Research of Image Dehazing Based on Image Gradient Distortion Prior

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Abstract. In view of the problem of image quality degradation caused by the scattering of outdoor atmospheric particles in dusty weather, this paper proposed a research of dehazing image based on gradient distribution prior. Firstly, the method is to obtain a prior model of the gradient distribution of images from a large number of high quality natural image data sets. Secondly, the gradient distribution of hazy image is changed to make the infinite approximation the learned prior model. Finally, the Poisson equation is used to solve the reconstructed image to obtain dehazing image. According to a large number of experimental data, it shows that this research can remove the haze of image effectively. Compared with the most advanced methods, the image processed by this algorithm not only retains more details of the original image, but also improves the image definition largely.

Keywords: Dehazing image · Prior model · Gradient distortion model · Laplace distortion model · Poisson equation

1 Introduction

In haze weather, the image degraded because of the scattering of dust, fog and other particles. The contrast and definition of the acquired image are often poor, which affects the visual effect of the image. Therefore, it is of great significance to study a fast and effective method to make the haze image clear [1, 2]. Performance of the algorithm is very important for certain application including safety monitoring systems and power distribution management.

There are many existing methods to remove the haze image, but there are some shortcomings. Grewe [3] et al. put forward the method of defogging based on wavelet transform. The visual effect of the processed image is better. The disadvantage of this method is that the efficiency of image fusion is low. Tan [4] et al. proposed to realize dehazing by enhancing local color contrast. This method not only enhances the image contrast, but also enhances the image noise. Tarel [5] et al. Proposed to achieve a certain effect of defogging through the pre-processing of foggy image and median filtering. With the requirement of real-time, the disadvantage of this method is that it can blur the boundary with large gray change and lose a lot of detail information. He [6] et al. Put forward the method of fog removal based on the prior of dark channel, using the

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prior knowledge to estimate the air transmittance, and then through the principle of soft matting to optimize the estimation of the air transmittance, to achieve the purpose of image fog removal. However, due to the large amount of computation required in the process of soft matting, it is difficult for this method to have the real-time demand. In recent years, many similar defogging algorithm models have been proposed, such as [7–10]. But it is difficult to achieve real-time and effective defogging. Priori model have been verified efficiently in image dehazing, with the above observation, this paper proposes a method of defogging based on the prior of gradient distribution. Firstly, a priori model of gradient distribution is obtained from a large number of high-quality natural image data. Secondly, the gradient distribution of the fog image is changed so that the prior model can be obtained by infinite approximation learning. Finally, poisson equation is used to solve the reconstructed image to get the defog image.

2 Related Work

2.1 Prior Model

2.1.1 First Order Prior

On the logarithmic scale, the gradient distribution of natural images has a heavy tail [11–13]. Traditionally, the gradient distribution is modeled as a generalized Laplace distribution:

$$\log(p(x)) = -k\|x\|^{\alpha} + \beta \tag{1}$$

Where, $k, \alpha,$ are parameters, x represent gradients, p are gradient probability distributions. This model includes some commonly used priors, such as total variation (TV) ($\alpha = 1$) [14], super Laplace ($\alpha = 0.6$) [12]. But the model has many shortcomings. First of all, the model and the actual distribution data can not be well consistent. Secondly, the previous work, k, α, β used as independent variables, which violated the standardized distribution ($\int_{-\infty}^{+\infty} pdx \neq 1$). In addition, the generalized Laplace model is computationally expensive. In this paper, we design a new model to overcome the above shortcomings.

2.1.2 Two Order Prior

In addition to first-order statistics (such as gradients), second-order statistics such as mean curvature (MC) [12] and Gaussian curvature [15, 16], which can also be applied to priors. Different orders of a priori can also be combined, for example, reference [14]. But in most cases, high-order statistics is not necessary. As shown in Fig. 1, $I(x)$ and $I(x + r)$ the relationship when the derivative is of different order:

$$Corr(d, r) := correlation\Big(\nabla^{d} I(x), \nabla^{d} I(x + r)\Big) \tag{2}$$

where $r = (r, 0)$, The larger the order, the more obvious the correlation decreases. This shows that the first-order and second-order priors are very effective for image processing, but higher order derivatives are not necessary to improve this result. One reason is that discrete images may not be high-order differentiable. For the task of image processing, the second order can already meet [16]. Therefore, we only consider the second derivative. All kinds of second-order differential operations, Laplace operation is the most effective, because it can generate Poisson equation like gradient distribution. Therefore, these two priors can realize image reconstruction by solving a Poisson equation at the same time [17–19].

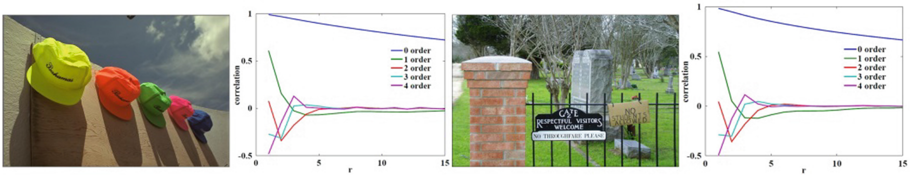

Fig. 1. Rapid reduction of higher derivative

2.2 Gradient Distribution Model

Considering that both G^x and G^y have heavy tails on the logarithmic scale, this feature can be modeled as a super Laplace distribution [20]. The traditional one-dimensional model is consistent with $p(G^x)$ on the logarithmic scale, but it can not meet this requirement $\int_{-\infty}^{+\infty} p(G^x)dG^x = 1$. Considering that cumulative distribution function (CDF) has been verified efficiently in image processing, we use CDF instead of probability density function (PDF). CDF of gradient is defined as:

$$C(G) = \int_{-255}^{G^x} \int_{-255}^{G^y} p(u, v)dudv \tag{3}$$

By observing the definition characteristics of $C(G)$, a parameter model for approaching CDF is proposed:

$$\tilde{C}(G) = \left(\frac{a\tan(T_1 G^x)}{\pi} + \frac{1}{2}\right)\left(\frac{a\tan(T_1 G^y)}{\pi} + \frac{1}{2}\right) \tag{4}$$

Among them, the choice of atan function is based on T distribution or Cauchy distribution. The model of formula (4) has only one parameter and T_1. The selection of atan function is based on t distribution or Cauchy distribution. The edge model with the same distribution of G^x is as follows:

$$\log(P(G^x)) = \log(\frac{T_1}{\pi}) - \log(1 + \left(T_1 G^x\right)^2\Big) \tag{5}$$

2.3 Laplace Distribution Model

In order to get the distribution of Laplacian operation response, this paper uses CDF to model, as follows:

$$L(t) = \int_{-\infty}^{t} p(\Delta I(x))\, d\Delta I(x) \tag{6}$$

For Laplace CDF, we propose a parameter model:

$$\tilde{L}(t) = \frac{a\tan(T_2 t)}{\pi} + \frac{1}{2} \tag{7}$$

Where T_2 is the only free parameter.

3 Image Defogging Algorithm

3.1 Priori Model Proposed

The prior model proposed in this paper is a linear combination of the prior of gradient distribution and the prior of Laplace distribution. First of all, we learn the prior information from the high quality natural image data set. Between these two priors, a new parameter model is provided, which is effective for improving the quality of haze image. The specific operation steps are as follows:

As shown in Table 1, there are 7 high-quality natural image data sets, and image x is grayed. Gradient is defined as:

$$G(x, y) = \left(\nabla_x I(x, y), \nabla_y (x, y)\right) \tag{8}$$

Among them, the first-order finite difference approximation: $\nabla_x I = I(x+1, y) - I(x, y)$ and $\nabla_y I = I(x, y+1) - I(x, y)$. On the boundary of the image, we use the homogeneous Dirichlet boundary condition. Because the gray image is processed, the gradient value range is [−255, 255] * [−255, 255]. Where, G^x and G^y are used to represent gradients G on the X and Y axes, respectively.

Laplace L is defined as:

$$L(x, y) = \Delta I(x, y) \tag{9}$$

Δ is Laplace operation, which is discretized by using the second-order 5-point finite-difference template. The value range is [−1020, 1020].

In order to transform histogram into probability distribution, all pixels m * n of the image are divided into feet, where m and N are the number of pixels along the X and Y axis of the image, respectively. For the centralized image processing in the data set, histogram is defined for each image, and the average distribution p_1^{pr} and p_2^{pr} of gradient and Laplace operation is calculated. For color image, the learned priori is applied to each color channel.

Table 1. Comparison of indexes of each algorithm in different background

	Algorithm	Contrast	AG	MSSIM	PSNR
Haze image 1	Original image	0.0049	9.9505	–	–
	Tarel [3]	0.0047	10.999	0.3118	4.5395
	He [4]	0.0065	11.2821	0.5185	15.1796
	Proposed	0.0095	14.3483	0.5702	15.8384
Haze image 2	Original image	0.0013	5.7416	–	–
	Tarel [3]	0.0033	8.5067	0.4245	5.3348
	He [4]	0.0028	6.429	0.5659	15.0917
	Proposed	0.0049	11.4446	0.8146	16.8252
Dense fog image 1	Original image	0.0001	1.073	–	–
	Tarel [3]	0.0019	4.389	0.3338	2.9309
	He [4]	0.0016	3.6113	0.4724	10.3185
	Proposed	0.0042	6.2846	0.7118	14.2116
Dense fog image 2	Original image	0.0011	10.561	–	–
	Tarel [3]	0.0016	12.0301	0.1965	4.5153
	He [4]	0.0019	11.8551	0.4041	14.9822
	Proposed	0.0031	16.248	0.6457	17. 9894

3.2 Proposed Model

Figure 2 is the flow chart of the defogging method in this paper. For the gradient distribution of image, a new parameter model is proposed. In logarithmic scale, we use cumulative distribution function (CDF) instead of probability density function (PDF) to model. By adjusting the gradient distribution of smog image, it infinitely approximates the gradient distribution prior model learned from high-quality image. Finally, we can reconstruct the image by solving the Poisson equation, so as to achieve the goal of image defogging.

4 Experimental Results and Analysis

4.1 Subjective Evaluation Analysis

Figure 3 is the defogging effect diagram of the algorithm and the schematic diagram of detail processing. In Fig. 4, the first two different fog images are taken under the condition of haze weather. From the image comparison of the first line, the algorithm in this paper can better restore the image degradation caused by haze, and make the color of the image more realistic. From the second line is image comparison, it can be verified that the algorithm can be applied to many types of scenes. The last two lines are images taken in dense fog. It can be found that the algorithm based on the prior

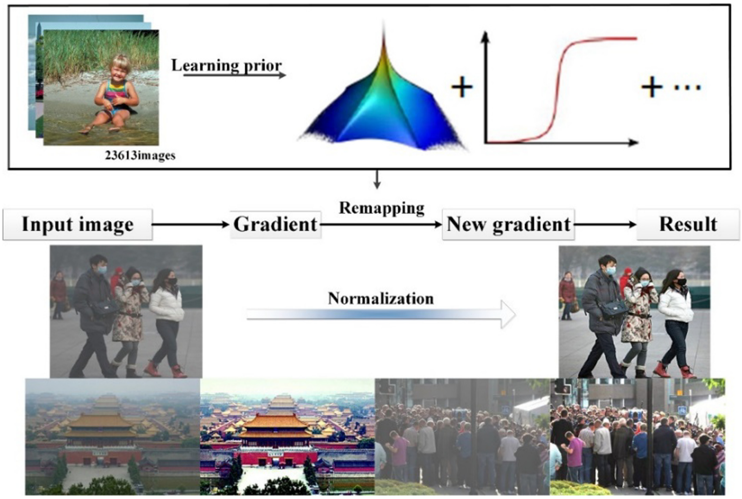

Fig. 2. Flow chart of the the proposed

gradient distribution proposed in this paper has significantly improved the visibility and contrast of haze images, especially in the processing of image details, and has achieved significant results.

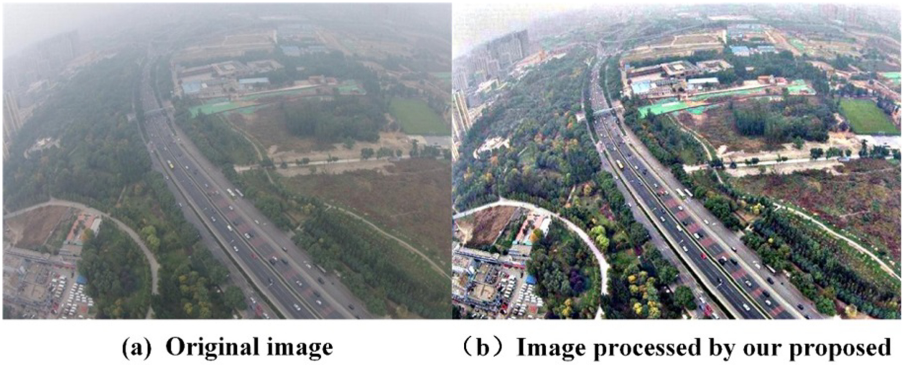

Fig. 3. Image dehazing with proposed method

In Fig. 4, from left to right, there are the original image, the tarel [5] algorithm processing image, the he [6] algorithm processing image, and the defog image based on the prior algorithm of image gradient distribution proposed in this paper. It can be seen from the second column that the tarel [5] algorithm is oversaturated when processing the foggy image, and the color of many areas in the image is biased; the third column is the image processed by the he [6] algorithm in different scenes. It can be seen that these two algorithms are not good for the overall effect of haze image processing. At the same time, we find that he [6] algorithm is easy to appear local blur phenomenon when

(a) Original image. (b) Fattal Result. (c) Algorithm result of He. (d) Proposed.

Fig. 4. Experimental results with different methods

processing dense scene image; the last column is the algorithm proposed in this paper to remove fog image in different scenes. Compared with the former two algorithms, our proposed algorithm has better results in edge and detail, and there is no oversaturation phenomenon. It shows that the algorithm in this paper is very effective to solve the distortion problems of dense fog area, scene light and atmospheric light similar area.

4.2 Objective Evaluation and Analysis

In order to evaluate the effectiveness and superiority of the algorithm more objectively, four general objective indexes are selected for evaluation. (1) Contrast; (2) Average gradient (AG) [21]; (3) MSSIM is the average value of structural similarity; (4) PSNR refers to the peak signal-to-noise ratio.

Table 1 shows the comparison results of tarel [5], he [6] algorithm and the algorithm in this paper for different images in four indicators, namely, contrast, average gradient, MSSIM, PSNR. The test results show that compared with the other two algorithms, the contrast and average gradient of the defog image processed by this algorithm are improved to a certain extent, which shows that the defog result graph of this algorithm not only highlights the edge details and other information in the original image, but also has a good visual effect. The value of MSSIM and PSNR has also been greatly improved, which shows that the image processed by the algorithm in this paper keeps a good structural similarity, at the same time, it can remove the haze more effectively and make the image clearer.

5 Conclusion

There is serious distortion in the haze image obtained in different scenes. In this paper, a method based on the priori of image gradient distribution is proposed. Firstly, the priori model of image gradient distribution is learned from a large number of high-quality natural image data. Secondly, the gradient distribution of the fog image is changed so that the prior model can be obtained by infinite approximation learning. Finally, the reconstructed image is solved by Poisson's equation to get the defog image, and the defog effect is better. Experimental data show that this method can effectively remove fog from haze image. Compared with the latest defog algorithm, the image processed by this method retains more detail information and greatly improves the clarity of the image.

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