Improved Single Image Dehazing using Dark Channel Prior

Yan Wang Bo Wu
College of Physics and Information Engineering
Henan Normal University
Xinxiang, China
wangyan@htu.cn

Abstract—**Atmospheric conditions induced by suspended particles, such as fog and haze, severely degrade image quality. Haze removal from a single image of a weather-degraded scene remains a challenging task, because the haze is dependent on the unknown depth information. In this paper, we introduce an improved single image dehazing algorithm which based on the atmospheric scattering physics-based models. We apply the local dark channel prior on selected region to estimate the atmospheric light, and obtain more accurate result. Experiments on real images validate our approach.**

Keywords-dehazing; dark channel; atmosphere scattering model; atmospheric light

I. INTRODUCTION

Images of outdoor scenes are usually degraded by atmospheric haze, a phenomenon due to the particles in the air that absorb and scatter light. The irradiance received by the camera from the scene point is attenuated along the line of sight. Furthermore, the incoming light is blended with the *airlight* [12] (ambient light reflected into the line of sight by atmospheric particles). The degraded images appear poor visibility and low vividness of the scene.

image dehazing is highly desired in both consumer/computational photography and computer vision applications. First, removing haze can significantly increase the visibility of the scene and correct the color shift caused by the airlight. In general, the haze-free image is more visually pleasuring. Second, most computer vision algorithms are designed for clear weather images. The performance of these algorithms (*e.g.*, feature detection, filtering, and photometric analysis) will inevitably suffers from the poor visibility scene radiance. Instead of extending each of algorithm from clear to foggy weather, it seems more adequate to perform on each input image a haze removal preprocessing. This preprocessing can be applied only when haze is detected to save even more computational time.

General contrast enhancement approaches can be applied for image dehazing, such as linear or gamma correction, unsharp-masking, or histogram equalization. As haze is not constant over an image, these techniques cannot be applied globally as they would degrade haze-free regions. Most recent researches are based on the atmospheric scattering model[1, 2, 3, 5, 13]. It describes the formation of a haze image as follows:

$$I(x) = J(x)t(x) + A(1 - t(x)) \qquad (1)$$

978-1-4244-6585-9/10/$26.00 ©2010 IEEE

where **I** is the observed haze image, **J** is the scene radiance, **A** is the global atmospheric light, and t is the medium transmission. It describes the portion of the light that is not scattered and reaches the camera. The goal of haze removal is to recover **J**, **A**, and t from **I**.

The first term $\mathbf{J}(\mathbf{x})t(\mathbf{x})$ on the right hand side of Equation (1) is called *direct attenuation* [1], and the second term $\mathbf{A}(1 - t(\mathbf{x}))$ is called *airlight* [1, 12]. Direct attenuation describes the scene radiance and its decay in the medium, while airlight results from previously scattered light and leads to the shift of the scene color. When the atmosphere is homogenous, the transmission t can be expressed as:

$$t(x) = e^{-\beta d(x)} \qquad (2)$$

where β denotes the extinction coefficient of the atmosphere. It indicates that the scene radiance is attenuated exponentially with the scene depth d.

Because the haze is dependent on the unknown depth information, the haze removal is under-constrained if the input is only a single haze image. Therefore, many methods have been proposed by using multiple images or additional information. Polarization based method [4, 10] remove the haze effect through two or more images taken with different degrees of polarization. In [5, 6, 11], more constraints are obtained from multiple images of the same scene under different weather conditions. Depth based methods [7, 8] require the rough depth information either from the user inputs or from known 3D models.

This kind of methods are very constraining for the acquisition and cannot be used on existing image databases. Very recently and for the first time in [1, 2, 3], several methods were proposed which work from a single image without using any other extra source of information.

By assuming that the transmission and the surface shading are locally uncorrelated, Fattal[2] first infers the transmission in the area affected by thin fog and then applies *Markov Random Field* on the transmission map in order to propagate the transmission to dense fog area and proceed with a statical smoothing. This approach is physically based and achieves good result. In most cases, this approach clarifies the airlight-albedo ambiguity and achieves good results. However, the method fails when all pixels on the image are affected by dense fog. Moreover, as the statistics is based on color information, it is invalid for grayscale images.

Tan's work [1] is based on two observations. One is that haze-free images have more contrast than images degraded by bad weather; The other is that the variations of airlight, which mainly depends on the distance of objects to the viewer, tend to be smooth. Therefore, the color and visibility can be recovered by maximizing the contrast in a local window of the foggy image. Although this approach may not be physically sound, the visual result is compelling. However, the output images usually tend to have larger saturation values. Besides, the result may contain halo effects near the depth discontinuities.

The algorithm proposed by He et al. [3] is one of the most simple and effective in these methods. They propose a very simple and elegant dark channel prior to solve the single image dehazing problem. Although the method is simple, the result is quite impressive. In [3], they propose an automatic estimation of atmospheric light. This approach is efficient at most of time but not always. It will be corrupt especially when image contains multiple large lamp, and we will illustrate this later.

In this paper, we introduce an improved single image dehazing algorithm, in which a novel estimation of atmospheric light is proposed. Compared to [3], this method can obtain better result. And we also resolve the problem that the substantial sky region of recovered image usually tends to be distortion.

II. IMPROVED SINGLE IMAGE DEHAZING ALGORITHM

In this section, our approach and the steps of the improved single image dehazing algorithm are detailed. As mentioned before, the haze removal is under-constrained if the input is only a single haze image. So a correct assumptions need to be made in order to obtain good results. Now, we first introduce a simple and elegant dark channel prior.

2.1.Dark Channel Prior

The dark channel prior is based on the following observation on haze-free outdoor images: in most of the non-sky patches, at least one color channel has very low intensity at some pixels. In other words, the minimum intensity in such a patch should has a very low value. Formally, for an image **J**, we define

$$J^{dark}(x) = \min_{c \in \{r,g,b\}} (\min_{y \in \Omega(x)} (J^c(y))) \tag{3}$$

where J^c is a color channel of **J** and $\Omega(\mathbf{x})$ is a local patch centered at **x**. Our observation says that except for the sky region, the intensity of J^{dark} is low and tends to be zero, if **J** is a haze-free outdoor image. We call J^{dark} the dark channel of **J**, and we call the above statistical observation or knowledge the dark channel prior.

The low intensities in the dark channel are mainly due to three factors: a) shadows. *e.g.*, the shadows of cars, buildings and the inside of windows in cityscape images, or the shadows of leaves, trees and rocks in landscape images; b) colorful objects or surfaces. *e.g.*, any object (for example, green grass/tree/plant, red or yellow flower/leaf, and blue water surface; b) lacking color in any color channel will result in low values in the dark channel; c) dark objects or surfaces. *e.g.*, dark tree trunk and stone. As the natural outdoor images are usually full of shadows and colorful, the dark channels of these images are really dark!

Due to the additive airlight, a haze image is brighter than its haze-free version in where the transmission t is low. So the dark channel of the haze image will have higher intensity in regions with denser haze. Visually, the intensity of the dark channel is a rough approximation of the thickness of the haze. In the next section, we will use this property to estimate the the atmospheric light and transmission.

2.2 Estimating the Atmospheric Light

In [3], the atmospheric light was estimated from haze image by using dark channel prior with a fixed patch size. This method is efficient in a variety of images. But in some special images, for example images with multiple light sources, the estimation will be invalid. If the min filtering is done with a too small window, then it may pick up light sources in the image, which can corrupt the estimation. Fig. 1 exemplifies such potential pitfalls. Using a window size of 15 in the first image, the atmospheric light will be corrupted by the train's headlights. If the window size is increased to 31, as in the second image, the atmospheric light will be properly estimated amongst the pixels on the far left, which show thick haze. The red pixels show the group (brightest belonging to dark channel) of pixels the algorithm finds the max R, G, and B values amongst to assemble the atmospheric light estimate. We do not want this group to include bright white objects or light sources, in general.

(a) window size of 15

(b) window size of 31

Figure 1: (a) Headlights (blotches of red pixels) corrupt atmospheric light estimation, (b) Proper atmospheric light estimation w/ larger window=31

We now introduce an important interactive process to avoid making a bad guess of the atmospheric light. In any case, often times the atmospheric light can be chosen interactively when it is obvious that, based on human recognition, a particular portion of the scene appears to be farthest from the camera. Firstly, one can find that region and use a rectangle to select it. Secondly, compute local dark channel in the rectangular region to estimate the atmospheric light. Fig. 2 shows the efficiency of this method.

2.3 Estimating the Transmission

Here, assume that the transmission in a local patch $\Omega(\mathbf{x})$ is constant. We denote the patch's transmission as $t(x)$. Taking the min operation in the local patch on the haze imaging Equation (1), we have:

$$\min_{y\in\Omega(x)}(I^c(y)) = t(x)\min_{y\in\Omega(x)}(J^c(y)) + (1-t(x))A^c \quad (4)$$

Notice that the min operation is performed on three color channels independently. This equation is equivalent to:

$$\min_{y\in\Omega(x)}(\frac{I^c(y)}{A^c}) = t\min_{y\in\Omega(x)}(\frac{J^c(y)}{A^c}) + (1-t(x)) \quad (5)$$

Then, we take the min operation among three color channels on the above equation and obtain:

$$\min_c(\min_{y\in\Omega(x)}(\frac{I^c(y)}{A^c})) = t(x)\min_c(\min_{y\in\Omega(x)}(\frac{J^c(y)}{A^c})) + (1-t(x)) \quad (6)$$

According to the dark channel prior, the dark channel J^{dark} of the haze-free radiance **J** should tend to be zero:

$$J^{dark}(x) = \min_c(\min_{y\in\Omega(x)}(J^c(y))) = 0 \quad (7)$$

As A^c is always positive, this leads to:

$$\min_c(\min_{y\in\Omega(x)}(\frac{J^c(y)}{A^c})) = 0 \quad (8)$$

Putting (8) into (6), we can estimate the transmission t simply by:

$$t(x) = 1 - \min_c(\min_{y\in\Omega(x)}(\frac{J^c(y)}{A^c})) \quad (9)$$

In fact, $\min_c(\min_{y\in\Omega(x)}(\frac{J^c(y)}{A^c}))$ is the dark channel of the normalized haze image $\frac{J^c(y)}{A^c}$. It directly provides the estimation of the transmission.

As we mentioned before, the dark channel prior is not a good prior for the sky regions. Fortunately, the color of the sky is usually very similar to the atmospheric light **A** in a haze image and we have:

$$\min_c(\min_{y\in\Omega(x)}(\frac{J^c(y)}{A^c})) \to 1, \textit{ and } t(x) \to 0$$

in the sky regions. Since the sky is at infinite and tends to has zero transmission, the Equation (9) gracefully handles both sky regions and non-sky regions. We do not need to separate the sky regions beforehand.

The estimated transmission map from an input haze image is roughly good. But it contains some block effects since the transmission is not always constant in a patch. Noticing the haze imaging Equation (1) has a similar form with the image matting equation and transmission map is exactly an alpha map. So, we apply a soft matting algorithm [9] to refine the transmission.

2.4 Solving the Underlying Scene Radiance

With the atmospheric light and transmission map, we can recover the scene radiance from input image according to (1). But the direct attenuation term $\mathbf{J}(\mathbf{x})t(\mathbf{x})$ can be very close to zero when the transmission $t(\mathbf{x})$ is close to zero. The directly recovered scene radiance **J** is prone to noise. Therefore, we restrict the transmission $t(\mathbf{x})$ to a lower bound t_0, which means that a small certain amount of haze are preserved in very dense haze regions. The final scene radiance $\mathbf{J}(\mathbf{x})$ is recovered by:

$$J(x) = \frac{I(x) - A}{\max(t(x), t_0)} + A \quad (10)$$

A typical value of t_0 is 0.1. It usually needs to be increased when an image contains substantial sky regions, otherwise the sky region may wind up having artifacts. An example showing the need to increase t_0 is shown in Fig. 3. The first image is with $t_0 = 0.1$. As can be seen the sky looks contoured since the transmission map was not smooth enough in this region. With $t_0 = 0.35$ the sky region becomes brighter and smoother, which looks more pleasing.

III. RESULTS AND COMPARISONS

We compare the performance of our dehazing approach with [3], as shown in Fig.2 and Fig.3. The first column are original images, and in the second the results obtained by [3]. The last column displays our results. As the presence of a large lamp in Fig. 2, He et al. get an incorrect estimation of atmospheric light by computing global dark channel and lead to the result leave much to be desired. Compared to [3], our result contains more details and texture, because we obtain correct estimation of atmospheric light by computing local dark channel to estimate. In Fig.3, by increasing the $t_0 = 0.35$, the substantial sky region in our result becomes brighter and smoother.

IV. CONCLUSION

In this paper, we propose a single image dehazing algorithm, which improves the contrast of haze-degraded images. Our approach is based on the dark channel prior, and we estimate the atmospheric light by using local dark channel prior in selected region. Experiments demonstrate this estimation method is valid. Moreover, we solve the distortion of large sky region in recovered image. Since the dark channel prior is a kind of statistic, it may not work for some particular images.

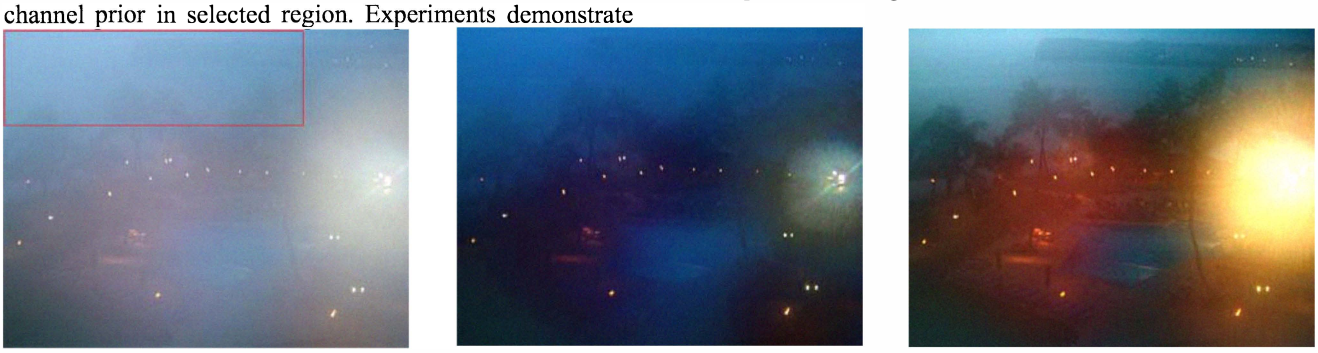

Figure 2. From left to right, the original image, the result from [3] (estimate an incorrect atmospheric light by computing global dark channel), our result (a correct atmospheric light is estimated by computing local dark channel on selected red rectangle region).

Figure 3. From left to right, the original image, the restoration obtained by t_0=0.1, the restoration obtained by t_0=0.35

REFERENCES

[1] R. Tan. Visibility in bad weather from a single image. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR'08), pages 1–8, 2008.

[2] R. Fattal. Single image dehazing. In SIGGRAPH, pages 1–9, 2008

[3] K. He, J. Sun, and X. Tang. Single image haze removal using dark channel prior. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR'09), pages 1956–1963, 2009.

[4] S. Shwartz, E. Namer, and Y. Y. Schechner. Blind haze separation. CVPR, 2:1984–1991, 2006.

[5] S. G. Narasimhan and S. K. Nayar. Chromatic framework for vision in bad weather. CVPR, pages 598–605, 2000.

[6] S. G. Narasimhan and S. K. Nayar. Contrast restoration of weather degraded images. PAMI, 25:713–724, 2003.

[7] J. Kopf, B. Neubert, B. Chen, M. Cohen, D. Cohen-Or, O. Deussen, M. Uyttendaele, and D. Lischinski. Deep photo: Model-based photograph enhancement and viewing. SIGGRAPH Asia, 2008.

[8] S. G. Narasimhan and S. K. Nayar. Interactive deweathering of an image using physical models. In Workshop on Color and Photometric Methods in Computer Vision, 2003.

[9] A. Levin, D. Lischinski, and Y. Weiss. A closed form solution to natural image matting. CVPR, 1:61–68, 2006.

[10] Y. Y. Schechner, S. G. Narasimhan, and S. K. Nayar. Instant dehazing of images using polarization. CVPR, 1:325, 2001.

[11] S. K. Nayar and S. G. Narasimhan. Vision in bad weather. ICCV, page 820, 1999.

[12] H. Koschmieder. Theorie der horizontalen sichtweite. Beitr. Phys. Freien Atm., 12:171–181, 1924.

[13] S. G. Narasimhan and S. K. Nayar. Vision and the atmosphere. IJCV, 48:233–254, 2002.