IMPROVED SINGLE IMAGE DEHAZING USING SEGMENTATION

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ABSTRACT

In the hazy weather, the image of outdoor scene is degraded by suspended particles. Scattering and absorption hinder scene radiance and bring in environment light into camera. In this work, a novel algorithm is introduced to restore the clear day image by the segmented hazy image. First, the existing visibility restoration model is analyzed and a conclusion is drawn that the model will violate the contrast enhancement constraint in some specific situations. Next, the graph-based image segmentation method is applied to segment the hazed image by choosing the optimal parameter. Then, the transmission maps prior are obtained according to the blackbody theory. After that, a bilateral filter is designed to amend the transmission map, which can make up the deficiency of restoration model and ensure the transmission map smooth under the contrast enhancement constraint. Last, the experimental results show that the method achieves rather good dehazing results.

Index Terms— Dehaze, image segment, blackbody theory, image restoration, bilateral filter

1. INTRODUCTION

Poor visibility, which arises in adverse weather such as fog, snow, rain and so on, is a difficult problem for many applications of computer vision. The lights reflected from objects and the atmosphere lights are absorbed and scattered by aerosol particles, which cause the visibility of a scene to be degraded. Images captured in adverse weather become blur, contrast decline, and chromatic lose. And the degradation would be more serious with increasing of the distance between camera and object.

Since it is very difficult to get depth from a single image, some methods are proposed using multiple images [8, 9, 10, 12, 13]. The basic idea is to exploit the differences between multiple images captured for the same scene under different atmosphere conditions. The approaches can get rather good results, but it is difficult to obtained multiple images in many practical applications. The optical polarization property is exploited in [15, 16], which use the multiple images captured the same scene with different degrees of polarization. The methods can also make good results, but they can not be applied to dynamic scenes. The methods in [6, 11, 17] only need a single image, but the geometric model of scene is required to be predefined or input by user interaction.

The research of single image dehazing is developed rapidly in recent years. R. Tan [5] observes that the haze-free image must have higher contrast than the haze image. Combined the maximization of local contrast with the assumption that neighboring pixels have suffered the same degradation, an optimal method based on Markov Random Field is used to remove haze. The method tends to produce over-enhanced images in practice. Fattal [4] considers the shading and transmission signals to be unrelated and uses Independent Component Analysis to estimate the transmission, and then infer the color of the whole image by MRF. The method works quite well for haze, but has difficulty with scenes involving fog, as the magnitude of the surface reflectance is much smaller than that of the airlight when the fog is suitably thick.

Based on the blackbody radiation theory, He *et al.* [2] employs a dark channel prior which assumes every local patch (15×15) in the haze-free image have at least one color component near zero. This assumption is sometime violated when there is no black body in some local patches. Instead of using an MRF, a soft matting algorithm is used to refine the transmission values, which is computational expensive.

Tarel [7] proposes a bilateral filter to replace the optimization method, which improves the efficiency of algorithm and can be used in real-time. But the dehazing result is not so good when there are discontinuous in the depth of scene. The haze among gaps can not be removed.

The remaining of this paper is organized as follows. In Section 2, the analysis of image dehazed optics models and properties are introduced. In Section 3, image segmentation method and a bilateral filter is designed to restore the hazy image. In Section 4, comparable experimental results are shown. The

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discussion and conclusion are given in Section5.

2. OPTICAL MODELS AND PROPERTIES

2.1 Optical Models

According to physical properties of light transmission in atmospheric, optical model usually be used in dealing with bad weather, particularly in computer vision, is described as [2, 3, 4, 5, 6, 7, 8, 9, 10, 11]:

$$\mathrm{I}(x) = e^{-\beta d(x)}\mathrm{J}(x) + (1 - e^{-\beta d(x)})\mathrm{A} \quad (1)$$

Where I is the observed image luminance at location x, J is the scene intrinsic luminance, and A is the luminance of the sky. In addition, β is the attenuation coefficient assumed to be uniform across the entire scene, x is the 2D spatial location and the d is the scene depth (the distance between the object and the observer). In Equation (1), the first term $e^{-\beta d(x)}\mathrm{J}(x)$ is called direct attenuation, and the second term $(1 - e^{-\beta d(x)})\mathrm{A}$ is called airlight.

2.2 Blackbody Theory

The blackbody theory can be described as follows. As for a blackbody object in the scene, the object itself has no reflection. If the object is imaged, its pixel value should be very close to zero. However, the imaging processes are usually influenced by the diffused stray light from other objects, especially in adverse weather. So the pixel values of blackbody objects in hazy image are not to be zero and the non-zero part can be used to describe the characteristic of stray light in environment as follow equation [14]:

$$\mathrm{I}_b(x) = \int_0^d \mathrm{A}\beta e^{-\beta d(x)}dx = (1 - e^{-\beta d(x)})\mathrm{A} \quad (2)$$

He *et al.* [2] applies this theory to make a dark channel prior that there are always some pixels(called "dark pixels") having low intensity in any local patch and approximately regard these dark pixels as blackbody. Then $\mathrm{I_b}(\mathrm{x})$ can be obtained by scanning every patch of image. If the global atmospheric light A is known, $e^{-\beta d(x)}$ can be computed as follow equation:

$$t(x) = e^{-\beta d(x)} = 1 - \frac{\mathrm{I}_b}{\mathrm{A}} \quad (3)$$

where $t(x)$ is called transmission map and reflects the main properties of the light transmission. Assume that the atmosphere is homogenous, β is a constant value. So the scene radiance is attenuated exponentially with the scene depth d .

2.3 Analysis of Visibility Restoration Model

According to above analysis, the image restoration model can be obtained by combining with the Equation (1), (2) and (3), which is shown as follows:

$$\mathrm{J}(x) = \mathrm{I}(x)e^{\beta d(x)} + (1 - e^{\beta d(x)})\mathrm{A} = \frac{\mathrm{I}(x) - \mathrm{I}_b}{t(x)} \quad (4)$$

It can be seen that the input of the model is the degraded image I and the output is the restored haze-free image J .

According to the equation (4), the following equation could be inferred:

$$\mathrm{J}_1 = \mathrm{I}_1 k_1 + (1 - k_1)\mathrm{A}$$
$$\mathrm{J}_2 = \mathrm{I}_2 k_2 + (1 - k_2)\mathrm{A} \quad (5)$$

where I_1 and I_2 is the two pixels in the degraded image, J_1 and J_2 is the two pixels in the restored haze-free image, $k_1 = e^{\beta d_1}$, $k_2 = e^{\beta d_2}$, d_1 and d_2 is the corresponding depth of point I_1 and I_2 .

For the degraded image, the differences of two points are:

$$\Delta\mathrm{I} = \mathrm{I}_1 - \mathrm{I}_2 \quad (6)$$

For the restored haze-free image, the differences are:

$$\Delta\mathrm{J} = \mathrm{J}_1 - \mathrm{J}_2 \quad (7)$$

Without loss of generality, the $\Delta\mathrm{I}$ can be assumed to be non-negative. Then the $\Delta\mathrm{J}$ are to be discussed under three different conditions.

Under condition (1), where $d_1 = d_2$ and namely $k_1 = k_2$, it can be inferred as follows by assuming $k_1 = k_2 = k$:

$$\Delta\mathrm{J} = k\Delta\mathrm{I} \quad (8)$$

Since $k > 1$, the conclusion $\Delta\mathrm{J} > \Delta\mathrm{I}$ can be drawn, which implies the contrast of the restored haze-free image has been enhanced.

Under condition (2), where $d_1 < d_2$ and namely $k_1 < k_2$, it can be inferred as follows by assuming $k_1 = k$ and $k_2 = k + \Delta k$:

$$\Delta\mathrm{J} = k\Delta\mathrm{I} + \Delta k(\mathrm{A} - \mathrm{I}_2) \quad (9)$$

Since $k > 1$, $\Delta k > 0$ and generally $\mathrm{A} > \mathrm{I}_2$, the conclusion $\Delta\mathrm{J} > \Delta\mathrm{I}$ can be drawn, which also implies the contrast of the restored haze-free image has been enhanced.

Under condition (3), where $d_1 > d_2$ and namely $k_1 > k_2$, it can be inferred as follows by assuming $k_2 = k$ and $k_1 = k + \Delta k$:

$$\Delta\mathrm{J} = k\Delta\mathrm{I} + \Delta k(\mathrm{I}_2 - \mathrm{A}) \quad (10)$$

Since $k > 1$, $\Delta k > 0$ and generally $\mathrm{A} > \mathrm{I}_1$, the second term of equation (10) is negative which means it cannot ensure $\Delta\mathrm{J} > \Delta\mathrm{I}$ and it is ambiguous whether or not the contrast of image J has been enhanced. So the deficiency of the restoration model has been found. It maybe fail in such a situation that a region has larger image intensity while its imaging distance is greater too. The solution of this issue will be introduced in section 3.2.

3. IMAGE DEHAZING USING SEGMENTATION

3.1 Segmentation

As described in [2], the dark channel $\mathrm{I_b}$ can be obtained by the following equation:

$$\mathrm{I}_b(x) = \min_{c \in \{r,g,b\}}(\min_{y \in \Omega(x)}(\mathrm{I}_c(y))) \quad (11)$$

Where I_c is a color channel of I and $\Omega(x)$ is a 15×15 local patch centered at location x . Then the transmission map can be obtained by specifying the global atmospheric light A as shown in Figure 1(b). With the transmission map, the haze-free image can be recovered according to equation (1). The result with no use of soft matting is shown as Figure 1(c).

It can be obviously seen there are halo artifacts at the depth-discontinuous edges, as shown in the figure1(c).The reason can be inferred that the depth in every patch $\Omega(x)$ is assumed to be the same. But this assumption is often violated, especially in the image edge region. Soft matting is adopted to resolve the problem in [2], which consumes too much time.

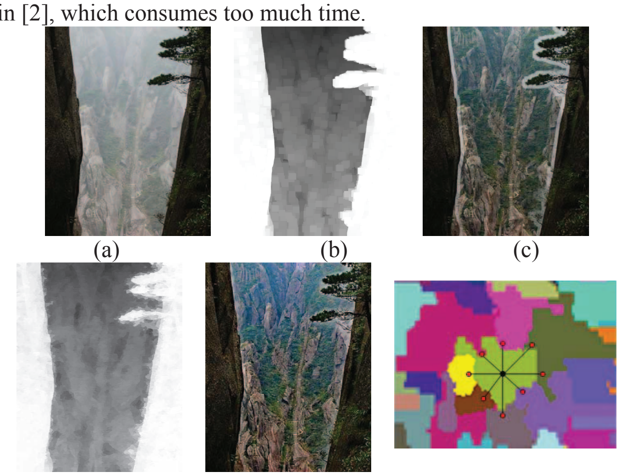

Figure 1(a) The input image (b) The He *et al's* transmission(c) The restored haze-free image with halo (d) The revised transmission map (e) The dehazing result (f) The Geometric image

In this paper, image segmentation is applied to resolve the problem. The image segmentation is used to calculate the dark channel instead of patch. Since the abrupt change of depth usually happens in the image edge regions, so this method can reduce the depth discontinuities within each patch and avoid halo artifacts to a large extent.

The image segmentation algorithm described in [1] is adopted, which runs in time nearly linear in the number of graph edges and is also fast in practice. There are three parameters control the result of segmentation: σ , k and $\min\_size$, where σ is to smooth the image, k is a constant for threshold function and $\min\_size$ is the minimum component size. In our experiment, we set $\sigma = 0$, $k = 10$, $\min\_size = 10$. The dark channel I_b is calculated in each segmented patch.

3.2 Smoothing under the contrast enhancement constraint

The transmission map $t(x)$ can be inferred from I_b according to Equation (3), after the global atmospheric light A is given as described in reference [2]. A good transmission map should be constant except along the boundaries of large depth discontinuity, otherwise it will cause halo artifacts in the restored image. So the obtained transmission map $t(x)$ needs to be smoothed enough. Moreover, according to the analysis in section 2.3, the transmission map must be modified to decrease the ambiguous of contrast enhancement under condition (3).

In this paper, a bilateral filter mask W is proposed to smooth transmission map $t(x)$ under the contrast enhancement constraint. The bilateral filter is introduced as equation:

$$\mathrm{W}[k,n] = \mathrm{W}_D[k,n] * \mathrm{W}_R[k,n] \tag{12}$$

where $\mathrm{W}_D[k,n] = e^{-\frac{n^2}{2\delta_D^2}}$, $\mathrm{W}_R[k,n] = e^{\frac{(t(k)-t(k-n))(\mathrm{I}(k)-\mathrm{I}(k-n))}{2\delta_R}}$

$\mathrm{W}[k,n]$ is the bilateral filtering mask centered at the current patch k and surrounded by $(2n+1)*(2n+1)-1$ adjacent patches. There are two terms, the domain filter W_D is designed to ensure the smoothness of I_b and the range filter $\mathrm{W}_R[k,n]$ is designed to improve contrast enhancement. Next, we will focus on the analysis of effect of W_R . Assuming that $\Delta t = t(k) - t(k-n)$ and $\Delta \mathrm{I} = \mathrm{I}(k) - \mathrm{I}(k-n)$. The $t(k)$ is the transmission map of any point in the patch k because the transmission map is the same in the same patch. The $\mathrm{I}(k)$ is the luminance of patch k, which is the average value of luminance in the patch k. The $t(k-n)$ is the n_th neighbor transmission map of patch k and the $\mathrm{I}(k-n)$ is the n_th neighbor luminance of patch k. There are four situations that ($\Delta t > 0$, $\Delta \mathrm{I} < 0$), ($\Delta t < 0$, $\Delta \mathrm{I} > 0$), ($\Delta t < 0$, $\Delta \mathrm{I} < 0$), and ($\Delta t > 0$, $\Delta \mathrm{I} > 0$). As for the first two situations, these patches are not satisfied with the condition (3). The range filter $\mathrm{W}_R[k,n]$ is attenuated exponentially with $|\Delta t * \Delta \mathrm{I}|$ and works similarly like the conventional bilateral filter. As for the last two situations, these patches are satisfied with the condition (3). The range filter $\mathrm{W}_R[k,n]$ is enhanced exponentially with $|\Delta t * \Delta \mathrm{I}|$ and works to enhance the influence of the neighbor patches. Therefore, the difference between two neighbor patches is reduced which eliminates the ambiguous of contrast enhancement according to Equation (10).

In our experiment, the geometric illuminating image is shown in figure 1(f). The dark point represents the cent of the current patch and along its direction of 8 neighborhood, the 8 adjacent regions are found, namely the 8 red points. In order to ensure 8 neighborhood's effect less than current patch, δ_R should be a relatively large value meeting the requirements of $\max(\Delta \mathrm{I} * \Delta \mathrm{t} / 2\delta_{\mathrm{R}}) < \mathrm{n}^2 / 2\delta_{\mathrm{D}}^2$. The revised transmission map is shown in figure 1(d), and the dehazing result can be seen in figure 1(e).

4. COMPARISON EXPERIMENTS

In order to verify the validity of our methods, several comparison experiments are made. There are mainly three stages in the implementation of our method, image segmentation, transmission map computing and image dehazed. Determined by the complexity of image segmentation, the complexity of our method is $O(n \log n)$ for an image with the size of n ($n = Height \times Width$), while most of the existing methods is $O(n^2)$.

The comparison experiment result with He *et al.*'s method is shown in Figure 2. It can be seen that our method significantly overcomes the dense fog and recovers more detail around the locomotive areas, whereas there are still a small amount of haze left to be removed using He's method.

In Figure 3, our method is compared with R. Tan's. His method is motivated by the fact that contrast is reduced in a haze image, so the haze can be removed by maximizing the local contrast. So his results are often over-saturated, and the color fidelity cannot be maintained. In additional, R. Tan's method consumed much more computational time than ours.

In Figure 4, our method is compared with Tarel' s. His approach is similar to He's and use median filter instead of optimal algorithm. Its main advantage is its speed since its complexity is only ($O(n)$).But it can be seen from Figure 6 the haze is not removed between the small leaves. This is because only a geometric criterion is used to decide whether the observed white region is due to the haze or the object's color.

5. DISCUSSIONS AND CONCLUSIONS

In this paper, a novel single image dehazed method is proposed. The most differences of our method from previous methods are mainly in three aspects. First, our method is based on image segmentation which can greatly eliminated the block halo effects in the dehazed image. Second, our method can make up the inherent deficiency of restoration model which can obtain better dehazed results. Third, our method has no using of optimization algorithm which can consume less computational time. The experimental results show our method's validity and effective.

However, our method can only solve the problem to some extent when color of the scene object is similar to the atmospheric light, since the errors in the dark channel prior still remains. It can be seen from the Figure 3, the color of neck of the first swan is incorrect. This will be the next job for us to find out a more reasonable method to obtain the global atmosphere light A and eliminate the errors in the dark channel prior.

(a) The input image (b)He *et al*.'s result (c) Our result
Figure2compare with He's result

(a) The input haze image (b) R. Tan's result (c) Our result
Figure 3.Compare with R. Tan's result

(a)The input haze image (b) Tarel' s result (c) Our result
Figure 4.Compare with Tarel' s result matting as a refinement

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