

IMAGE DEHAZING BASE ON TWO-PEAK CHANNEL PRIOR

Han Xiaoxu ,Feng Hongwei ,Bu Qirong ,and Feng Jun* , Liu Xiaoning

School of Information Science and Technology, Northwest University, P.R. China

Email of correspondence author: fengjun@nwu.edu.cn

ABSTRACT

Haze is one of the major factors that degrade outdoor images. Removing haze from an image is a challenge problem. In this paper, a two-peak channel prior model is proposed for general image dehazing. Firstly, the estimation of medium transmission function is derived and analyzed comprehensively. Secondly, a new calculation method estimating atmospheric light is proposed for more robust dehazing with a new compensation parameter. The experimental results illustrate that the proposed method is able to achieve more satisfied dehazing results than two state-of-the-art methods [12][13].

Index Terms— dehazing, statistical distributions, image restoration, transmission function

1. INTRODUCTION

In recent years, foggy days have frequently appeared in most parts of China and made the images taken in that weather condition always contaminated by haze, as shown in Fig1. Apparently, the scattering of atmospheric particles of the haze makes the visibilities of pictures poor and hinder further image processing steps, especially for the pictures taken from a long distance.

Early image processing methods for haze removal mainly relied on user interaction or additional information [1-6]. Although these methods can enhance the visibilities of hazy images, they cannot be used in general applications, in which additional information are not always available. To achieve automatic and efficient image dehazing, researchers attempted different prior or assumptions [7]. Tan supposed that haze-free images might have higher contrast. However, sometimes the hypothesis may not be physically valid [8]. Fattal estimated some parameters of the haze-free images such as constant vector albedo, the surface shading, and the scene transmission by Independent Component Analysis (ICA) [9], but the algorithm failed when the above parameters were statistically uncorrelated. Kratz et al. modeled images as Factorial Markov Random Fields. Unfortunately, the results often tended to be over enhanced, especially when the colors of the scene and the atmosphere were very similar [10]. Meng et al. proposed an efficient contextual regularization method that benefits much from an

exploration on the inherent boundary constraint of the transmission function with a weighted L1-norm. However, it often led to excessive or inadequate enhancements for some scenes [11].

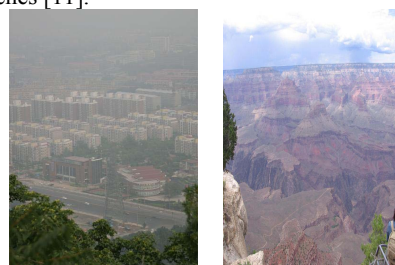


Fig. 1.haze images taken from long distance and close shot

To overcome the above problems and facilitate generalization of image dehazing, Tang et al. systematically investigated a variety of haze features in a multi-resolution regression framework based on Random Forest [12]. However, this dehazing framework may boost noise for the images with low signal-to-noise ratio and heavy haze. He et al. proposed a pleasant surprise law of nature with dark channel prior [13]. They found statistically that in most of the local images regions some pixels must have very low intensity in at least one color (RGB) channel. Therefore, these dark pixels can directly provide an accurate estimation for haze transmission. By combining one peak of dark channel model with a soft matting interpolation, they produced a good depth map, and then acquired high-quality dehazed images. However, the dark channel prior may be invalid when most of the foreground objects have similar intensities as the background, especially when there is a large background region without shadow illumination (for instance, gray sky, snowy ground or a white wall) [7].

In this paper, we propose a new prior model, which is an extension of He's work. Our idea comes from a comprehensively investigation of more generalized dehazed images. We find new channel, *white channel*, of the dehazed images besides the dark channel proposed by He et.al. Specifically, we propose a two-peak prior to model dehazed images. In our two-peak model, the pixels of the first peak (i.e., dark channel) have very low intensities in at least one color (RGB) channel, while the pixels in the second peak (i.e., white channel) have high intensities. Furthermore, we derive the estimation of the transmission function based on our two-peak channel prior model. The experimental results

demonstrate that the proposed methods achieve more satisfied dehazing images compared with two state-of-the-art methods recently published on ICCV and CVPR qualitatively and quantitatively.

2. TWO-PEAK CHANNEL PRIOR MODEL

Usually, a haze image can be formalized as [7, 8, 11, 12]:

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

where I is the observed intensity of coordinate x of an image, J is the scene image without haze, A is the global atmospheric light vector in RGB space, and t is medium transmission function that describes the portion of the light that is not scattered and can reach the camera. Apparently, the objective is to recover real scene J , i.e.:

$$J(x) = \frac{I(x) - A}{t(x)} + A \quad (2)$$

Therefore, the estimation of the global atmospheric light value A and the medium transmission t are key points of this task. Many researchers tried to model them using prior knowledge or assumption as described in Section 1.

In equation (1), the first term $J(x)t(x)$ on the right-hand side is often called *direct attenuation*, which characterizes the scene radiance and its decay in the medium [11], and the second term $A(1-t(x))$ is called *airlight*, which comes from previously scattered light and leads to the shift of the scene colors. It has been proved that *direct attenuation* is a *multiplicative* distortion of the scene radiance, and *airlight* is an *additive* term [8]. Since the atmosphere is often supposed to be homogeneous, the transmission function $t(x)$ is often expressed as:

$$t(x) = e^{-\beta d(x)} \quad (3)$$

where β is the scattering coefficient of the atmosphere and $d(x)$ is the scene depth function. This equation indicates that the scene radiance $J(x)t(x)$ is attenuated exponentially with the depth [7].

Fattal et. al have proved geometrically that in RGB color space, the vectors A , $I(x)$, and $J(x)$ of equation (1) are coplanar and their end points are collinear [9]. Therefore, the transmission $t(x)$ can be expressed as the ratio of two line segments:

$$t(x) = \frac{\|A - I(x)\|}{\|A - J(x)\|} = \frac{A^c - I^c(x)}{A^c - J^c(x)} \quad (4)$$

where $c \in \{r, g, b\}$ is the color channel index in RGB space. Then the equation (1) can be modified as:

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

In [7], He et.al proposed a dark channel prior of $J^c(x)$,

$$J^{dark}(x) = \min_{y \in \Omega(x)} \left(\min_{c \in \{r, g, b\}} (J^c(y)) \right) = 0 \quad (6)$$

where J^c is a color channel of J and $\Omega(x)$ is a local patch centered at x . A dark channel is the outcome of two minimum operators: $\min_{c \in \{r, g, b\}}$ is performed on each pixel, and $\min_{y \in \Omega(x)}$ is a minimum filter on RGB channels. These two minimum operators are commutative.

Furthermore, He et.al observed that $J^{dark} \rightarrow 0$ due to three factors, i.e., shadows, colorful object or surfaces, and dark objects or surfaces. Subsequently they proposed a dark channel prior with one dark peak to model dehazed images and deduced the equation below for transmission function estimation:

$$\tilde{t}(x) = 1 - \min_{y \in \Omega(x)} \left(\min_c \left(\frac{I^c(y)}{A^c} \right) \right) \quad (7)$$

The experimental results showed that the proposed prior achieved very good performance in most of the open database.

However, after comprehensive investigation we find the above assumption is invalid under the circumstances of large image patches with homogeneous and relative high intensities, for instance, the large patches of light sky, snowy ground, white walls, etc. In this paper, we propose a new two-peak channel prior to cover these cases. He's dark channel prior can be considered as a special case of our model.

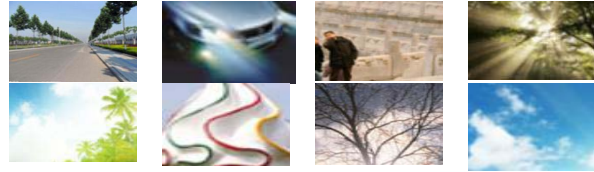
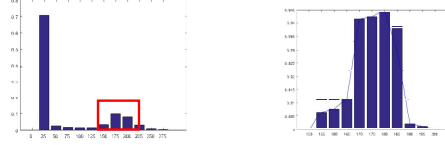


Fig.2. Some cases which in-conformity with He's assumption

Based on our observation, although most of the images can found dark channel prior as proposed in [7], there do exist some pictures or image patches that do not have low intensity pixels. We illustrate three cases in Fig. 2. Firstly, the image patches, such as the sky in the sunny day, lamplight of the cars, and smooth cement roads, usually have very high intensity close to 255. Furthermore some image patches with light-color, such as the dim lights at night, people's skin, junction of the sky, and the architecture, have much higher intensity (150-200) than zero. Secondly, outdoor objects shining in the sun, such as loft and the top of tree, often reflect white lights, and may have high intensity colors without dark channel. Thirdly, the images taken in the midday have no shadow are also not follow He's assumption.

To prove the above discovery, we collected 1000 haze-free images, including the above three cases as shown in Fig. 2, and analyzed the intensity histograms of 1000 images. Fig.3 (a) illustrates the intensity histogram of the minimum of RGB channels of 1000 images. We can observe two peaks from the histogram curve clearly. Fig. 3(b) is a close-up of the red box in Fig. 3(a) to show the detail of the

second peak. The first peak occupies about 70% of the pixels with the intensities below 25 and the second peak occupies about 20% of the pixels with the intensities from 150 to 200, which is a very strong evidence demonstrating the limitation of He's assumption.



(a) Histogram of 1000 images with the bin size is 25 (b) Enlarged Histogram of (150-200) with the bin size 5
Fig. 3. Intensity histogram of the minimum of RGB channels of 1000 images

The proposed two-peak channel prior modeling these two peaks are defined as below :

$$\begin{cases} J^{dark}(x) = \min_{y \in \Omega(x)} (\min_{c \in \{r, g, b\}} (J^c(y))), J < K \\ J^{white}(x) = \min_{y \in \Omega(x)} (\min_{c \in \{r, g, b\}} (J^c(y))), J \geq K \end{cases} \quad (8)$$

where K is the boundary between the two peaks, which can be calculated by Watershed algorithm. $J^c(x)$ is a color channel of J , $\Omega(x)$ is a local patch, and the minimum operators are also commutative, which is the same as in equation (6).

J^{dark} is the dark channel of J proposed by He et.al in [7], while J^{white} is the white channel proposed in this paper. In the next section, we will derive the transmission estimation based on two-peak color channel prior.

3. DEHAZING BASE ON TWO-PEAK CHANNEL

3.1 ESTIMATION OF TRANSMISSION FUNCTION

Suppose the transmission function $\tilde{t}(x)$ in a local patch $\Omega(x)$ is constant, we can get (9) by taking the minimum operation in equation (5)

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

According to the two-peak channel prior, J^{white} of the haze-free radiance J tends to be a value, say H , which must be lower than K . i.e.

$$\begin{cases} J^{dark}(x) = \min_{y \in \Omega(x)} (\min_c (J^c(y))) = 0, J < K \\ J^{white}(x) = \min_{y \in \Omega(x)} (\min_c (J^c(y))) = H, J \geq K \end{cases} \quad (10)$$

Putting equation (10) into (8), we can estimate the transmission $\tilde{t}(x)$ simply by:

$$\begin{cases} \tilde{t}^{dark}(x) = 1 - \min_{y \in \Omega(x)} (\min_c (\frac{I^c(y)}{A^c})), & J < K \\ \tilde{t}^{white}(x) = \frac{1 - \min_{y \in \Omega(x)} (\min_c (\frac{I^c(y)}{A^c}))}{A^c - H} * A^c, & J \geq K \end{cases} \quad (11)$$

Since t is exponential function distribution, it must be greater than 0 and less than 1. Combing with the Equation (11), we get:

$$0 < \tilde{t}^{white}(x) = \frac{1 - \min_{y \in \Omega(x)} (\min_c (\frac{I^c(y)}{A^c}))}{A^c - H} * A^c < 1 \quad (12)$$

This equation is equivalent to:

$$0 < \frac{A^c - \min_{y \in \Omega(x)} (\min_c (I^c(y)))}{A^c - H} < 1 \quad (13)$$

Since atmospheric light value A is close to the largest value in the image [8], the numerator and denominator of equation (13) must be positive, and the numerator must be less than the denominator. Hence, H is smaller than K . In this paper, we select H as the valley floor of two peaks, which is close to the second peak.

3.2 ESTIMATION OF ATMOSPHERIC LIGHT

State-of-art methods for A estimation are often based on the brightest pixels [9]. However, these methods are prone to noise, which results in color distortion consequently. He et.al tried to solve this problem using pixel average in largest dark channel [7]. Tang improved the robustness of the estimation by taking the median of all the 0.1% pixels with largest dark channel values [12]. However, as discussed in Section 3.1, their estimation methods failed in the three cases that have white channels.

In this paper, the top 0.1% brightest pixels for each channel in RGB space are selected. A three-dimensional vector A_c is acquired by median calculation. The experimental results show that our proposed estimation is better than both [7] and [12].

3.3 TRANSMISSION FUNCTION COMPENSATION

Based on the observation of a large amount of experiments, we find that estimation transmission function $\tilde{t}(x)$ often preserves a small amount of haze after dehazing, which was also mentioned in [9]. He et.al. [7] assume that the transmission t is a locally constant and the lower bound

$\min_c (\min_{y \in \Omega(x)} (\frac{I^c(y)}{A^c}))$ filtered by a "min" filter can serve as a tight lower bound of t . As a result, this method tends to over-estimate the thickness of the haze in real-world photos. Therefore, in this paper, we propose a new compensation value v ,

$$J(x) = \frac{I(x) - A}{\max(t(x), t_0) - v} + A \quad (14)$$

We follow the equation in [7], which restricted the transmission $t(x)$ by a lower bound t_0 . Typical value of t_0 is 0.1 by trial-and-error in [7]. Moreover, we increase v

value to balance t . The value of v is about 0.06 after trial-and-error using the 1000 images.

State-of-Art methods for image dehazing include spatial filter, soft-matting [7], and guided filter [14]. Since soft matting is computation expensive, we select guided filter that can well preserves the edges of the objects. To accelerate the searching of $t(x)$, Marcel van Herk's fast algorithm is performed during the local minimum calculation [15]. In this way, the complexity of our method is linear to the image size. Furthermore, we employ multi-scale channel features in [12] to achieve more robust dehazing images.

4. EXPERIMENTAL RESULTS AND ANALYSIS

The image database used in this paper are from [7] and [12] and collected by our group. The patch size is set to 15×15 in the experiments. We show a few examples of the dehazing results in this section due to the page limitation. More instances can be found on the project website (<http://www.nwu-ipmi.cn/firstpage/Look.aspx?type=3&id=0>).

In Fig.4, we compare our proposed two-peak prior model with He's dark channel prior model [7] and Tang's multi-scale features framework [12]. Two typical images, long distance scene and close shot portrait are selected as examples. The first example is a nature hazy scene while the second image is a portrait overlapped simulated haze. Both of them are widely used in the state-of-art dehazing literature.



Fig.4. Comparisons of different dehazing methods

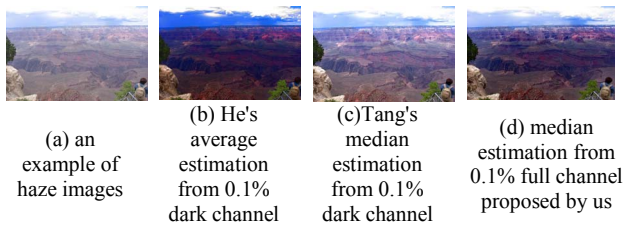


Fig.5. Comparisons of different atmospheric light A estimation

We can easily notice the existence of the white channel from these images. The dehazing results produced by He's dark channel priors in Fig 4(b) are rather dark since no white channel is considered in their model. Although

multiple scale features is employed by Tang et.al. to keep some of the white intensities, some important details (e.g., edges) are also smoothed out as shown in Fig.4(c). Comparatively, our proposed two-peak prior model is able to recover better depth mapping, which keeps global overview as well as object details in close shot without halo artifacts. More importantly, the dehazed images yielded by our method look more natural and closer to the original haze-free pictures subjectively.

In Fig. 5, we show the comparison results using different atmospheric light A estimation. Tang's multi-scale framework is employed in all of this experiment. We can see that the average estimation of He's work is partial black, while Tang's estimation can only exhibit one minimum channel information, which results in lower contrast. Our proposed estimation is able to provide more plentiful and hierarchical depth information.

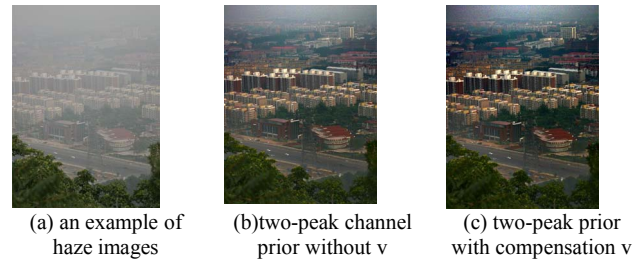


Fig.6. Comparisons of compensation value v by our method

Fig.6 demonstrates the compensation effect of v . We can notice that the dehazed results in Fig 6(c) is more clear than that of Fig. 6. (b) without compensation.

5. CONCLUSIONS

In this paper, we propose a two-peak prior of the minimum RGB channel for dehazed images modeling. Besides the dark channel proposed by He's work, a new white channel is investigated and analyzed to form our two-peak channel prior modeling. Moreover, the estimation of medium transmission function to fit two-peak model is derived step by step. Meanwhile, atmospheric light A is recalculated and a new compensation parameter v is proposed and estimated by trial-and-error. The experimental results demonstrate that the proposed methods can achieve more satisfied dehazing images compared with the two state-of-the-art methods [12][13]both in both depth mapping and detail description.

6. ACKNOWLEDGEMENTS

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7.REFERENCES

- [1] 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," *ACM Trans. Graphics*, vol. 27, no. 5, pp. 116:1-116:10, 2008.
- [2] Oakley J P,Satherley B L.,"Improving image quality in poor visibility conditions using a physical model for contrast degradation",[J].IEEE Transcation on Image Processing, 1998,7(2):167-179.
- [3] S.K. Nayar and S.G. Narasimhan, "Vision in Bad Weather." *Proc. Seventh IEEE Int'l Conf. Computer Vision*, vol. 2, pp. 820-827, 1999.
- [4] S.G. Narasimhan and S.K. Nayar, "Chromatic Framework for Vision in Bad Weather", *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, vol. 1, pp. 598-605, June 2000
- [5] S.G. Narasimhan and S.K. Nayar, "Vision and the Atmosphere" ,*Int'l J. Computer Vision*, vol. 48, pp. 233-254, 2002.
- [6] S.G. Narasimhan and S.K. Nayar, "Contrast Restoration of Weather Degraded Images", *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 25, no. 6 pp. 713-724, June 2003.
- [7] K. He, J. Sun, and X. Tang."Single image haze removal using dark channel prior". *Transactions on Pattern Anal Ysis and Machine Intelligence*, vol. 33, No.12, June 2000 2011.
- [8] Tan R T. Visibility in bad weather from a single image[C]// *CVPR. 2008*:1-8.
- [9] Fattal R. Single image dehazing[J]. *Acm Transactions on Graphics*, 2008, 27(3):1--9.
- [10] Kratz L, Nishino K. Factorizing Scene Albedo and Depth from a Single Foggy Image[C]// 2009:1701-1708.
- [11] Meng G, Wang Y, Duan J, et al. Efficient Image Dehazing with Boundary Constraint and Contextual Regularization[C]// *IEEE International Conference on Computer Vision. 2013*:617-624.
- [12] Tang K, Yang J, Wang J. Investigating Haze-Relevant Features in a Learning Framework for Image Dehazing[C]// *Computer Vision and Pattern Recognition. IEEE, 2014*:2995-3002.
- [13] He K, Sun J, Tang X. Single Image Haze Removal Using Dark Channel Prior[C]// *Conference on Computer Vision and Pattern Recognition. 2011*:2341-53.
- [14] He K, Sun J, Tang X. Guided Image Filtering[J]. *Pattern Analysis & Machine Intelligence IEEE Transactions on*, 2013, 35(6):1397-1409.
- [15] Herk M V. A fast algorithm for local minimum and maximum filters on rectangular and octagonal kernels[J]. *Pattern Recognition Letters*, 1992, 13(7):517-521.