Image Dehazing Algorithm Based on Particle Swarm Optimization for Sky Region Segmentation

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***Abstract*—The well-known Dark Channel Prior (DCP) dehazing algorithm does not work well in the sky area, thus, we propose an image dehazing method for segmented sky regions based on Particle Swarm Optimization (PSO). First, we apply PSO to the Otsu segmentation method to accurately segment sky and non-sky regions in the hazy image. Second, the transmission of non-sky regions is derived by DCP. A transmission compensation method is proposed to obtain the transmission for the sky regions. The transmission is then refined by gradient-domain guided filtering. Finally, the restored haze-free image is obtained through the Atmospheric Scattering Model (ASM). Quantitative and qualitative experiments show that the proposed method has a better dehazing effect, especially for hazy images with the sky areas.**

***Keywords*-image dehazing; Ostu; sky area segmentation; DCP**

I. INTRODUCTION

In hazy weather, ambient light is absorbed or scattered by atmospheric particles, resulting in a series of degradation and degradation phenomena such as reduced contrast and unclear details in the images obtained by the machine vision system. Image degradation has a great impact on subsequent technical work in computer vision fields such as target detection and tracking, and image recognition, and has brought great inconvenience to work in medicine, military, industry, and transportation. Therefore, this is important for normal operation of the machine vision system to study how to restore the clear image under hazy conditions.

There are three existing dehazing methods: image enhancement-based methods [1], model-based methods [2], and learning-based methods [3]. The first method is mainly histogram equalization, Retinex image enhancement theory, Gaussian filter, median filter, fast Fourier transform, and wavelet transform. The physical model-based method is based on the ASM proposed by Narasimhan and Nayar [2], and solves the model and restores hazy-free images according to different prior knowledge and atmospheric light estimation methods. The more outstanding work is the DCP proposed by He et al [4]. But He et al [4] also pointed out that DCP fails in the sky region. Therefore, in order to use the dark channel prior more effectively, we propose an dehazing method based on particle swarm optimization for sky region segmentation. In the non-sky area, the transmission is estimated by DCP, and in the sky area, we design a compensation function to estimate it.

II. RELATED WORK

A. ASM

ASM stands for imaging process of scenes under hazy conditions [5]:

$$H(\mathbf{x}) = R(\mathbf{x})T(\mathbf{x}) + L(1 - T(\mathbf{x})) \tag{1}$$

$$T(\mathbf{x}) = e^{-\beta d(\mathbf{x})} \tag{2}$$

where $H(\mathbf{x})$ is the observed image at pixel $\mathbf{x}$ under hazy weather, $R(\mathbf{x})$ is the ideal recovered image, and L is the atmospheric light that is considered constant during daytime dehazing value, $T(\mathbf{x})$ is the transmission, β is the attenuation factor after scattering by particles in the fog, and $d(\mathbf{x})$ is the optical thickness or distance between the camera and the scene, known as the depth.

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B. DCP

DCP theory shows that in most non-sky local areas, for the three color channels of RGB for each pixel of each image, some pixels will always have at least one color channel with very low values [4]. The dark channel is represented as follows:

$$R_{dark}(\mathbf{x}) = \underset{y\in\omega(\mathbf{x})}{min}\left\{\underset{c\in\{R,G,B\}}{min}\left[R_c(\mathbf{y})\right]\right\} \tag{3}$$

where R_c represents a color channel of haze-free image, $\omega(\mathbf{x})$ represents the neighborhood image patch centered at the pixel position $\mathbf{x}$, and R_{dark} represents the dark channel of the actual haze-free image. The principle of DCP shows that the value of R_{dark} always approaches 0. Then $T(\mathbf{x})$:

$$T(\mathbf{x}) = 1 - w * \underset{\mathbf{y}\in\Omega(\mathbf{x})}{min}(\underset{c}{min}\frac{H^c(\mathbf{y})}{L^c}) \tag{4}$$

where w is 0.95, and a method for estimating A was also proposed by He et al. [4], then $R(\mathbf{x})$ can be restored by:

$$R(\mathbf{x}) = \frac{H(\mathbf{x}) - L}{max\left[T(\mathbf{x}), t_0\right]} + L \tag{5}$$

In general, t_0 is taken as 0.1.

III. Method

A. Sky Region Segmentation

We apply the PSO [6] to the Otsu segmentation method to accurately segment sky and non-sky regions in the hazy image. The correlation function in PSO:

$$P(i) = \frac{pixelCount(i)}{totalNum} \tag{6}$$

where $pixelCount(i)$ indicates the amout whose gray value is i , $totalNum$ represents the total number of pixels, $P(i)$ represents the probability of the occurrence of the pixel whose gray value is i. Suppose th is the division threshold of sky area and non-sky area in the image obtained by the PSO algorithm. Then the gray value of $[0, th]$ is the segmented non-sky area, $[th+1, 255]$ is the segmented sky area, and w_0 and w_1 represent the probabilities of the two areas respectively:

$$w_0 = \sum_{i=0}^{th} P(i), w_1 = \sum_{i=th+1}^{255} P(i) \tag{7}$$

Then calculate the mean u_0 and u_1 of the gray value :

$$u_0 = \frac{\sum_{i=0}^{th} i * P_i}{w_0}, u_1 = \frac{\sum_{i=th+1}^{255} i * P_i}{w_1} \tag{8}$$

Then get the overall gray value mean u of the image:

$$u = w_0 * u_0 + w_1 * u_1 \tag{9}$$

Then according to the OSTU, the optimal segmentation threshold th is obtained by calculating the Maximum between-cluster variance σ^2 of the image:

$$\sigma^2 = w_0 * (u_0 - u)^2 + w_1 * (u_0 - u_1)^2 \tag{10}$$

We use Equation (10) as the fitness function of the PSO algorithm. In our experiments, we use 500 particles and the maximum number of iterations is 300 to obtain the optimal threshold of th. Fig. 1 shows the effect of the proposed particle swarm optimization Otsu method for segmenting the sky region.

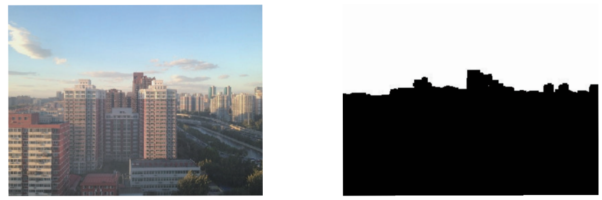

Figure 1. Hazy image and corresponding sky region segmentation effect.

B. Parameter Estimation and Image Dehazing

After accurately segmenting the sky region and non-sky region, the unknown parameters in Equation 4 need to be estimated to recover a clear image $R(\mathbf{x})$, where $T(\mathbf{x})$ and L are estimated using the method of He et al. [4]. Regarding the transmission in the sky area, we design a transmission compensation function to estimate:

$$T(\mathbf{x}) = T(\mathbf{x}) + (1 - T(\mathbf{x}))/2 \tag{11}$$

This function will try to get the transmission value of the sky area as close to 1 as possible to reduce the distortion of the restoration of the sky area in the image. The estimated overall transmission $T(\mathbf{x})$ is then refined by Gradient Domain Guided Filtering [7] to reduce blocking artifacts. Finally, the restored hazy-free image $R(\mathbf{x})$ can be obtained by Equation (5).

IV. Experiments

A. Subjective Evaluation

We select some hazy images for experiments on the RESIDE dataset [8], and compare the proposed method with He [4], Meng [9], Ren [10] , Cai [3], and Li [11]. Fig. 2 shows the results of synthetic images. The images recovered by He's, Ehsan's, and Li's method are darker. Meng's , Ren's , and Cai's method will cause color distortion. Moreover, the sky area of the images recovered by these methods has poor visual effect and severe color shift. Our method is similar to GT, especially the sky area. Fig. 3 shows the comparison of the dehazing effect of the realistic image. The images recovered by the methods of He's, Cai's, and Li's are too dark and somewhat oversaturated. The images recovered by Meng's, Ren's, and Ehasn's method also have residual fog. Our method can reduce image color distortion while dehazing.

B. Objective Evaluation

We use PSNR, SSIM [13], and FADE [14] indicators for experimental verification. As shown in Table 1, the images recovered by our proposed method have the highest PSNR and SSIM metrics, which demonstrates the effectiveness of the proposed method for restoration. As shown in Table 2, the FADE metric of our method is the lowest, which indicates that the image recovered by our proposed method

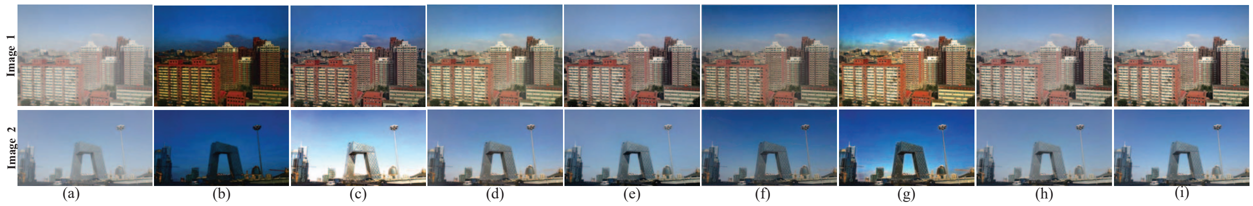

Figure 2. Comparison of dehazing effects of synthetic images.(a) Hazy images, (b) Results by He [4], (c) Results by Meng [9], (d) Results by Ren [10], (e) Results by Cai [3], (f) Results by Li [11], (g) Results by Ehsan [12], (h) Our's results, (i) Ground Truth (GT).

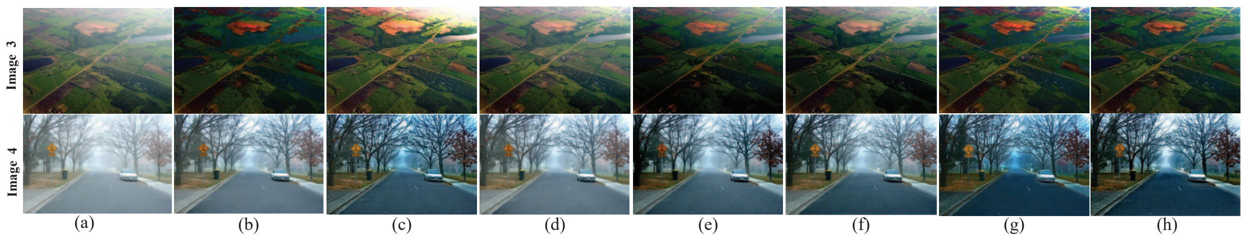

Figure 3. Comparison of dehazing effects of realistic images.(a) Hazy images, (b) Results by He [4], (c) Results by Meng [9], (d) Results by Ren [10], (e) Results by Cai [3], (f) Results by Li [11], (g) Results by Ehsan [12], (h) Our's results.

Table I
PSNR/SSIM METRIC FOR FIG. 2.

Image	He	Meng	Ren	Cai	Li	Ehsan	Our
Image 1	7.4913/ 0.4252	15.7104/ 0.9008	16.8682/ 0.8328	14.8471/ 0.8240	12.6114/ 0.7904	18.0677/ 0.8503	25.4944/ 0.9528
Image 2	7.8511/ 0.4547	15.0565/ 0.8199	18.3426/ 0.8820	16.4368/ 0.8665	11.461/ 0.7224	15.7134/ 0.8171	26.3083/ 0.9454

Table II
FADE METRIC FOR FIG. 3.

Image	He	Meng	Ren	Cai	Li	Ehsan	Our
Image 3	0.2667	0.3190	0.3833	0.2362	0.2170	0.2746	0.2108
Image 4	0.3055	0.1990	0.5169	0.2754	0.2968	0.2209	0.1695

has the lowest haze concentration, and thus the proposed method has the best dehazing ability.

V. CONCLUSION

We propose an image dehazing algorithm based on DCP and sky region segmentation. We use particle swarm optimization for the Otsu method to accurately segment the sky and non-sky regions of the image. In the non-sky region, we estimate the transmission with DCP, and in the non-sky region, we propose a transmission compensation function to correct the transmission, and finally use gradient domain guided filtering for refinement. In the experiment, we found that the sky area segmentation algorithm based on PSO is not fully adaptive, and the main reason may be that the fitness function setting is not accurate enough. Therefore, in future work, we plan to design a better fitness function to further improve the accuracy of segmentation.

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