Nighttime Haze Removal with Glow Decomposition Using GAN

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Abstract. In this paper, we investigate the problem of a single image haze removal in the nighttime. Glow effect is inherently existing in nighttime scenes due to multiple light sources with various colors and prominent glows. As the glow obscures the color and the shape of objects nearby light sources, it is important to handle the glow effect in the nighttime haze image. Even the convolutional neural network has brought impressive improvements for daytime haze removal, it has been hard to train the network in supervised manner in the nighttime because of difficulty in collecting training samples. Towards this end, we propose a nighttime haze removal algorithm with a glow decomposition network as a learning-based layer separation technique. Once the generative adversarial network removes the glow effect from the input image, the atmospheric light and the transmission map are obtained, then eventually the haze-free image. To verify the effectiveness of the proposed method, experiments are conducted on both real and synthesized nighttime haze images. The experiment results show that our proposed method produces haze-removed images that have better quality and less artifacts than ones from previous studies.

Keywords: Nighttime image haze removal · Generative adversarial network · Perceptual losses · Glow decomposition · Fully convolutional structure

1 Introduction

Haze is an atmospheric phenomenon that particulates obscure the visibility and clarity of scenes. Scattering effect, in which moisture particles scatter an incident light reflected from objects, is the main cause of the haze. As the light passes through the atmosphere filled with particles, the light is attenuated in proportion to the distance between a camera and objects [13]. As a result, images captured in bad weather have characteristics of low contrast and shifted colors. These corrupted images bring adverse effects on many applications of computer vision and image processing. In nighttime, the problem becomes more serious due to various active light sources in the scene. For instance, headlights of vehicles yield atmospheric light spatially variant and consequently the glow effect. An

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objective of the nighttime haze removal is to obtain images with clear visibility and least artifacts. Especially, appropriate handling of the glow effect is a key to the success.

Most previous studies of haze removal follow the optical haze model that is represented by a linear equation composed of the transmission map and the atmospheric light. To get a haze-free image in daytime, therefore, the transmission map and the atmospheric light need to be predicted. The haze removal, however, is an ill-posed problem because it has to estimate various unknown parameters in the single formula. To solve the problem, many classic methods used to take multiple images or polarizing filters. Narasimhan et al. [12] proposed a method of estimating the atmospheric light chromaticity using multiple images of the same scene taken in different haze density. Schechmer et al. [19] introduced a polarization-based method according to the principle that the atmospheric light scattered by particles is partially polarized.

Recently, there have been various studies of haze removal using a single image. He et al. [8] introduced an algorithm using dark channel prior (DCP). DCP is a statistical property that founded from the observation that most outdoor objects in clear weather have a significant low intensity at least one color channel. The atmospheric light and the transmission map are estimated based on the DCP. There have been many DCP-based dehaze algorithms because of its simplicity and effectiveness. Moreover DCP is applied to other applications such as deblurring [15]. Fattal [4] introduced a haze removal method employing color-lines. The method assumes that pixels of small image patches generally exhibit a 1D distribution in RGB color space (aka color-line), and haze is removed based on the lines' offset from the origin. With recent breakthroughs in deep learning techniques, learning-based haze removal approaches have emerged and show great performance. Cai et al. [3] proposed a haze removal algorithm based on a supervised learning framework of convolutional neural network (CNN). Zhang et al. [24] suggested an end-to-end densely connected pyramid dehazing network (DCPDN). DCPDN is a haze removal method based on a generative adversarial network (GAN) trained with synthetic daytime haze images.

The nature of nighttime haze images hinders direct application of the dehaze algorithms developed for daytime images. Li et al. [10] defined a nighttime optical haze model that describes physics of the night haze scene and glow effect. To get a haze-free image, they removed the glow effect with layer separation technique, then estimates a transmission map using DCP. The algorithm produces a haze-free image with acceptable quality, but noise and halo artifacts are often amplified. Ancuti et al. [2] suggested a method of estimating the atmospheric light using multi-scale fusion. In an algorithm proposed by Park et al. [16], the glow effects from an input image are removed based on a notion of relative smoothness and the transmission map is estimated using the weighted entropy. Zhang et al. [25] suggested a heuristic assumption, maximum reflectance prior (MRP), to estimates the ambient illumination of the nighttime haze image. The prior is based on the observation that each color channel has high intensity in most daytime haze-free image patches. MRP is employed to estimate the ambient illumination and the transmission map. However, indirect handling of the glow effect results in limited success in dehazing. In an algorithm offered by Yang et al. [22], the glow effect is handled with layer separation technique. To estimate the atmospheric light, the input image is divided into super-pixels and the brightest intensity is selected in each of the super-pixels. Though some morphological artifacts are effectively removed when compared with the patch-based methods, the glow and the flare effects are not completely removed because the operation mainly relies on the gradient.

In this paper, we introduce a nighttime dehazing method by efficient handling of the glow effect, mainly consisting of the glow decomposition. In the implementation, the nighttime optical model in [10] is assumed. It needs to be noted that a generative adversarial learning technique [5] is employed to recover clear and perceptually natural glow-removed images, and then eventually haze-free images. In the first stage, the input image is decomposed into the glow image and the glow-free image by the generator. Then, in training session, the discriminator judges the authenticity of the glow-removed image estimated by the generator, and the judgement is to make the generator decompose more accurately. In the second stage, the glow-removed image is divided into super-pixels with simple linear iterative clustering (SLIC) [1] for estimating the atmospheric light and the transmission map, and both are refined by a guided image filter (GIF) [7]. DCP is adopted in estimating the transmission map. The final haze-free image is obtained with the atmospheric light and the transmission map based on the optical haze model.

Our main contribution can be summarized as active application of adversarial learning in glow removal for nighttime dehazing. Experiment results indicate that the GAN based approach significantly reduces halo artifacts and color distortion, comparing to the previous glow removal methods.

2 Preliminary Knowledge

2.1 Conditional Generative Adversarial Network

The generative adversarial network (GAN), introduced by Goodfellow et al. [5], is composed of two network modules, the generator and the discriminator. The generator produces a fake data that is identical with the real data. The discriminator judges the authenticity of the fake data. These network modules are trained simultaneously until the generator is able to consistently produce results that the discriminator cannot distinguish the real and the fake. Mathematically, this can be expressed as:

$$\min_{G}\max_{D} V(G,D) = \mathbb{E}_x[logD(x)] + \mathbb{E}_z[log(1 - D(G(z)))] \tag{1}$$

where G, D indicate the generator and the discriminator, respectively. V is the value function and x is a discriminator input. z indicates a generator input that uniformly distributed noise variable. However, in our task, the input z is a color image, not just a noise. So, the generator input z is treated as a latent variable conditioned with the color image y. Therefore, (1) is rewritten as:

$$\min_G \max_D V(G, D) = \mathbb{E}_x[logD(x|y)] + \mathbb{E}_z[log(1 - D(G(z|y)))] \tag{2}$$

2.2 Atrous Convolution

To integrate knowledge of the global context, people often use a spatial pooling. However, the spatial pooling losses some detailed information. To address the problem, Yu et al. [23] introduced the atrous convolution that is also called "dilated convolution." Atrous convolution enables a network to solve multi-scale problems without increasing the number of parameters. Atrous convolution between signal f and kernel k is expressed as (3):

$$(k \oplus_l f)_t = \sum_{\tau=-\infty}^{\infty} k_\tau \cdot f_{t-l\tau} \tag{3}$$

where $\oplus_l$ indicates the atrous convolution with dilation rate l and the standard convolution $f_{t-\tau}$ is modified to $f_{t-l\tau}$. A dilation rate l defines size of receptive field. In the atrous convolution, the kernel only touches the signal at every l^{th} entry. The size of the receptive field expressed as $(l * (k-1) + k)^2$.

3 Single Image Nighttime Haze Removal

3.1 Nighttime Haze Optical Model

As previously mentioned, an atmospheric particle scatters an incident light then the intensity of the light is attenuated. Based on the optical phenomenon, Narasimhan et al. [13] expressed a daytime optical haze model as:

$$I_c(\mathbf{x}) = R_c(\mathbf{x})t(\mathbf{x}) + A_c(1 - t(\mathbf{x})) \tag{4}$$

where $c \in \{r, g, b\}$ indicates rgb color channels, I_c is an observed haze image, R_c is a haze-free image, t is a transmission map that represents the portion of a light go through the haze, and A_c is an atmospheric light. $R_c(\mathbf{x})t(\mathbf{x})$ and $A_c(1 - t(\mathbf{x}))$ is called the direct transmission and the airlight, respectively. On the other hand, Li et al. [10] expressed a nighttime optical haze model as:

$$I_c(\mathbf{x}) = R_c(\mathbf{x})t(\mathbf{x}) + A_c(\mathbf{x})(1 - t(\mathbf{x})) + A_a(\mathbf{x}) * APSF \tag{5}$$

In nighttime, as previously mentioned, the atmospheric light is no longer globally constant because of various light sources, such as street lights. Therefore A_c in (5) has matrix form. A_a indicates the intensity of active light sources and APSF(atmospheric point spread function) reveals the analytical expression for the glow effect derived by Narasimhan et al. [14].

Fig. 1. Results of glow decomposition: For the input image pair in (a), the glow and the glow-removed images, respectively; (b, c) by [10] and (d, e) by the proposed algorithm. In (b, c), the glow effect is boosted and the color is unnatural due to the wrongly predicted glow layer. However, in (d, e), the shape and the color of the glow images are close to the input images and the glow-removed images is more natural. (Color figure online)

3.2 Glow Removal with Generative Adversarial Network

The glow effect is a significant problem should be taken care of in nighttime dehaze. The glow obscures the color and the shape of objects that nearby light sources. Consequently, the glow should be handled properly in order to produce the result image with great visibility. We regard the glow removal as a layer separation problem and thus (5) is rewritten as:

$$I_c(\mathbf{x}) = J_c(\mathbf{x}) + G_c(\mathbf{x}) \tag{6}$$

where, $J_c(\mathbf{x}) = R_c(\mathbf{x})t(\mathbf{x}) + A_c(\mathbf{x})(1-t(\mathbf{x}))$ and $G_c(\mathbf{x}) = A_a(\mathbf{x}) * APSF$ represent the glow-removed night haze image and the glow image, respectively. Li et al. [10] applied a glow removal algorithm on the basis that the glow effect of nighttime haze has "short tail" distribution. However, when the shape and the color of the illuminants are complex, it is insufficient for separating glow layer by just considering in gradient domain, as can be seen in Fig. 1(c). It indicates that high-level information needs to be involved. Since the glow effect is influenced by the shape, color and location of the illuminants, it needs to consider not only low-level information but also high-level semantic information of the glow effect.

Our glow decomposition network is devised to separate layer with fine glows and handle some image degradation problems, including noise, halo artifacts, and color distortion. The network is designed based on the structure of Zhang et al. [28], in which the network is composed of fully convolutional layers. In the initial stage, features are extracted from five convolutional layers of VGG-19 network [20] pre-trained with ImageNet dataset [18]. The extracted feature maps are resized as the same size as the input image. And the resized feature maps are concatenated in channel-wise, and the concatenated feature maps are called hypercolumn features [6]. Through the hypercolumn features, the network extracts multi-level information of the glow and the illuminants. Performing

1×1 convolution to the condensed hypercolumn features to reduce the number of channels is followed by the continuous atrous convolution [23] to produce the glow layer and the glow-removed layer. The network's architecture is described in Fig. 2.

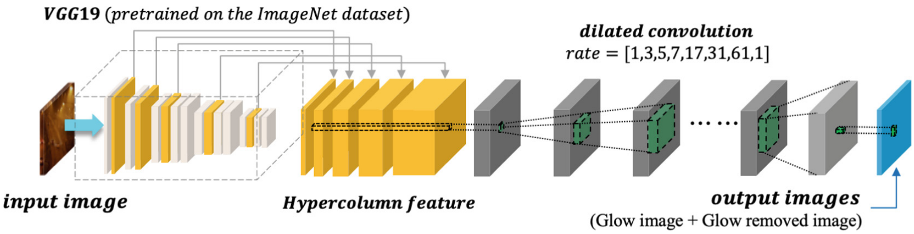

Fig. 2. Architecture of the generator

To train the network, we need a large number of glow and glow-free image pairs of the same spatiotemporal scenes. Based on our observation, structural property of the glow in feature level is similar to that of the corresponding reflection image which can be taken from glass. A reflection image is composed of brightest spots which produces high contrast and large gradients due to illuminant. In addition, the image is blurred with low intensity and thus consists of small gradients. By taking into account these aspects, we train the network with refection images synthesized by Zhang's method [28]. About 13,000 night-time images, consisting of diverse environments, were collected from Youtube and Flicker.

In the generative adversarial network, the generator produces a fake glow-removed image, $\hat{J}_c$. The generated image is fed into a discriminator alongside a stream of images taken from the ground-truth image, J_c^{gt}. The discriminator judges the authenticity of the generated image by returning the probability. The generator is to produce realistic fake glow-removed images, and the discriminator is to identify the image coming from the generator.

The Fig. 1 shows the glow-removed images by [10] and the proposed method. The network extracts multi-level features of the glow image and thus predict the shape and colors of the glow layer perceptually well. The figure shows that the proposed network excels at comprehensively disassembling the glow layer near the light sources.

In order to train the glow decomposition network effectively, we adopt the objective function by combining several loss terms as follows.

$$L_{glow} = \lambda_1 L_1 + \lambda_p L_p + \lambda_a L_a + \lambda_e L_e + \lambda_{dh} L_{dh} \tag{7}$$

We adopt perceptual loss (L_p), adversarial loss (L_a), and exclusion loss (L_e), which are used in state-of-the-art approaches [5,9,28] In addition, we include dense haze loss (L_{dh}) motivated from [27]. We also simply add L_1 loss defined as $L_1 = \sum_{(I_c, J_c^{gt}) \in \mathfrak{D}} \left\| \hat{J}_c - J_c^{gt} \right\|_1$. For simplicity, we denote $J_c(\mathbf{x})$ and $G_c(\mathbf{x})$ as J_c and G_c, respectively. We build a dataset $\mathfrak{D} = (I_c, J_c^{gt}, G_c^{gt})$, where I_c is the input image synthesized by Zhang's method [28], J_c^{gt} is the glow-removed image, and G_c^{gt} is the reflection image of I_c. λ represents the weight of each loss. Each term in (7) is briefly described as following:

Perceptual loss (L_p): As mentioned earlier, the network has to be trained with not only low-level features but also high-level features of the glow image. Therefore, we use a perceptual loss:

$$L_p = \sum_{I_c, J_c^{gt} \in \mathfrak{D}} \sum_{l} \lambda_l \left\| \Phi_l(J_c^{gt}) - \Phi_l(\hat{J}_c) \right\|_1 \tag{8}$$

The perceptual loss is computed by comparing the multi-level representations of ground-truth glow-removed image, J_c^{gt}, and the predicted glow-removed image, $\hat{J}_c$. In the equation, Φ represents the pretrained VGG-19 network and l indicates layer of the network. λ_l is a hyperparameter used as a weight.

Adversarial loss (L_a): The adversarial loss is used to show the distance between two different distributions of $P(\hat{J}_c)$ and $P(J_c^{gt})$. The role of the adversarial loss is to make the two probability distributions similar so that it makes the generator to produce photo-realistic glow-removed image and to handle some artifacts.

$$L_a = \sum_{I_c \in \mathfrak{D}} -logD(J_c^{gt}, \hat{J}_c) \tag{9}$$

In the equation, D indicates the discriminator of the glow decomposition network. We use $-logD(J_c^{gt}, \hat{J}_c)$ instead of $log(1 - D(J_c^{gt}, \hat{J}_c))$ due to the gradient problem [5].

Exclusion loss (L_e): The exclusion loss, introduced by Zhang et al. [28], helps to separate different layers well in gradient domain. As there is little correlation between the edges of the glow layer and the edges of the glow-removed layer, we use the exclusion loss to minimize correlation of the two different layers in gradient domain.

$$L_e = \sum_{I_c \in \mathfrak{D}} \sum_{n=1}^{N} \left\| \Psi(\hat{J}_c^n, \hat{G}_c^n) \right\|_F \tag{10}$$

$$\Psi(J_c, G_c) = tanh(\lambda_J \left| \nabla J_c \right|) \odot tanh(\lambda_G \left| \nabla G_c \right|) \tag{11}$$

where, $\|\cdot\|_F$ is Frobenius norm, $\odot$ indicates element-wise multiplication, n is the image downsampling factor, and λ_J and λ_G mean normalization factors. In our implementation, we set $N = 3$.

Dense haze loss (L_{dh}): Color ambiguity problem can be expected when objects are seen through dense haze, which causes object color saturation. Motivated by Zhang et al. [27], we introduced a loss term to deal with the color ambiguity problem, by expecting the network takes care of overall color tone of the image and produces vibrant and realistic colorizations.

$$L_{dh} = \frac{1}{3} \sum_{(I_c, J_c^{gt}) \in \mathfrak{D}} \sum_{l=1}^{3} \left\| h_{gray}(J_c^{gt})^l - h_{Lab}(J_c^{gt})^l \right\| \tag{12}$$

In the equation, $h_{gray}(J_c^{gt})$ means the transition to grayscale image from ground truth glow-removed image J_c^{gt}, and $h_{Lab}(J_c^{gt})$ means the transition to CIE Lab color space from the image J_c^{gt}. Each 3 channel of the grayscale image is identical. l indicates channels of CIE Lab color space. As shown in Fig. 3, it turns out to be effective when the network predicts the saturated object colors in dense haze.

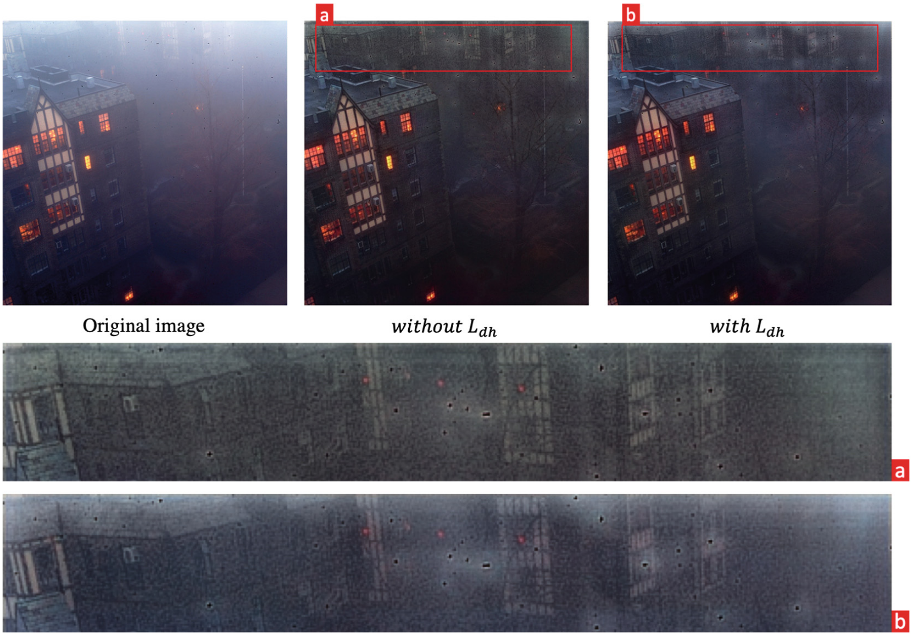

Fig. 3. Role of the *dense haze loss*, L_{dh}: the network can predict effectively the colors of objects in dense haze, which are seriously saturated. (Color figure online)

3.3 Computation of Atmospheric Light

Once the glow effect is removed from the night haze image, the glow-removed night haze image, $J_c(\mathbf{x})$, is obtained. As shown in (13), we find the atmospheric light, $A_c(\mathbf{x})$, and the transmission map, $t(\mathbf{x})$, in order to get the haze-free image, $R_c(\mathbf{x})$.

$$J_c(\mathbf{x}) = R_c(\mathbf{x})t(\mathbf{x}) + A_c(\mathbf{x})(1 - t(\mathbf{x})) \tag{13}$$

Yang et al. [22] exploit a way to compute the atmospheric light with fine preserved structure based on super-pixel representation. Therefore, the method in [22] can be applied to get the atmospheric light from the glow-removed image by rewriting (13) as (14) on the basis of image formation model.

$$J_c(\mathbf{x}) = A_c(\mathbf{x})R_c^r(\mathbf{x})t(\mathbf{x}) + A_c(\mathbf{x})(1 - t(\mathbf{x})) \tag{14}$$

The scene radiance $R_c(\mathbf{x})$ is decomposed into the illumination, $A_c(\mathbf{x})$, and the reflectance, $R_c^r(\mathbf{x})$.

We begin the decomposition by segmenting $J_c(\mathbf{x})$ via SLIC algorithm [1]. The intensity of the atmospheric light and the transmission values are assumed to be constant in the super-pixel Ω. Then (14) can be derived as:

$$\begin{aligned} \underset{\mathbf{x}'\in\Omega(\mathbf{x})}{max}\{J_c(\mathbf{x}')\} &= \underset{\mathbf{x}'\in\Omega(\mathbf{x})}{max}\{A_c(\mathbf{x}')R_c(\mathbf{x}')t(\mathbf{x}')) + A_c(\mathbf{x}')(1-t(\mathbf{x}'))\} \\ &= \underset{\mathbf{x}'\in\Omega(\mathbf{x})}{max} A_c(\mathbf{x})\{R_c(\mathbf{x}')\}\, t(\mathbf{x}) + A_c(\mathbf{x})(1-t(\mathbf{x})) \end{aligned} \tag{15}$$

Based on the maximum reflectance prior [25], we assume that $\underset{\mathbf{x}'\in\Omega(\mathbf{x})}{max}\{R_c^r(\mathbf{x}')\} = 1$. Therefore, the atmospheric light can be computed as:

$$A_c(\mathbf{x}) = \underset{\mathbf{x}'\in\Omega(\mathbf{x})}{max}\{R_c(\mathbf{x}')\} \tag{16}$$

After the computation of the atmospheric light, we apply the guided image filter (GIF) [7] to remove the morphological artifacts and to make result image smooth.

3.4 Estimation of Transmission Map

To estimate the transmission map of a glow-removed image, we adopt dark channel prior (DCP) [8] defined as (17).

$$\underset{c\in\{r,g,b\}}{min}(\underset{\mathbf{x}'\in\Omega(\mathbf{x})}{min} J_c(\mathbf{x}')) \approx 0 \tag{17}$$

Then the transmission map computed as:

$$\underset{\mathbf{x}'\in\Omega(\mathbf{x})}{min}\ \underset{c}{min}\frac{J_c(\mathbf{x}')}{A_c(\mathbf{x}')} = t(\mathbf{x}) \underset{\mathbf{x}'\in\Omega(\mathbf{x})}{min}\ \underset{c}{min}\left(\frac{R_c(\mathbf{x}')}{A_c(\mathbf{x}')}\right) + (1-t(\mathbf{x})) \tag{18}$$

$$t(\mathbf{x}) = 1 - \underset{\mathbf{x}'\in\Omega(\mathbf{x})}{min}\ \underset{c}{min}\frac{J_c(\mathbf{x}')}{A_c(\mathbf{x}')} \tag{19}$$

3.5 Scene Recovery

We need to introduce the lower bound of the transmission, t_0, since noise exists in the result image when the transmission value is close to zero. We set the value of t_0 as 0.15, in our implementation.

$$R_c(\mathbf{x}) = \frac{J_c(\mathbf{x}) - A_c(\mathbf{x})}{max(t(\mathbf{x}), t_0)} + A_c(\mathbf{x}) \tag{20}$$

Normally, the atmospheric light is darker than the scene reflection as removed haze reduces the overall brightness of the image. So we increase the intensity of $R_c(\mathbf{x})$ multiplying by a ratio of C. Therefore the average intensity of $R_c(\mathbf{x})$ is equal to the average intensity of $J_c(\mathbf{x})$.

(a) Input haze image (b) without L_a

(c) without L_e (d) without L_p

(e) without L_{dh} (f) with four loss terms

Fig. 4. Ablation experiment results with four loss terms: (b) the glow effect is still remaining, (c) illumination of the image is unnatural and the glow effect is not separated well, (d) heavy color distortion and artifacts are observed, (e) the glow effect at far distance are still remaining, and (f) image obtained with four loss terms. (Color figure online)

4 Experiment Results

To prove the effectiveness of the proposed algorithm, we conduct qualitative and quantitative analyses.

4.1 Qualitative Analysis

Ablation study: To figure out the role of each term in the objective function defined in (7), a set of experiments has been carried out. In each experiment, a

(a) Input haze image (b) He et al.[7] (c) Zhang et al.[26]

(d) Li et al.[10] (e) Yang et al.[22] (f) Proposed method

Fig. 5. Comparison with other methods: (a) input haze image; (b, c, d, e) dehazed images by the method in [7], [26], [10], [22], respectively, and (f) dehazed image by the proposed method.

loss term is eliminated and the generator network is re-trained, and we analyze how the term affects to the over quality of the result image.

Figure 4 shows the ablation experiment results. Without L_a, the glow effect is not removed completely. Without L_e, illumination of the image is unnatural and color distortion appears. Without L_p, the output image suffers from heavy color distortion. The dense haze loss, L_{dh}, helps removing the glow at far distance and making the result cleaner.

Comparison with Other Methods. The performance of the proposed algorithm is compared with four other methods of [7], [26], [10], [22] as shown in Fig. 5. The method by He et al. [7], devised for daytime haze removal, is not working properly to the nighttime scene. The glow and haze aren't removed. Even though the remaining three algorithms were designed for the nighttime scenes, different kinds of defects are observed in the result images. The method in [26] removed the glow, but strong halo artifact is observed. Li's method [10] decomposed the glow better than the method in [26], but halo artifact and noise are observed. The method in [22] suppressed the halo artifact well, however, the shifted color make the result image unnatural. The result image of the proposed method, on the other hand, suppressed noise and halo artifact in the sky region. In addition, our method is able to maintain realistic colors with better glow removing.

4.2 Quantitative Analysis

We also made comparison with other methods in quantitative manner in terms of the structural similarity index (SSIM [21]). For the comparison, we use a synthetic image generated using PBRT [17] as the ground truth is needed. Fig. 6 shows the ground truth image, the synthesized haze image, and the dehazed image by our method, respectively. Table 1 shows the quantitative results against the other methods. Higher SSIM value means the haze-free image is more similar to the ground-truth image. The result proves that our haze removal method works better in nighttime than the other methods.

Table 1. SSIM for the dehazing results on synthetic hazy images generated using PBRT

Methods	SSIM
Zhang et al.'s [26]	0.9952
He et al.'s [8]	0.9978
Meng et al.'s [11]	0.9984
Li et al.'s [10]	0.9987
Park et al.'s [16]	0.9989
Our method	0.9989

(a) Ground truth (b) Synthetic haze image (c) Dehazed image

Fig. 6. Quantitative evaluation using SSIM [21] on a synthetic image generated using Photorealistic Rendering and the Ray-Tracing Algorithm(PBRT)[17].

5 Conclusion

This paper presented a novel glow decomposition method using GAN for the nighttime haze removal. The generative adversarial network is devised to handle the glow effect by decomposing the input image into the glow image and the glow-free image. In addition, a way to train the network by data synthesized from night images collected. Significantly reduced halo artifact and noise in the result image brought perceptually better quality comparing to the state-of-the-art methods. Experiment results prove that the effectiveness of the proposed method in both qualitatively and quantitatively.

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