Automatic Image Haze Removal Based on Luminance Component

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***Abstract*—In this paper, we propose a simple but effective method for visibility restoration from a single image. The main advantage of the proposed algorithm is no user interaction is needed, this allows our algorithm to be applied for practical applications, such as surveillance, intelligent vehicle, etc. Another advantage compared with others is its speed, since the cost of obtaining transmission map is greatly cut down by using Retinex algorithm on luminance component. A comparative study and quantitative evaluation is proposed with the main present-day methods which demonstrate that similar or better quality results are obtained.**

Keywords-haze removal; YCbCr; luminance component; Rentinex; transmission map

I. INTRODUCTION

Haze removal is highly desired in computer vision application, removing haze can significantly increase the visibility of the scene. Since the scene visibility is decreased and the features, such as the contrast and color of the image objects are attenuated under haze condition, so we need to eliminate the haze effect of the scene objects.

Recently, the methods of image haze removal can be classified into two major types: haze image enhancement based on image processing and image restoration based on physical model. The image enhancement method can effectively increase the contrast and improve the visual effects, but may cause some lose to the stressed information. The classic methods of this kind are histogram equalization, homomorphic filter [1], wavelet transform [2], Retinex algorithm [3], luminance and contrast transform and so on. While the image restoration is researching on the degradation process of haze image, establishing the degradation model to get the undisturbed original image or its best estimator, so the quality of the haze image can be improved. Compared with the image enhancement method, this kind of method can get natural result, and assure no information will be lost to obtain the ideal restoration effect.

The degradation model that is widely used in image restoration method is the haze image model proposed by McCartney [4], and a few approaches have been proposed. Very recently and for the first time in [5, 6, 7], three approaches were proposed which work from a single image with a stronger prior or assumption. Fattal [5] estimates the albedo of the scene and then infers the medium transmission. This approach cannot well handle heavy haze images and may fail in the cases that the assumption is broken. Tan [6] removes the haze by maximizing the local contrast of the restored image, but his approach may not always achieve equally good results on very saturated scenes. In comparison, He's approach [7] is the most attracting one. This approach based on the dark channel prior. Using this prior, the thickness of the haze can be directly estimated and a high quality haze-free image can be obtained. However, the disadvantage of these three algorithms is a processing time of 35 seconds, 5 to 7 minutes and of 10 to 20 seconds on a 600*400 image, respectively.

Here, we propose an automated dehazing approach which is much faster compared to [5, 6, 7]. This approach is based on the observation that when the haze image transforms from RGB to YCbCr color space, and uses Multi-Scale Retinex (MSR) algorithm to the luminance component, then does subtraction operation and median filter on the map, the transmission map whose function is similar to He's approach is obtained. It is much faster since the cost of obtaining transmission map is cut down, and it is able to achieve equally and sometimes even better results.

II. BACKGROUND

A. Haze Image Model and Dark Channel Prior

Haze image model (also called image degradation model), proposed by McCartney [4] in 1975, the model consists of direct attenuation model and air light model. Direct attenuation model describes the scene radiance and its decay in the medium, while air light results from previously scattered light and leads to the shift of the scene color. The formation of a haze image model is as following:

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

Where I is the observed luminance and is also the input haze image, J is the scene radiance and is also the restored haze-free image, A is the global atmospheric light which can be obtained by using dark channel prior, and t is the medium transmission describing the portion of the light that is not scattered and reaches the camera. Theoretically, the goal of haze removal is to recover J, A, and t from I.

The dark channel prior proposed by He's approach [7] is a kind of statistics of the haze-free outdoor images. It is based on a key observation that most local patched in the haze-free outdoor images contain some pixels which have very low

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intensities in at least one color channel. Formally, for an image *J*, we define

$$J^{dark}(x) = \min_{c\in\{r,g,b\}} (\min_{y\in\Omega(x)} (J^c(y))) \quad (2)$$

Where J^c is a color channel of *J* and $\Omega(x)$ is a local patch centered at *x*. we call J^{dark} the dark channel of *J*, and we also call the above statistical observation the *dark channel prior*. Using this prior with the haze imaging model, the value of air light *A* can be directly estimated to recover a high quality haze-free image. In our approach, we also use the haze image model and dark channel prior to remove the haze effect.

B. Retinex used in luminance component

Retinex theory deals with compensation for illumination effects in images. The primary goal is to decompose a given image *S* into two different images, the reflectance image *R*, and the illumination image *L*, such that, at each point (x, y) in the image domain, S(x, y) = R(x, y) *L(x, y). The Retinex methodology was motivated by Land's landmark research of the human visual system [8]. The benefits of such decomposition include the possibility of removing illumination effects, enhancing image edge, and correcting the colors in images by removing illumination induced color shifts.

The original idea of our approach lies in the process of obtaining transmission map. According to He's approach, the transmission map is in fact an alpha map with clear edge outline and depth layer of the scene objects, which is used to estimate the thickness of the haze. While the MSR algorithm covers the features of multi-scale by adjusting the scale parameters, the algorithm synthesize the advantages of the dynamic range compression, edge detail enhancement of the small scale, and the balance of the color of the medium and large scale. So image sharpness, dynamic range compression of gray level, contrast enhancement and color balance can be realized at the same time. Applying MSR to the luminance component of the haze image in YCbCr color space, then does linear transformations and median filter operation, the transmission map of our approach can be obtained, so it realizes the automatic and quick acquisition of transmission map.

III. IMAGE HAZING REMOVAL METHOD BASED ON LUMINANCE COMPONENT

A. Estimating the Transmission Based On luminance Component

Note that, the haze imaging Equation (1) has a similar form with the image matting equation. A transmission map is exactly an alpha map. Therefore, He's approach applied a soft matting algorithm [9] to refine the transmission. While the specific steps of our approach to estimate transmission map based on luminance component is as following:

Here, we first choose the transformed color space. For a RGB image, in order to separate its luminance component from chroma component, color space should be transformed to HIS, YUV, etc to assure the steps can be done only in luminance component. Recently, the most widely used is HIS. However, the transformation between HIS and RGB has to do trigonometric function calculation, which costs much time and needs a lot of calculating works. So we choose YCbCr, the reason is that the transformation between YCbCr and RGB is refer to simple algebraic operation, so it needs little calculating work and the speed of the calculation is relatively fast.

Then, we use MSR algorithm to the luminance component, the process can be expressed as follows:

$$R_m(x,y) = \sum_{n=1}^{N} w_n (\log Y(x,y) - \log[F_n(x,y) * Y(x,y)]) \quad (3)$$

Where *Rm(x, y)* is the output of the transformation to the luminance component image by using MSR algorithm, *N* is the number of the scale (usually choose three), *Wn* is the weight corresponding to each scale, *Y(x, y)* is the distribution of luminance image, *Fn(x, y)* is the *nth* wrap around function whose form is Gaussian, and the around function should cover all kinds of scale. Experiment shows that the scale should be chosen with small, medium and large value for most images. The measurement of choosing scale is keeping the color of luminance component image balance and making the contrast of the component image enhance. The sum of the scale value should be one. The new luminance image obtained by this step is the fundamental of obtaining transmission map whose function is similar to the one obtained by soft matting algorithm in He's approach.

Note that the differences between the new luminance image and the alpha map obtained by soft matting algorithm, we want to make both image tend to the same effect and function. The solution to this problem is using the transmission adjusting parameter *C* minus the value of each pixel. Specifically, there are two steps to adjust transmission map: the first one is determining the value of atmospheric light *A*. We first picking the top 0.1% brightest pixels in the dark channel, the pixel with highest luminance in the input image *I* is selected as the atmospheric light. The second step is determining the value of *C* on condition that the value of *A* is determined. The value of *C* is application-based. We fix it to 1.08 for all results reported in this paper.

B. Medium Filter and Recovering the Scene Radiance

According to the haze image model we can recover the scene radiance with the transmission map. Because the direct attenuation term *J(x)t(x)* can be very close to zero, so the transmission *t(x)* is restricted to a lower bound t_0, a typical value of t_0 is 0.1. The final scene radiance *J(x)* is recovered by:

$$J(x) = \frac{I(x) - A}{\max(t(x), t_0)} + A \quad (4)$$

From the above expression we can see that the nearer the outline of scene objects in the new luminance image to the input haze image, the easier to lose details in restored image. We can see from Fig. 1, if the transmission map shown as the green continuous curve is similar to the input image shown as the black continuous curve, the result will be a flat curve shown as the red line after division operation. On the contrary, if the green curve is more flat, the red curve will be more variable, which means the dehaze result will contain more details. Therefore, in order to flatten the outline of scene objects in luminance image, and make the haze removal image contains more details, we use medium filter to the luminance image. Fig. 2 shows an example of the transmission map obtained without or with medium filter and their respective restored haze-free result. Besides, experiment results show that if the local patch chosen too small, the scene objects in haze removal image seem lack of three-dimensional appearance; while if the local patch is too large, the color of scene objects in restored image seems too dark. When the patch size is set to 5*5 for a 200*200 image, the haze removal effect is the best. In this way, the function of the new luminance image after medium filter can estimate the thickness of the haze.

Since now we already know the input haze image *I(x)*, the transmission map *t(x)* and the atmospheric light *A*, we can take these values into (4) to obtain the final restored haze-free image *J(x)*. Fig. 3 (b) is the transmission map estimated from color image Fig. 3 (a) using our approach. Fig. 3 (c) is our final recovered scene radiance to Fig. 3 (a).

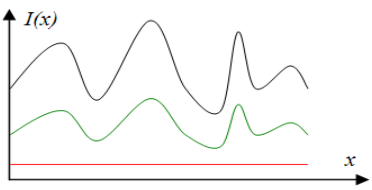

Figure 1. The input haze image is shown as the black continuous curve. The transmission map is shown as green continuous curve. The restored haze-free result is shown as the red line.

(a) (b) (c) (d)

Figure 2. Medium filter result. (a) restored haze-free result without filter. (b) transmission map obtained without filter. (c) restored haze-free result with filter. (d) transmission map obtained with filter.

(a) (b) (c)

Figure 3. Haze removal result. (a) input color image. (b) transmission map after using method based on luminance component. (c) final dehazing image using our method.

IV. Experimental Results and Analysis

A. *Qualitative Comparison*

In our experiments, we perform the improved method by executing MATLAB on a PC with 3.00GHz Intel Pentium Dual-Core Processor. Fig. 4 shows a comparison between results obtained by Fattal [5] and our algorithm. It can be seen that our approach outperforms Fattal's in situations of dense haze. Fattal's method is based on statistics and requires sufficient color information and variance. If the haze is dense, the color is faint and variance is not high enough for his method to reliably estimate the transmission. Next, we compare our approach with Tan's work [6] in Fig. 5. The colors of his result are often over saturated. Since his algorithm is not physically based and may underestimate the transmission. Our method can generate comparable results without any halo artifacts. We also compare our method with He's very recently work [7] in Fig. 6. The overall result of our approach is approximately the same as He's approach. Compared with the input haze image, the contrast and clarity of the images are enhanced significantly. Fig. 7 allows the comparison of our results with three state of the art visibility restoration algorithms: Fattal [5], Tan [6] and He [7]. Notice that the results obtained with our algorithm seems visually close to the result obtained by He, with less halo artifacts compared with Tan.

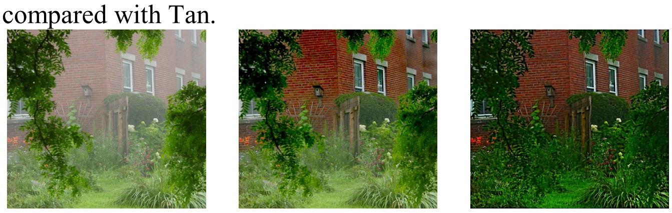

Figure 4. Comparison with Fattal's work[5]. Left: input image. Middle: Fattal's result. Right: our result.

Figure 5. Comparison with Tan's work[6]. Left: input image. Middle: Tan's result. Right: our result.

Figure 6. Comparison with He's work[7]. Left: input image. Middle: He's result. Right: our result.

Figure 7. From left to right, the input image and the results obtained by Fattal [5], Tan [6], He [7] and our algorithm.

B. *Quantitative Evaluation*

To quantitatively assess and rate these four methods, we first consider the processing time. Our method takes about 10-12 seconds to process a 600*400 pixel image in Matlab programming environment. From Tab. I, we can see that our method is about two times and three times faster than the speed of He's and Fattal's method respectively and is far faster than Tan's method.

Then, we use the method of visible edges segmentation proposed in [10]. Here, we transform the color level image to the gray level image, and use three indicators e, $\overline{r}$ and σ to compare two gray level images: the input image and the restored image. The visible edges in the image before and after restoration are selected by a 5% contrast thresholding, which allows computing the rate e of edges newly visible after restoration. Then, the ration $\overline{r}$ of the average gradient after and before restoration is computed. This indicator $\overline{r}$ estimates the average visibility enhancement obtained by the restoration algorithm. At last, the percentage of pixels σ which becomes completely black after restoration is computed.

These indicators e, $\overline{r}$ and σ are evaluated for Fattal [5], Tan [6], He [7] and our approach on four images, see Tab. II, Tab. III and IV. In each approach, the aim is to increase the contrast without losing some visual information. Hence, good results are described by high values of e and $\overline{r}$ and low values of σ. From Tab. II, we deduce that depending of the image, Tan algorithm has more visible edges than He, Fattal and our algorithm. From Tab. III, we can order the four algorithms in decreasing order with respect to average gradient: Tan, our, He and Fattal. This confirms our observations on Fig. 4, Fig. 5, Fig. 6 and Fig. 7, and one can notice that the contrast of the Tan's algorithm has been increased probably too strongly. Tab. IV gives the percentage of pixels which become completely black after restoration. Compared to others, ours and He's algorithm give the smallest percentage.

TABLE I. COMPARISON OF ALGORITHMS RUNNING TIME (S)

Figure	Fattal	Tan	He	Our
Fig. 4(441*450)	29.8756	324.4260	15.8185	8.4680
Fig. 5(835*557)	67.9213	746.7254	42.3780	29.7660
Fig. 6(1000*327)	47.2354	249.2972	23.1539	12.6090
Fig. 7(576*768)	64.9538	527.5627	32.1535	25.5160

TABLE II. RATE e OF NEW VISIBLE EDGES

e	Fattal	Tan	He	Our
Fig. 4	1.01	1.54	1.42	1.47
Fig. 5	7.21	7.62	7.36	7.40
Fig. 6	0.94	2.74	1.22	0.92
Fig. 7	0.23	1.71	0.80	1.78

TABLE III. RATIO $\overline{r}$ OF THE AVERAGE GRADIENT

$\overline{r}$	Fattal	Tan	He	Our
Fig. 4	1.29	1.59	1.34	1.40
Fig. 5	2.18	2.32	2.24	2.30
Fig. 6	1.26	1.48	1.28	1.38
Fig. 7	1.09	1.40	1.27	1.37

TABLE IV. PERCENTAGE OF PIXELS WHICH BECOMES COMPLETELY BLACK AFTER RESTORATION(%)

σ	Fattal	Tan	He	Our
Fig. 4	1.11	1.29	0.82	0.92
Fig. 5	1.02	0.49	0.34	0.27
Fig. 6	0.88	0.36	0.17	0.25
Fig. 7	1.05	0.76	0.30	0.29

V. CONCLUSIONS

In this paper, we have proposed an automatic image hazing removal method based on luminance component, for single image haze removal. The approach introduces the MSR algorithm to the luminance component with the color space transform, and then does subtraction operation and median filter on the component. Its main advantages are its speed and no user interaction is needed. Results shows that it achieves as good or even better results compared to the main present-day algorithms as illustrated in the experiments. The proposed method may be used with advantages as pre-processing in many systems, such as surveillance, topographical survey, intelligent vehicles, etc.

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