HDP-Net: Haze Density Prediction Network for Nighttime Dehazing

Yinghong Liao, Zhuo Su(✉), Xiangguo Liang, and Bin Qiu

School of Data and Computer Science, National Engineering Research Center of Digital Life, Sun Yat-sen University, Guangzhou, China
suzhuo3@mail.sysu.edu.cn

Abstract. Nighttime dehazing is a challenging ill-posed problem. Affected by unpredictable factors at night, daytime methods may be incompatible with night haze removal. In this paper, we propose an end-to-end learning-based solution to remove haze from night images. Different from the most-used atmospheric scattering model, we use a novel model to represent a night hazy image. We first present an estimator to predict the haze density in patches of the image. Based on this, a CNN, called Haze Density Prediction Network (HDP-Net), is adopted to obtain a haze density map so that it can be subtracted by the original hazy input to generate the desired haze-free output. The range of hue in night images may be altered by artificial light sources. To improve the dehazing capability in the certain range of hue, we devise four datasets under white light and yellow light conditions for network training. Finally, our method is compared with the state-of-the-art nighttime dehazing methods and demonstrated to have a superior performance. The project is available at https://github.com/suzhuoi/HDP-Net.

Keywords: Nighttime image dehazing · Image enhancement
Density prediction · Convolutional neural network

1 Introduction

Haze is a common atmospheric phenomenon caused by dust, smoke and other particles in the air. Light scattering and light attenuation caused by haze can result in the severe degradation of the visibility of images and videos. In particular, for a nighttime photograph which suffers from low ambient illumination and poor visibility, its visual quality can be further seriously affected by the presence of haze. Therefore, how to effectively remove haze in the night image is a challenging issue in image enhancement and is of great significance to the applications such as self-driving and traffic surveillance.

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In recent years, some daytime dehazing methods [2,4,12] mainly remove haze by the atmospheric scattering model [8] which describes a hazy image as the linear combination of the direct attenuation term and scattering term. These methods could recover a haze-free image via estimating the unknown parameters in the model (the transmission map and the atmospheric light). The atmospheric light is estimated from the brightest region of the image and considered as consistent globally. However, the estimation of the atmospheric light during night time faces great difficulty in two aspects: the low illuminance intensity of the natural atmospheric light and the existence of artificial light sources. Without the accurate value, the error from the estimation thus becomes the main cause of color distortion in dehazed images. On the other hand, daytime images have wide range of hue in terms of that in HSV color model, because white light generated by the sun is the composite of various monochromatic lights. But in the dark environment, the presence of artificial light sources will cause the range of hue to shrink, e.g., a yellow street light may turn the picture yellowish. Several researchers have proposed some nighttime dehazing methods [6,10,14,15] that are mainly based on the atmospheric scattering model, but color distortion is still existed due to their excessive dehazing. Therefore, our goal is to design a nighttime dehazing model that can address color distortion issue and restore a haze-free image close to the reality without estimating the atmospheric light. And our model could be effective for haze removal in night images with different range of hue.

In this paper, we propose an end-to-end Haze Density Prediction Network (HDP-Net) to perform nighttime dehazing. Instead of estimating the transmission map and the atmospheric light in the atmospheric scattering model [8], we create a novel prediction function to obtain the haze density map of a night image. The haze-free map could be recovered after the original hazy image subtracts the haze density map. Distinguished from DehazeNet [1], AOD-Net [5] and DCPDN [13], we adopt a network architecture similar to a fully convolutional network (FCN) to estimate haze density. In HDP-Net, two shortcuts are added to connect same-size feature maps to reduce training error, and three structures resembling the bottleneck in ResNet [3] are applied to make the network more trainable. To make data-driven HDP-Net work effectively on an image with varying range of hue, we design four datasets of night synthetic hazy images under white light and yellow light environment for training respectively. Based on large-scale data, HDP-Net could accurately estimate the haze density and remove the night haze.

In summary, the contributions of our work are as follows:

- Propose a haze density prediction function and a novel model describing a night hazy image that is different with the atmospheric scattering model.
- Design a network architecture based on the model above to obtain a haze density map.
- Devise datasets NightHaze under white light condition and YellowHaze under yellow light condition to make the network dehaze effectively for different range of hue of night hazy images.

2 Related Work

In general, dehazing methods are divided into two categories: prior-based methods and data-driven methods. We will introduce the application of these two types of methods in haze removal in day time and night time, respectively.

Daytime Dehazing. Early approaches are based on various image priors. They use the atmospheric scattering model to represent a hazy image and explore the cues between the parameters in the model and the features from the image, such as the Dark Channel Prior (DCP) [4], the Maximize Contrast [12], the Color Lines [2]. In recent years, with the extensive application of deep learning in the field of computer vision, researchers began to apply the convolutional neural network (CNN) to image dehazing. The CNN-based methods are trained with designed hazy inputs and given haze-free outputs so that the optimal value of the parameters or their derived ones could be obtained after limited times of training iteration. For instance, Cai et al. proposed DehazeNet in [1], Li et al. introduced AOD-Net in [5], Zhang and Patel presented DCPDN in [13]. Some approaches remove haze without the atmospheric scattering model, e.g. Ren et al. [11] proposed Gated Fusion Network (GFN).

Nighttime Dehazing. The majority of daytime methods might not be suitable for nighttime dehazing, though many methods have presented effectiveness under daytime environment. Affected by complex and unpredictable factors of night, e.g., insufficient intensity and imbalanced distribution of atmospheric light, the removal of night haze is more challenging. There are a few approaches in eliminating haze from night images and they are almost prior-based. Pei and Lee [10] first turned the original hazy image into the gray one and dehazed it with the DCP [4]. Li et al. [6] proposed the Glow and Multiple Light Colors (GMLC) by adding a glow term to the atmospheric scattering model. The glow term is estimated by APSF function in [9] and used to reduce the effects from the glow generated by artificial light sources. The DCP is used as the final step to finish dehazing. Zhang et al. [15] presented a New Imaging Model (NIM), which initially adopted a light compensation on hazy inputs to obtain an illumination balanced one and then dealt it with a color correction step. The method is ended with the same DCP operation. Furthermore, Zhang et al. [14] proposed another approach that used Maximum Reflectance Prior (MRP) to remove night haze. This method estimates the ambient illumination of image by maximizing the reflectance. With the calculated ambient illumination, color effects are removed and the transmission is then estimated. The haze-free image is obtained by using the DCP finally. The DCP that these methods use is sensitive to the extreme value in local patch and cannot produce ideal dehazing effects in the region such as sky. Based on the atmospheric scattering model, these methods usually obtain the image with severe color distortion.

3 Our Method

In this section, we illustrate our nighttime dehazing method. We first analyze limitations of the atmospheric scattering model in the removal of night haze. Then we introduce the designed haze density prediction function. With the function, we propose a novel model to describe a night hazy image and verify its rationality. Finally, we give the details of our proposed nighttime dehazing network, HDP-Net.

3.1 Limitations of the Atmospheric Scattering Model

Most daytime dehazing methods adopt the atmospheric scattering model [8] to represent a hazy image, its form is as follows

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

where $I(x)$ denotes the observed hazy map, $J(x)$ denotes the desired haze-free map, A is the intensity of the atmospheric light and $t(x)$ is the medium transmission. Some daytime haze removal approaches, including prior-based methods and data-driven methods, restore a haze-free image by the estimation of unknown variables, the transmission $t(x)$ and the atmospheric light A in Eq. (1).

However, this model has two limitations of in nighttime dehazing.

Difficult Estimation of the Atmospheric Light A. Natural daytime atmospheric light is parallel light with high intensity, so the value of A could be obtained from the brightest pixels of the image and set as consistent globally. However, natural atmospheric light is not strong at night and there are also artificial light sources with strong glow. The bright patches formed by artificial light sources and the dark areas generated by insufficient night atmospheric light make the uneven distribution of image illumination. Therefore, the atmospheric light A cannot be estimated from the brightest regions and is hard to be predicted.

Color Distortion. Atmospheric light A in Eq. (1) could be represented by RGB and HSV color model. Hue is the parameter in HSV color model that describes the colorfulness of an image and is defined as follows:

$$tan(h) = \frac{\sqrt{3} \cdot (G - B)}{2R - G - B}, \tag{2}$$

where h is hue whose range is $[0, \pi]$. R, G and B are the red, green and blue channel of an image, respectively. An image is considered colorful by the wide range of hue. Natural daytime atmospheric light is white light, which is composed of multiple monochromatic lights, thus the range of hue is wide in daytime hazy images. In night time, there is no strong atmospheric light but artificial light sources. Artificial light sources may narrow down the range of hue, e.g., street light with low color temperature (2700 K–3200 K) produces yellow light that makes the picture to become yellow. If the estimation of A is not accurate, the hue of A and the dehazing result are affected and color distortion occurs consequently. After the analysis, a new model is needed to perform nighttime dehazing.

3.2 Haze Density Prediction Function

To address the issue of night haze, we design a haze density prediction (HDP) function as follows:

$$I_h = P(I(x)), \tag{3}$$

where $I_h(x)$ denotes the haze density, $P(\cdot)$ denotes the proposed prediction function that estimates haze density. The range of haze density is $[-1, 1]$, which will be proved in Sect. 3.4.

The function is hard to be hand-designed because the density and the distribution of night haze vary in images. Thus we use CNN to build a network architecture that constructs HDP function. In one thing, CNN can perform complex non-linear transformations and use shared parameters to estimate varying haze density. In other thing, CNN is data-driven, which obtains optimal parameters for various conditions.

3.3 Nighttime Hazy Image Model with HDP Function

According to the composition of hazy image, our model is re-defined as:

$$I(x) = J_s(x) + J_t(x) + I_h(x), \tag{4}$$

where J_s and J_t are the structure and texture of haze-free map respectively, I_h is the haze density. With Eq. (4), the desired dehazing result $J(x)$ can be represented as:

$$J(x) = I(x) - I_h(x). \tag{5}$$

Therefore, we first obtain a haze density map $I_h(x)$ by Eq. (5). Then we recover a night haze-free image $J(x)$ from the hazy input $I(x)$ by subtracting $I_h(x)$ with the preserved structure $J_s(x)$ and texture $J_t(x)$. Compared with the atmospheric scattering model in Eq. (1), our model predicts only the haze density $I_h(x)$ of the hazy map without computing the transmission $t(x)$ and the atmospheric light A. Thus the cost of computing two parameters is avoided and color distortion caused by estimating A could be prevented.

3.4 The Rationality of Nighttime Dehazing with HDP Function

We can obtain another form of haze density $I_h(x)$ by Eq. (5):

$$I_h(x) = I(x) - J(x). \tag{6}$$

The rationality of night haze removal with HDP function can be demonstrated by proving the range of the haze density is $[-1, 1]$.

Proof. Here the atmospheric scattering model in Eq. (1) is introduced to prove the rationality of the HDP function. The HDP function could be derived from the atmospheric scattering model but it advoids the computation of the atmospheric light A and the transmission $t(x)$.

From the atmospheric scattering model in Eq. (1), we obtain

$$I_h(x) = J(x)t(x) + A(1 - t(x)) - J(x). \tag{7}$$

The normalization is usually performed on an image for network training (divided by 255). Thus the range of $I(x)$, $J(x)$ and A is narrowed down to [0, 1]. From Eq. (7) we have

$$I_h(x) = (A - J(x))(1 - t(x)). \tag{8}$$

The range of $t(x)$ is [0, 1], so $(1 - t(x))$ is in [0, 1]. In daytime, A is obtained from the brightest pixels in hazy image $I(x)$, that is $A \geq I(x)$. And we get

$$A \geq J(x)t(x) + A(1 - t(x)). \tag{9}$$

From Eq. (9) we have

$$(J(x) - A)t(x) \leq 0. \tag{10}$$

Since $t(x) \geq 0$, so $(J(x) - A) \leq 0$, then $A \geq J(x)$ is obtained. In the daytime, the atmospheric light A is in the range of [0.6, 1] and $(A - J(x))$ is thus [0, 1]. But A cannot be estimated in the night image by the brightest patch and $A \geq J(x)$ is not true. The range of A and $J(x)$ are both [0, 1], so the term $(A - J(x))$ is $[-1, 1]$. And $(1 - t(x))$ is [0, 1], thus the range of Eq. (8) is $[-1, 1]$. Therefore, haze density range is proved as $[-1, 1]$. The haze density map could be obtained by extracting the feature value in $[-1, 1]$ by CNN without the estimation of A and $t(x)$. And the model could be derived from the atmospheric scattering model, the rationality of our model is demonstrated.

3.5 Network Architecture

The purpose of HDP function is to estimate haze density map from a night hazy image and preserve image details. After a series of experiments, we finally devise a network for nighttime dehazing with HDP function.

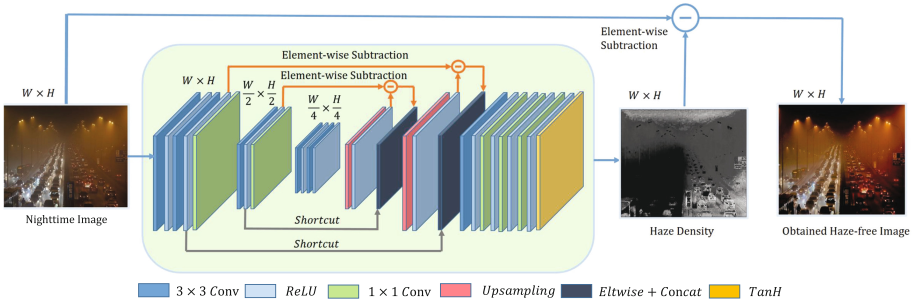


Fig. 1. The architecture of HDP-Net.

The network architecture we designed is illustrated in Fig. 1. The network structure includes 11 convolutional layers, each of which except the last layer is followed by a ReLU as non-linear activation function. Different kernels, strides and pads are applied in convolutional layers to realize three functions. Feature extraction layers are used with kernel 3, stride 1 and pad 1. Pooling layers with kernel 1, stride 2 and pad 0 have the same down-sampling operation to generate half-size feature maps. Mapping layers with kernel 1, stride 1 and pad 0 perform multistage mapping to obtain a color haze density map that matches the size of the input. In addition, we import two deconvolutional layers to do up-sampling so that the feature map size is recovered. Details and colors of the image are distributed in low-level features, so we bring two shortcuts to concatenate same-size feature maps for retaining low-level features. And three subtraction structures are appended to make the network more trainable, which are similar to ResNet bottleneck [3]. TanH with range $[-1, 1]$ is adopted as the activation function to control haze density range in the final layer.

Overall, our network architecture resembles the fully convolutional network (FCN) [7]. Inspired by FCN, we design this network to predict haze density map. The layer number of HDP-Net is based on training images with the size of 128×128. Satisfying dehazing results could be produced after the multi-scale operations of feature extraction, fusion and mapping by 11 layers. The details of HDP-Net architecture are presented in Table 1.

Table 1. The details of HDP-Net architecture.

Formulation	Type	Input Size	Num	Filter	Stride	Pad
Feature Extraction	Conv	$3 \times 128 \times 128$	8	3×3	1	1
		$8 \times 128 \times 128$	16	3×3	1	1
		$16 \times 128 \times 128$	32	1×1	2	0
		$32 \times 64 \times 64$	32	3×3	1	1
		$32 \times 64 \times 64$	64	1×1	2	0
		$64 \times 32 \times 32$	64	3×3	1	1
		$64 \times 32 \times 32$	64	3×3	1	1
Fusion	Deconv	$64 \times 32 \times 32$	32	2×2	2	0
		$32 \times 64 \times 64$	16	2×2	2	0
Feature Extraction	Conv	$16 \times 128 \times 128$	16	3×3	1	1
Mapping	Conv	$16 \times 128 \times 128$	16	1×1	1	0
		$16 \times 128 \times 128$	8	1×1	1	0
		$8 \times 128 \times 128$	3	1×1	1	0

4 Experiment

This section presents the experiments on our proposed HDP-Net. We introduce four synthetic datasets of night hazy images for training. Then we make quantitative and qualitative experiments to compare our methods with state-of-the-art nighttime dehazing methods on synthetic images and real images, respectively.

4.1 Implementation Details

Caffe stands out with its excellent support for CNN and outstanding capability of training lots of classical models. Thus, we use the Caffe implementation to train the designed network. The cost function in training is defined as follows:

$$Loss = \sum ||J - (I - I_{conv})||_2, \tag{11}$$

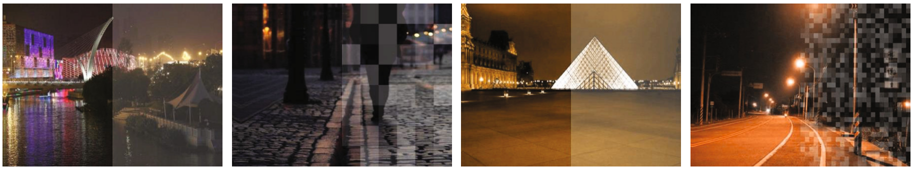
where I_{conv} represents the output of our network, standing for the predicted haze density. Mean squared error (MSE) is adopted to measure the difference between night hazy image and real haze-free image to supervise the training. The calculation of $I - I_{conv}$ could be implemented by element-wise layer in Caffe.

To train the network efficiently, we use Xavier Filler to initialize the parameters of our network. The training error is decreased by optimization algorithm of Stochastic Gradient Descent (SGD) during back propagation. We found that the constant learning rate smaller than 0.001 could have ideal convergence effects, but the speed of the convergence is relatively slow. To achieve better convergence effects, the learning rate is initially set as 0.001 to accelerate the convergence and gradually decreases for better optimal parameters when the training error is stable in a certain range. Thus the learning policy is set as *inv* with initial learning rate as 0.001, gamma as 0.001 and power as 0.75. The momentum and weight decay are fixed as 0.9 and 0.005, respectively, so that the optimization algorithm of SGD could produce more stable and fast convergence.

4.2 Training Datasets

The selected training dataset is important for the data-driven nighttime dehazing network. In daytime dehazing, DehazeNet [1], AOD-Net [5] and DCPDN [13] designed hazy and haze-free datasets for experiments. But few hazy and haze-free datasets in night time have been designed so far. Our method does not predict the value of transmission and atmospheric light, so the problem of violating the laws of physics caused by range is not taken into account. Predicting haze density by our model has no limitations to use the synthetic datasets obtained by Eq. (1). Moreover, we also focus on dehazing effects on the hazy images under the nighttime yellow light condition to improve the performance of HDP-Net on dark images in narrow range of hue.

Our datasets are based on bright and clean nighttime photographs, including night view of cities, night scenes of streets and other common nighttime images.



NightHaze-1 NightHaze-2 YellowHaze-1 YellowHaze-2

Fig. 2. Samples of NightHaze-1, NightHaze-2, YellowHaze-1 and YellowHaze-2. (Color figure online)

We select 10,000 of them as a basic training dataset and then use the atmospheric scattering model to generate the corresponding synthetic hazy images. We roughly estimate the value of the transmission $t(x)$ and the atmospheric light A in natural night environment by using the DCP [4]. After the statistical analysis and the experimental observation, we find out the main range of atmospheric light A and transmission $t(x)$ are [0.6, 0.9] and [0.7, 0.4], respectively. In order to explore night haze removal under yellow light environment, the hue of images is also modified by HSV color model, and the range is defined in [0.05, 0.10], which is within the range of yellow light.

For the convenience of training, we set the image size to 128×128. Based on different hazing effects and considering the impacts of yellow light, we generate four hazy image datasets. NightHaze-1, the collected night images are globally added by haze with the same density. NightHaze-2, the collected images are locally hazed by various density. A picture is divided into 32×32 or smaller patches where the haze is added at a certain probability, and some patches have no haze. The purpose is to improve the capability of the network to detect haze density. YellowHaze-1 and YellowHaze-2 are processed in the same manner as NightHaze-1 and NightHaze-2, except the hue is modified as yellow. The corresponding samples in each dataset are shown in Fig. 2.

4.3 Quantitative Evaluation on Synthetic Dataset

To quantify the dehazing effects of the network, we pick out the remaining 944 pictures from our collections to synthesize hazy images for the test, with the size of 480×740. These pictures are in yellow light and white light environment, respectively. The dehazing results are then in the comparison with those generated by other night haze removal models. Two indicators are used to measure the dehazing effects: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM).

At present, mainstream nighttime dehazing methods are prior-based and we select representative three of them for comparison. They are Glow and Multiple Light Colors (GMLC) [6], New Imaging Model (NIM) [15] and Maximum Reflectance Prior (MRP) [14].

Dehazing results of some night hazy images by different methods are illustrated in Fig. 3. Three images with night haze are shown in Fig. 3(a) and the

Fig. 3. The dehazing results on synthetic dataset. (Color figure online)

obtained results by GMLC [6], NIM [15] and MRP [14] are displayed in Fig. 3(b)–(d). Our dehazing images are given in Fig. 3(e), the first of which is the output from trained YellowHaze and the last two of which are the effects by trained NightHaze. The first in Fig. 3(a) is a hazy map under yellow light. The dehazing results by NIM in Fig. 3(c) and MRP in Fig. 3(d) have obvious color distortion. GMLC in Fig. 3(b) can effectively extract details, such as the floor textures and the reduced glow of light. By comparison, our result is closer to the original hue and has clear object outlines, such as the lines of the bridge. The second picture in Fig. 3(a) is a hazy image under night white light. GMLC and NIM are shown to be sensitive to white light and have excessive dehazing effects, resulting in the severe color distortion like whitened sky. In contrast, our method could remove the haze that covers the picture while retaining the original color composition. The last picture in Fig. 3(a), a challenging synthetic night hazy image is used to test the dehazing effects of these three methods and our method, by adding haze with different density in patches. The results show that GMLC, NIM and MRP could not well remove the haze in varying density. Our method could basically remove the low-density haze and reduce the high-density haze while retaining the hue of the original image.

The quantitative evaluation of all methods is displayed in Table 2. It is obvious that our method has the best results in two indicators. Prior-based methods produce good effects in extracting details but have the problem color distortion due to the excessive haze removal, which results in low value of PSNR and SSIM.

Table 2. The average PSNR and SSIM in dehazing results on synthetic dataset.

	GMLC [6]	NIM [15]	MRP [14]	Ours
PSNR	6.759	11.090	11.853	**15.984**
SSIM	0.121	0.290	0.159	**0.589**

4.4 Qualitative Evaluation on Real Images

To further evaluate the effectiveness of HDP-Net, in Fig. 4, we select images under yellow light and white light in [6,14,15] to give a qualitative comparison on real images. Figure 4(a) gives night hazy images. Figure 4(b)–(d) show results obtained by GMLC [6], NIM [15] and MRP [14], Fig. 4(e) displays the effects of our method. In Fig. 4(b)–(d), most of the haze is removed, and the details of the objects and scenes are well restored, but there are phenomena of over-enhancement (e.g., the sky areas of the fourth pictures in Fig. 4(c) and (d)). In addition, NIM and MRP could not deal well with the effects of artificial light sources, and there is a noticeable color distortion in the first picture. Light source glow is processed better by GMLC, but the color distortion is more severe in global, especially in pictures under yellow light. Prior-based methods in Fig. 4(c) and (d) inevitably overestimate features of images, such as transmission and reflectance, resulting in the change of colors. In contrast, our method could estimate features accurately, and colors and details of pictures are well retained.

(a) Hazy Inputs (b) GMLC [6] (c) NIM [15] (d) MRP [14] (e) Ours

Fig. 4. Dehazing effects on real images. (Color figure online)

5 Conclusion

In this paper, we present a novel data-driven method to address nighttime dehazing and design a corresponding network model. We also design some datasets to train the network and test its dehazing effects at night. For further evaluation of night images with different hue range, we devise datasets under night yellow light and white light respectively. Our method are compared with other nighttime dehazing methods. The results in data measurement and visual quality prove that HDP-Net has a better performance than the current nighttime dehazing methods.

References

1. Cai, B., Xu, X., Jia, K., Qing, C., Tao, D.: Dehazenet: an end-to-end system for single image haze removal. IEEE Trans. Image Process. **25**(11), 5187–5198 (2016)
2. Fattal, R.: Dehazing using color-lines. ACM Trans. Graph. **34**(1), 13:1–13:14 (2014)
3. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: IEEE Computer Vision and Pattern Recognition, pp. 770–778 (2016)
4. He, K., Sun, J., Tang, X.: Single image haze removal using dark channel prior. In: IEEE Computer Vision and Pattern Recognition, pp. 820–824 (2009)
5. Li, B., Peng, X., Wang, Z., Xu, J., Feng, D.: Aod-net: All-in-one dehazing network. In: IEEE International Conference on Computer Vision, pp. 4780–4788 (2017)
6. Li, Y., Tan, R.T., Brown, M.S.: Nighttime haze removal with glow and multiple light colors. In: IEEE International Conference on Computer Vision, pp. 226–234 (2015)
7. Long, J., Shelhamer, E., Darrell, T.: Fully convolutional networks for semantic segmentation. In: IEEE Computer Vision and Pattern Recognition, pp. 3431–3440 (2015)
8. Mccartney, E.J.: Optics of the Atmosphere: Scattering by Molecules and Particles, p. 421. Wiley, New York (1976)
9. Narasimhan, S.G., Nayar, S.K.: Shedding light on the weather. In: IEEE Computer Vision and Pattern Recognition, pp. 665–672 (2003)
10. Pei, S.C., Lee, T.Y.: Nighttime haze removal using color transfer pre-processing and dark channel prior. In: IEEE International Conference on Image Processing, pp. 957–960 (2012)
11. Ren, W., Ma, L., Zhang, J., Pan: Gated fusion network for single image dehazing. In: IEEE Computer Vision and Pattern Recognition (2018)
12. Tan, R.T.: Visibility in bad weather from a single image. In: IEEE Computer Vision and Pattern Recognition, pp. 1–8 (2008)
13. Zhang, H., Patel, V.M.: Densely connected pyramid dehazing network. In: IEEE Computer Vision and Pattern Recognition (2018)
14. Zhang, J., Cao, Y., Fang, S., Kang, Y., Chen, C.W.: Fast haze removal for nighttime image using maximum reflectance prior. In: IEEE Computer Vision and Pattern Recognition, pp. 7016–7024 (2017)
15. Zhang, J., Cao, Y., Wang, Z.: Nighttime haze removal based on a new imaging model. In: IEEE International Conference on Image Processing, pp. 4557–4561 (2014)