# Nighttime Haze Removal with Glow and Multiple Light Colors

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## Abstract

*This paper focuses on dehazing nighttime images. Most existing dehazing methods use models that are formulated to describe haze in daytime. Daytime models assume a single uniform light color attributed to a light source not directly visible in the scene. Nighttime scenes, however, commonly include visible lights sources with varying colors. These light sources also often introduce noticeable amounts of glow that is not present in daytime haze. To address these effects, we introduce a new nighttime haze model that accounts for the varying light sources and their glow. Our model is a linear combination of three terms: the direct transmission, airlight and glow. The glow term represents light from the light sources that is scattered around before reaching the camera. Based on the model, we propose a framework that first reduces the effect of the glow in the image, resulting in a nighttime image that consists of direct transmission and airlight only. We then compute a spatially varying atmospheric light map that encodes light colors locally. This atmospheric map is used to predict the transmission, which we use to obtain our nighttime scene reflection image. We demonstrate the effectiveness of our nighttime haze model and correction method on a number of examples and compare our results with existing daytime and nighttime dehazing methods' results.*

## 1. Introduction

The presence of haze significantly degrades the quality of an image captured at night. Similar to daytime haze, the appearance of nighttime haze is due to tiny particles floating in the air that adversely scatters the line of sight of lights rays entering the imaging sensor. In particular, light rays are *scattered-out* to directions other than the line of sight, while other light rays are *scattered-in* to the line of sight. The scattering-out process causes the scene reflection to be attenuated. The scattering-in process creates the appearance of a particles-veil (also known as airlight) that washes out the visibility of the scene. These combined scattering effects adversely affect scene visibility that in turns negatively impacts subsequent processing for computer vision applications.

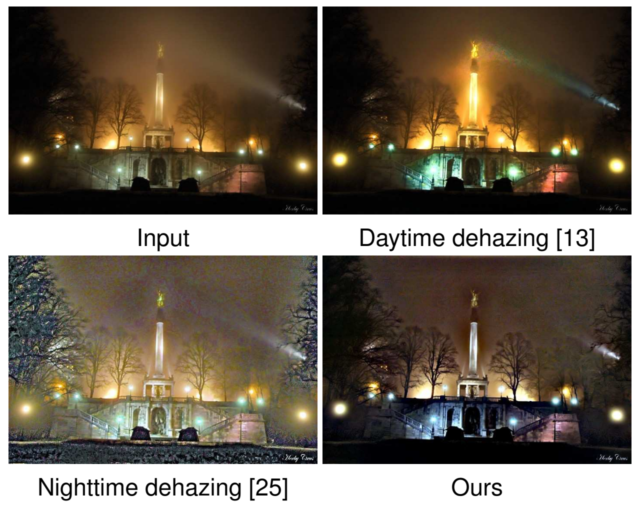


Figure 1. A daytime dehazing method [13] fails to handle glow and haze. A nighttime dehazing method [25] is erroneous in dealing with glow and boosts the intensity unrealistically. Our result shows reduced haze and looks more natural.

A number of methods have been developed to address visibility enhancement for hazy or foggy scenes from a single image (*e.g*. [5, 6, 8, 13, 21, 22]). The key to their success relies on the optical model and the possible estimation of its parameters, particularly the atmospheric light and transmission. The standard haze model [10] describes a hazy scene as a linear combination of the direct transmission and airlight, where the direct transmission represents the reflection of a scene whose intensity is reduced by the scattering-out process, and the airlight represents the intensity resulted from the scattering-in process of the surrounding atmospheric light. In the model, the transmission conveys the fraction of the scene reflection that reaches the camera (as the other fractions are scattered out from the line of sight).

Based on the model, existing daytime dehazing methods first estimate the atmospheric light. Most of methods (except [20]) assume that the atmospheric light is present in the input image and can be estimated by the brightest region in the image. Although, this estimation is a crude approximation, in most cases it works adequately. Having estimated the atmospheric light, these methods estimate the transmission using various cues, such as local contrast [21], independence between shading and transmission [5], dark channel [8], image fusion [2], and more. The methods differentiate themselves from each other mainly on the cues used for estimating the transmission.

While these methods are effective to handle daytime haze, they are not well equipped to correct nighttime scenes (see Fig 1). This is not too surprising, as the standard daytime haze model does not fit well with the conditions of most nighttime hazy scenes. Nighttime scenes generally have active light sources, such as street lights, car lights, building lights, etc. These lights add to the scattering-in process, giving more brightness to the existing natural atmospheric light. This implies that the airlight is brighter when the active lights are present in the scene. More importantly, nighttime light sources also introduce a prominent glow to the scene. This glow is a result from both strong lights directly traveling to the camera and light scattered around the light sources by haze particles [14]. This noticeable glow is not accounted for in the standard haze model.

Furthermore, unlike daytime haze, the atmospheric light cannot be obtained from the brightest region in nighttime images. Due to the presence of active lights and their associated glow, the brightest intensity in the scene can differ significantly from the atmospheric light. Also, because of the multiple light sources, the atmospheric light cannot be assumed to be globally uniform. Consequently, normalizing the input image with the brightest region intensity will cause a noticeable color shift in the image.

**Contribution** To address nighttime dehazing, we introduce a new nighttime haze model that models glow in addition to the direct transmission and airlight. The basic idea is to incorporate a *glow term* into the standard haze model. This results in a new model that has three terms: the direct attenuation, airlight and glow. Working from this new model, we propose an algorithm to first decompose the glow from the input image. This results in a new haze image with reduced glow, but still containing haze and potentially multi-colored light sources. To address this, a spatially varying atmospheric light map which locally encodes different light colors is estimated. From this atmospheric map, we calculate the transmission, and finally obtain the nighttime scene reflection. Our estimated scene reflection has better visibility, with reduced glow and haze and does not suffer from color shifts due to the spatially varying lights.

The remainder of this paper is organized as follows: Sec. 2 discusses existing methods targeting daytime dehazing, underwater and nighttime dehazing. Sec. 3 introduces our nighttime haze model and compares it to the standard haze model. Sec. 4 overviews our nighttime dehazing method based on our proposed model. Sec. 5 shows experimental results. A discussion and summary concludes the paper in Sec. 6.

## 2. Related Work

As mentioned in Sec. 1, there are many methods dedicated to daytime dehazing for single images, such as [2, 5, 6, 8, 13, 15, 21, 22, 23]. All methods employ a standard haze model [10] and assume that the atmospheric light can be reasonably approximated from the brightest region in the input image. An exception applies to [6], which utilizes the atmospheric light estimation proposed in [20]. The method [20] estimates the globally uniformed color of the atmospheric light by using small patches of different reflections that form color lines in RGB space and estimates the magnitude of the atmospheric light by minimizing the distance between the estimated shading and the estimated transmission for different levels of transmission. The main differences of these dehazing techniques are in the cues and algorithms to estimate the transmission. Other related methods are those developed for underwater visibility enhancement, *e.g.*, [1, 4, 18, 19]. All of these aforementioned methods, including underwater visibility enhancement, use the standard daylight dehaze model that is not well-suited for nighttime haze.

There are significantly fewer methods that address nighttime haze. Pei and Lee [16] propose a color transfer technique as a preprocessing step to map the colors of a nighttime haze image onto those of a daytime haze image. Subsequently, a modified dark channel prior method is applied to remove haze. While this approach produces results with improved visibility, the overall color in the final output looks unrealistic. This is due to the color transfer, which changes colors without using a physically valid model. Zhang *et al.*'s [25] introduce an imaging model for the nighttime haze that includes spatially varying illumination compensation, color correction and dehazing. The overall color of their results looks more realistic than those of [16], however, the model does not account for glow effects, resulting in noticeable glow in the output. The method also involves a number of additional adhoc post processing steps such as gamma curve correction and histogram stretching to enhance the final result (see Fig. 1). In contrast to these methods, we model nighttime haze images by explicitly taking into account the glow of active light sources and their light colors. This new model introduces a unique set of new problems, such as how to decompose the glow from the rest of the image and how to deal with varying atmospheric light. By resolving these problems, we found our results are visually more compelling than both existing daytime and nighttime methods.

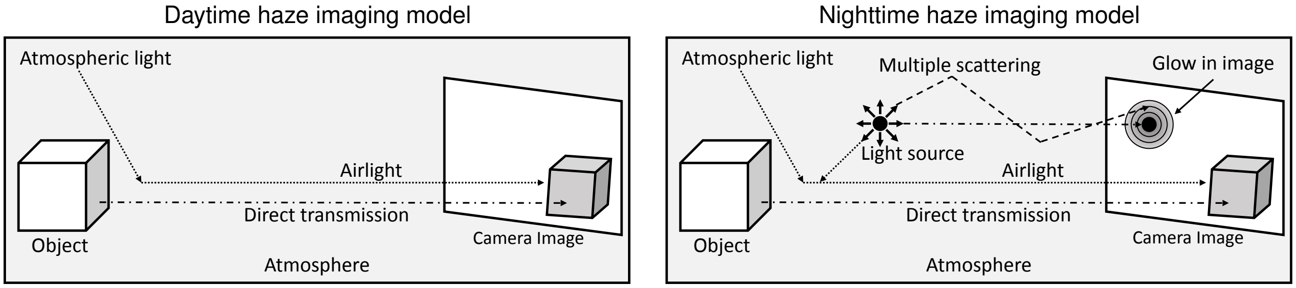


Figure 2. (Left) shows a diagram of the standard daytime haze model. The model assumes that the atmospheric light is globally uniform and contributes to the brightness of the airlight. The model has another term called the direct transmission, which describes light travelling from the object or scene reflection making its way to the image plane. (Right) shows a diagram of our proposed nighttime haze model. Aside from the airlight and direct transmission, the model also has a glow term, which represents light from sources that gets scattered multiple times and reaches the image plane from different directions. In our model, light sources potentially have different colors that contribute to the appearance of the airlight.

## 3. Nighttime Haze Model

This section describes our nighttime haze model. We begin by first describing the standard daytime haze model. This is followed by our new model that considers the presence of visible multi-colored light sources as well as their associated glow due to scattering.

For daytime haze scenes, the most commonly used optical model assumes that the scattered light in the atmosphere captured by the camera is a linear combination of the direct transmission and airlight as [10]:

$$\mathbf{I}(\mathbf{x}) = \mathbf{R}(\mathbf{x})t(\mathbf{x}) + \mathbf{L}(1 - t(\mathbf{x})), \tag{1}$$

where $\mathbf{I}(\mathbf{x})$ is the observed color at pixel $\mathbf{x}$, $\mathbf{R}(\mathbf{x})$ is the scene reflection or radiance when there is no haze or fog particles. The term $t(\mathbf{x}) = \exp(-\beta d(x))$ is the transmission that indicates the portion of scene reaching the camera. The term $\beta$ is the attenuation factor of the particles, and $d$ is the optical thickness or distance between the camera and the object or scene. The two terms $\mathbf{R}(\mathbf{x})$ and $t(\mathbf{x})$ multiply together to form the direct transmission. The last term $\mathbf{L}(1 - t(\mathbf{x}))$ is the airlight, representing the particle veil induced by the scattering-in process of the atmospheric light, $\mathbf{L}$, which is assumed to be globally uniform. In daytime hazy images, the atmospheric light is mainly generated by sky light and indirect sunlight that has been scattered by clouds or haze particles.

Given a color image $\mathbf{I}$, the main goal of single image dehazing is to recover the scene's reflection $\mathbf{R}$, or at least to enhance the visibility of $\mathbf{R}$. The most commonly employed steps to achieve this goal is to first estimate the globally uniform atmospheric light, $\mathbf{L}$, and then to estimate the transmission $t$. Having obtained these two parameters, estimating $\mathbf{R}$ for every pixel becomes straightforward.

As discussed in Sec. 1, nighttime scenes typically have active light sources that can generate glow when the presence of particles in the atmosphere is substantial. This glow has been analyzed by Narasimhan and Nayar [14] who describe it as light from sources that gets scattered multiple times and reaches the observer from different directions. They model this glow as an atmospheric point spread function (APSF). Inspired by this, we model the entire nighttime hazy scenes by adding the glow model into the slightly modified standard haze model:

$$\mathbf{I}(\mathbf{x}) = \mathbf{R}(\mathbf{x})t(\mathbf{x}) + \mathbf{L}(\mathbf{x})(1 - t(\mathbf{x})) + \mathbf{L}_a(\mathbf{x}) * APSF, \tag{2}$$

where $\mathbf{L}_a$ is the active light sources, which the intensity is convolved with the atmosphere point spread function, $APSF$, yielding a glow effect in the image [14]. Unlike the standard haze model, $\mathbf{L}$, in our model is no longer globally uniform, and thus can change at different locations. This is because various colors from different light sources can contribute to the atmospheric light as a result of the scattering process. While this represents a rather simple modification to the standard haze model, to the best of our knowledge this model is novel and offers a useful means to describe nighttime haze images with glow and active light sources.

For illustration, Fig. 2 shows diagrams of both the daytime haze and nighttime haze models. In the nighttime haze, aside from the natural atmospheric light, the airlight obtains its energy from active light sources, boosting the brightness in the image. The active light sources also creates its own presence in the image by having its direct light to the image and its scattered light that manages to reach the camera after multiple bounces inside the medium. In the image, these manifest themselves as glow, which is separate imagery from other objects in the scene. In the real world, the presence of glow can be significantly prominent in terms of the affected areas and the brightness. Also, due to the scattering, the brightness of the glow effect gradually decreases, making its appearance smooth.

Note that our model is different from the model proposed by Zhang et al. [25]. Zhang et al.'s model is similar to the standard haze model that employs the two terms, yet adds

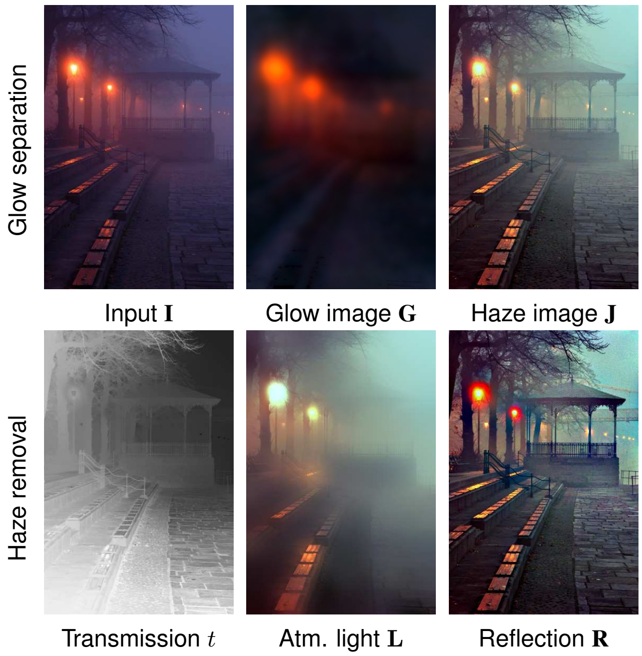

Figure 3. Pipeline: (top row) given an input $\mathbf{I}$, we decompose it into a glow image $\mathbf{G}$, and haze image $\mathbf{J}$; (bottom row) we further dehaze the haze image $\mathbf{J}$, yielding the transmission $t$, atmospheric light $\mathbf{L}$ and scene reflection $\mathbf{R}$.

a new parameter accounting for various light colors and brightness values. This varying light color and brightness is similar to the varying atmosphere light, $\mathbf{L}(\mathbf{x})$ in our model in Eq. (2). We note that our model is also related to some extent to Schechner and Karpel's model [19] for underwater images, which takes image blur into account by convolving the forward scattering with a Gaussian function. However, Schechner and Karpel do not intend to model glow, instead they want to model the scene blur caused by the significant amount of particles in underwater scenes.

# 4. Nighttime Haze Removal

Given an input image $\mathbf{I}$, our goal is to estimate the scene reflection, $\mathbf{R}$, for every pixel. Fig. 3 shows the images involved in our pipeline. From the input image, $\mathbf{I}$, we decompose the glow image $\mathbf{G}$ to obtain the nighttime haze image $\mathbf{J}$. Having obtained the nighttime haze image that is ideally free from glow, we further dehaze it, and recover the transmission $t$, the varying atmospheric light $\mathbf{L}$, and finally the scene reflection, $\mathbf{R}$. More details to our nighttime dehazing process is provided in the following sections.

## 4.1. Glow Decomposition

Narasimhan and Nayar's method [14] models glow by convolving a light source with the atmospheric point spread function (APSF) represented by a Legendre polynomial and the attenuation factor represented by the Lambert-Beer law.

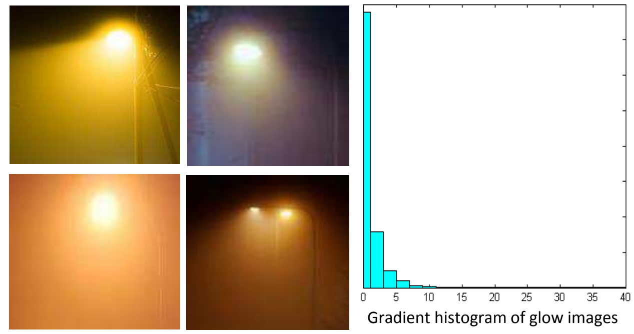

Figure 4. Some glow patches and their gradient histogram profile. Even though the color, shape, direction of the glow are different, the images gradient histogram are well modeled using a short tail distribution [11].

The model is then used to estimate the optical thickness (the distance of a light source to the camera) and the forward scattering parameter of the Henyey-Greenstein phase function, which represents the scattering degrees of different aerosols. Having estimated these two parameters, the deconvolution of the glow can be applied and as a result, the shapes of the light sources can be obtained. Since the optical thickness is known, the depth of the scene nearby the light sources can also be recovered. Although Narasimhan and Nayar's method can be used to estimate the glow's APSF parameters, it was neither meant to enhance visibility nor decompose glow from the input image. It also assumes that the locations and the areas of individual light sources are known, which is problematic to obtain automatically.

To resolve this, we take a different approach. We notice that the appearance of the glow can be dominant in nighttime haze scenes and degrade the visibility. In some areas, the brightness of the glow can be so dominant that the nearby objects to the light sources cannot be seen at all. Thus, to enhance visibility, we need first to remove the effects from glow. Our approach is to decompose this from the rest of the scene. To enable this decomposition process, we rewrite our model in Eq. (2) as:

$$\mathbf{I}(\mathbf{x}) = \mathbf{J}(\mathbf{x}) + \mathbf{G}(\mathbf{x}), \tag{3}$$

where $\mathbf{J} = \mathbf{R}(\mathbf{x})t(\mathbf{x}) + \mathbf{L}(\mathbf{x})(1 - t(\mathbf{x}))$ and $\mathbf{G}(\mathbf{x}) = \mathbf{L}_a(\mathbf{x}) * APSF$. We call the former the nighttime haze image, and the latter the glow image. In this form, decoupling glow becomes a layer separation problem, with the two layers: $\mathbf{J}$ and $\mathbf{G}$, which need to be estimated from a single input image, $\mathbf{I}$.

As discussed in Sec. 3, due to the multiple scattering surrounding light sources, the brightness of the glow decreases gradually and smoothly. We exploit this smoothness attribute and employ the method of Li and Brown [11] that targets layer separation for scenes where one layer is significantly smoother than the other. The key idea of the method


Figure 5. Effect of our first and second constraints for the glow decomposition. From the input image $\mathbf{I}$, we decompose the glow by using solely the first constraint, resulting in the color shift in the estimated glow image (column 2) and the estimated haze image (column 3). Based on the same input, we add the second constraint, and now the estimated glow image (column 4) and haze image (column 5) are more balanced in terms of their colors.


Figure 6. Glow decomposition results. (Left column) shows the input images. (Middle column) shows the estimated glow images. (Right column) shows the estimated haze images. As one can notice, the presence of glow in the haze images is much reduced.

[11] is that the gradient histogram of the smooth layer has a "short tail" distribution. As shown in Fig. 4, the glow effect of nighttime haze also shares this characteristic, and thus we can model it with a short tail distribution.

Following [11], we design our objective function for layer separation such that the glow layer is smooth and the large gradients appear in the remaining nighttime haze:

$$E(\mathbf{J}) = \sum_{\mathbf{x}} \left( \rho(\mathbf{J}(\mathbf{x}) * f_{1,2}) + \lambda((\mathbf{I}(\mathbf{x}) - \mathbf{J}(\mathbf{x})) * f_3)^2 \right) \quad \text{s.t.} \quad 0 \leq \mathbf{J}(\mathbf{x}) \leq \mathbf{I}(\mathbf{x}), \quad \textstyle\sum_{\mathbf{x}} \mathbf{J}_r(\mathbf{x}) = \sum_{\mathbf{x}} \mathbf{J}_g(\mathbf{x}) = \sum_{\mathbf{x}} \mathbf{J}_b(\mathbf{x}). \tag{4}$$

where $f_{1,2}$ is the two direction first order derivative filters, $f_3$ is the second order Laplacian filter and the operator $*$ denotes convolution. The second term uses the $L_2$ norm regularization for the gradients of the glow layer, $\mathbf{G}$, where $\mathbf{G}(\mathbf{x}) = \mathbf{I}(\mathbf{x}) - \mathbf{J}(\mathbf{x})$, which forces a smooth output of the glow layer. As for the first term, a robust function $\rho(s) = \min(s^2, \tau)$ is used, which will preserve the large gradients of input image $\mathbf{I}$ in the remaining nighttime haze layer $\mathbf{J}$. The parameter $\lambda$ is important, since it controls the smoothness of the glow layer. In our experiments we set it to 500 (further discussion on determining the values of $\lambda$ is given in Sec.6). Since the regularization is all in gradient values, we do not have the information for $0$-$th$ order offset information of the layer colors. To solve this problem, the work in [11] proposes to add one inequality constraint to ensure the solution is in a proper range. However, since this constraint is applied to each color channel (*i.e.* $r, g, b$) independently, it may still lead to color shift problem. From our tests on nighttime haze images, this problem happens frequently. An example of such a case is shown in Fig. 5. Inspired by the Gray World assumption in color constancy [3], we add the second constraint: $\sum_{\mathbf{x}} \mathbf{J}_r(\mathbf{x}) = \sum_{\mathbf{x}} \mathbf{J}_g(\mathbf{x}) = \sum_{\mathbf{x}} \mathbf{J}_b(\mathbf{x})$ to address the color shift problem. This constraint forces the range of the intensity values for difference color channels to be balanced. With the two constraints combined together, we can obtain a glow separation result with less overall color shift. This effectiveness of this additional constraint is shown in Fig. 5. The objective function in Eq. (4) can be solved efficiently using the half-quadratic splitting technique as shown in [11].

### 4.2. Haze Removal

Having decomposed the glow image $\mathbf{G}$, from the nighttime haze image $\mathbf{J}$, we still need to estimate the scene reflection $\mathbf{R}$. Presumably, since the glow has been significantly reduced from the image $\mathbf{J}$, we should be able to enhance the visibility by using any existing daytime dehazing method. However, as previously mentioned, daytime dehazing algorithms assume the atmospheric light is globally uniform, which is not valid for nighttime scenes due to the presence of active lights.

To address this issue, we assume that atmospheric light is locally constant and the brightest intensity in a local area is the atmospheric light of that area. This brightest intensi-

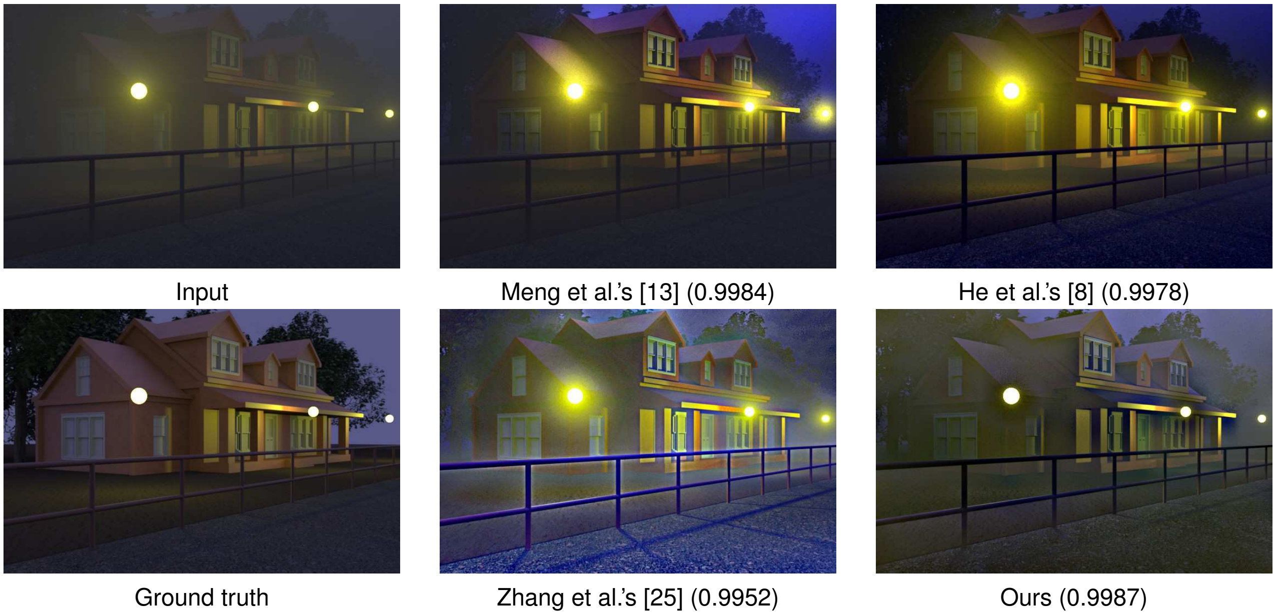


Figure 7. Quantitative evaluation using SSIM [24] on a synthetic image. Our result has the largest SSIM index, implying that it is more close to the ground truth than others. The synthetic data is generated using PBRT [17].

ty assumption is similar to that used in color constancy that assumes the color represents the illumination [9]. To implement this idea, we split the image $\mathbf{J}$ into a grid of small square areas ($15 \times 15$) and find the brightest pixel in each area. We then apply a content-aware smoothness technique, such as the guided image filter [7] on the grid to obtain our varying atmospheric light map.

Using the atmospheric light map, we estimate the transmission. If we employ the dark channel prior [8], the estimation is done by:

$$t(\mathbf{x}) = 1 - \min_{\mathbf{y}\in\Omega(\mathbf{x})} \left( \min_{c} \frac{J^c(\mathbf{y})}{L^c(\mathbf{y})} \right) \tag{5}$$

where $\Omega$ is a small patch, and $\mathbf{y}$ is the location index inside the patch. Unlike the original dark channel prior, the atmospheric light spatially varies.

Fig. 3 shows the examples of our estimation on the atmospheric light $\mathbf{L}$, the transmission, $t$, and the scene reflection $\mathbf{R}$. As shown the figure, the estimated scene reflection has better visibility than the original input image.

## 5. Experimental Results

We have gathered hazy and foggy nighttime images from the internet, with various quality and file formats. Based on these images, we evaluated our method and compared the results with those of daytime dehazing methods of [13], [8] and nighttime method [25]. Our data set and demo code are available on our website.

We have two comparison scenarios. First, given an input of hazy nighttime image, we process it with our method, two daytime dehazing methods of [13], [8] and a nighttime method [25]. Second, given an input of a hazy nighttime image, we decompose the glow from the haze image, and further process the haze image with varying atmospheric light using our method and using the method of [13]. The main purpose of the first scenario is to show the importance of the glow-haze decomposition, and the main purpose of the second scenario is to show the importance of addressing the varying atmospheric light. Having decomposed the glow and estimated the varying light, our method uses the dark channel prior to obtain the transmission map (although, other dehazing methods could also be used).

Fig. 10 shows results for scenario 1. As can be observed, for nighttime scenes with the presence of glow, the daytime dehazing methods [8] [13] tend to fail (the first and second rows of the figure). As for the nighttime dehazing method [25] (the third row), the glow is not handled properly, and due to the additional adhoc post processing, the intensity and colors of some areas are visibly exaggerated. Our results are shown in the fourth row in the figure, which look relatively better in terms of visibility and exhibit more natural colors.

Fig. 8 shows two results for scenario 2. Having decomposed the glow, the haze image was processed using [13], a daytime dehazing method. In comparison to our results, for less varying colors of the atmospheric light, they are similar to our results in terms of the dehazing quality. However, when the varying colors of the atmospheric light are significantly visible, the color shift problem becomes more apparent. In the middle column, Meng et al.'s method [13]

Haze image **J** Meng et al.'s [13] Ours

Figure 8. The left column shows the haze images **J**, after decomposing it from the glow images. The middle column shows the dehazing results using an existing daytime dehazing method [13]. The colors are noticeably shifted due to the varying atmospheric light. Right column shows our results, where the color shift is less significant since varying atmospheric light is used.

Input Zhang *et al*.'s [25] Our Result Meng *et al*.'s [13]

Figure 9. Evaluation on a nighttime image with globally uniform atmospheric light. These results show that our method's result is similar to that of Meng et al.'s [13], a daytime dehazing method.

shows visible color shift. The blue sky in the first row becomes reddish, and the white wall in the second row becomes bluish. Our results, shown in the right column, retain the colors of the scenes.

We also quantitatively evaluated our result using structural similarity index (SSIM index [24]). With the ground truth image as reference, SSIM index can measure the similarity of our result to the ground truth. For this quantitative evaluation, we used a synthetic image generated using P-BRT [17]. Since, it is considerably difficult to obtain real nighttime haze and ground truth image pairs that keep all other outdoor conditions, except the haziness level, fixed. Fig. 7 shows our result and the SSIM indexes against the other methods' results. Our SSIM value is larger than that of the other methods, implying that our result is more similar to the ground truth.

Fig. 9 shows an example of applying our method to a nighttime image with no active light sources (no glow), where we can assume a globally uniform atmospheric light. The result shows that our method behaves like existing daytime dehazing methods, *e.g*. [13], while nighttime dehaze method of [25] over-boosts the contrast such that in the bottom area of the image (red rectangle), the green channel gets boosted more than the other channels.

## 6. Discussion and Conclusion

This paper has focused on nighttime haze removal in the presence of glow and multiple scene light sources. To deal with these problems, we have introduced a new haze model that incorporates the presence of glow and allows for spatially varying atmospheric light. While our model represents a straightforward departure from the standard daylight haze model, we have shown its effectiveness for use in nighttime dehazing.

In particular, we detailed a framework to first decompose the glow image from the nighttime haze image, by assuming that the brightness of the glow changes smoothly across the input image. Having obtained the nighttime haze image a spatially varying atmospheric light map was introduced to deal with the problem of multiple light colors. Using the normalized nighttime haze image, we estimated the transmission and finally the scene reflection. Our approach was compared with a number of examples against several competing methods and was shown to produce favorable results.

There are a few remaining problems, however, that need further attention. First, our estimation of the varying atmospheric light is admittedly a rough approximation. In the method we assume it is locally constant and obtained from the brightest intensity in each of the local area. Although the brightest intensity is used in color constancy [9], optically it is not always true, since the intensity value is dependent on other various parameters, such as reflectance and particle properties. This is a challenging problem, even in the color constancy community and requires additional work.

Aside from the estimation of the varying atmospheric light, there are two parameters necessary to be tuned. One is $\lambda$ in Eq. 4, which controls the glow smoothness, and the other is the smoothness parameter in the guided image filter, which is used in estimating the varying atmospheric light. Ideally, these two parameters should be estimated automatically, however, their values depend on various factors, such as particle density (or haziness of a scene), depth, and types of light sources (whether it is diffuse light or directional light, etc). To estimate all these factors from a single image is intractable. Nevertheless, we consider the problem important for future work.

Another issue we noticed is the boosting of noise and compression artifacts in the dehazed results (*e.g*. blocking artifacts in the rightmost result in Fig. 10) as dehazing in-

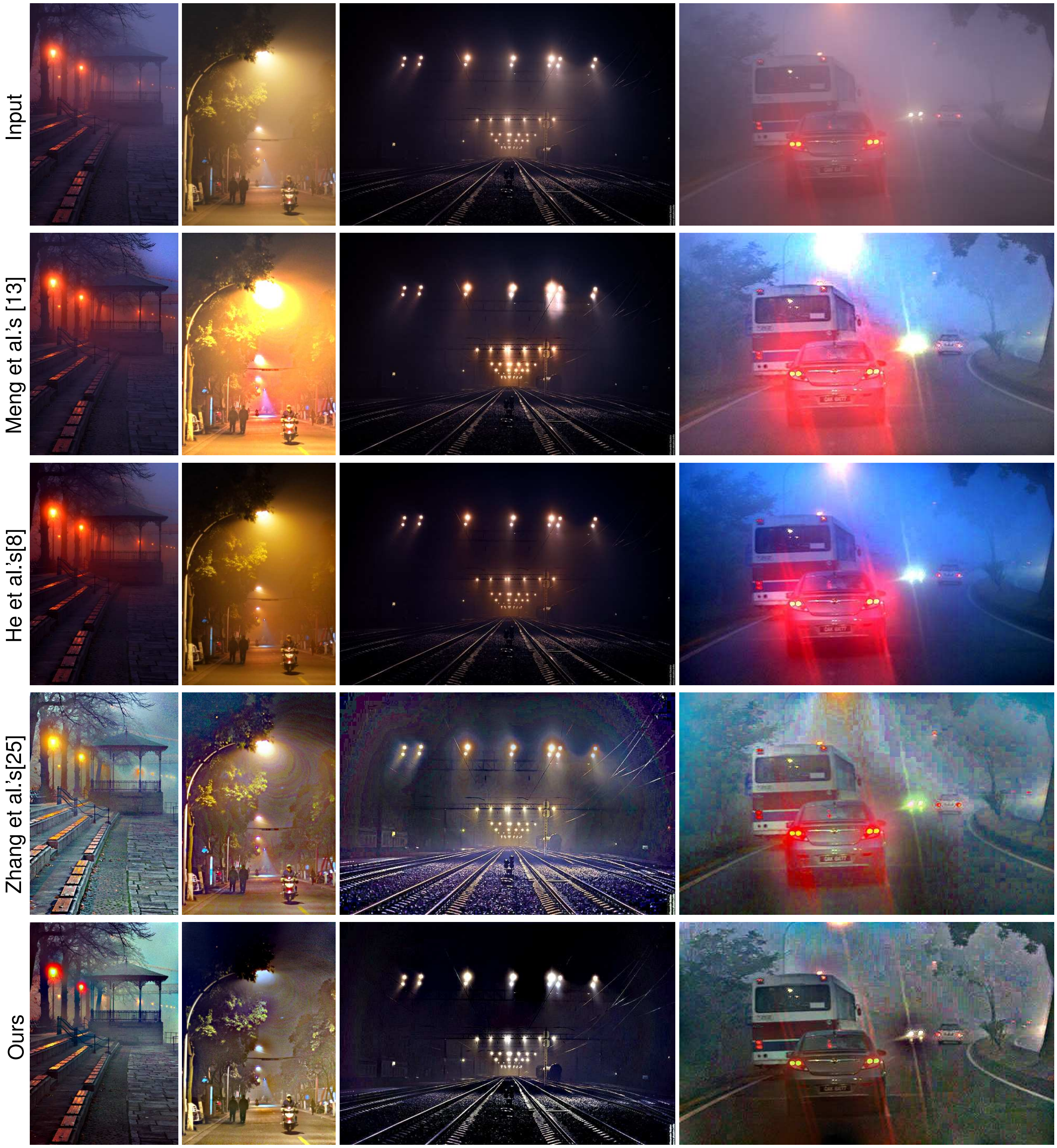


Figure 10. The qualitative comparisons of Meng et al.'s method [13], He et al.'s method [8], Zhang et al.'s method [25], and ours using various nighttime images.

creases the contrast of the image so as the noise and artifacts levels. This may be solved by techniques like [12].


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