

# An Improved Hybrid Method for Defogging Single Image

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**Abstract:** *In this article, we suggest a different method for addressing the issue of nighttime single image dehazing. Because a nighttime landscape frequently includes several light sources, ambient lighting for haze period is usually not globally isotropic. Existing nighttime dehazing algorithms have tried to treat these two zones using the same prior assumptions. We propose a novel blending approach for resolving them in this work. A channel difference guided filtering with contrast stretch approach is presented to estimate ambient light, which creates a spatially variable low-frequency passband that selectively retains high-frequency edge information.*

**Keywords:** *Nighttime Single Image Dehazing, Contrast Stretch, Guided Filtering*

## 1. Introduction

Images taken in foggy or hazy situations suffer from the presence of suspended particles and water droplets in the air. Hazy photos have a poor visual look and visibility due to weaker contrast and faded hues. As a result, the performance of many applications for computer vision, such as object detection, saliency detection, and so on<sup>[1]-[4]</sup>.

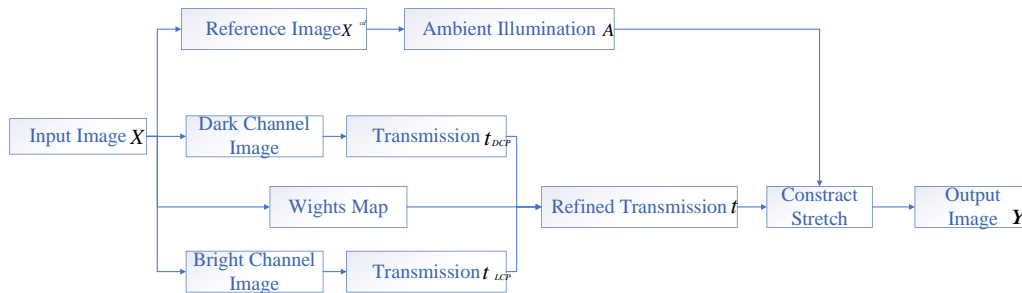
In recent years, there have been many methods of fog removal for daytime photography, including methods based on image enhancement and models. But, when these approaches are used directly to foggy photographs obtained at night, the results are frequently disappointing. The ambient illumination phrase distinguishes daylight dehazing methods from nocturnal dehazing methods. It is a constant value in the daytime dehazing model because sunlight is typically the main and dominant light source in daytime situations, resulting in uniform ambient lighting. Due to the scattering of various light sources, the ambient lighting is spatially variable. So priors that are often employed in daylight dehazing processes are no longer suitable for nighttime situations.

Existing nighttime picture dehazing approaches<sup>[5], [6], [7], [8], [9]</sup> often improve dehazing effectiveness by employing image enhancement techniques<sup>[10]</sup> or altering daytime models.

These approaches, on the other hand, tend to overestimate ambient illumination. Because they are essentially a local adaptation of the bright pixel approach used in daytime dehazing, with either a fixed or adaptive filtering window size. According to the atmospheric scattering model<sup>[11]</sup>, the bright pixel in sky regions corresponds to infinite depth and 0 transmission, so ambient illumination is very close to the bright pixel in sky regions. However, in nighttime foggy situations, when applying this notion with local bright pixels as ambient illumination, the estimation is inaccurate because most local windows do not contain sky regions. Furthermore, the widely utilized dark channel prior in existing approaches is invalid in light source regions, because there is no dark channel in white lights with high intensity values. So we employ the light pixel strategy to deal with it.

Due to the scattering of various light sources, hazy photos shot at night show spatially varied ambient illumination. We reformulate the atmospheric scattering model into a Retinex-like model, so that high quality ambient illumination may be calculated using a low-pass filter. Instead of merely employing the local maximum pixel as is done in prior approaches, we give a channel differential diagram as a reference.

## 2. Our Nighttime Dehazing Method



*Figure 1: Nighttime dehazing method*

The flow chart of our proposed nighttime dehazing method is stated in Figure 1.

Details for each step are presented in the follows.

### 2.1. Atmospheric Scattering Model

This model divides the hazy images into two components. The first is light attenuation, which refers to the direct attenuation of scene radiance from object surfaces over the haze to the camera. The other is the scattering term, which refers to dispersed light that causes scene hues to shift.

$$X(x) = Y(x)t(x) + A(x)(1 - t(x)) \quad (1)$$

In this formula,  $X$  is the hazy image obtained by the camera,  $Y$  is the haze-free image to be recovered.  $A$  is a constant color line describing the global ambient illumination in the air, and  $t$  is the channel transmission in terms of each pixel's depth, which is indicated by  $x$ . Here is the formula for  $t(x)$ :

$$t(x) = e^{-\theta d(x)} \quad (2)$$

$t(x)$  represents the fraction of light that the camera receives from  $Y$ ,  $d(x)$  is the distance to the camera,  $\theta$  is the scattering coefficient with respect to the atmosphere.

We want to recover the haze-free image  $Y(x)$  from the ambient illumination map  $A(x)$  and transmission map  $t(x)$ .

### 2.2. Ambient Illumination Estimation

Existing ambient light estimating approaches in nighttime fuzzy situations rely mostly on the local extension of the maximum pixel method employed in daytime defogging. However, due to the spatially variable illumination and the absence of sky in small patches, it does not hold at nighttime foggy scenes.

The human eye recognizes the brightness of an item based on ambient illumination and the reflection of the object surface, according to retinex theory<sup>[9]</sup>. The mathematics can be expressed by the following formula:

$$Y(x) = A(x)R(x) \quad (3)$$

Equation (2) may be written as follows:

$$X(x) = A(x)R(x)t(x) + A(x)(1 - t(x)) \quad (4)$$

So a retinex-like model may be reformulated as:

$$X(x) = A(x)(R(x)t(x) + (1 - t(x))) \quad (5)$$

By adding a low-pass filter on the foggy picture  $X$ , it is possible to estimate  $A$  effectively. The classic Gaussian filtering approach is isotropic, and edge information is not effectively represented. In this situation, the guided filter may take the place of the Gaussian filter.

Here we use a channel difference map as the reference image to guide the low-pass filtering.

As shown in, the channel difference map  $X^{cd}$  is calculated as the difference between the highest and least color channel values for each pixel  $x$  as in (6).

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

The ambient illumination  $A$  is expressed guide picture  $X^{cd}$  in a window  $\omega_k$  with the pixel  $k$  as its center.

$$A(x) = i_k I^{cd}(x) + j_k, x \in \omega_k \quad (7)$$

We derive the parameters by minimizing the difference between the goal picture  $X$  and a linear transform of the guiding image  $X$  using the following cost function:

$$E(i_k, j_k) = \sum (i_k I^{cd}(x) + j_k - I(x)) + \lambda i_k^2 \quad (8)$$

$i_k$  and  $j_k$  can get form the linear regression model as:

$$i_k = \frac{\frac{1}{|\omega|} \sum_{i \in \omega_k} I_i^{cd} I_i - \mu_k \bar{I}_k}{\sigma_k^2 + \lambda} \quad (9)$$

$$j_k = \mu_k - i_k \mu_k \quad (10)$$

$\mu_k$  and  $\sigma_k$  are the mean and variance.

### 2.3. Light Channel Prior

In this work, we use the bright channel priori of the light source region. LCP is defined mathematically as:

$$Y_{DCP}(x) = \min_{Y \in \omega_x} Y^c(Y) \rightarrow 0, c \in \{r, g, b\}, x \in NLSR \quad (11)$$

$$Y_{LCP}(x) = \max_{Y \in \omega_x} Y^c(Y) \rightarrow 1, c \in \{r, g, b\}, x \in LSR \quad (12)$$

Note that the LCP calculation is based on statistics from the light source region.

### 2.4. Blending Compute

Having obtained  $A$  using the guided filter, we can compute the corresponding transmission maps  $t_{LCP}$  and  $t_{DCP}$  as:

$$t_{DCP}(x) = 1 - \min_{Y \in \omega_x} \left( \min_{c \in \{r,g,b\}} \frac{X^c(Y)}{A^c(Y)} \right) \quad (13)$$

$$t_{LCP}(x) = \max_{Y \in \omega_x} \left( \max_{c \in \{r,g,b\}} \frac{X^c(Y) - A^c(Y)}{1 - A^c(Y)} \right) \quad (14)$$

Note that  $t_{LCP}$  and  $t_{DCP}$ , It is required to combine the dark and light source areas independently. So we can add them together.

To determine the probability  $P(x)$  of each pixel belonging to the light source region, we apply a brightness-aware weighting technique in this paper.

$$P(x) = \max_{c \in \{r,g,b\}} (X^c)^y \quad (15)$$

After that, the blended transmission map  $t$  is calculated as:

$$t(x) = t_{DCP}(x) * P(x) + t_{BCP}(x) * (1 - P(x)) \quad (16)$$

### 2.5. Contrast Stretch

Since the color contrast of the transition defogging image is not very obvious, in order to get a better contrast, we carry out contrast stretching processing for the transition image. Through experiments, it is found that a good contrast effect can be obtained when the color range [0.1, 0.9] is stretched. The Image  $Y$  is calculated as:

$$Y(x) = f\left(\frac{X(x) - A(x)(1 - t(x))}{t(x)}\right) \quad (17)$$

Where function  $f$  stands for contrast stretching operation.

### 3. Comparison of Experimental Effects

Experimental results are obtained through our proposed algorithm, as shown in Figure 2. The computer used in the experiment is Lenovo Y7000P, CPU is I7-10875H, graphics card is RTX2060, computer system is Window 10 home edition, and experimental platform is MATLAB 2018B.

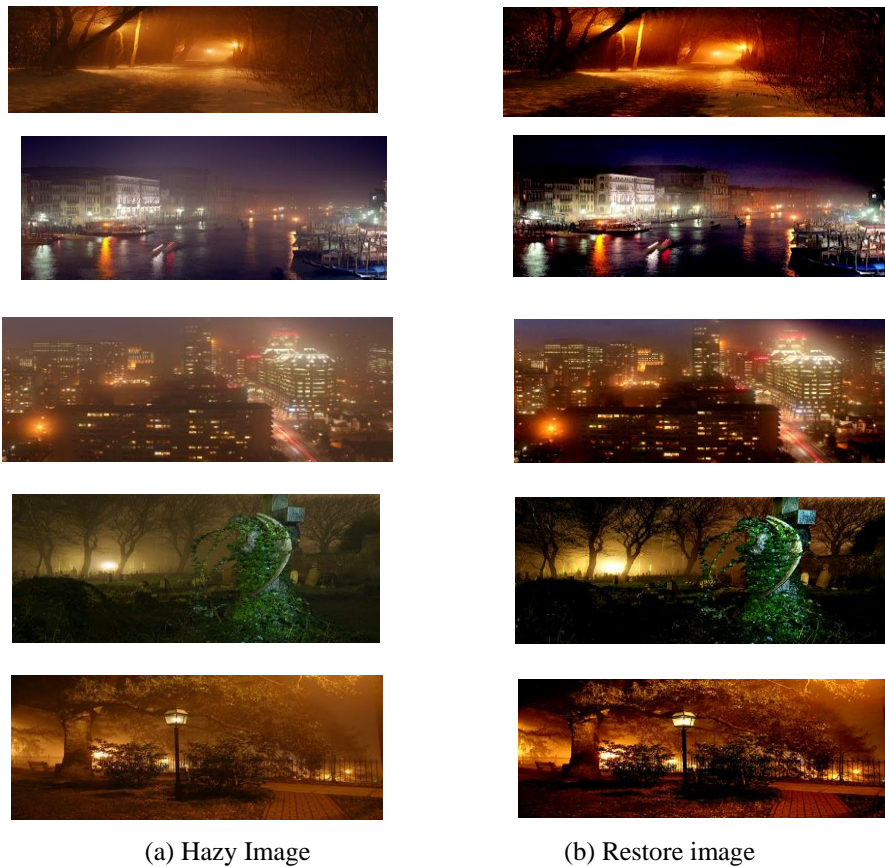


Figure 2: Comparison of experimental effects

The method can efficiently boost the brightness of the image and eliminate the foggy sensation of the image when compared to the original image.

### 4. Discussions and Conclusion

We have proposed an effective nighttime image dehazing method in this paper. To achieve night demisting, we convert the scattering model into a Retinex-like format, then perform channel differential guided filtering, and finally contrast stretching. The light source and non-light source areas are then processed using LCP and classical DCP to generate transmission estimates. To get the final transmission map, a blending approach led by the brightness-aware map is presented. Comprehensive experimental evaluation shows that the dehazing effect of our method is excellent.

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