Automatic Image De-Weathering Using Physical Model and Maximum Entropy

Xin Wang, Zhenmin TANG
Dept. of Computer Science & Technology
Nanjing Univ. of Science and Technology
Nanjing, China
E-mail: rongtian_helen@yahoo.com.cn

Abstract: **Images captured under bad weather conditions usually have poor contrasts and colors. Due to the scattering of light, the degradation of an image increases exponentially with the depths of the scene points. Previously implemented methods are limited, because an interactive step was required to select the sky brightness and the vanishing point of the image, as well as the information about the atmospheric conditions. In this paper, we propose an automatic method based on physical model and maximum entropy to remove weather effects using only a single image. First, we segment the sky region by optimal estimated normal distribution and select the lowest point of the sky region as the vanishing point. Then, we exploit the physics-based model to remove weather effects from the image. At last, to overcome the defect of a single image lacking exact atmospheric information, we propose an algorithm based on maximum entropy to select the optimal scattering coefficient of the atmosphere. Our automatic method for image de-weathering is suitable not only for gray level images but also for RGB color images. Compared with other methods, our method is robust and has good efficiency.**

***Keywords*—de-weathering, image restoration, dichromatic atmospheric scattering model, scene depth, maximum entropy**

1. INTRODUCTION

Images of outdoor scenes taken in bad weather conditions (fog, rain, snow, etc.) usually suffer from poor contrasts and colors. It is known that the degradation of image quality is due to the effect of the scattering medium, which is dependent on the distance between the object and the sensor. And such situation brings many difficulties in many aspects, such as supervisions in outdoors, automatic navigation, target tracking and so on. So it has great realistic significance to remove weather effects from images.

Recently, there has been considerable work for the restoration of images under bad weather. Many algorithms are available for it. And from different views, these methods have been mainly divided into two kinds. One was thought as a problem about image contrast enhancement from image processing view. Among these algorithms, histogram equalization was the well-known one. The algorithm was to change the distribution of gray levels. Unfortunately, it had a defect that the computation is too much. So, much research focused on the improvement of efficiency. For example, Zimmerman et al. [1] proposed an adaptive histogram equalization algorithm and Zhu et al. [2] improved their method by block-overlapped histogram equalization. However, weather degradation had a close relationship with the distance between each scene point and the observer. Histogram equalization did not take it into account, so these methods could not get satisfying effects.

In another aspect, from the view of physical cause of degradation, researchers solved such problems using image restoration based on different physical models. According to the work of Oakley and Tan et al. [3,4,5], a multi-parameter physical model was used to restore image contrasts or colors when scene depth was known beforehand. As a result, it needed complex hardware equipments to get depth information, which made such methods quite inconvenient. Kopeika's method [6] needed precise information about atmospheric conditions to get a less blurred image. Narasimhan and Nayar [7] proposed an interactive method to de-weather by a single image of a scene without using precise depth information or weather conditions. However, it needed people to estimate atmospheric scattering coefficient and depth trends, as well as to select the sky region. Obviously, this interactive method had some limitations in many applications.

Also, there were many other algorithms. Some researchers used polarization to obtain a great improvement of scene contrast and correction of color [8,9]. It was based on the fact that the natural illuminating light scattered by atmospheric particles is partially polarized. But this method was only effective on haze, not on dense fog. Grewe and Brooks[10] presented a wavelet fusion based method to de-weather by multiple images. For it did not take geometry information into account, the results were not satisfying. Lately, the retinex theory had been developed for image enhancement [11,12]. Based on the color constancy theory, color degradation was assumed as illumination variation. The disadvantage of this method was that it had good effect only for color images.

In this work, we present an automatic algorithm based on physical model and maximum entropy theory to deweather a single image. We begin by introducing a dichromatic atmospheric scattering model described in [7]. Based on the model, we improve it by three steps. First, we segment the sky region by optimal estimated normal distribution and select the lowest point of the sky region as the vanishing point. Because the scattering coefficient is one of the most important factors, in the second step, we suppose three different values of it and apply them to the physical model to remove weather effects from the image respectively. At last, we use maximum entropy theory to estimate the best scattering coefficient, and then we can obtain the optimal restoration results. Compared with other algorithms, our method can get good results and efficiency.

2. CONTRAST RESTORATION USING AN AUTOMATIC ALGORITHM

An obvious character of former deweathering methods is that they always have several interactive steps. To solve this problem, this paper combines physical model and maximum entropy theory to get the best estimation of restoration results automatically.

2.1 Dichromatic atmospheric scattering model

Vision is caused by light and the most important characters of light are the mutual effects with the atmosphere. These effects are divided into three categories: scattering, absorption and dispersion. In bad weather conditions, scattering is the biggest factor influencing human's vision. Scattering is a very complicated process. However, Nayar et al. [13] point out that in any scattering process there exist two important factors: 'Attenuation' and 'Airlight'. The first one is the attenuation of a beam of light as it travels through the atmosphere. This causes the radiance of a scene point to fall as its depth from the observer increases. The second one causes the atmosphere to behave like a source of light. This phenomenon is caused by the scattering of environmental illumination by particles in the atmosphere. Based on the two mechanisms, the dichromatic atmospheric scattering model is presented by [7].

This model describes that the color of a scene point $\mathbf{E}$ in fog, captured by a color image, is a vector combination of clear day color $p\hat{\mathbf{D}}$ and airlight color $q\hat{\mathbf{A}}$ (Fig.1). Mathematically,

$$\begin{aligned} \mathbf{E} &= p\,\hat{\mathbf{D}} + q\,\hat{\mathbf{A}} \\ p &= R\,\mathrm{e}^{-\beta d} \\ q &= E_\infty\left(1-e^{-\beta d}\right), \end{aligned} \tag{1}$$

Where, $\hat{\mathbf{D}}$ and $\hat{\mathbf{A}}$ respectively represent the directions of a clear day color and airlight color of a scene point, p and q are the amplitudes correspondingly. E_∞ is the sky brightness, R is the clear day point radiance which is we want to get, d is the depth of the scene point and β is the scattering coefficient of the atmosphere.

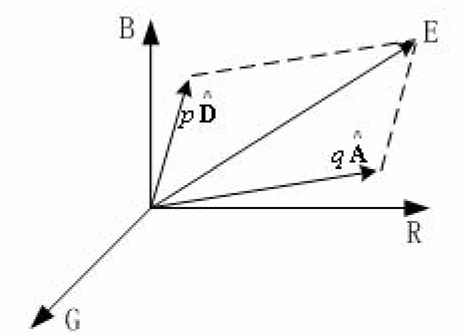


Figure1: Dichromatic atmospheric scattering model.

Rearranging terms of (1), the desired clear day radiance can be found as:

$$R = E_\infty - \left(E_\infty - E\right)e^{\beta d} \tag{2}$$

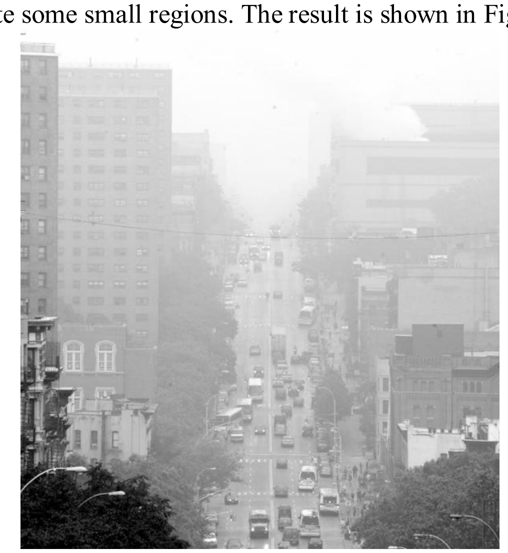
It is easy to know that only three unknown terms need to be determined to solve this equation. The maximum sky brightness E_∞ can be calculated by segmenting the sky region based on optimal estimated normal distribution. The depths of each scene point can be calculated by depth heuristics [7]. The scattering coefficient is always estimated by people, for we are not able to get it from a single image. But in this paper, we will use maximum entropy theory to solve this problem to obtain the best value of β automatically.

In the follow sections, we will concretely describe how to get the sky brightness, depth heuristic values and the scattering coefficient.

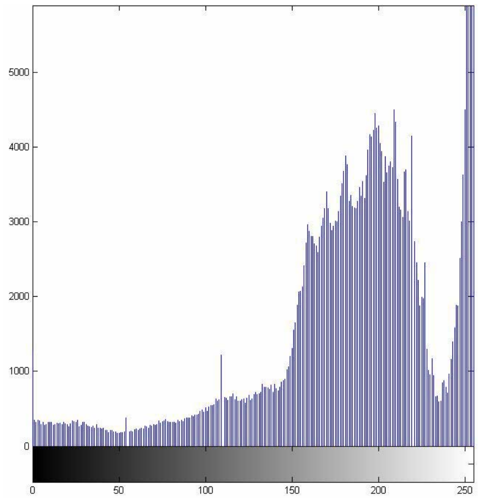
2.2 Calculation of the sky brightness

Images captured in outdoors always have sky regions. Narasimhan and Nayar [7] got the sky brightness by people and such an interactive step made their algorithm inefficient. Here, we exploit an automatic method based on the optimal estimated normal distribution to detect the sky regions [2] and let the average gray value of the regions to be the sky brightness.

In fog-degraded images, the gray levels of sky regions are always higher than other regions because of the scattering effect (see Fig.2 (a)). Accordingly, the gray histogram of the image usually has a very steep peak in the higher gray levels (see Fig.2 (b)). The areas where the peak locates just represent the sky regions. Considering that gray values of the sky regions in an image usually meet the normal distribution, so we can segment the sky regions by the following method. Firstly, we seek the variance of the optimal estimated normal distribution by searching the histogram of the image. Secondly, we can get the sky regions by the distribution and then segment them by a threshold. Finally, we use close operation to delete some small regions. The result is shown in Fig.2(c).



(a)



(b)

(c)

Figure 2: Sky region segmentation of fog degraded image. (a) is the original foggy image. (b) is the gray histogram of (a). (c) is the segmentation result of sky regions

2.3 Improved algorithm to get scene depth

For subtle weather effects within small depth ranges can not be captured by a camera with limited dynamic range, precise distances are not required for effective deweathering. Based on depth heuristics [7], we propose an improved method for depth calculation.

First, a vanishing point should be selected in the sky region [7,14]. We can select the lowest point of the sky region (see the red point in Fig.2 (c)) and it is always reasonable in most situations. Then, we make a series of concentric circles regarding the vanishing point as the center of the circles [15]. So, the points on the same circle have the same depth change trend. The depth of each pixel of the image can be computed by:

$$d = d_{\min} + k\left(d_{\max} - d_{\min}\right), 0 \le k \le 1 \tag{3}$$

Where, $d_{\min}$ and $d_{\max}$ are respectively the minimal and maximal depth of the scene point, k is the adjustment factor of scene depth. And the depth increases with k. When $k=1$, $d = d_{\max}$. Let $\alpha \in [0,1]$ represent the fractional image distance from a pixel to the vanishing point. As is known to us that the degradation of image quality due to bad weather is exponential in the depths of scene points, and the nearer the point is to the vanishing point ($\alpha \approx 0$), the more serious the degradation is, so we could construct a function as follows:

$$k = 1 - \alpha^t, 0 < t < 1 \tag{4}$$

Where, t is the adjustment factor of atmospheric degradation. Obviously, k increases with t proportionately. Combining (3) and (4), so the final depth can be computed by:

$$\begin{aligned} &d = d_{\min} + \left(1-\alpha^t\right)\left(d_{\max} - d_{\min}\right) \\ &0 \le \alpha \le 1, 0 < t < 1, \end{aligned} \tag{5}$$

According to the physical model and heuristic depths, it is easy to see that we can get better restoration results by adjusting the factor t. Besides, we can select suitable $d_{\min}$ and $d_{\max}$ by the corresponding scattering coefficient. When the fog is thick, whether the scene is nearer to or further from the observer, the degradation are both serious and we should select bigger $d_{\min}$ and $d_{\max}$. While the fog is thin, only points further from the sensor are degraded badly, and a smaller $d_{\min}$ and a bigger $d_{\max}$ should be defined in order to improve the contrast of the image.

2.4 Estimation of the scattering coefficient

Entropy, a familiar conception in thermodynamics, is a measure of the randomness in a system. And image entropy first proposed by B. R.Frieden [16] is a quantity, which is used to describe the 'business' of an image. Low entropy images have very little contrast, while high entropy images have a great deal of contrast from one pixel to the next. It can be calculated by [17]:

$$H(X) = -\sum_{i,j} P(i,j)\log P(i,j) \tag{6}$$

Where, $p(i,j) = \dfrac{x(i,j)}{\sum_{i,j} x(i,j)}$, $x(i,j)$ is the gray value at pixel (i,j).

Presently, there have been many image restoration methods based on maximum entropy theory, which was firstly proposed in 1957 by E. T. Jaynes. In image processing fields, B. R. Frieden began to use the theory to restore images. Maximum entropy image restoration is a nonlinear restoration method and its principle is choosing the image having maximum entropy as the final solution among all the feasible solutions to the image restoration problem.

Thus, maximum entropy theory can be absolutely regarded as a measurement to value the results of image restoration. In this paper, we use this theory to choose the optimal atmospheric scattering coefficient β. At first, let $\beta = 0.2$, 0.5, or 0.8 (respectively represent haze, moderate fog and thick fog). And then we use them and the physical model to restore an image. Thirdly, we calculate the entropy values of all defogged images. At last, the image owning maximum entropy is the optimal estimation of a clear day image.

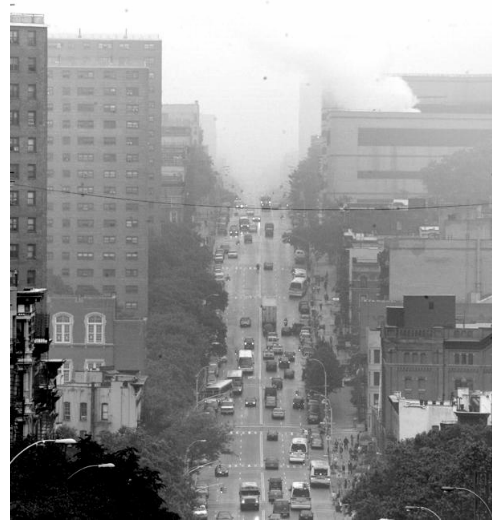
After we find the best result, we should adjust it by stretching its contrast to enhancing the whole brightness.

3. Experimental Results

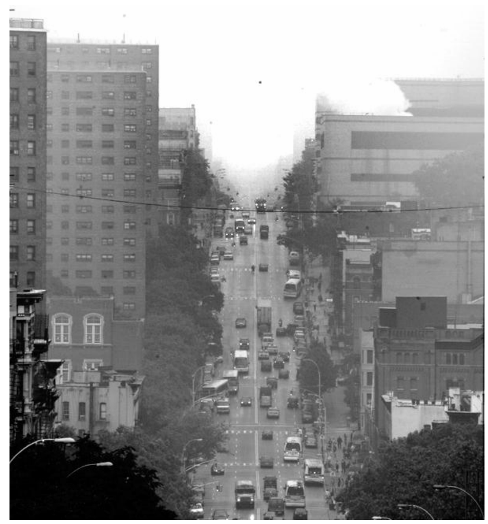
Based on the method discussed above, we carry out a great many experiments. Now, We first test the use of maximum entropy theory in the estimation of the scattering coefficient. Experiments with two outdoor scenes under thick fog and moderate fog are shown in Fig.3 and Fig.4.The first of the two scenes is imaged under the foggy condition, and is shown inFig.3 (a). The second scene is imaged under the moderate fog as shown in 4(a). Fig.3 (b), (c), and (d) show the corresponding recovered images for the parameter set $\beta = \{0.2,\ 0.5,\ 0.8\}$ of Fig.3 (a)(For comparison, the other parameters are set the same.). We can easily see that Fig. 3(d) is clearer than 3(b) and (c). Similar experiments are made on Fig.4 (a). It is obvious that targets are mainly enhanced in Fig.4 (c). Table1 shows entropy values of the results of these two situations. Notice that Fig.3 (d) and Fig.4 (c) own the maximum entropy values respectively in each situation. So the maximum entropy theory is reasonable and useful for evaluating the quality of restoration results.

(a)

(b)



(c)



(d)

Figure 3: Restoration of a foggy image by choosing different values for β . (a) original foggy image.(b)defogged image ($\beta = 0.2$). (c) defogged image ($\beta = 0.5$). (d) defogged image ($\beta = 0.8$)

(a)

(b)

(c)

(d)

Figure 4: Restoration of an image of moderate fog by choosing different values for β . (a) original hazy image.(b)dehazed image ($\beta = 0.2$). (c) dehazed image ($\beta = 0.5$). (d) dehazed image ($\beta = 0.8$)

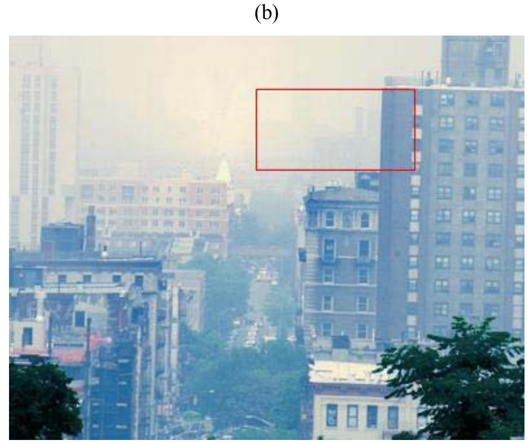
Table 1. Entropy values for images in Fig.3 and Fig.4

Figure 3	*(a)*	*(b)*	*(c)*	*(d)*
Entropy Values	7.2727	7.3323	7.3483	7.394
Figure 4	*(a)*	*(b)*	*(c)*	*(d)*
Entropy Values	7.1355	7.4104	7.7804	6.1972

In addition, we compare our algorithm with other methods. Fig.5 (a) is a color image, and its contrast is very low. Fig.5 (b) is the enhanced image by histogram equalization. The further regions have little restoration. Fig.5 (c) is the restored result by Narasimhan's method [7]. The enhanced effect is much better, but the whole brightness is a little low. On the other hand, β is selected by people, so the result may be not exact. In fact, in Fig5(c), we can see some contour lines in the red rectangle. But, in Fig5 (b), we can't find them. Fig.5 (d) shows the result of our algorithm. Because of the modification of depths, the optimal estimation of β , and the adjustment of the whole brightness in the end, we get a satisfying effect.

(a)

(b)



(c)

(d)

Figure 5: The defogged results for a color image by different methods. (a) original foggy image.(b)enhanced image by histogram equalization. (c) the result by Narasimhan's method. (d) the result of our algorithm.

4. CONCLUSION

In this study, we have discussed a new automatic method to remove weather effects from a single image. By using physical model and maximum entropy theory, the method has no longer required precise information about the scene depth and the weather conditions. Since the implement of the method does not need any interactive step, it is very efficient. And compared with other methods, our experimental results show that the quality of restored image is much better for both gray and color images.

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