NIGHTTIME HAZE REMOVAL BASED ON A NEW IMAGING MODEL

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ABSTRACT

Nighttime haze removal is important for different applications such as nighttime video surveillance in haze environment. Different from the imaging conditions in the daytime, nighttime haze images may suffer from non-uniform illumination from artificial light sources. In this paper, we proposed a novel efficient dehazing method with illumination estimation for nighttime haze condition. First, we estimate the light intensity and enhance it to obtain an illumination balanced result. Then, we process a color correction step after estimating the color characteristics of the incident light. Finally, we remove the haze by using the dark channel prior along with estimating the pointwise environmental light. Experimental results show that the proposed method can achieve both illumination balanced and haze free results. Moreover, it also has good color rendition ability.

Index Terms— nighttime haze removal, guided filter

1. INTRODUCTION

Haze may change the colors and reduce the contrast of the captured images. The degradation is mainly caused by the light scattering and light attenuation in the atmosphere. It is important to remove the haze from the degraded images for different applications.

Many dehazing methods have been proposed to deal with daytime haze images. Multiple-image based methods require two or more images of the same scene either under different atmospheric conditions (e.g., the dichromatic method proposed in [1, 2]) or polarization states (e.g., the polarization-based methods [3, 4]) for turning the ill-posed problem into a well-posed or over-constrained one. Since it is difficult to obtain the required images, many researchers have proposed some single image based haze removal methods by using different priors [5, 6, 7]. For instance, He et al. propose an effective method based on the dark channel prior [7], which can obtain fairly good result with low computational cost [8]. However, these methods are not very effective for nighttime haze images, due to the different imaging conditions, e.g., non-uniform illumination from the artificial light sources. Consequently, the nighttime dehazing problem is much more challenging than the daytime case.

Recently, Pei et al. propose a method for nighttime haze removal [9]. To use the refined dark channel prior effectively, they firstly transfer the input nighttime haze image into a grayish one. Then, they obtain a dehazed result based on such prior. Finally, they apply a post-processing step by using bilateral filter in local contrast correction. Their method can achieve result with more details. However, in the color transfer procedure, it changes the color characteristics of the input nighttime haze image from a given target image (usually a daytime haze image) by statistic correction. Since the different scene contents and imaging conditions, the global color transfer method leads to a complete grayish scene. Such a result may be different from the expected illumination balanced one and will affect the final dehazed result.

In this paper, we propose an efficient method that builds on a new imaging model for nighttime haze condition. This new model takes into account both the non-uniform light condition and the color characteristic of artificial light source. Based on this model, we give a novel dehazed method including three steps: light compensation, color correction and dehazing. First, we estimate the light intensity and enhance it to obtain an illumination balanced result. Then, we process a color correction step after estimating the color characteristics of the incident light. Finally, we remove the haze by using the dark channel prior along with estimating the pointwise environmental light. Experimental results show that our method can achieve illumination balanced and haze free results. Moreover, it also has good color rendition ability.

2. PROBLEM ANALYSIS

Images captured in nighttime, i.e., low natural illumination and non-uniform artificial light sources condition, may exhibit some properties, such as low overall brightness and non-uniform illumination. In addition, the haze may degrade the image quality for its scattering and attenuation effects [7, 10]. Thus, images are generally in low contrast and lose some details. Moreover, the artificial light sources

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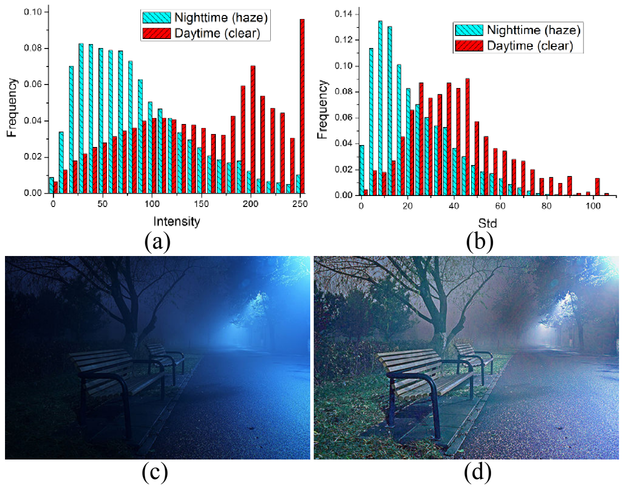

Fig. 1. (a) Statistics of illumination intensities of clear and nighttime haze images. (b) Statistics of standard deviations of values on local patches. (c) An example of nighttime haze image. (d) The dehazing result of the proposed method.

usually radiate color light which will be scattered by the haze. Consequently, different parts of the scene may be dominated by one or more kinds of particular colors.

To give an illustration, we selected 20 illumination balanced images captured in the daytime which have lots of clear details and 20 haze images captured in the nighttime from Flickr. Statistics of illumination intensities (values in V channels of images in HSV color space) are shown in Fig. 1(a). It can be seen the nighttime haze images have more low-intensity pixels than the clear ones. Moreover, we calculated the standard deviations of values on local patches. And the statistics of them are shown in Fig. 1(b). Images in the daytime shows higher variances which corresponds to their more clear details than haze images in the nighttime. For instance, in Fig. 1(c), we give an example of a haze image captured in the nighttime. We can see that the overall brightness of the image is low, especially in the left part. And the right part is a little brighter but dominated by the blue light. One can hardly distinguish the details of the trees and benches due to the influence of low natural illumination and scattering effect of haze in artificial light condition. Fig. 1(d) shows the dehazing result of the proposed method, which has many details and is visual pleasing.

3. A NEW IMAGING MODEL AND SOLUTION

3.1. Imaging model for daytime haze environment

In the literatures of daytime image dehazing [1, 2, 3, 4, 5, 7], the following model is common adopted:

$$I_i^\lambda = J_i^\lambda t_i + A^\lambda (1 - t_i) = R_i^\lambda A^\lambda t_i + A^\lambda (1 - t_i), \quad (1)$$

where I_i^λ is the intensity of captured haze image at location i (we adopt a lexicographical order representation of an image.), λ represents one of the RGB channels, J_i^λ is the expected clear image (scene radiance), t_i is the transmission at location i, A^λ is the atmospheric light component of λ channel, and R_i^λ is the reflectance which refers to the ratio of the reflected light to the incident light. It is related to the reflection characteristic of object surface. The first term of Eq. (1) relates the attenuation of scene radiance and the second term relates the scattering of global atmospheric light in haze environment. This model shows its effectiveness for daytime image dehazing, especially when coupled with the dark channel prior [7, 10]. However, this model is limited to the daytime haze environment since it relies on the assumption that the atmospheric light is a constant (which is usually white light) and the mainly light source of the scene. In the nighttime haze environment, the light source is mainly artificial light rather than the natural illumination (i.e., atmospheric light). Thus, the scene radiance as well as the scattered light will be affected by the particular color and location of artificial light source.

3.2. A new imaging model for nighttime haze environment

Base on the above analysis, we propose a new imaging model for nighttime haze environment. Mathematically, its explicit form can be expressed as follows:

$$I_i^\lambda = L_i t_i^\lambda R_i^\lambda t_i + L_i t_i^\lambda (1 - t_i). \quad (2)$$

Here I_i^λ, λ, t_i and R_i^λ have the same meanings with the ones in Eq. (1). L_i is a scalar representing the incident light intensity that reaches at location i. t_i^λ is a quantity accounts for the color characteristic of incident light. Compared with the previous model in Eq. (1), this new model replaces the constant atmospheric light with pointwise variables (L_i and t_i^λ), which can account for the non-uniform intensities and color characteristics of incident lights from different artificial light sources. Given an input haze image, solving the variables in Eq. (2) is indeed an ill-posed problem, which seems more difficult since this new model involves more variables. In the following section, we propose a sequential solution to obtain the unknown variables based on simple assumptions. This method consists of three steps, i.e., light compensation, color correction and dehazing, which rely on optimizing L_i, t_i^λ and t_i sequentially. Finally, it obtains a haze-free and illumination balanced result. A diagram of the method is shown in Fig. 2.

3.3. A sequential solution based on simple assumptions

The proposed method to obtain the unknown variables relies on the following three assumptions: 1), t_i^λ is assumed to be piecewise smooth; 2), R_i^λ is assumed to be piecewise

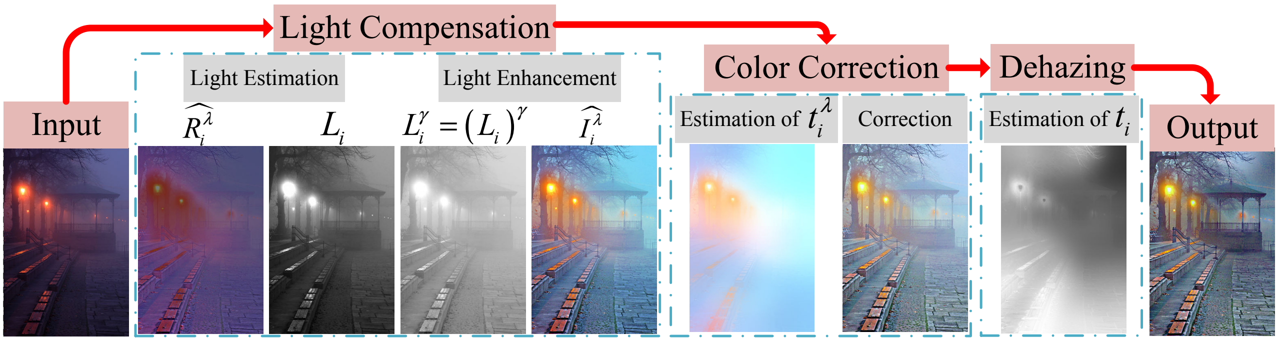

Fig. 2. A diagram of the proposed method.

smooth; 3), t_i is assumed to be spatially smooth except the depth discontinuity regions. The last two assumptions are widely adopted in literatures abut retinex [11, 12] and image deahzing [7, 10]. The first one is also reasonable since the incident light from the light source changes slowly and is related to the distance between a particular position and the light source. And sudden changes usually occur in occlusion regions, which are indeed the edge regions of an image.

3.3.1. Light compensation

Re-write Eq. (2) as follows:

$$I_i^{\lambda} = L_i \widehat{R_i^{\lambda}}, \tag{3}$$

where $\widehat{R_i^{\lambda}} = t_i^{\lambda} R_i^{\lambda} t_i + t_i^{\lambda}(1 - t_i)$, is called surrogate reflectance in this paper. Given an input image, different methods to estimate light intensity and reflectance have been proposed in literatures about retinex[11, 12]. From the above assumptions, we have that $\widehat{R_i^{\lambda}}$ is also piecewise smooth. Consequently, we use a similar method to the one proposed in [12]. The only difference is the filter we used in this paper is the guided filter [8], which has the similar edge-preserving ability but no gradient reversal artifacts compared with the bilateral filter [13] used in [12]. For simplicity, we do not give the details here, but we recommend referring [12] which includes a thorough description. After obtaining the estimation of L_i and $\widehat{R_i^{\lambda}}$, we apply a gamma correction to the light intensity to balance the overall illumination of the image. Mathematically, it can be expressed as follows:

$$\widehat{I_i^{\lambda}} = (L_i)^{\gamma} \widehat{R_i^{\lambda}} = L_i^{\gamma} t_i^{\lambda} R_i^{\lambda} t_i + L_i^{\gamma} t_i^{\lambda}(1 - t_i). \tag{4}$$

This process is illustrated in the "light compensation" part in Fig. 2.

3.3.2. Color correction

Sicne R_i^{λ} lies in the range of $[0, 1]$, so we have:

$$\widehat{I_i^{\lambda}} \le L_i^{\gamma} t_i^{\lambda} t_i + L_i^{\gamma} t_i^{\lambda}(1 - t_i) = L_i^{\gamma} t_i^{\lambda}. \tag{5}$$

Then, we can obtain the lower bound of t_i^{λ} as $\underline{t_i^{\lambda}} = \widehat{I_i^{\lambda}} \big/ L_i^{\gamma}$. More robustly, we calculate the maximum on each overlapped patch as the lower bound of every pixel on that patch, and then average the overlapped ones. Based on the frist assumption, we formulate the optimization about t_i^{λ} as follows:

$$t^{\lambda} = \arg\min_{t^{\lambda}} \left\| t^{\lambda} - \underline{t^{\lambda}} \right\|^2 + \lambda (t^{\lambda})^T L t^{\lambda}. \tag{6}$$

where L is the matting laplacian matrix [14], and the second term accounts for the smoothness penalty. The optimization problem can be efficiently solved (approximately) by using guided filter. Since t_i^{λ} is only the lower bound of the expected t_i^{λ}, we enhance the result of Eq.(6) by multiplying an amplifying factor. This amplifying factor is calculated according to the ratio $\left(\frac{1}{3}\sum_{\lambda} t^{\lambda}\right)^{\gamma_0} \big/ \left(\frac{1}{3}\sum_{\lambda} t^{\lambda}\right)$. The parameter γ_0 is set to $1/1.2$ in this paper. Divided by t_i^{λ} in both side of Eq.(4), it becomes:

$$\widetilde{I_i^{\lambda}} = \widehat{I_i^{\lambda}} \Big/ t_i^{\lambda} = L_i^{\gamma} R_i^{\lambda} t_i + L_i^{\gamma}(1 - t_i). \tag{7}$$

Here $\widetilde{I_i^{\lambda}}$ in the left side represents the color correction result. This process is illustrated in the "color correction" part in Fig. 2.

3.3.3. Dehazing

Because the estimation of t_i^{λ} may not be so accurate, we add a new term Δt_i^{λ} in the right side of Eq.(7) to accounts for the residual color effect of the incident light. It can be expressed as:

$$\begin{aligned} \widetilde{I_i^{\lambda}} &= L_i^{\gamma} \Delta t_i^{\lambda} R_i^{\lambda} t_i + L_i^{\gamma} \Delta t_i^{\lambda}(1 - t_i) \\ &\triangleq J_i^{\lambda} t_i + A_i^{\lambda}(1 - t_i) \end{aligned}, \tag{8}$$

where J_i^{λ} represents the expected clear image, and A_i^{λ} is the environmental light. Eq.(8) is similar to Eq.(1), which only differs in the environmental light (atmospheric light A^{λ} in Eq.(1)) in the scattering term. The estimation method of t_i and A_i^{λ} is similar to method in [7] by using dark channel prior. However, since A_i^{λ} is a local variable rather than a global constant A^{λ} in Eq.(1), we estimate it in a local neighborhood

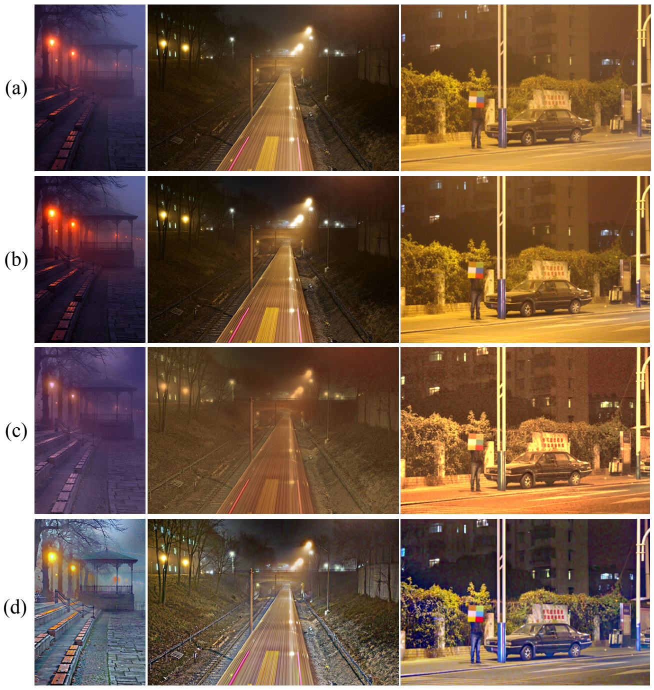

Fig. 3. (a) Nighttime haze images. (b) Results of He et al.'s method [7, 8]. (c) Results of Pei et al.'s method [9]. (d). Results of the proposed method.

rather than the whole image as described in [7].This process is illustrated in the "dehazing" part in Fig. 2. The final output is also shown in Fig. 2. It can be seen that the proposed method can obtain a haze-free and illumination balanced result.

4. EXPERIMENTS

To demonstrate the effectiveness of the proposed method, we collected 20 haze images captured in the nighttime environment from Flickr to form a test dataset. We compared our dehazing results with the ones obtained by using methods in [7, 8, 9]. The radius of local patch size was set to 5 (when estimating t_i^λ and A_i^λ) and overlapped patch size was 5×5. The parameter γ was set to $1/3$ in Eq.(4). The radius of window size and the regularization parameter in guided filter were set to 32 and 1e-2, respectively.

Figure 3 shows the results obtained by different methods for three test images[1]. It can be seen that He et al.'s method [7, 8] only achieved a little better result than the input. It is because that the dark channel prior is invalid in nighttime environment, i.e., low natural illumination and non-uniform artificial light sources of different colors. And Pei et al.'s method [9] achieved a little more illumination balanced result than the input. The contrast is higher and more details can be found in their result. As for the proposed method, it achieved

[1]For more results, please contact the authors.

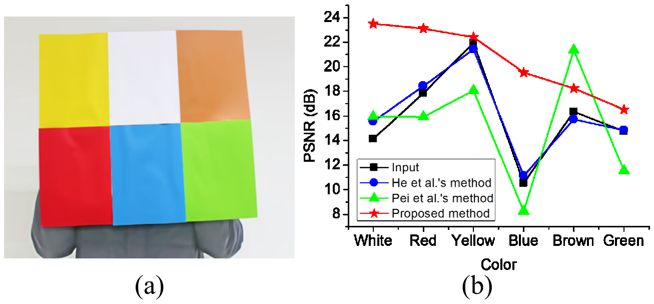

Fig. 4. (a) The groud truth color set. (b) PSNR indexes of different results for six colors on the color set.

the best results which exhibit more balanced illumination, less color distortion, clearer details and higher contrast. By reviewing Section 3 and the illustration in Fig. 2, it can be seen that these results convince the effectiveness of the new imaging model and the resulting sequential solution for nighttime haze removal. We recommend viewing these results in the electronic version of this paper.

Moreover, we also conducted an experiment to evaluate the color rendition abilities of different methods. We used a color set including colors of yellow, white, brown, red, blue and green. The image captured in nighttime haze environment and the corresponding results of different methods are shown in the last column in Fig. 3. The groud truth is shown in Fig. 4(a), which is captured in indoor environment with daylight lamp. We calculated the PSNR indexes of different results for the above six colors. The results are plotted in Fig. 4(b). It can be seen that our method achieved the highest PSNR indexes for all colors except brown. The average PSNR indexes of input, result of He et al.'s method, result of Pei et al.'s method and our result are 15.93dB, 16.18dB, 15.18dB and 20.55dB, respectively. The proposed method shows better color rendition ability than He et al.'s method and Pei et al.'s method for nighttime image dehazing.

5. CONCLUSION

In this paper, we propose an efficient model-based method with illumination estimation. This new model takes into account both the non-uniform light condition and the color of artificial light source, and leads to a solution of three steps: light compensation, color correction and dehazing. Based on simple assumptions, the variables in the model can be efficiently estimated. Experimental results show that the proposed method can achieve illumination balanced and haze free results. It also has better color rendition ability compared with previous methods. The computational cost is low, since the estimation procedures of variables are very similar to the ones in He et al.'s method. The future work may concentrate on developing efficient dehazing method for nighttime haze videos by exploiting the spatial-temporal information.

6. REFERENCES

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