COLOR-PRESERVING DEFOG METHOD
FOR FOGGY OR HAZY SCENES

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Abstract: Bad weather, such as fog and haze, can significantly degrade the imaging quality, which becomes a major problem for many applications of computer vision. In this paper, we propose a novel color-preserving defog method based on the Retinex theory, using a single image as an input without user interactions. In the proposed method, we apply the Retinex theory to fog/haze removal form foggy/hazy images, and conceive a new strategy of fog/haze estimation. Experiment results demonstrate that the proposed method can not only remove fog or haze present in foggy or hazy images, but also restore real color of clear-day counterparts, without color distortion. Besides, the proposed method has very fast implementation.

1 INTRODUCTION

Many outdoor applications of vision community such as surveillance, target tracking and object recognition, require high quality input images to detect robust features. Unfortunately, the visibility and color of images are degraded greatly under bad weather condition, especially foggy/hazy weather. Therefore, it is imperative to enhance visual quality and good visibility of the degraded images.

The exact nature of fog/haze is very complex and depends on many factors including the types, orientations, size and distributions of particles, polarization states and directions of the incident light (Narasimhan & Nayar, 2003a). In the literature, many approaches have been proposed to tackle the problem. General contrast enhancement is obtained by tone-mapping techniques including linear mapping, histogram stretching and equalization, and gamma correction. However, these methods perform poorly for the problem mentioned above. Incorporating local information, some more sophisticated operators (Stark, 2001; Kim et al., 2002) achieve relative good performance at the cost of computational complexity. Recently, some approaches provide impressive results by assuming the scene depth (Narasimhan & Nayar, 2003b), two

photographs given (Shwartz et al., 2006; Schechenr et al., 2001) or multiple images taken from foggy scenes with different densities at the same point (Narasimhan & Nayar, 2003a; Narasimhan & Nayar, 2003c). However, requirements of the specific inputs make them impractical, particularly in real-time applications. To overcome the drawbacks, a method using a single input image has been proposed to enhance the visibility of an image (Tan, 2007; Tan, 2008). This method shows compelling results. However, it is computational expensive and also causes evident color distortion.

Land proposed the Retinex theory based on lightness and color constancy. Because of its advantages such as dynamic range compression, color independence and color and lightness rendition, the Retinex theory has been extensively used in image processing task. Among Land's algorithms, the center/surround Retinex (Land, 1986) attracts researchers' interests because of lower computational complexity and no calibration for scenes.

Based on the Retinex theory, we propose a novel color-preserving defog method for foggy or hazy scenes. In the proposed method, we estimate the illumination by applying two-step smoothing to the degraded image and then enhance contrast by

applying adaptive contrast stretching to the reflectance estimate. This method can achieve fog removal and color restoration simultaneously for foggy or hazy images. It has three advantages as follows: 1) No user interactions; 2) A single image as an input; 3) High efficiency. The rest of the paper is organized as follows: Section 2 introduces the Retinex theory; Section 3 analyzes the Retinex theory from a new viewpoint and details the proposed approach; Experiments are provided in Section 4.

2 RETINEX

Let $I(x, y)$ be a digital image. According to the Retinex theory, $I(x, y)$ is the product of the object reflectance $R(x, y)$ and the scene illumination $L(x, y)$, that is,

$$I(x, y) = R(x, y) L(x, y) \qquad (1)$$

where the object reflectance $R(x, y)$ represents intrinsic properties of object surface, and the scene illumination $L(x, y)$ determines dynamic range compression of pixels. The goal of the Retinex theory is to obtain the reflectance image $R(x, y)$ from input image $I(x, y)$ by removing effects of illumination image $L(x, y)$.

In the logarithmic domain, Equation (1) can be written as

$$
\begin{aligned}
i(x, y) &= \log I(x, y) = \log \big[R(x, y) L(x, y) \big] \\
&= \log R(x, y) + \log L(x, y) \qquad (2) \\
&= r(x, y) + l(x, y)
\end{aligned}
$$

where $r = \log R$, $l = \log L$. Although various Retinex algorithms have different processes, they usually include two mutual steps. Firstly, the input image is converted to the logarithmic domain, which is described in Equation (2). Secondly, the illumination image is estimated by different algorithms. Then the reflectance image is computed by subtracting the illumination image from the original image. The output is the reflectance image.

3 DEFOG

3.1 Method

In this section, we explain the Retinex theory from a new viewpoint and apply it to remove fog/haze effects from degraded images. Our method is available for color images because gray images have no color information. The main idea of our explanation is described as follows. First of all, the illumination is estimated. Then, the input image is divided by the estimated illumination $\tilde{L}(x, y)$ to get an estimate of the reflectance $\tilde{R}(x, y)$, such that

$$\tilde{R}(x, y) = I(x, y) \big/ \tilde{L}(x, y) \qquad (3)$$

To avoid the division computation, we convert the operation to the logarithmic domain. Suppose that we define

$$
\begin{aligned}
\tilde{r}(x, y) &= \ln \tilde{R}(x, y) \\
&= \ln I(x, y) - \ln \tilde{L}(x, y)
\end{aligned}
\qquad (4)
$$

In this way, we obtain the logarithm of the reflectance by subtracting the logarithm of the illumination from the logarithm of the degraded image. This flowchart of our method is depicted in Figure 1.
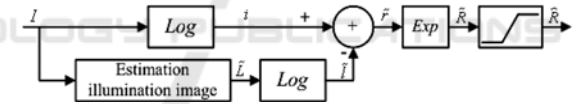

Figure 1: Flowchart of our method.

3.2 Fog/ Haze Estimation

The key of our method is how to estimate the illumination, that is, fog/haze for foggy/hazy images. The illumination component of an image is generally characterized by slow spatial variations, while the reflectance component tends to vary abruptly. These characteristics lead to associating the low frequencies of an image with illumination and the high frequencies with reflectance. The proposed method is based on channel-to-channel processing. Define $F(x, y)$ to be zero-mean Gaussian with standard derivation σ, which is a typical low-pass smoothing function. Firstly, the degraded image is convoluted with the smoothing function, that is,

$$\hat{L}(x, y) = I(x, y) * F(x, y) \qquad (5)$$

where " $*$ " denotes the convolution operation, and $F(x, y)$ is the smoothing function and given by

$$F(x, y) = K e^{-(x^2 + y^2)/\sigma^2} \qquad (6)$$

where K is normalized factor and makes the coefficients sum to 1, σ is standard deviation and controls the degree of blurring. Specifically speaking, assuming that the function has a $w \times w$ support, we determine K satisfying with

$$\sum_{x=-(w-1)/2}^{(w-1)/2} \sum_{y=-(w-1)/2}^{(w-1)/2} F(x, y) = 1 \qquad (7)$$

According to 3σ rule, the relationship between σ and w is given by

$$3\sigma = (w-1)/2 \qquad (8)$$

Next, for $\forall (x, y)$, the illumination estimate $\tilde{L}(x, y)$ is obtained by computing the mean of $\hat{L}$, meaning that the degraded image is smoothed for the second time.

$$\tilde{L}(x, y) = \frac{1}{HW} \sum_{x=1}^{H} \sum_{y=1}^{W} \hat{L}(x, y) \qquad (9)$$

And then, the reflectance is given by

$$\tilde{r}(x, y) = \ln I(x, y) - \ln \tilde{L}(x, y) \qquad (10)$$

At last, exponential transformation is indispensable and used for contrast enhancement and dynamic range stretching.

$$\tilde{R}(x, y) = \exp(\tilde{r}(x, y)) \qquad (11)$$

Figures 2(a)~(c) illustrate the process described above. Figure 2(a) shows the original image. Figures 2(b) and 2(c) illustrate the fog/haze estimate and the reflectance estimate, respectively.

3.3 Adaptive Contrast Stretching

The lower pixel values degrade the visibility of the Retinex output. To overcome the problem, we first find the lowest and highest pixel values, T_{low} and T_{high} , currently present in the image, and then scale each pixel I_k such that

$$I_o = a + (I_k - T_{low}) \frac{b-a}{T_{high} - T_{low}} \qquad (12)$$

where a and b are the lower and upper limits, respectively. A single outlying pixel with a very high or a very low value can severely affect the value T_{low} and T_{high} , which leads to very undesirable scaling. Therefore, we propose an adaptive method to select the two thresholds according to a cumulative distribution function (CDF) as follows.

$$T_{low} = \arg_{I_m} \left(C(I_m) \ge Th, C(I_m) > C(I_{m-1}) \right)$$
$$\qquad (13)$$
$$T_{high} = \arg_{I_m} \left(C(I_m) \ge 1 - Th, C(I_m) > C(I_{m-1}) \right)$$

where $C(I_m)$ is the cumulative histogram of $\tilde{R}$. We define a probability Th to determine T_{low} and T_{high} for preventing outliers from affecting the scaling. For color images, all the channels will be stretched using the same T_{low} and T_{high} in order to preserve the correct color ratios. Figure 2(d) illustrates the final result of adaptive contrast stretching.

4 SIMULATIONS

All experiments are implemented on a computer with P4 3.0GHz, 1GB memory and MATLAB development environment. The images with haze/dense fog are provided to demonstrate the feasibility and efficacy of the proposed method. The performance is evaluated by subjective criterion including visibility enhancement and color rendition. Empirically, we select the standard deviation as $\sigma = 5$. The two thresholds T_{low} and T_{high} are calculated in term of $Th = 0.02$. Figure 3(a) shows Beijing University of Technology Olympic Gymnasium involved in a haze and the visibility of the gymnasium is degraded severely by the haze. Figure 3(b) is the result of our method. As can be observed, the gymnasium gets rid of the awful haze and looks more magnificent. Figures 4(a) and 5(a) are two snapshots of the movie "The mist" covered with fog. As shown in Figure 4(b), more details of the scene are recovered obviously. Seen from Figure 5(a), the back of a man looms through the dense fog, while in Figure 5(b), the dense fog is cleared and the man appears distinct. Besides, the color of clear-day counterparts recurs to our method. We implement our method 10 times and calculate the average time for each image. Table 1 lists the computation time for the images of various sizes, which shows our method has fast implementation. We compare our method with Tan's (Tan, 2007;

(a) Original foggy image.

(b) Fog/haze estimate.

(c) The reflectance estimate.

(d) Final result of adaptive contrast stretching.

Figure 2: Illustration of our method.

Tan, 2008). Figures 6 (a) and 6 (b) illustrate results of Tan's method and the proposed method, respectively. The original image shown in Figure 6(a) is covered with dense fog. The result of Tan's method achieves good visibility, but produces evident color distortion, leading to severe artifacts. As shown in Figure 6(b), the sky takes on bright, the water dark green, and the boundary between them is distinct. It's obvious that the proposed method greatly improves the visibility without color distortion. The average computation time of the proposed method is 3.515 seconds for the image of size 443×594. More compelling results appear in

Tan's method (Tan, 2008). However, there are more severe color distortions and the computation time approximates to 5 to 7 minutes for images of size 400×600.

Table 1: Computation time for various image sizes.

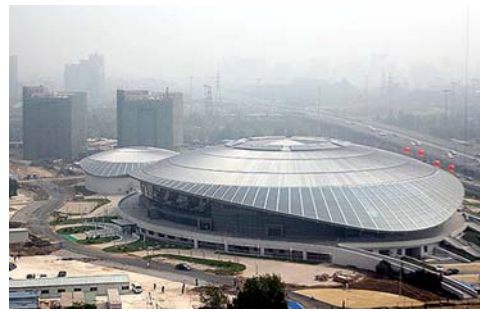|	Figure 5	Figure 6	Figure 7
Time(s)	2.109	3.765	3.907
Size	319×500	398×718	408×719

5 CONCLUSIONS

We have proposed a novel color-preserving defog method for foggy or hazy scenes. Experiment results show that the improvement in image quality can be achieved by the proposed method. Also, the method has high-efficiency implementation.

REFERENCES

Kim J. Y., Kim L. S. and Hwang S. H. (2002). An advanced contrast enhancement using partially overlapped sub-block histogram equalization. *IEEE Trans. on Circuits and Systems for Video Technology*, 11(4): 475-484.

Land E. (1998). An alternative technique for the computation of the designator in the retinex theory of color vision. In: *Proceedings of National Academy of Sciences*, 83: 3078-3080.

Narasimhan S. and Nayar S. K. (2003a). Contrast restoration of weather degraded images. IEEE Trans. on PAMI, 25(6): 713-724.

Narasimhan S. and Nayar S. K. (2003b). Interactive (De) weathering of an image using physical models. In: *Proceedings of ICCV Workshop on Color and Photometric Method in Computer Vision,* 25(6): 713-723.

Narasimhan S. and Nayar S. K. (2003c). Shedding light on the weather. In: *Proceedings of IEEE CVPR,* 1: 665-672.

Schechenr Y. Y., Narasimhan S. G. and Nayar S. K. (2001). Instant dehazing of images using polarization. In: *Proceedings of IEEE CVPR,* 1: 325-332.

Shwartz S., Namer E. and Schechner Y. (2006). Blind haze separation. In: *Proceedings of IEEE CVPR,* 2: 1984-1991.

Stark J. A. (2001). Adaptive image contrast enhancement using generalizations ofhistogram equalization. *IEEE Trans. on Image processing,* 9(5): 889-896.

Tan R.T. (2007). Visibility enhancement for roads with foggy or hazy scenes. In: *Proceedings of the IEEE Intelligent Vehicles Symposium,* 19-24.

Tan R.T. (2008). Visibility in bad weather from a single image. In: *Proceedings of IEEE CVPR,* 1-8.
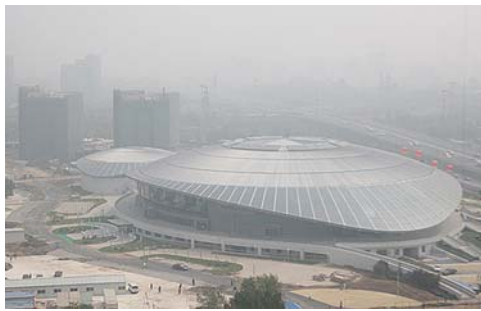
(a) Original image covered by haze.   (b) Defog result of (a).

Figure 3: Beijing University of Technology Olympic Gymnasium (Size: 319×500).

(a) Original image covered by fog.   (b) Defog result of (a).

Figure 4: Snapshot 1 of Movie "The Mist" (Size: 398×718).

(a) Original image covered by dense fog.   (b) Defog result of (a).

Figure 5: Snapshot 2 of Movie "The Mist" (Size: 408×719).

(a) Tan's method.   (b) Our method.

Figure 6: Comparison between Tan's method and our method (Size: 443×594).