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Dehazed Image Quality Assessment by Haze-Line Theory

Yingchao Song^{1,2,3,4}, Haibo Luo^{1,3,4}, Rongrong Lu^{1,2,3,4}, Junkai Ma^{1,2,3,4}

¹Shenyang Institute of Automation, CAS, Shenyang, 110016, China

²University of Chinese Academy of Sciences, Beijing, 100049, China

³Key Laboratory of Opto-Electronic Information Processing, CAS, Shenyang, 110016, China

⁴The Key Lab of Image Understanding and Computer Vision, Liaoning Province, Shenyang, 110016, China

Abstract. Images captured in bad weather suffer from low contrast and faint color. Recently, plenty of dehazing algorithms have been proposed to enhance visibility and restore color. However, there is a lack of evaluation metrics to assess the performance of these algorithms or rate them. In this paper, an indicator of contrast enhancement is proposed basing on the newly proposed haze-line theory. The theory assumes that colors of a haze-free image are well approximated by a few hundred distinct colors, which form tight clusters in RGB space. The presence of haze makes each color cluster forms a line, which is named haze-line. By using these haze-lines, we assess performance of dehazing algorithms designed to enhance the contrast by measuring the inter-cluster deviations between different colors of dehazed image. Experimental results demonstrated that the proposed Color Contrast (CC) index correlates well with human judgments of image contrast taken in a subjective test on various scene of dehazed images and performs better than state-of-the-art metrics.

1. Introduction

Image dehazing has become a necessary pre-processing step in computer vision application. Recently, plenty of excellent dehazing algorithms have been proposed to restore degraded images, such as [1-18]. However, very few quality metrics were proposed to evaluate dehazing algorithms. Although image quality assessment has been extensively studied in the past few decades, traditional full-reference image quality indexes, such as the mean square error (MSE), the peak signal to noise ratio (PSNR), and the structural similarity index^[20] (SSIM) are not appropriate for quality assessment of dehazed image as it is difficult to get a clear day reference image.

In this paper, an indicator of contrast enhancement is proposed basing on the newly proposed haze-line theory^[1]. The theory assumes that pixels with similar colors in the haze-free image form a line in the corresponding hazy image. Finding out these haze-lines, we can cluster pixels of the dehazed image and assume pixels of each cluster have similar colors. Then we measure the inter-cluster deviation on each local image patch. A higher deviation implies a higher color contrast in the corresponding image patch.

To evaluate the performance of our proposed metric, a human subjective test was performed using a dataset of 50 hazy images and 150 corresponding dehazed images. As there is no available benchmark dataset to support our test, we assembled the dataset by ourselves. Fig.1 shows some examples of hazy image in the dataset. We collect these images from several professors' homepage^[1-5,10-11,15] whom have



proposed effective dehazing algorithms. Experimental results demonstrate that the proposed Color Contrast index (CC) correlates well with human judgments of image contrast on this images dataset.



Figure 1. Examples of hazy image in the dataset

2. Related works

2.1. Descriptor of visible edge

Among the few methods of dehazed image assessment, the most widely used is the indicator of visibility enhancement proposed by Hautiere et al^[21]. The method includes two contrast descriptors namely the rate of new visible edges e and the gain of visibility level \bar{r} . The value of e evaluates the ability of dehazing method to restore edges which were not visible in hazy image but are in dehazed image. The value of \bar{r} denotes the mean ratio of gradient norms before and after dehazing. They are defined as follow:

$$e = \frac{n_r - n_o}{n_o} \quad (1)$$

$$\bar{r} = \exp\left[\frac{1}{n_r} \sum_{P_i \in \wp_r} \log r_i\right] \quad (2)$$

Here, n_r and n_o denote respectively the numbers of visible edges in the dehazed image and in the original image. \wp_r is the set of visible edge in the dehazed image. P_i denotes the pixels that belong to \wp_r . r_i is the ratio of the gradient at P_i in the dehazed image and in the original image.

The two descriptors have been applied by many dehazing methods^[2,6,11] to evaluate their performance on visibility enhancement. However, the method obtains visible edge and solves gradient value by gray-scale images. It is not a good idea for color images, as the method of finding visible edges and solving gradient values is different from the one in gray-scale image. In addition, the two indicators often produce inconsistent evaluation results when assessing the same image.

2.2. Fog aware density evaluator

Fog Aware Density Evaluator^[2] (FADE) is a newly proposed contrast descriptor which predicts the visibility of a foggy scene by measuring deviations from statistical regularities in natural scene foggy and fog-free images. A lower value of FADE implies better performance of visibility enhancement. The method extracts 12 fog-related features from the test image, and fits these features to a Multivariate Gaussian (MVG) model. Then, it computes the deviation using a Mahalanobis-like distance between the MVG fit of the test image and the MVG fit of a corpus of 500 fog-free images and another corpus of 500 foggy images, respectively. Each corresponding distance is defined as a foggy level D_f and a fog-free level D_{ff} . Finally, the perceptual fog density D of the test image is expressed as the ratio of the foggy level to the fog-free level.

$$D = \frac{D_f}{D_{ff} + 1} \quad (3)$$

The predicted fog density using FADE correlates well with human judgments of fog density taken in subjective experiments on a foggy image database^[2]. However, sometimes a lower fog density is not exactly equivalent to a higher contrast.

2.3. CNC measurement system

The CNC measurement system (Contrast-Naturalness-Colorfulness), proposed by Guo et al^[22], evaluates the dehazing effect from three aspects: contrast e' , Color Naturalness Index (CNI)^[23] and Colorfulness Index (CCI)^[23]. It is defined as:

$$CNC = e^{\frac{1}{n_1}} CNI + CCI^{\frac{1}{n_2}} CNI \quad (4)$$

Where, n_1 and n_2 are the adjustable parameters, $e' = n_r/n_o$ is a contrast descriptor, n_r and n_o denote respectively the numbers of visible edges^[21] in the dehazed image and in the original image. The CCI index reflects the degree of color vividness, which is defined as the summation of average saturation and standard deviation of saturation of the test image. The CNI^[23] index reflects the degree of color naturalness. It classifies pixels of test image into three classes ('skin' 'grass' and 'sky') according to their hue, then measuring the differences between the average saturation and the prototypical saturation of each class through a Gaussian function.

The CNC index claims that it correlates well with human visual perception of the overall dehazing effect. However, colors of natural scene are rich and colorful, and will vary with time and light condition. It is impossible to use just three prototypical colors to represent the whole natural colors.

3. The proposed evaluation metric

3.1. Background

The widely used atmospheric scattering model can be expressed as^[18]:

$$\mathbf{I}(x) = \mathbf{J}(x) \cdot t(x) + \mathbf{A} \cdot (1 - t(x)) \quad (5)$$

$$t(x) = e^{-\beta d(x)} \quad (6)$$

Where x is the pixel coordinates, \mathbf{I} denotes the hazy image, \mathbf{J} denotes the haze-free image, \mathbf{A} denotes the airlight, and t is the medium transmission which denotes the proportion of scene radiance captured by camera and without being scattered. d is the scene depth, β is the scattering coefficient of atmospheric medium.

3.2. Haze-line theory

The haze-line theory^[1] bases on the observation that a haze-free image can be expressed by a small number of distinct colors, which form tight clusters in RGB space. Each cluster has similar colors. The presence of haze makes pixels that belong to the same color cluster end up with different acquired colors, since they have different scene depth and scattered by atmospheric medium in different degree. The color coordinates of these pixels are distributed along a line spanned by the original color \mathbf{J} and the airlight \mathbf{A} . These are the haze-lines.

By transforming Eq.(5) to the linear form of Eq.(7), and express $\mathbf{I}_A(x)$ in spherical coordinates as Eq.(8), we can see from Eq.(9) that for given \mathbf{J} and \mathbf{A} , changes in t affects only r without changing either θ or φ . Therefore, pixels have similar RGB values of \mathbf{J} if their values of $[\theta, \varphi]$ are similar. Clustering $[\theta, \varphi]$ in the spherical coordinate system, we can get haze-lines.

$$\mathbf{I}_A(x) = \mathbf{I}(x) - \mathbf{A} = (\mathbf{J}(x) - \mathbf{A}) \cdot t(x) \quad (7)$$

$$\mathbf{I}_A(x) = [r(x), \theta(x), \varphi(x)] \quad (8)$$

$$r(x) = \|\mathbf{I}_A(x)\| = \|\mathbf{J}(x) - \mathbf{A}\| \cdot t(x) \quad (9)$$

3.3. The proposed Color Contrast index (CC)

The underlying principle of haze-line theory is that a haze-line in the hazy image respects a color cluster in the corresponding haze-free image, and pixels belong to the same color cluster have similar colors.

Our proposed method based on the observation that deviations of different colors in a local area can reflect the local contrast of color image. The larger the color deviation of different colors in the haze-free image, the higher the contrast. The proposed Color Contrast index (CC) is composed of four essential steps: 1) estimating the airlight, 2) clustering the pixels into haze-lines, 3) computing inter-cluster deviations in each local patch, and 4) computing the final CC of the whole image.

3.3.1. Estimating the airlight. Method [1] assumes that \mathbf{A} is given by the method of airlight estimation illustrated in [19]. In fact, there are many approaches of airlight estimation used in field of single image haze removal^[1-19]. Each has its own advantages and disadvantages, and maybe suitable for some particular scenes. In this section, for the sake of simplicity and generality, we introduce the widely used method proposed by He et al^[10]. The method uses the dark channel to detect the most haze-opaque region, then picks up the top 0.1% brightest pixels of the most haze-opaque region and chooses the single pixel with the highest intensity in the hazy image as the estimation of \mathbf{A} . He's method can always get a value of \mathbf{A} with higher brightness and lower saturation, which will not produce large color distortion in the dehazed image. Fig.2 gives some examples of airlight estimation using He's^[10] method. The red solid points in the top of images are the estimation points of \mathbf{A} .



Figure 2. Airlight estimation using He's^[10] method

3.3.2. Clustering the pixels into haze-lines We use method illustrated in literature [1] to cluster pixels into haze-lines. The method expresses physical model of hazy image in spherical coordinates as Eq.(8), then samples the unit sphere uniformly using 1000 points. Each point corresponds to a haze-line, and then groups the pixels of hazy image according to the closest sample point based on their values of $[\theta, \phi]$.

3.3.3. Computing the inter-cluster deviations locally After obtain haze-lines, pixels of the haze-free image can be clustered. Then, we compute the inter-cluster deviations of haze-free image in each local patch. In literature [20], the standard deviation (the square root of variance) was used to measure image contrast. Here, we use the inter-cluster standard deviation in each local square window (patch p) to measure the local color contrast (CC_p) of haze-free image.

The CC_p is defined as:

$$\bar{\mathbf{J}}_{pk} = \frac{1}{N_{pk}} \sum_{x \in \varphi_{pk}} \mathbf{J}(x) \quad (10)$$

$$\mathbf{J}_p = \frac{1}{N_k} \sum_{k=1}^{N_k} \bar{\mathbf{J}}_{pk} \quad (11)$$

$$CC_p = \sqrt{\frac{1}{N_k - 1} \sum_{k=1}^{N_k} (\bar{\mathbf{J}}_{pk} - \mathbf{J}_p)^2} \quad (12)$$

Where, k is the index of color cluster, p is the index of image patch, $\mathbf{J}(x)$ is the color value of haze-free image in coordinates x , φ_{pk} is a set of pixels which belong to the k -th color cluster in patch p , N_{pk} is the number of pixels in φ_{pk} , $\bar{\mathbf{J}}_{pk}$ is the mean value of pixels in φ_{pk} . N_k is the number of clusters in patch p ,

$\bar{\mathbf{J}}_p$ is the mean value of $\bar{\mathbf{J}}_{pk}$, CC_p is the unbiased estimate of inter-cluster standard deviation in patch p which denotes the Color Contrast of patch p .

3.3.4. Computing the overall Color Contrast (CC) Finally, we use the mean value of CC_p to measure the Color Contrast (CC) of the whole haze-free image:

$$CC = \frac{\frac{1}{N_p} \sum_{p=1}^{N_p} CC_p}{\sqrt{\frac{1}{H \cdot W - 1} \sum_{i=1}^H \sum_{j=1}^W (\mathbf{I}_{i,j} - \bar{\mathbf{I}})^2}} \quad (13)$$

Where, N_p is the number of patches in the whole haze-free image. $[H, W]$ denote the dimensions of the image. $\mathbf{I}_{i,j}$ is the color value of the hazy image in coordinates (i, j) . $\bar{\mathbf{I}}$ is the mean color of the hazy image \mathbf{I} . The denominator of Eq.(13) is the standard deviation of the original hazy image, it used to normalize the value of CC.

4. Experiment and analysis

Since there is no feasible way to compare the performance of our proposed method with other contrast indexes, we evaluated the performance of our methods against the results of a human subjective test.

4.1. Human subjective test setup

4.1.1. Test images. As far as we know, there is no available benchmark dataset to support task of dehazed image assessment. In order to evaluate the effects of our method, we assembled a dataset by ourselves. The dataset contains 50 widely used hazy images and 150 corresponding dehazed results which produced by famous dehazing algorithms of [1-15]. We pick up these images from several professors' homepage^[1-5,10-11,15], whom have proposed effective dehazing algorithms. Some examples of hazy image in the dataset are shown in Fig.1.

These test images form 50 groups, each with 1 hazy image and 3 corresponding dehazed results. If a hazy image has more than 3 dehazed results, we will split them into multiple groups. Similarly, if a hazy image has less than 3 dehazed results, we will use methods of [11] and [13] to produce dehazed images so that each group has 3 dehazed results.

4.1.2. Subjects. A total of 40 subjects attended the subjective experiments. They are students or staff in Shenyang Institute of Automation, Chinese Academy of Sciences. About half of them are major in image processing or related, and the others are naive. All subjects were between the ages of 20 and 40. No vision test was performed although a verbal confirmation of soundness of (corrected) vision was obtained from the subjects.

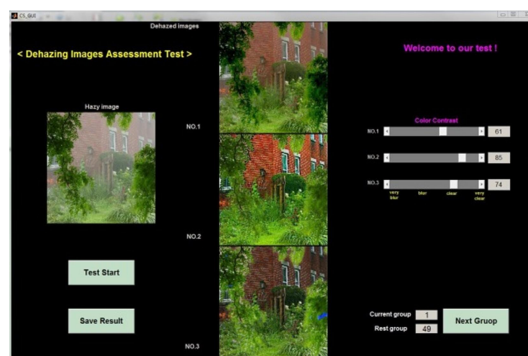


Figure 3. Screenshot of the subjective test interface

4.1.3. Test approach. We developed the user interface for the test on a Windows PC using the GUI tool of MATLAB. Fig.3 shows the subjective test interface. The scoring term, with 4 markings 'very blur', 'blur', 'clear', and 'very clear' to indicate the contrast of dehazed images, is the Color Contrast

(CC) index. Subjects were requested to score dehazed images of each group using the continuous slider bar. The subjective judgments were mapped to the integer interval [0,100] displaying on the right side of the slider bar. Operating instructions are interpreted before each subject starting the test.

4.1.4. Processing of subjective scores. All test data were used to form a Mean Opinion Scores^[2] (MOS) for each image. The MOS is defined as:

$$MOS_j = \frac{1}{N_j} \sum_i S_{ij} \quad (14)$$

Here, S_{ij} denotes the score assigned by subject i to the test image j and N_j is the total number of scores received for test image j .

4.2. Performance in subjective test

We computed the Pearson's linear correlation coefficient (PLCC) and the Spearman's rank ordered correlation coefficient (SROCC) between evaluation results of our proposed CC index and values of MOS on each group of the test images. Then, we computed the mean value of PLCC and SROCC on the whole dataset of 50 groups test image. Table 1 tabulates the mean value of PLCC and SROCC over diverse patch sizes ranging from 16×16 to 128×128 pixels on the dataset. The results indicate that the best performing patch size for assessing contrast enhancement was 64×64 .

Table 1. LCC and SROCC between CC scores and the MOS over different patch sizes.

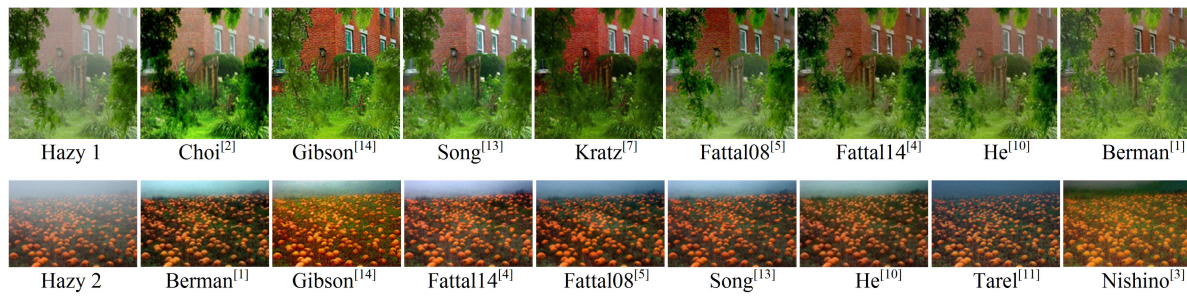
Patch Size	16×16	32×32	48×48	64×64	96×96	128×128
PLCC	0.8039	0.8022	0.8351	0.8462	0.8188	0.8092
SROCC	0.8241	0.8241	0.8519	0.8519	0.8426	0.8056

4.3. Results of dehazed image assessment

In this section, we executed a quantitative evaluation of dehazing algorithms using the contrast enhancement indexes of Hautière et al^[21], the perceptual fog density FADE^[2], the CNC index and our proposed Color Contrast index(CC). Fig.4 and Fig.5 demonstrate several widely used hazy images and the corresponding dehazed results produced by dehazing algorithms of [1-15]. Objective evaluation results are shown in Tab2-Tab5, we use bold format to indicate the best result and underline format to indicate the worst result of each metric. Here, we compute CC value using a patch size of 64×64 . Among these metrics, a lower value of FADE denotes a good job of contrast enhancement, while a higher value of other metrics denote good job of haze removal.

In hazy 1, values of CC denote that Choi, Gibson and Song do a better job on contrast enhancement, while Berman and He have a worse performance. These evaluation results correlate well with our subjective feeling. The values of e denote that Gibson produces the worst result on visibility enhancement, but values of \bar{r} denote that Gibson produces the best result on visibility enhancement. The evaluation results of the two indicators (e and \bar{r}) are inconsistent. The value of FADE denotes that level of fog residual in He, Gibson, and Kratz are same, but they looks very different on foggy level. Values of CNC index denote that Song achieve the worst performance on the overall dehazing effect. However, result of Kratz looks even worse, as it tends to be over-saturated and color distort.

In hazy 2, Berman and Fattal14 perform better on contrast enhancement, while Nishino and Tarel produce worse results. Values of e denote that Tarel achieves the best performance on visible edge enhancement, but subjectively, it looks bad in visibility. Values of the CNC index denote that Nishino perform better to Berman, Fattal, Song, and He on the overall dehazing effect, but obviously this is not the case. Values of FADE denote that result of Nishino leave less fog than result of Fattal14, however, little fog residue does not represent better visibility and higher contrast.

**Figure 4.** Dehazing results of several popular algorithms**Table 2.** Objective assessment of Hazy 1

	Choi	Gibson	Song	Kratz	Fattal08	Fattal14	He	Berman
CC	1.845	1.758	1.671	1.483	1.314	1.236	1.127	<u>1.088</u>
e	0.06	<u>0.04</u>	0.09	0.12	0.09	0.14	0.11	0.11
\bar{r}	1.70	2.21	1.45	1.37	1.58	1.48	<u>1.23</u>	1.41
FADE	0.13	0.15	<u>0.18</u>	0.15	0.14	0.14	0.15	<u>0.18</u>
CNC	1.02	1.13	<u>0.92</u>	1.05	1.17	1.54	1.21	1.25

Table 3. Objective assessment of Hazy 2

	Berman	Gibson	Fattal14	Fattal08	Song	He	Tarel	Nishino
CC	1.812	1.685	1.650	1.596	1.561	1.512	1.471	<u>1.353</u>
e	0.24	0.37	0.18	<u>0.14</u>	0.26	0.29	0.78	0.38
\bar{r}	1.98	3.43	1.90	1.74	<u>1.57</u>	1.62	1.93	2.48
FADE	0.19	0.16	0.25	0.22	<u>0.27</u>	0.24	0.25	0.20
CNC	2.15	2.25	2.14	2.14	2.13	2.14	<u>2.10</u>	2.17

In hazy 3, values of CC, \bar{r} , and FADE denote that Tan get the best result on contrast enhancement, and result of e denotes that Tarel achieves the best result on visible edge enhancement. However, values of FADE denote that result of Fattal08 have little fog residue than He's result, but subjectively the reverse is true. Values of e denote that Fattal14 gets the worst result of visible edge enhancement, but subjectively, we think that result of Fattal14 is more clearly than results of Kopf and Fattal08.

In hazy 4, results of CC and FADE denote that Berman achieves the best performance and Tarel gets the worst result on contrast enhancement, which correlate well with our subjective feeling. However, values of e consider that Tarel achieves the best result on visible edge enhancement, but subjectively, we think Berman and Fattal14 perform better than Tarel.

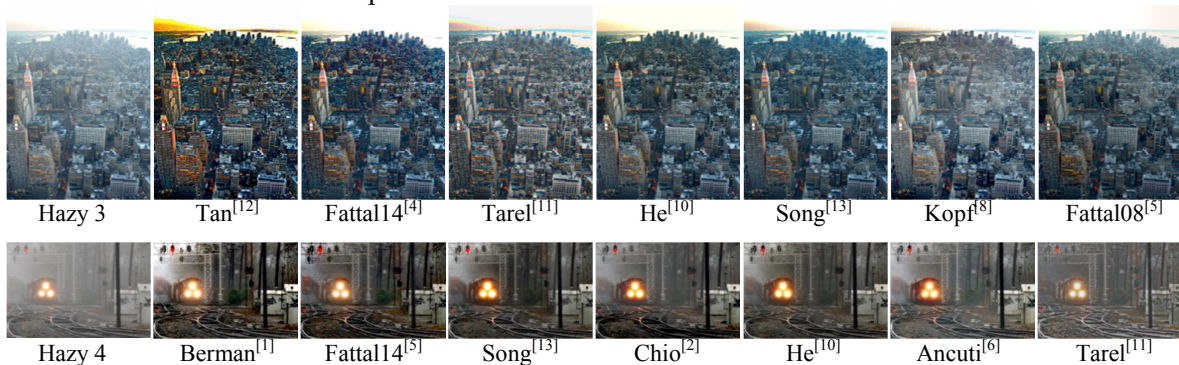
**Figure 5.** Hazy images and corresponding dehazed results

Table 4. Objective assessment of Hazy 3

	Tan	Fattal14	Tarel	He	Song	Kopf	Fattal08
CC	1.834	1.448	1.344	1.326	1.291	1.171	<u>1.039</u>
e	0.07	<u>-0.16</u>	0.14	0.04	0.07	0.03	-0.06
\bar{r}	2.18	1.83	1.76	1.40	<u>1.26</u>	1.41	1.29
FADE	0.23	0.24	0.32	0.47	0.47	<u>0.53</u>	0.32

Table 5. Objective assessment of Hazy 4

	Berman	Fattal14	Song	Choi	He	Ancuti	Tarel
CC	1.566	1.402	1.381	1.357	1.250	1.196	<u>1.034</u>
e	1.16	1.26	1.32	<u>0.94</u>	1.29	0.99	1.58
\bar{r}	3.44	3.13	2.05	<u>1.84</u>	1.93	2.10	2.50
FADE	0.15	0.15	0.31	0.27	0.35	<u>0.45</u>	<u>0.45</u>

To sum up, among metrics mentioned in this paper, the CNC index is sometimes inconsistent with the subjective judgment of overall dehazing effect as it based only on the dehazed image itself while does not take the original hazy image as the reference. The contrast descriptor e computes the visible edge in gray-scale image, which is not suitable for color image. The contrast descriptor \bar{r} focuses on enhancement of gradient value which produces more reasonable evaluation results on contrast enhancement. As for FADE, it does good jobs on measuring the fog residue of dehazed image. However, a lower fog density not always equivalent to a higher contrast or good visibility. Our proposed Color Contrast index CC mainly focuses on contrast of different colors in local region, which could always produce relative reasonable evaluation results on contrast enhancement.

5. Conclusion

In this paper, we proposed an indicator of contrast enhancement of dehazed image basing on the haze-line theory. We demonstrated the performance of our proposed (CC) index by a subjective study on dehazed images of a variety of hazy scene. Experimental results demonstrate that the proposed CC index correlate well with human judgments of image contrast taken in the subjective test and performs better than state-of-the-art metrics.

However, there are also some deficiencies in our method. Firstly, the performance of our method relies on the clustering of haze-lines. If this step fails to produce good results, evaluation results achieved by our methods will be unreliable. Besides, purpose of image haze removal is not only to enhance the contrast, but also to restore the colorful color. Phenomenon of over-saturation or color distortion are can't be identified by existing contrast indicators. Therefore, color similarity evaluation is very necessary when assessing quality of dehazed image, and this will be the focus of our next research.

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