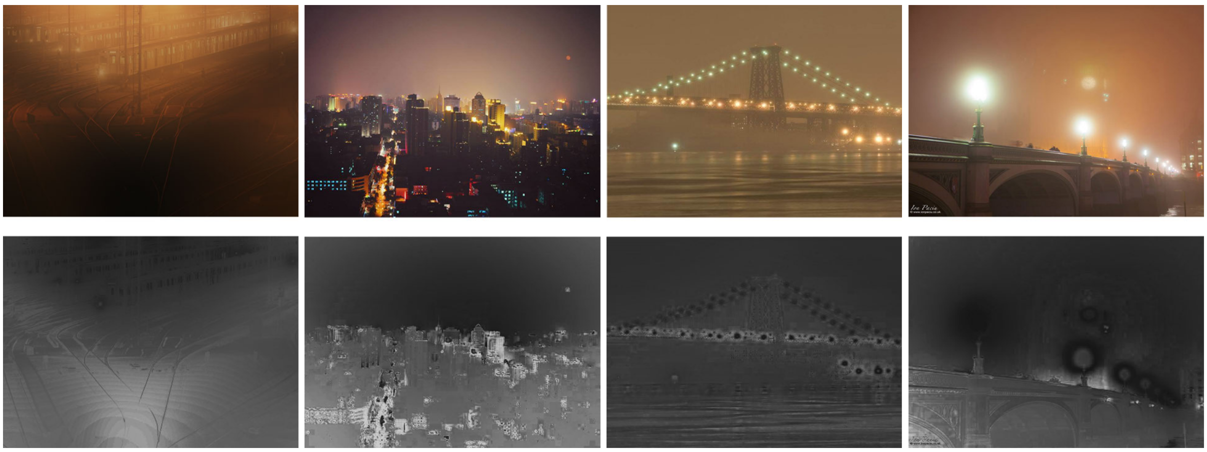


FIGURE 6. Example images and the estimated transmission maps. Top row: the input hazy images. Bottom row: the transmission maps are estimated using Eq. (6) and Eq. (7).

derivative operator, i.e., the laplacian component. In addition, the weights in our formula are obtained through a learning model rather than the hand-designed weights computed in their method.

D. DEHAZING

At nighttime scenes, the atmospheric light is spatially variant. Base on the assumption that the atmospheric lights are the main components of the low frequency part of an nighttime hazy image [49], we use a self-guided filter to estimate the atmospheric light intensity L^{λ}, in which the image after color correction itself servers as both the reference image and target image. It extracts the low frequency part, i.e, the atmospheric light intensity L^{λ}, as well as preserves the main edge structures of the input image. In this way, after obtaining the estimation of L^{λ} and $t(x)$, we are able to recover the haze-free image from Eq. (9).

$$J(x)^{\lambda} = \frac{\widehat{I(x)} - L^{\lambda}(1 - t(x))}{\max(t(x), t_0)}, \tag{9}$$

where t_0 is a small value to avoid producing too much noise. For better visualization, we conduct the gamma correction as a post processing.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

To prove the effectiveness of our proposed approach, we collect hazy and foggy night images of various quality and file formats from the published articles and conduct a series of experiments, comparing them with the state-of-the-art methods [19], [33], [47], [49]. We evaluate the dehazing results of the same images used in existing studies both in subjective and objective ways. To be fair, all of the code used for comparison come from the original code provided by the authors on their websites. Our experiment consists of four parts: qualitative comparison of nighttime image, quantitative evaluation of experimental results, computational complexity and running time, and dehazing results of daytime image. In our experiments, the size of local patch is fixed to 15×15. The kernel sizes of guided filter for ambient illumination estimation and color correction are 64 and 100, respectively, and the smoothing coefficients of both are set to 0.01. t_0 is set to 0.1.

A. QUALITATIVE COMPARISON OF NIGHTTIME IMAGE

To demonstrate the effectiveness of the proposed dehazing method, we present the dehazing results on real nighttime hazy images. Recently, a lot of methods based on deep learning have been proposed to remove haze, but they are only effective for daytime images and not for nighttime scenes. In order to make the experimental results more reliable, we also include some typical deep learning methods, although they are designed for daytime scenes, such as Qu *et al.* [33]. The visually inspected results are shown in Fig. 7 (b)-(f), and

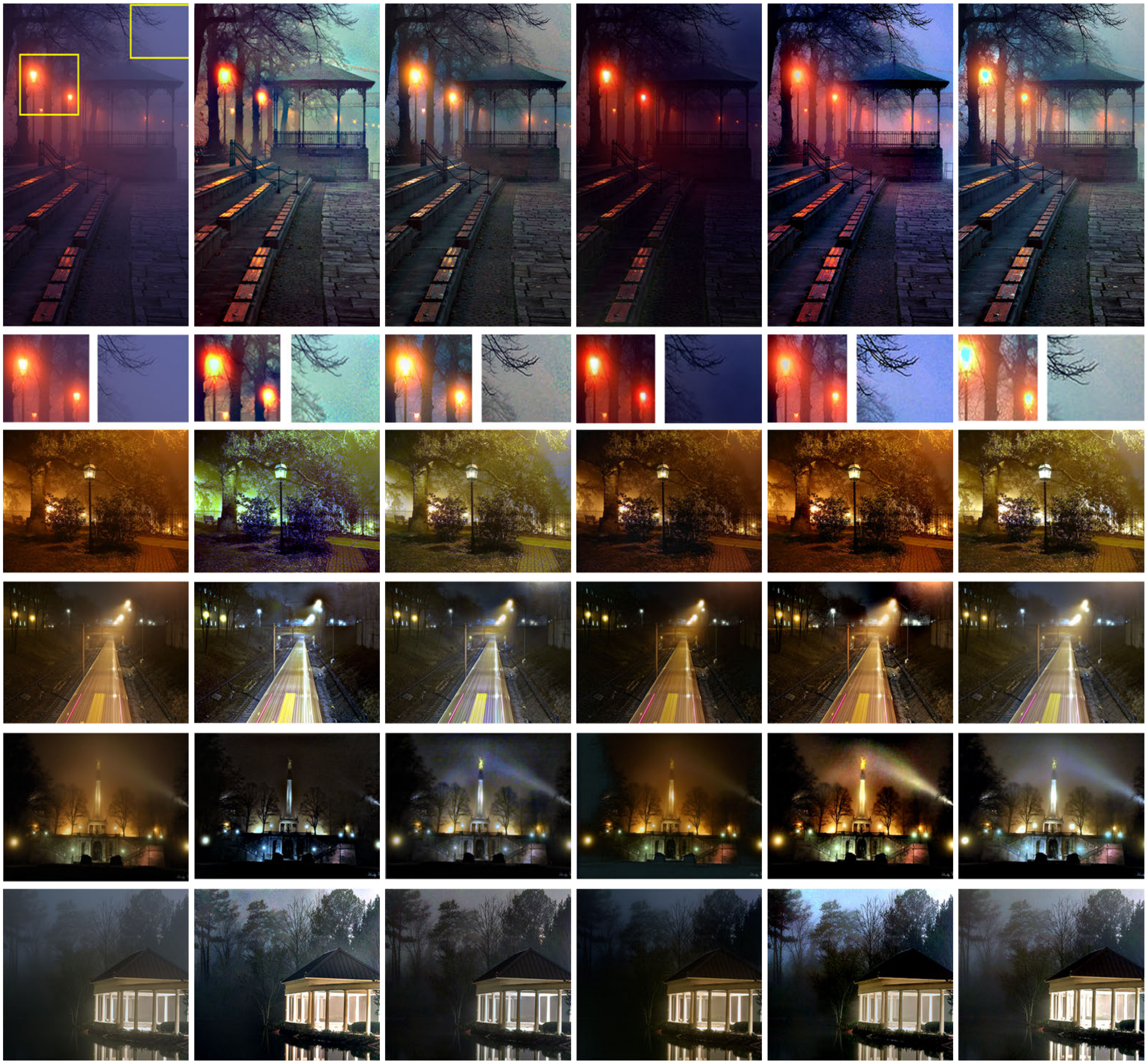


FIGURE 7. The visual comparisons of haze removal effect of real images.

some close-up views of the dehazing results are shown in the second line.

As can be seen in Fig. 7, Yu *et al.*'s [47] and Jing *et al.*'s [19] methods do not handle the light source area well and may produce color artifacts or over-magnification (see the zoom-in views in Fig. 7). Our method can keep the original shapes and edges of the light sources better. When looking at the sky area, we can find that Zhang *et al.*'s and Li *et al.*'s methods tend to produce excessive color distortions and noises, while our method can reduce these distortions and noises in the process of removing haze. In the third image, we can clearly see that Li *et al.*'s method produces color distortion and changes the original color on leaves and low bushes, and Zhang et al's method produces excessive noise in the sky area. In the fourth image, Zhang *et al.*'s, Li et al's and our methods all keep the edge of the light source area well. Zhang *et al.*'s method has better visibility in the light source area, but both of their methods produce color distortions in the sky areas. In the latter two images, our method shows a good effect of haze removal and the preservation ability of the original color.

Although both the deep learning-based method [33] and the Yu *et al.*'s [49] method can well maintain the edge of the light source area, the former is not able to adequately remove

(a) (b) (c) (d) (e)

FIGURE 8. **(a) The synthetic nighttime hazy images. (b) The original images. (c) The result of Yu *et al.* [47]. (d) The result of Jing *et al.* [19]. (e) Our method.**

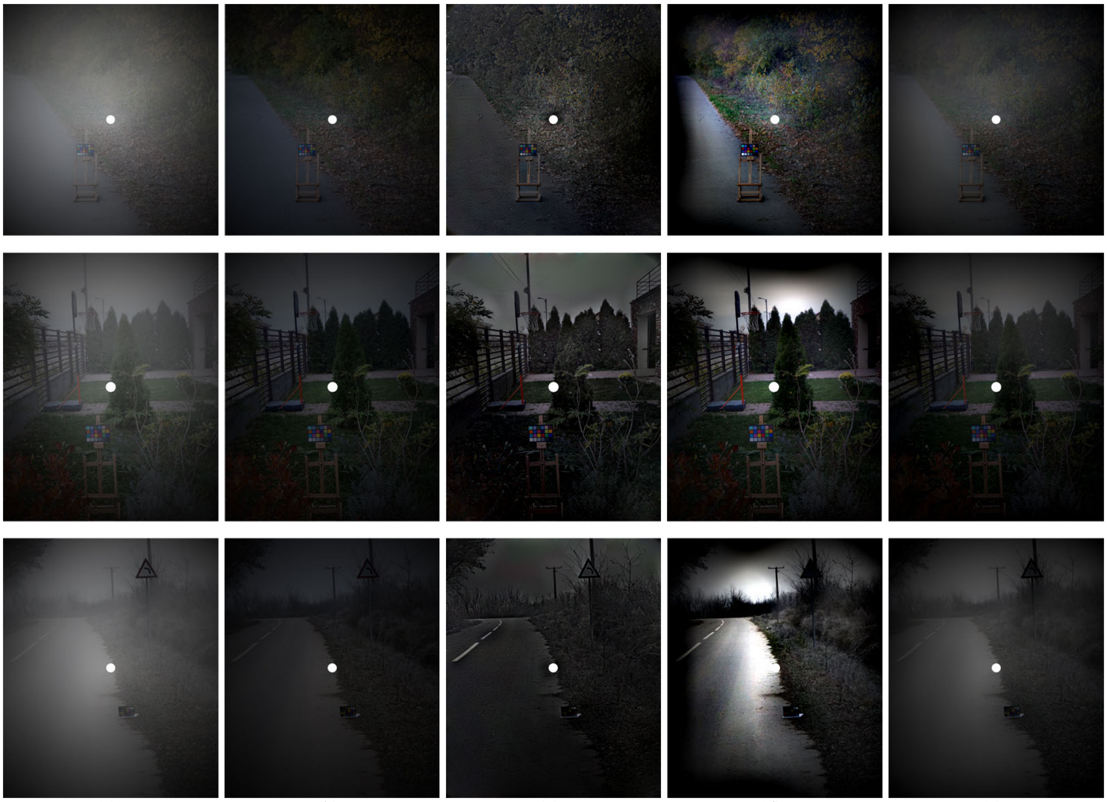
(a) (b) (c) (d) (e)

FIGURE 9. **(a) The hazy images from the I-HAZE dataset. (b) The realistic images. (c) The result of Yu *et al.* [47]. (d) The result of Jing *et al.* [19]. (e) Our method.**

the haze to restore the visibility of the image, and the latter can not well restore the original color of the image, as shown in Fig. 7 (d)-(e). Note that the proposed method does not always eliminate some blurring effects of the texture areas, but it looks more visually impressive because of the removal of the chroma distortion. Therefore, in general, our proposed method is comparable to state-of-the-art method on removing haze for the nighttime images.

B. QUANTITATIVE EVALUATION OF EXPERIMENTAL RESULTS

In order to further prove the reliability of our method, we make a quantitative comparison of the synthetic hazy images. We apply two metrics, i.e., SSIM and PSNR of the dehazeing results for comparison. The Middlebury 2005 and 2006 datasets [34] are used to synthesize the nighttime hazy images. Inspired by the Yu *et al.*'s [49] method, we select the ground truth clear images and disparity maps to simulate the real nighttime scene with light sources. We calculate the lighting intensity of the scenic spot as $L^{\lambda} = 1 - \alpha d(x)$, where α is the synthesis coefficient and $d(x)$ is the normalized distance from a scene spot to the center of the light source. The transmission map is expressed as $t(x) = 0.8d$, where d is the normalized disparity map. We then take the original real image as the reflectivity R and assume that the light source is at the center of the image. In the end, we generate the image of nighttime hazy images according to Eq. (3). In the following



(a) (b) (c) (d) (e)

FIGURE 10. (a) The hazy images from the O-HAZE dataset. (b) The realistic images. (c) The result of Yu *et al.* [47]. (d) The result of Jing *et al.* [19]. (e) Our method.

TABLE 1. SSIM and PSNR values for the dehazing results of synthetic images.

Methods		Li et al. [47]			Zhang et al. [19]			**Our Method**	
α	0.5	0.7	0.9	0.5	0.7	0.9	0.5	0.7	0.9
Metrics	SSIM PSNR	SSIM PSNR	SSIM PSNR	SSIM PSNR	SSIM PSNR	SSIM PSNR	SSIM PSNR	SSIM PSNR	SSIM PSNR
Art	0.36 08.31	0.36 10.12	0.43 14.70	0.39 11.26	0.41 12.72	0.44 14.16	0.49 13.30	0.51 14.49	0.53 15.44
Books	0.56 11.86	0.55 13.19	0.65 19.04	0.59 13.85	0.65 15.89	0.69 17.89	0.77 19.09	0.78 20.47	0.78 21.72
Dolls	0.39 11.00	0.40 13.23	0.52 18.72	0.37 12.75	0.38 14.26	0.43 16.04	0.50 17.23	0.52 18.59	0.56 19.87
Laundry	0.35 09.10	0.39 11.63	0.54 18.95	0.33 11.40	0.38 13.26	0.43 15.02	0.48 15.79	0.50 17.12	0.52 18.11
Moebius	0.38 10.31	0.41 12.47	0.61 20.73	0.36 11.32	0.44 13.10	0.51 14.77	0.61 16.63	0.63 17.41	0.65 18.02
Reindeer	0.23 08.61	0.28 10.88	0.32 15.86	0.25 11.11	0.28 12.40	0.33 13.81	0.33 13.26	0.35 14.20	0.37 15.04
Rock	0.30 12.28	0.30 14.54	0.41 18.70	0.19 11.90	0.21 13.56	0.25 15.19	0.29 15.09	0.30 16.27	0.33 17.36
Midd	0.29 07.87	0.29 09.51	0.32 13.77	0.23 09.69	0.26 11.43	0.30 13.14	0.36 12.53	0.38 13.84	0.40 14.99
Average	0.36 09.92	0.37 11.95	0.48 17.56	0.34 11.66	0.38 13.33	0.43 15.00	**0.48 15.38**	**0.49 16.55**	**0.52 17.57**

experiment, we set α as 0.5, 0.7 and 0.9 and use the images synthesized by these three parameters for more objective comparison. Fig. 8 shows examples for dehazing results using the synthetic images. Furthermore, we collect images from the I-HAZE dataset and the O-HAZE dataset for quantitative evaluation of experimental results [3] [4]. Since our algorithm is dedicated to solve the problem of night image, and these two databases only contain the images captured in the daytime, we modify these images into nighttime ones. The first step is taking the daytime haze image as the input and using the method of dark channel prior to figure out the transmission map. Then, we reduce the brightness and contrast of the ground truth image as the nighttime haze-free image. Finally, the image of night haze is synthesized using the method mentioned above. Some visual experimental results of different methods are shown in Fig. 9 and Fig. 10. The SSIM and PSNR values of different methods against our method are shown in Table 1 and Table 2 for the quantitative comparison results. We can see that our method achieves the maximum values of SSIM and PSNR, which indicates the superiority of our proposed method.

C. COMPLEXITY AND RUNNING TIME

In addition, the proposed method has the advantage of high calculation efficiency. In the whole process of restoring the original image, we use three times of guided filtering with complexity O(N). In estimating the color map η^{λ} with color correction, we use the Max/Min operation. Since the

(a) Hazy Image (b) He et al. [16] (c) Berman et al. [6] (d) Qu et al. [33] (e) Our Method

FIGURE 11. The visual comparisons of haze removal effect of daytime images.

Max/Min operation we perform is for all color channels, and the number of channels and the size of local patch are fixed, the output of the operation is a linear function of the input, whose complexity is O(N). In order to compare with other methods, we use Matlab to analyze the running time of our experiment. Li *et al.*'s code is from their webpage and Zhang *et al.*'s code is provided in C++. In order to make the experimental results more convincing, we rewrite their methods in Matlab, completely following the experimental steps and parameters provided by them. In order to make the experimental results more general, we adjust the 50 input images into three different sizes, 320×240, 640×480 and 1280×720, and take the average of the three experimental results as the final result, as shown in Table 3. One can see that our method is almost 30 times faster than Li *et al.*'s method, and a little bit faster than Zhang *et al.*'s method.

D. DEHAZING RESULTS OF DAYTIME IMAGE

What's more, the method proposed not only has a good effect on removing haze for nighttime images, but also has a pleasant effect on daytime image dehazing. To illustrate the effectiveness of our approach for daytime scenarios, we compare our method with He *et al.*'s method [16], Qu *et al.*'s method [33] and Berman *et al.*'s method [6], as shown in Fig. 11. Our experimental results are obtained through direct de-hazing of the original image without color correction, in which the estimation of the transmission is based on the

TABLE 2. SSIM and PSNR values for the dehazing results of realistic images.

Methods	Li et al. [47]				Zhang et al. [19]				**Our Method**			
Datasets	I-HAZE		O-HAZE		I-HAZE		O-HAZE		I-HAZE		O-HAZE	
Metrics	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR
01	0.62	21.36	0.65	23.30	0.53	14.30	0.60	19.36	0.85	25.25	0.79	23.94
02	0.59	22.35	0.66	21.81	0.47	15.21	0.73	17.73	0.78	24.51	0.77	28.44
03	0.64	23.96	0.39	18.55	0.56	16.29	0.55	19.25	0.66	20.47	0.83	25.80
04	0.61	22.13	0.72	25.07	0.48	16.36	0.49	13.09	0.64	19.78	0.87	23.39
05	0.69	22.41	0.75	26.78	0.51	17.29	0.40	14.16	0.85	24.46	0.58	17.01
Average	0.63	22.84	0.63	23.10	0.51	15.89	0.56	16.72	**0.76**	**22.89**	**0.77**	**23.72**

TABLE 3. Results of runtime evaluation.

Methods	Li et al. [47]	Zhang et al. [19]	**Our Method**
320×240	07.15	0.39	0.36
640×480	29.61	1.28	1.08
1280×720	89.27	3.00	2.81
Average	42.01	1.56	**1.41**

method integrating the haze density proposed above, and the estimation of atmospheric light is based on the method used in the dark channel prior approach [16]. In Fig. 11, we can visually observe the superiority of our approach. Our method can well restore the color of the image itself, and look more natural and vivid than other methods. For the image containing large sky region, method of Berman *et al.* [6] produces obvious noise in the sky region, while our method can effectively alleviate the noise.

We agree that our method benefits from the assembling of several algorithms when compared with those one-step image enhancement methods. However, our method is still computationally efficient compared with the state-of-the-art nighttime dehazing methods as in Table 3, since our proposed method for transmission estimation is a pixel-level operation, avoiding the refinement step caused by the block-level operation in most of the existing methods.

V. DISCUSSIONS AND CONCLUSION

In this paper, we propose a fast and effective method to remove the haze and restore the original colors from the nighttime hazy images. Instead of using those image priors that are invalid in many nighttime scenes, our approach utilizes the visual properties of hazy images and integrates three haze-relevant features into a linear model for transmission estimation, followed by a learning approach for solving the unknown coefficients. This pixel-wise approach requires no further refinement and avoids the failure cases of those prior-based methods. In addition, a novel color correction method has also been developed to avoid halo effect around the light sources. Both the qualitative and quantitative experimental results demonstrate that our proposed method is superior to the state-of-the-art nighttime image dehazing methods, and it also provides a novel thought for image dehazing other than the widely used image priors. However, our methods also shares the limitations as most of the methods using atmospheric scattering model, like that the model is not sophisticated enough to handle some heave hazy and complex scenes. We will continue to work on developing more parametric and more advanced models for image dehazing in the future.

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