Detecting Hazy Images and Estimating the Haze Thickness

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Abstract:

Partial visibility in haze climate intensely impacts the correctness and the overall functions of almost all outdoor video surveillance or driver support systems. The real climate state is valuable information to raise corresponding methodologies. Built on the atmospheric scattering model analysis and the statistics of several outdoor images, for most foggy images, we find that the lowest and highest value in colour channels tends to be the same value of atmospheric light. A function for estimating the haze thickness is established for the programmed recognition of the foggy image with unlike haze thickness. The proposed haze classification method attains high performance shown in experimental results.

Keywords: Haze Thickness, Dehazing; Atmospheric scattering model;

1. Introduction

Now a day's maximum outdoor video surveillance, driver assistance and optical remote sensing systems have been intended to work under decent visibility and climate circumstances. Poor visibility frequently arises in foggy or hazy climate circumstances and can heavily affect the accuracy or even the overall functionality of such vision systems. Therefore, it is significant to introduce real climate circumstance data to the proper processing method. In recent times, substantial development has been made in haze removal from a single image [1, 2]. Built on the hazy climate classification, focussed approaches, such as a dehazing process, can be working to improve recognition. Figure 1 displays a model processing flow of the proposed dehazing method.

Even though its outstanding value, defining weather data from a single image has not been comprehensively studied. Traditional algorithms are deliberated for definite applications or need human involvement. Weather recognition systems for vehicles that depend on vehicle-specific priors have been proposed [3-6]. One more proposed system [7] can automatically tag images with high assurance by allocating weather tags, such as sunny, or cloudy; however, manual input restrictions are mandatory.

In contradiction of this background, the core goal of the present research is to cultivate a set of stable algorithms for the identifying foggy images and marking the haze thickness of images by using a factor with generalised applications. In this paper, proposed a haze degree thickness function to automatically differentiate foggy images and mark images with their equivalent haze thickness. We influenced by on the atmospheric scattering model analysis and statistics derived from various outdoor images in order to develop the estimation function.

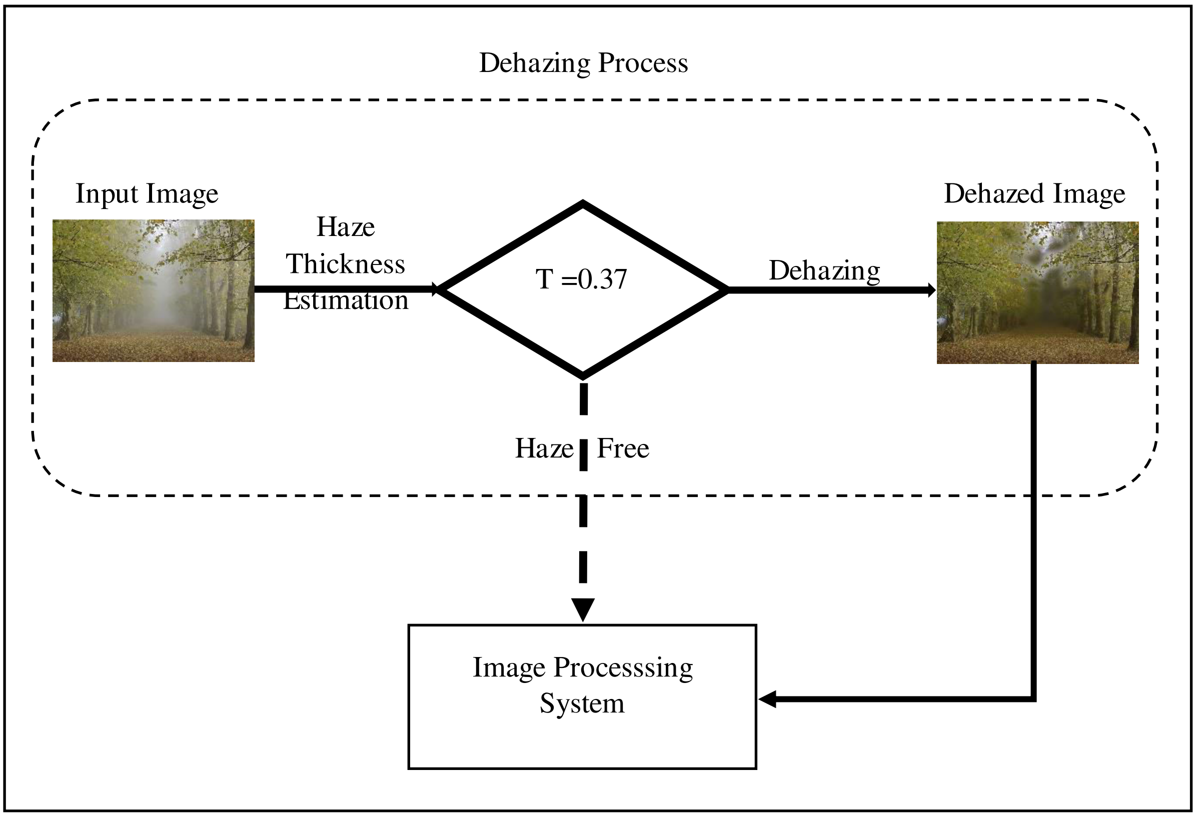


Figure 1: Model dehazing flows by using haze thickness estimation, where *T* is Haze Thickness

2. Atmospheric Scattering Model Investigation

By default, we discuss the case of image that uses the RGB color model. A hazy image can be modeled as shown in [1,8] (Figure 2):

$$I(x) = J(x)\,t(x) + A\,(1 - t(x)) \tag{1}$$

where x signifies the pixel location, I(x) is the seen haze image, and J(x) is the haze-free image. For n ∈ {r, g, b}, In (x) is one of three color channels of I(x), and Jn(x) is one of three color channels of Jn (x). A is the global atmosphere light and is generally a fixed element A_0 in all three color channels, A_n=A_0. t(x) is the medium transmission and it is supposed to be the same in all three color channels at one pixel location. When the atmosphere is homogeneous, $t(x) = \exp\left(-\beta.\mathrm{dep}(x)\right)$

Here, β is the scattering coefficient of the atmosphere, and dep(x) is the scene depth. To determine the haze thickness of an image quickly and reliably, we define the following:

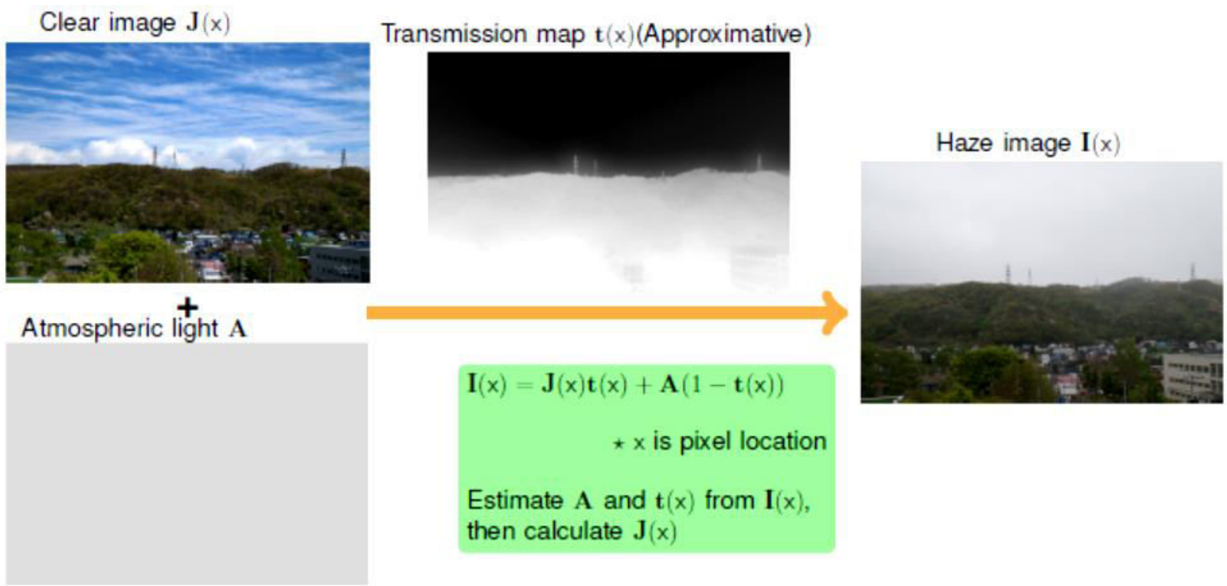


Figure 2: Atmospheric Scattering model used.

$$L^I = \min_{n\in\{r,g,b\}} I^n(x) \tag{2}$$

$$M^I = \max_{n\in\{r,g,b\}} I^n(x) \tag{3}$$

$$N^I = L^I - M^I \tag{4}$$

$$L = \frac{\sum L^I(x)}{|p_x \times p_y|},\ \ M = \frac{\sum M^I(x)}{|p_x \times p_y|} \tag{5}$$

$$N=L-M \tag{6}$$

where L(x) is the minimum value of three channels, and M(x) is the maximum value. L and N, which are the average values of L^I (x) and N^I (x), are referred to as the dark and contrast values, respectively. Here, we assume that the size of image I is $|p_x \times p_y|$. Take the minimum and maximum of the three channels on both sides of Equation 1:

$$L^I(x) = \left(\min_{n\in\{r,g,b\}} J^n(x)\right) t(x) + A_0\left(1 - t(x)\right)$$

$$L^I(x) = L^J(x)\, t(x) + A_0\left(1 - t(x)\right) \tag{7}$$

$$M^I(x) = \left(\max_{n\in\{r,g,b\}} J^n(x)\right) t(x) + A_0\left(1 - t(x)\right)$$

$$M^I(x) = M^J(x)\, t(x) + A_0\left(1 - t(x)\right) \tag{8}$$

$$A_0 - L^I(x) = \left(A_0 - L^J(x)\right) - t(x) \tag{9}$$

By Equation 8-Equation 7, we get the following

$$N^I(x) = \left(\max_{n\in\{r,g,b\}} J^n(x) - \min_{n\in\{r,g,b\}} J^n(x)\right) t(x) \tag{10}$$

$$N^I(x) = (M^J(x) - L^J(x))\, t(x)$$

$$N^I(x) = N^J(x)\, t(x)$$

For most haze-free outdoor images, L^J (x)<A_0 even L^J (x) $\ll A_0$, Equation 9 and Equation 10 show that the smaller t(x), N^I(x) and $A_0 - L^I$(x) are closer to 0. As above, the values d and c may be correlated with the overall haze thickness of an image. In the next section, we use astatistical method to evaluate the relationships. Note that, for simplicity, we estimate A as follows. Clearly, M ≤ A_0 max M^I(x) is established, and then, A_0 can be expressed as

$$A_0 = \lambda\, \max_{X\epsilon x} M^I(x) + (1-\lambda)M, \quad 0 \le \lambda \le 1 \tag{11}$$

Here, we set λ=1/3

3. Haze Thickness Estimation Function

We selected 300 outdoor images that use the RGB color model (component values are stored as integer numbers in the range 0-255) and manually divided them into six groups according to the standards in Table 1. Figure 3 shows the sample images from the six groups. A grade from 0 to 5 representing the haze degree is assigned to each group; the higher the grade, the hazier the image. Figure 4 shows the values of $(A_0 - L)$ (horizontal axis) and N (vertical axis) of images from six groups and the haze Thickness of all selected images. The point colors represent the groups, and the point size indicates the haze degree, i.e., the larger points indicate greater haziness. It is evident that for most images from groups 3 to 5, $(A_0 - L)$ is less than 75 and N is less than 50. For most haze-free images

(group 0, the smallest blue points), $(A_0 - L)$ is greater than 100 and N is larger than that in other groups. To limit $T \in (0, 1)$, we introduce the following to estimate the haze factor T:

$$T = \exp\left\{-\frac{1}{2}(\mu x_1 + v x_2) + \sigma\right\},\ x_1 = \frac{A_0 - L}{A_0},\ x_2 = \frac{N}{A_0} \tag{12}$$

Obviously, ln (T) is a linear function of x1, x2 and σ. Each haze-degree was assigned an T in Table 1. Using multiple linear regression analysis on our data set $\{\ln \overline{T}, x_{i1}, x_{i2}\}300_{i=1}$, we can get raw μ, ν and σ. Because μ, ν, σ are experience constants, we recommend μ=5.1, ν=2.9, σ=0.2461.

The main process of our algorithm is as follows:

1. Input processing image I(x).

2. Obtain M^I (x), $L^I(x)$, $N^I(x)$ from I(x)

3. Calculate L, M, N, estimate the air light A

4. Get haze factor T by using Equation (12)

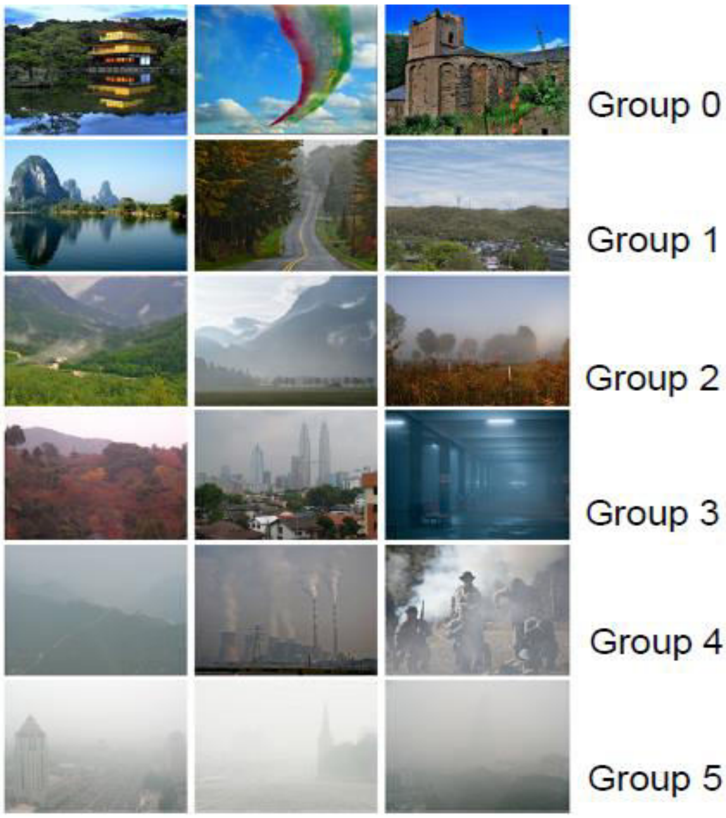
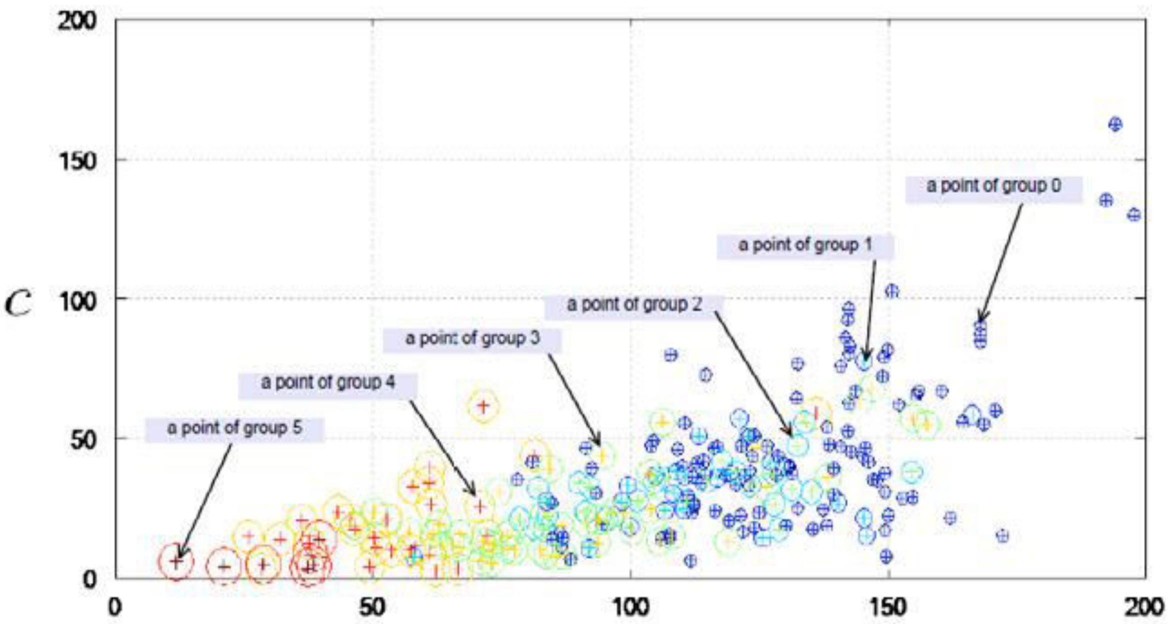


Figure 3: Database images



A0 – L

Figure 4: A0−L (horizontal axis) and c (vertical axis) of images from six groups. Larger points correspond to higher haze Thickness

Corresponding $\bar{\mathbf{T}}$	Standards	
	Haze area proportion	Haze density
0.10	0-10%	Clear
0.30	11-30%	Thin haze
0.50	31-50%	Moderate Haze
0.70	51-70%	Thick Haze
0.90	71-90%	Very Thick Haze

4. Experimental Results

We used the Foggy Road Image Database (FRIDA) [9,10] to test he haze factor estimation function Equation 12. FRIDA is comprised of 90 synthetic images of 18 urban road scenes. Each image is 640×480 pixels. (Mean execution time is 230 ms on an Intel Core I7 CPU). Each image without fog (Lima set) is associated with four foggy images. Different types of fog are added to each of the four associated images: uniform fog (U080), heterogeneous fog (K080), cloudy fog (L080), and cloudy heterogeneous fog (M080), as an example Figure 5 shows the No.1 and No.10 images from five sets of FRIDA.

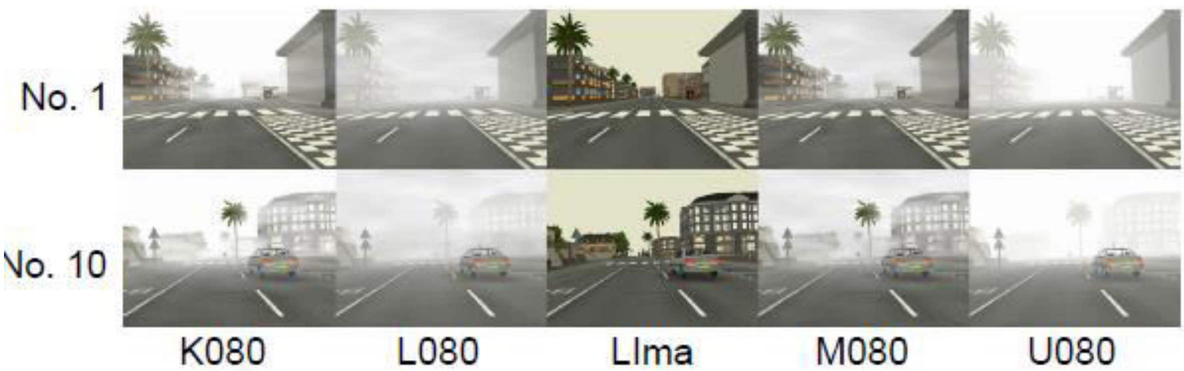


Figure 5: Sample images from FRIDA Database.

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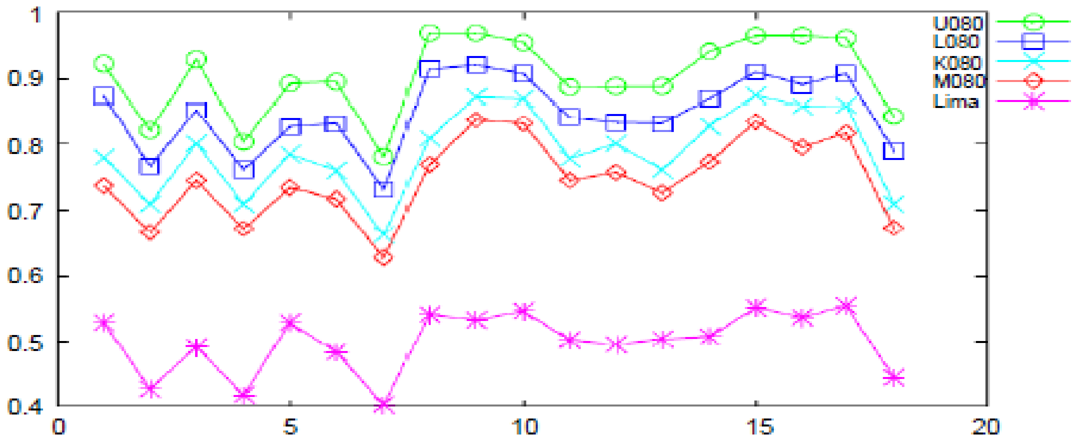

Figure 6: Estimated haze factor ω of the five sets of FRIDA, the horizontal axis is Image No. (1-18) and the vertical axis is the haze-factor T.

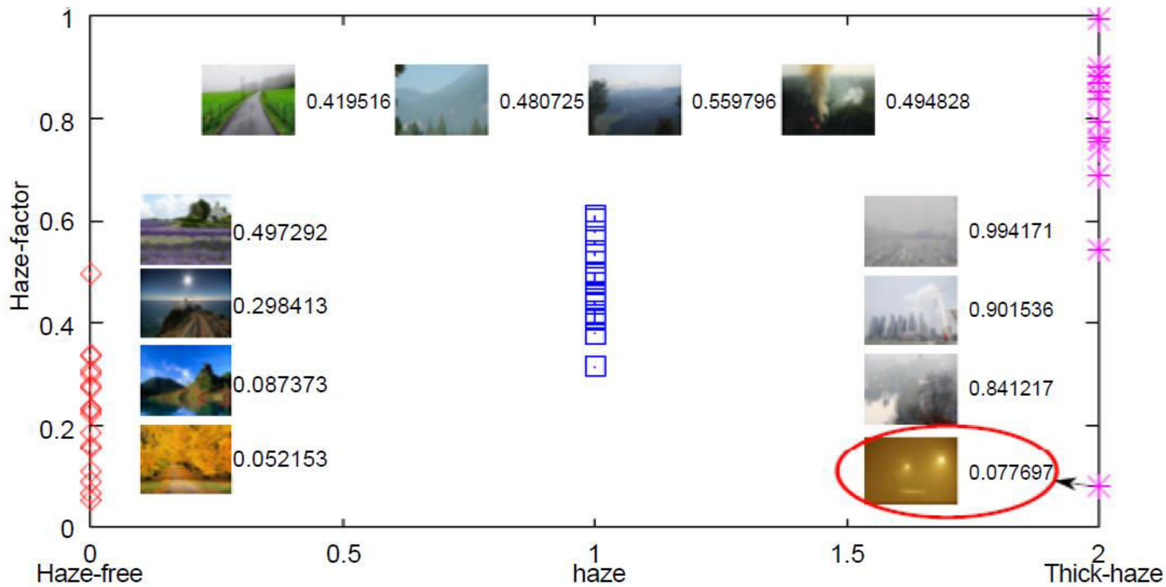

Figure 7: Estimated haze factor T of real images divided in three groups and their sample images with the haze factor on the right.

As Figure 6 shows, the lowest haze degree (between 0.4 to 0.6) is found for images of Lima. Note that the sky area of images from the Lima set is different from a real situation. Real fog-free image in our experimental results, have a degree of below 0.3. The four associated foggy images have regularity values (between 0.6 and 1) that correspond to different types of fogs. Images from U080 set always get the highest degree and M080 always get the lowest. For different images in the same set, for instance, No.1 and No. 10, No. 10 gets higher degree than No. 1, which is consistent with the actual situation. The experimental results show that Equation 12 can accurately distinguish haze degree.

In addition, we also randomly collected 48 real images to test our method dividing them by artificially picking three groups: haze-free, haze, and thick-haze. Figure 7 shows the haze factors of three groups and provides some sample images and the factor value. About 94% haze-free images get a haze-factor value below 0.4, 88% haze images get a value between 0.4 and 0.6, and, 85% thick images get a value between 0.7 and 1. Note that photo in the red circle, has haze-factor below 0.1, despite being a thick-haze airport night view obviously, this is because this picture has a monochrome light source, which means that A was not the same in three channels which make our model fail.

5. Conclusion

We introduced a numerical foggy image detecting method by using the atmospheric scattering model analysis and statistics of various outdoor images, which can estimate the haze-factor from single image by using an adjustable empirical function without manual input constraint. Because its complexity is linear, it can be applied as an initial classification step of dehazing processing and does not exhaust processing resources.

Experimental results show that the method can be applied to usual weather conditions in video-surveillance, driverassistance and optical remote sensing system with high accuracy. Our proposed prior is inspired by the atmospheric scattering mode, and supposes that the air light is equal in all three channels which might not always be true. Moreover, our method can-not be applied to the case of a monochrome light source. Thus we leave these problems for further research.

6. References

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