IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 6, 2019, accepted August 14, 2019, date of publication August 19, 2019, date of current version August 29, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2936049

Nighttime Single Image Dehazing via Pixel-Wise Alpha Blending

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This work was supported in part by the National Natural Science Foundations of China under Grant 61772277, in part by the National Key Research and Development Program under Grant 2017YFC0804002, and in part by the Natural Science Foundation of Jiangsu Province under Grant BK20171494.

ABSTRACT In this paper, we propose a novel method to address the nighttime single image dehazing problem. Estimation of the ambient illumination map and transmission map are the key steps of modern dehazing approaches. For hazy scenes at night, ambient illumination is usually not globally isotropic as a nighttime scene typically contains multiple light sources. Frequently, Light source regions and non-light source regions exhibit distinct color features. However, existing nighttime dehazing methods have been attempting to process these two regions based on identical prior assumptions. Moreover, the commonly-used local maximum pixel method tends to over-estimate the ambient illumination. These two drawbacks result in color distortions and halo artifacts around the light source regions in the output images. In this work, we present a pixel-wise alpha blending method for estimating the transmission map, where the transmissions estimated from dark channel prior (non-light source region) and the proposed bright channel prior (light source region) are effectively blended into one transmission map guided by a brightness-aware weights map. Based on the Retinex theory, a channel difference guided filtering method is proposed to estimate the ambient illumination, which produces a spatially variant low-frequency passband that selectively retains the high-frequency edge details. Extensive experiments on the benchmarks demonstrate that our method outperforms the state-of-the-art methods for nighttime image dehazing, especially in terms of color consistency and halo artifacts reduction in the dehazed images.

INDEX TERMS Nighttime image dehazing, image restoration, alpha blending.

I. INTRODUCTION

Images or videos captured at foggy or hazy weathers are usually degraded due to the presence of suspended particles and water droplets in the air. With lower contrast and faded colors, hazy images show poor visual appearance and visibility. It leads to decreased performance of many computer vision applications, such as object detection, saliency detection, and so on [4]–[6], [31].

In recent years, the problem of daytime image dehazing has received extensive attention. Many image dehazing methods have emerged, including the image enhancement-based methods and the model-based methods. However, when these methods are directly applied to the hazy images captured at night, the performance is often unsatisfactory [22]. The main difference between daytime dehazing methods and nighttime dehazing methods is the ambient illumination term. It is a constant value at daytime dehazing model since sunlight is usually the only and dominate light source at daytime scenes, making the ambient illumination spatially uniform. However, the ambient illumination is spatially variant due to the scattering of multiple light sources. The widely-used priors in daytime dehazing methods are no longer appropriate for the nighttime scenes. For example, the well-known dark channel prior (DCP) would mostly fail around the light source regions of an image.

The existing methods for nighttime image dehazing [1], [12], [13], [22], [29] typically achieve improved dehazing

The associate editor coordinating the review of this article and approving it for publication was Huimin Lu.

performance by using image enhancement technique [22] or modifying the daytime models, for example, by introducing variable ambient illumination [13], glow factor [29], reflectance [12], and so on.

However, these above methods tend to over-estimate the ambient illumination, because they simply extend the bright pixel method used in daytime dehazing in a local manner, with either fixed or adaptive filtering window size. The theoretical basis behind it lies in that the bright pixel comes from sky regions corresponds to the infinite depth and 0 transmission, thus the ambient illumination is very close to the bright pixel in sky regions according to the atmospheric scattering model [9]. But when using this idea with local bright pixel as the ambient illumination in nighttime hazy scenes, the estimation is not accurate, because most of the local windows do not contain the sky regions. In addition, the widely used dark channel prior in the existing methods is not valid in the light source regions, since no dark channel exists in white lights area with high intensity values. As a result, these methods tend to produce unwanted artifacts, such as color distortions and halos, in the output images.

In this paper, to address these existing problems resulted by inaccurate ambient illumination estimation and invalid prior assumption in light source regions, we present a novel method for nighttime dehazing. Based on the retinex theory [14], [15], [28], we first estimate the ambient illumination map through a low-pass filter [10] guided by a channel difference map. For the transmission estimation, we process the light source regions and non-lights source regions using two distinct channel priors, i.e. the dark channel prior and a novel bright channel prior (BCP). Then, the two estimated transmission maps are subsequently fused together using the proposed pixel-wise alpha blending in a brightness-aware manner, to produce the final transmission map. In the end, the dehazed image are obtained through the nighttime atmospheric scattering model with the estimated illumination map and transmission map. Experimental results indicate that the dehazed results by our proposed method can better keep the color consistence, present less noise and reduce halo artifacts compared to the state-of-the-art algorithms. Fig. 1 shows a simple comparison example.

The contributions of our paper can be summarized as follows:

1. Hazy images captured at night have spatially variant ambient illumination due to the scattering of multiple light sources. Rather than simply using the local maximum pixel as done in the existing methods, we reformulate the atmospheric scattering model into a Retinex-like model, so that high quality ambient illumination can be estimated using a low-pass filter. By proposing a channel difference map as the guidance for filtering, the output can obtain the local low-frequency passband as well as retain the edge details. This method is more theoretical sound and provides a novel way for ambient illumination estimation at nighttime hazy scenes.

2. Based on the fact that a nighttime hazy scene usually contains multiple light sources, we propose a novel assumption named bright pixel prior to compute the transmission for the light source regions. By blending the transmission maps using DCP and BCP in a brightness-aware manner, the estimated transmission map contributes to dehazed images that are visually more pleasant with much less color distortions and halos. This novel idea treats the light source regions and non-light source regions with separate prior assumptions, which guarantees a boundary and shape preserving restoration of the light source regions.

(a) Hazy image (b) Li et al. (ICCV'15) [29]

(c) Zhang et al. (CVPR'17) [12] (d) Our method

FIGURE 1. (a) Input hazy image. (b)-(d) Dehazing results of Li et al. [29], Zhang et al. [12], and our method, respectively. (b) and (c) produce halos around the light sources, exhibits excessive noise in the sky areas, and fail to recover the consistent colors with the input.

II. RELATED WORKS

Currently, most of the daytime haze removal methods [2], [3], [3], [7]–[9], [16]–[21], [23], [24], [26], [27], [30], [32] are based on the atmospheric scattering model [11], the model is either solved by image priors [2], [8], [9], [17], [20], [21], [23], [30] or using a learning framework [3], [16], [18], [19], [24], [27], [32]. They have achieved pleasant dehazing results at daytime scenes. However, when these methods are

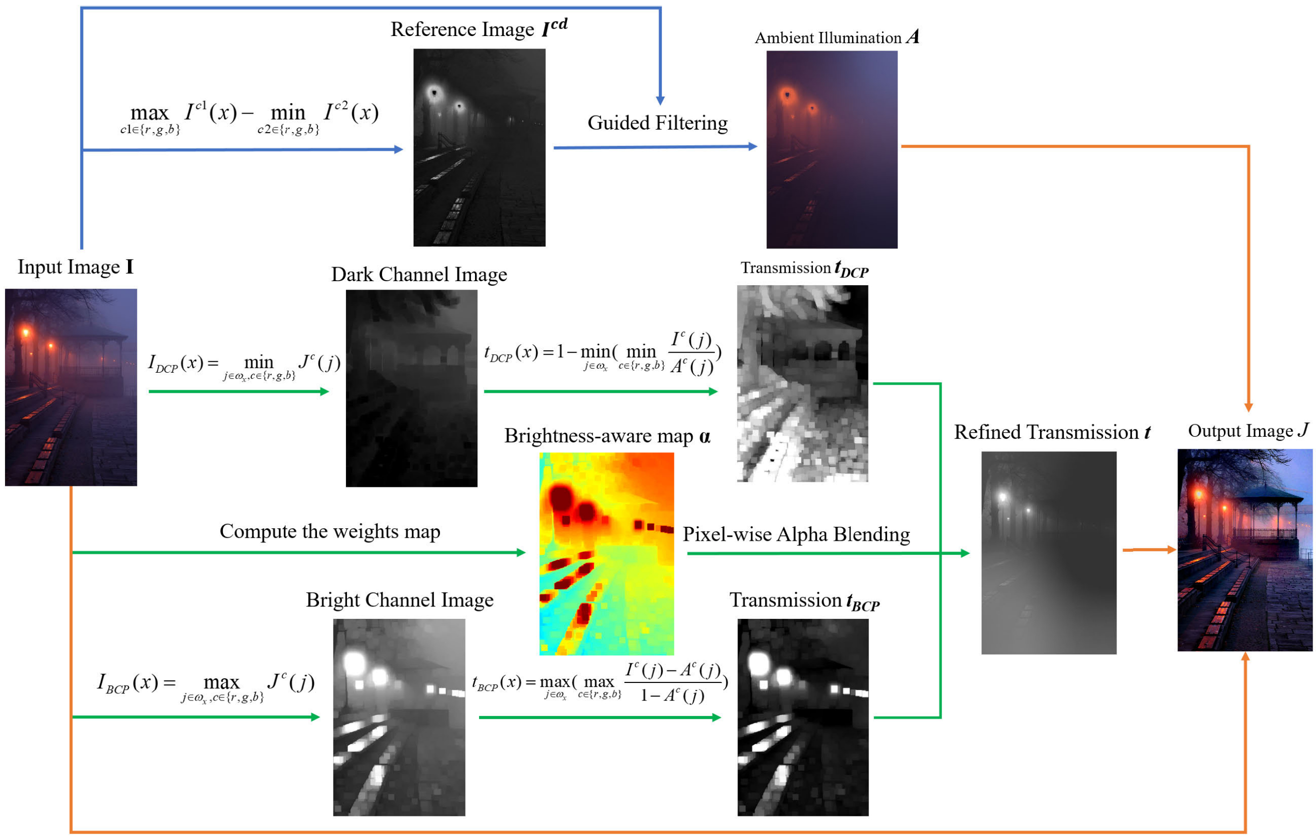


FIGURE 2. Flow chart of the proposed nighttime dehazing method.

directly applied to hazy images captured at night scenes, the results are unsatisfactory.

Recently, more researchers have started to carry out research on nighttime image dehazing. Pei et al. [22] map the nighttime hazy images to a daytime one by performing a color transfer technique, followed by a modified dark channel prior for haze removal. Although this method improves the visibility in the dehazed images, whereas the overall appearance seems unrealistic. Zhang et al. [13] use gamma correction to compensate the ambient illumination, and then perform color correction by utilizing the characteristics of incident lights. These involved post-processing technique achieves improved results, but they also produce some unpleasant artifacts such as glow and halos. Li et al. [29] modify the atmospheric scattering model by adding an atmospheric point spreading term to model the glowing effect in the light source regions. Then they decompose the glow from the hazy image by using a layer separation algorithm. Their results contain less glow artifacts, but it is prone to cause excessive enhancement of the light-source area, making the output images look unnatural. Ancuti et al. [1] estimate the ambient illumination by using a maximum operator on local patches, then a multi-scale dark channels are fused together with a laplacian pyramid. Saturation and contrast features are used to generate the weighting maps. Recently, based on the statistics of outdoor daytime images, Zhang et al. [12] propose a maximum reflectance prior by assuming the maximum intensities at each color channel have the value of 1 in daytime haze-free images, which is then used for estimating the ambient illumination. Dark channel prior [9] is applied for transmission estimation to recover the haze-free images.

All the above methods estimate the ambient illumination based on the assumption that the brightest pixels in local patches of a hazy image can capture the properties of ambient illumination. However, this assumption only makes sense when the patches are in a sky region with 0 transmission value. In addition, the dark channel prior is extensively used to estimate the transmission maps, whereas it is invalid in the light-source regions, thus leading to artifacts in that regions of the output images.

III. PROPOSED NIGHTTIME DEHAZING METHOD

The flow chart of our proposed nighttime dehazing method is illustrated in Fig. 2. The key steps for nighttime dehazing is the computation of ambient illumination map and transmission map. Details for each step are presented in the following subsections.

A. ATMOSPHERIC SCATTERING MODEL

For the problem of daytime dehazing, the atmospheric scattering model is widely used. This model divides the hazy images into two components as in (1). One is the light attenuation

(a) Input (b) Channel Difference (CD) Map (c) Input-Guided Filtering (d) CD-Guided Filtering

FIGURE 3. Example of ambient illumination estimation.

term, representing the direct scene radiance attenuation from object surfaces across the haze to the camera; the other one is the scattering term, representing the scattered light leading to the shift of scene colors.

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

Here, I is the hazy image obtained by the camera, J is the haze-free image to be recovered. A is a constant color vector describes the global ambient illumination in the air, and t is the medium transmission with respect to the depth of each pixel denoted by x. The transmission $t(x) = e^{-\theta d(x)}$ denotes the percentage of light received by the camera from J, $d(x)$ is the distance from the scene point to the camera, and θ is the scattering coefficient with respect to the atmosphere.

In case of the nighttime dehazing, the situation is more challenging. Unlike a single strong light source (sunlight) in daytime, the nighttime scene usually contains multiple light sources, such as moonlight, streetlights, vehicle lights, and so on. Rather than a global vector, the ambient illumination A at night becomes a spatially-varying map $A(x)$. Based on the above analysis, we rewrite (1) as.

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

The task of nighttime dehazing is estimating the ambient illumination map $A(x)$ and transmission map $t(x)$ so as to recover the haze-free image $J(x)$ from (2). Mathematically, it is an ill-posed problem.

B. AMBIENT ILLUMINATION ESTIMATION

Existing methods estimate the ambient illumination of nighttime hazy scenes mainly rely on the local extension of maximum pixel method used in daytime dehazing. This method works well in daytime mainly because that the maximum pixel usually comes from the sky area, where the transmission is close to 0 and the ambient illumination A equals to the hazy pixel $I(x)$ approximately. Obviously, the above theoretical basis does not hold at nighttime hazy scenes due to the spatially varying illumination and absence of sky in local patches.

The word Retinex is made up of a combination of the words retina and cortex. Retinex theory mainly contains two aspects [15]: the color of an object is determined by the ability of the object to reflect long-wave, medium-wave and short-wave light, rather than the absolute intensity of the reflected light; the color of the object is consistent and unaffected by the non-uniform illumination. According to retinex theory, the human eye perceives the brightness of an object depending on the ambient illumination and the reflection of the object surface. Mathematically, a haze-free image J can be written as a multiplication of two terms, the ambient illumination A and the reflectance R as follows:

$$J(x) = A(x)R(x). \tag{3}$$

Accordingly, Equation (2) can be expressed as

$$I(x) = A(x)R(x)t(x) + A(x)(1 - t(x)). \tag{4}$$

We reformulate (4) in a retinex-like model as

$$I(x) = A(x)(R(x)t(x) + (1 - t(x))). \tag{5}$$

A is assumed to be spatially-smooth and regarded as a low frequency term, $(R(x)t(x) + (1 - t(x))$ serves as the high frequency term. A can be effectively estimated by applying a low-pass filtering to the hazy image I. Traditional retinex algorithms use Gaussian filter for the low frequency component estimation, whereas the Gaussian smoothing is isotropic and not edge-preserving.

In this paper, we propose to solve the problem of ambient illumination estimation using a guided filter, which is able to smooth the image as well as preserve edges. Instead of using the input image, we put forth a channel difference (CD) map as the reference image to guide the low-pass filtering. The channel difference map I^{cd} is computed as the difference of

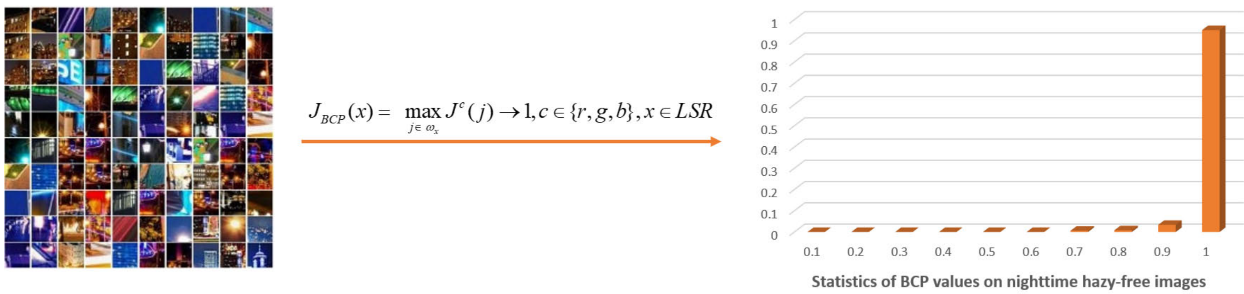


FIGURE 4. Statistics of BCP from light source patches.

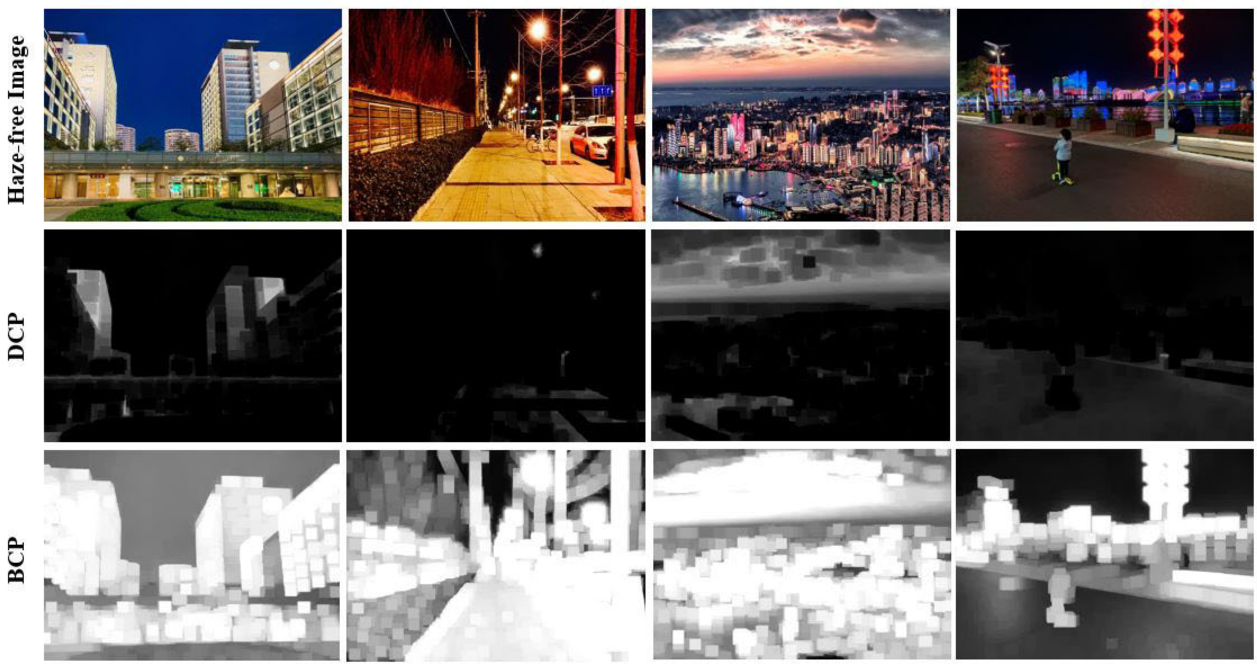


FIGURE 5. Examples of DCP and BCP from nighttime haze-free images.

maximum color channel and minimum color channel value for each pixel x as in (6).

$$I^{cd}(x) = \max_{c1\in\{r,g,b\}}(I^{c1}(x)) - \min_{c2\in\{r,g,b\}}(I^{c2}(x)) \tag{6}$$

The ambient illumination A is written as a linear transform of guide image I^cd in a window ω_k centered at the pixel k,

$$A(x) = a_k I^{cd}(x) + b_k, x \in \omega_k, \tag{7}$$

where (a_k, b_k) is assumed to be constant in ω_k, then we obtain the parameters by minimizing the difference between the objective image I and the a linear transform of the guide image I^{cd} with the following cost function:

$$E(a_k, b_k) = \sum_{x\in\omega_k}(a_k I^{cd}(x) + b_k - I(x)) + \lambda a_k^2). \tag{8}$$

Here, ω_k is the filtering window, λa_k^2 is the smoothing term. Equation (8) is solved by using the linear ridge regression model as

$$a_k = \frac{\frac{1}{|\omega|}\sum_{i\in\omega_k} I_i^{cd} I_i - \mu_k \overline{I_k}}{\sigma_k^2 + \lambda} \tag{9}$$

$$b_k = \mu_k - a_k\mu_k. \tag{10}$$

Here μ_k and σ_k^2 are the mean and variance of all pixels in the window ω_k from I^{cd}, $|\omega|$ is number of pixels, $\overline{I_k}$ is the mean of pixels in the window ω_k from I.

Having obtained the coefficients a_k and b_k, we can compute A by (7). Since a pixel x is involved in many filtering windows, we can finally obtain $A(x)$ by taking an average of values from all windows overlapping pixel x:

$$A^c(x) = \frac{1}{|\omega|}\sum_{k\in\omega_x}(a_k I^{cd}(x) + b_k) \tag{11}$$

Fig. 3 illustrates example results for ambient illumination estimation. One can see that compared to filtering with input image, the proposed channel difference (CD) guided filtering can better keep the element structures of the night scene. Note that the light spots appear dark in the illumination map, this is reasonable since the haze-free variable J of a light source is frequently high, leading to the direct attenuation term $J(x)t(x)$ is almost close the hazy image I, the scattering term $A(x)(1-t(x))$ can be regarded as a very small value that close to 0.

C. BRIGHT CHANNEL PRIOR

Unlike the hazy images captured at daytime, there are often multiple light sources in the hazy images at nighttime, and the color characteristics of the light source regions (LSR) are quite different from those of the non-light source regions (NLSR). Previous works have been attempting to handle these two distinct regions using one image prior, such as the dark channel prior (DCP) or the max reflectance prior (MRP), but the effects are unsatisfactory, since DCP is not valid in the light source region and MRP fails to handle the dark object regions such as the grayish roads and walls.

In this work, we propose a novel prior, the bright channel prior (BCP) for the light source regions. Intuitively, the light source pixels frequently contains one color channel with a high intensity value, such as all the color channels in white lights, red or green channel in yellow lights, blue channel in blue lights, and so on. Based on the above analysis, the BCP assumes that, in light source regions of a haze-free image, the maximum intensity in a local patch is close to 1 for each color channel. Note that BCP is based on a statistics from light source regions. Theoretically, it is more robust than the max reflectance prior resulted from all regions of haze-free images. Mathematically, BCP is defined as

$$J_{DCP}(x) = \min_{j\in\omega_x} J^c(j) \rightarrow 0,\ c \in \{r, g, b\}, \quad x \in NLSR \tag{12}$$

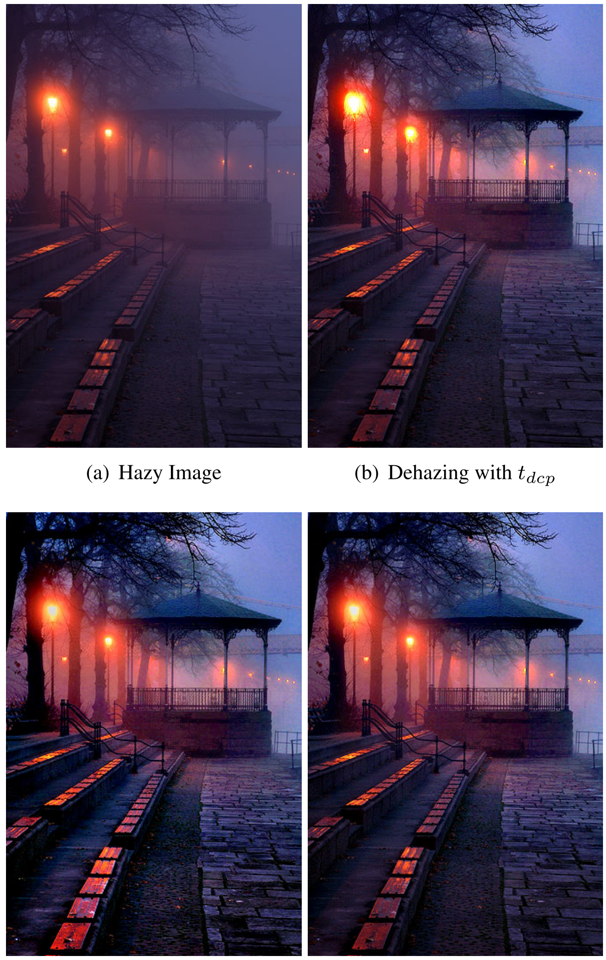
$$J_{BCP}(x) = \max_{j\in\omega_x} J^c(j) \rightarrow 1,\ c \in \{r, g, b\}, \quad x \in LSR \tag{13}$$

To demonstrate the effeteness of BCP, 5000 patches (size 15×15) are randomly cropped from 500 nighttime haze-free images, then these patches are manually labeled as light source patches and non-light source patches. Fig. 4 shows the example patches and the statistics of BCP values of light source patches, it can be seen that over 95% BCP values are in the range of $0.9 \sim 1$. Fig. 5 shows 4 examples of hazy-free images and their corresponding DCP and BCP maps, one can see that DCP mostly fails in the light source regions, where the BCP work quite well. It proves that the BCP can serve as a good complementary to DCP in the light source regions.

D. PIXEL-WISE ALPHA BLENDING

Having obtained A using the guided filter, we can compute the corresponding transmission maps t_{DCP} and t_{BCP} by applying the DCP and BCP as

$$t_{DCP}(x) = 1 - \min(\min_{j\in\omega_x} \min_{c\in\{r,g,b\}} \frac{I^c(j)}{A^c(j)}) \tag{14}$$



(a) Hazy Image (b) Dehazing with t_{dcp}

(c) Dehazing with t_{bcp} (d) Dehazing with t^c

FIGURE 6. (a) Input nighttime hazy image, (b)-(d) are the dehazing results using t^c_{DPP}, t^c_{BCP}, and t^c.

$$t_{BCP}(x) = \max(\max_{j\in\omega_x} \max_{c\in\{r,g,b\}} \frac{I^c(j) - A^c(j)}{1 - A^c(j)}) \tag{15}$$

Note that t^c_{DCP} and t^c_{BCP} are only valid in non-light source and light source regions separately, it is necessary to blend them together in order to compute the final transmission t. One way is segmenting the light sources and non-light source regions with clear border lines in the image, whereas it is hard to determine the belonging of pixels near the boundaries. So in this paper, we propose a brightness-aware weighting method to compute the probability $\alpha(x)$ of each pixel that belongs to the light source region.

Usually in the light source regions, there exists at least one pixel with a high intensity in one of the RGB channels, the higher that value is, the more likely that pixel belongs to a light source region. So mathematically, we can define the weight map α in a brightness-aware manner as

$$\alpha(x) = \max_{c\in\{r,g,b\}} (I^c)^\gamma. \tag{16}$$

The blended transmission map t is then computed as

$$t(x) = t_{BCP}(x) * \alpha(x) + t_{DCP}(x) * (1 - \alpha(x)). \tag{17}$$

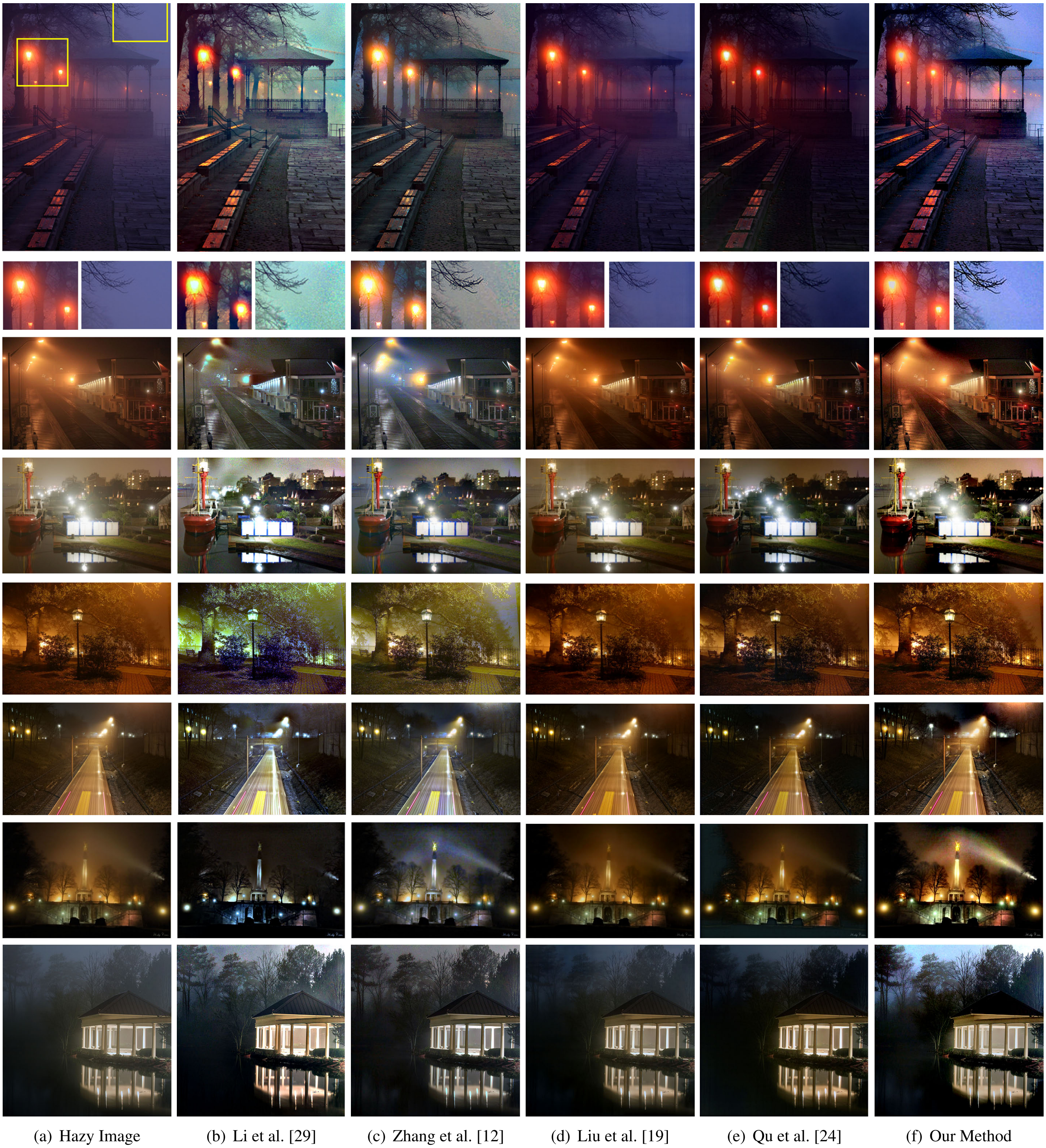


FIGURE 7. **Visual comparisons of our method vs. state-of-the-art methods.**

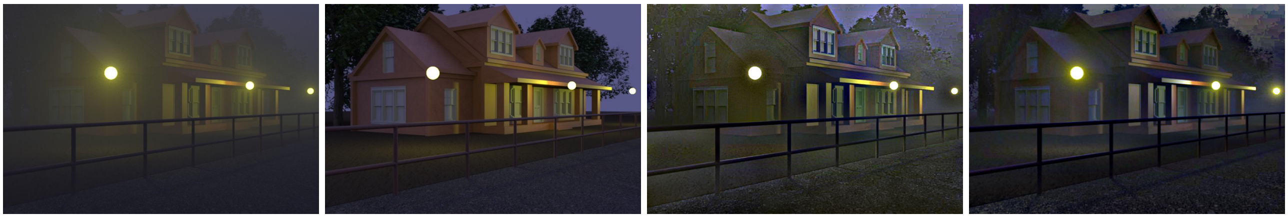
After that, we use a guided filtering to refine the final transmission map t.

There is an illustration of transmission maps t_{DCP}, t_{BCP}, and weights map $\alpha(x)$ in Fig. 2.

The output dehazed image J can be obtained using the ambient illumination map A, the transmission map t, and input hazy image I as

$$J(x) = \frac{I(x) - A(x)(1 - t(x))}{t(x)}. \tag{18}$$

Fig. 6 shows the dehazing results using t_{DCP}, t_{BCP}, and t. It can be seen that t_{DCP} tends to over-dehaze the light



(a) Hazy Image (b) Ground Truth (c) Li et al. [29] SSIM=0.4986 PSNR=20.1990 (d) Zhang et al. [12] SSIM=0.5777 PSNR=21.8603

(e) Zhang et al. [13] SSIM=0.3884 PSNR=14.2547 (f) Liu et al. [19] SSIM=0.4430 PSNR=17.8220 (g) Qu et al. [24] SSIM=0.4064 PSNR=16.8330 (h) **Our Method SSIM=0.6727 PSNR=22.3200**

FIGURE 8. Object comparison using the data in [29]. Below show the SSIM and PSNR values.

source regions while under-dehaze the dark areas. On the contrary, t_{BCP} presents pleasant results in the light sources with preservation of shapes and edges, while the dark areas seem over-enhanced. The result using t benefits from the effective pixel-wise alpha blending with both advantages of DCP and BCP.

IV. EXPERIMENTAL EVALUATION RESULTS

In this section, we present the experimental details and evaluation results by comparing the state-of-the-arts methods with our proposed method. In subjective evaluation, we compare the performance of different methods visually on the same images widely-used in the existing approaches [12], [29]. In object evaluation, the dehazing performance is evaluated in terms of PSNR and SSIM using the synthetic data. For the fairness of comparison, the data of the state-of-the-art methods are from the public codes and images of their authors. In experiments of our method, the size of DCP and BCP is fixed to 15×15. The kernel size of guided filer for ambient illumination estimation and transmission refinement is 64, the smoothing coefficients of both are set to 0.01.

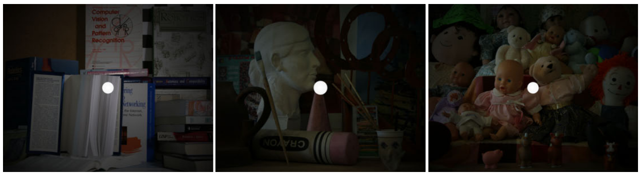
A. SUBJECT COMPARISON ON REAL IMAGES

To demonstrate the effectives of our dehazing method, we present the dehazing results on real nighttime hazy images used in the existing research [12]. Currently, there are quite few research aimed at nighttime image dehazing, we compare our results with the state-of-the-art nighttime dehazing approaches [12], [29]. Many deep learning based daytime dehazing methods have been proposed, but none of them works on nighttime dehazing. To make our results more convincing, we also include a representative deep learning based method, DehazeNet [3] for comparison. The visual comparisons are shown in Fig.7.

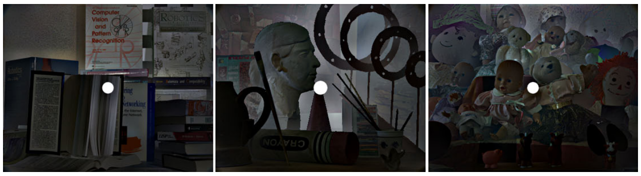
In Fig. 7, Li et al.'s [29] and Zhang et al.'s [12] methods tend to wash out and shift the original colors due to the excessive de-glow process. From the zoom-in views of the first image, we can see that our results can keep the original shapes and edges of the light sources. Because of the Dark Channel Prior, Li et al.'s and Zhang et al.'s methods over-dehaze the light sources, where appear clear burn-out effects in the zoom-in views. When looking at the sky regions, we can see there exist color distortion and noise in Li et al.'s and Zhang et al.'s methods, whereas our method successfully avoids producing excessive noise when doing the haze removal. In the third image, both our method and Zhang et al.'s method can keep the preserve the shape of light sources. Zhang et al.'s result has better visibility around the light-sources, but its color in the sky is distorted. In the fourth image, there are some color distortions in regions of grasses and leaves of the other two methods. In the last three images of Fig. 7, our results present more details and visibility in the dark areas, and also show better preservation of the original colors. Although the learning based methods [19], [24] can preserve the edges in light source regions, it fails to remove the haze and recover the visibility in almost all the night hazy images. Currently, the deep learning-based daytime dehazing methods are trained with daytime models and daytime datasets, and the network architecture is not designed for nighttime scenes. The other obstacle prevents the learning methods being used for nighttime dehazing is the lack of ground truth data (including hazy images and their corresponding hazy-free images, ambient illumination, and transmission).

From these visual comparisons, we can conclude that generally our method can better keep the color consistence with the input image. It also has the advantage in preserving the shape and edges of light sources, which is benefited

(a) Synthetic Hazy Images



(b) Ground Truth

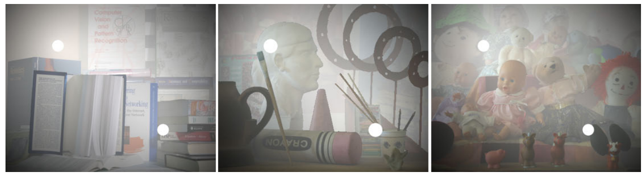


(c) Li et al. [29]

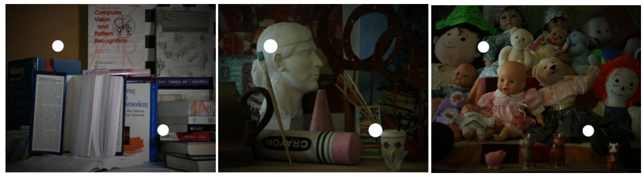
(d) Zhang et al. [12]

(e) Our method

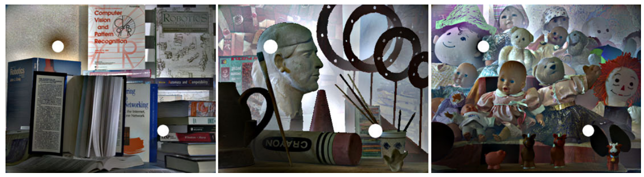
FIGURE 9. Sample results using synthetic images with 1 light source.



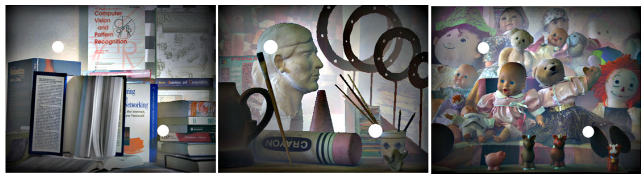
(a) Synthetic Hazy Images



(b) Ground Truth



(c) Li et al. [29]



(d) Zhang et al. [12]

(e) Our method

FIGURE 10. Sample results using synthetic images with 2 light sources.

from the proposed brightness-aware alpha blending method. In addition, our method tends to produce less artifacts in the sky regions.

B. OBJECT COMPARISON ON SYNTHETIC DATA

We also do quantitative evaluations on the dehazing results in terms of SSIM and PSNR. The synthetic data comes form Li et al.'s [29] paper with hazy image and its ground truth haze-free image as a reference. Fig. 8 shows the comparison results. We can see that our method achieves the highest SSIM value and PSNR values.

To conduct more objective comparisons. We follow the method in [12] to synthesize the nighttime hazy images. The Middlebury 2005 and 2006 datasets [25] are used for generating the synthetic data, the ground truth images (regarded as R) and disparity maps are selected to simulate the real nighttime scene with light sources. The light source is assumed to be in the middle of the image, and the ambient illumination map is computed as $A(x) = 1 - \alpha \times dp(x)$, where $dp(x)$ is the Euclidean distance from pixel location to the light source center. In case of the multiple light sources, the final $A(x)$ is a combination of all A_i from k light sources. The transmission map is computed as $t(x) = 0.8d(x)$, where d is the normalized disparity map with black holes filled with their nearest neighbors. The synthetic hazy images are obtained using (4). We synthesize nighttime hazy image with three α values (0.4, 0.6 and 0.8), two groups experiments are conducted with 1 light source and 2 light sources in the image. The SSIM and PSNR values of different methods against our method are shown in Table 1 and Table 2. Fig. 9 and Fig. 10 also shows examples for dehazing results using synthetic images. One can see that our method outperforms the state-of-the-art in all experiments using SSIM metric and 4 out of 6 experiments using PSNR.

TABLE 1. SSIM and PSNR values using image with 1 light source.

Methods	Li et al. [29]			Zhang et al. [12]			**Our Method**		
α	α=0.4	α=0.6	α=0.8	α=0.4	α=0.6	α=0.8	α=0.4	α=0.6	α=0.8
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	0.54 15.39	0.56 17.24	0.60 18.74
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 17.70	0.75 19.56	0.73 21.30
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	0.65 17.43	0.66 19.74	0.67 21.77
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	0.62 14.72	0.62 16.74	0.61 18.31
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 14.63	0.62 15.98	0.61 17.14
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	0.41 14.38	0.41 16.11	0.43 17.77
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	0.47 15.41	0.52 17.18	0.57 18.71
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	0.40 11.88	0.45 13.84	0.51 15.67
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	**0.56 15.19**	**0.58 17.05**	**0.59 18.68**

TABLE 2. SSIM and PSNR values using image with 2 light sources.

Methods	Li et al. [29]			Zhang et al. [12]			**Our Method**		
α	α=0.4	α=0.6	α=0.8	α=0.4	α=0.6	α=0.8	α=0.4	α=0.6	α=0.8
Metrics	SSIM PSNR	SSIM PSNR	SSIM PSNR	SSIM PSNR	SSIM PSNR	SSIM PSNR	SSIM PSNR	SSIM PSNR	SSIM PSNR
Art	0.37 05.09	0.37 05.76	0.41 08.44	0.31 05.50	0.37 07.53	0.41 09.39	0.37 05.08	0.44 07.80	0.50 11.20
Books	0.47 07.26	0.55 09.01	0.61 12.53	0.47 07.30	0.58 09.78	0.60 12.41	0.54 06.67	0.67 09.40	0.73 13.30
Dolls	0.34 05.59	0.29 06.61	0.42 11.25	0.31 06.30	0.34 08.86	0.39 11.49	0.45 05.91	0.54 09.25	0.60 13.15
Laundry	0.27 04.82	0.32 06.14	0.43 11.16	0.29 05.21	0.31 07.36	0.36 09.86	0.35 04.77	0.52 07.35	0.58 10.83
Moebius	0.32 04.51	0.37 07.09	0.47 12.12	0.34 04.90	0.40 08.17	0.39 09.73	0.40 04.47	0.52 07.19	0.58 10.44
Reindeer	0.30 04.72	0.23 05.26	0.30 09.02	0.24 05.13	0.23 07.24	0.27 09.17	0.37 04.98	0.41 07.39	0.41 10.45
Rock	0.19 05.99	0.24 08.27	0.28 11.23	0.15 06.10	0.17 08.07	0.20 10.24	0.26 05.97	0.33 08.65	0.40 11.46
Midd	0.26 04.02	0.25 04.94	0.28 07.89	0.20 03.86	0.23 06.00	0.26 08.46	0.23 03.68	0.28 05.71	0.36 08.86
Average	0.32 05.25	0.33 06.64	0.40 10.45	0.29 **05.54**	0.33 **07.88**	0.36 10.09	**0.37** 05.19	**0.47** 07.85	**0.52 11.21**

TABLE 3. Results of Runtime Comparison.

Methods	Runtime/s
Li et al.'s [29]	12.14
Zhang et al.'s [12]	0.53
Our method	**0.46**

C. COMPLEXITY ANALYSIS

The proposed method in this work is efficient. The main computation comes from the guided filtering and Max/Min operations. Guided filtering is applied 3 times in total for computing the ambient illumination and transmission maps with complexity $O(N)$. Since Max/Min operations are conducted spatially in all color channels, both the color channels and spatial mask size are constant, so the iteration is linear times of the input data, whose complexity is $O(N)$.

For the comparison with other methods, we conduct the experiments with runtime analysis using Matlab. Li et al.'s code is from their webpage. Zhang et al.'s code is provided in C++. For fair comparison, we reimplemented their algorithm exactly following the procedures and parameter values provided in the paper using Matlab. By resizing 20 input images into size of 640×480, we compute the average processing time of our method and the other approaches as shown in Table 3. Our method is more than 10 times faster than that of Li et al.'s method where the color version of guided filter is used, and a little faster than Zhang et al.'s method.

V. DISCUSSIONS AND CONCLUSION

In this paper, we have proposed an effective nighttime image dehazing method by focusing on the estimation of ambient illumination and transmission. For estimating the spatially-variant illumination, we reformulate the atmospheric scattering model in a Retinex-like form according to the Retinex theory, which is then solved by a channel difference guided filtering. For the transmission estimation, we utilize the proposed BCP and traditional DCP to deal with the light source regions and non-light source regions separately. Subsequently, a pixel-wise alpha blending method guided by the brightness-aware map is proposed to obtain the final transmission map. Comprehensive experimental evaluations show that our method outperforms the state-of-the-art approaches on both real and synthetic hazy images. Specially, our dehazing results show advantages on keeping the consistence of colors and preserving edges of the light source regions. However, our work also shares a common limitation with most of the methods using the atmospheric scattering model, it is relatively simple and may be invalid in some sophisticated scenes. More advanced models with more parameters need to be developed in the future. We believe that new learning networks and datasets will be proposed for nighttime dehazing in the future, which is also our next research direction.

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