Image Defogging

1st YuFan Feng
SIST
ShanghaiTech University
2019533141
fengyf2@shanghaitech.edu.cn

2nd Bin Yang
SIST
ShanghaiTech University
2019533230
yangbin@shanghaitech.edu.cn

3rd Shi Pu
SIST
ShanghaiTech University
2021233307
pushi@shanghaitech.edu.cn

***Abstract*—The i ts of haze or fog are seriously degraded by scattering of atmospheric particles, and the object features are always hard to identify by human eye or some computer vision system because of the reduced contrast and pale color. Thus, it is important in the field of computer vision to develop image defogging technology, which aim at removing the influence of haze in order to generate images with better visual effects. Different approaches can be roughly categorized into three aspects: image enhancement based methods, image fusion based methods and image restoration based methods. In this article, we'll be focusing on haze removal using dark channel and the advantages over other methods.**

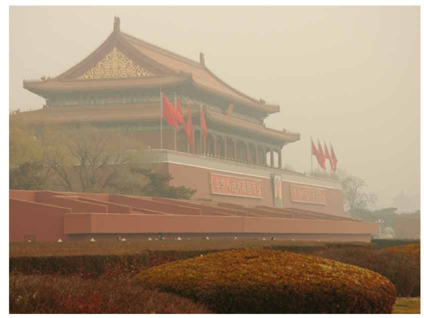
***Index Terms*—Image removal, dark channel, atmospheric scattering model.**

I. Introduction

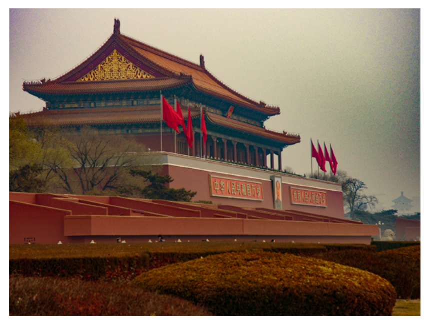
Image defogging is widely used in computer vision as the input image to those systems is the scene radiance, the foggy image will cause huge degradation to the performance which is not wanted. What's more, haze removal can greatly enhance contrast and fix the color offset caused by atmospheric light, and so that increase the visibility. Moreover, the haze removal can also provide depth information of the image which can be put to good use for some vision detection devices.

Before removal, we should know how fog is formed first in order to build a physical model. In simple terms, there are many particulates, especially water vapour, in the atmosphere, which will generate scattering and degrade the images of outdoors scenes. The farther away we are from the object being observed, the greater the scattering and the greater the effect of the fog. As for the comparison in Fig 1 we can see that the foggy image has a serious loss of contrast and color changing.

Fortunately, we all stand on shoulders of giants. Many researchers have already given their methods for this problem and made remarkable achievements. As mentioned before, there are three kinds of approaches [1]. Image enhancement like CLAHE, homomorphic filtering and wavelet transform are covered in detail in our course, so there's no need to talk more. Image fusion uses several derivative images, such as contrast image and brightness image which are generated through the original image to create multi-scale fusion. These methods can even be used defog for night images [2]. The rest algorithms are based on the atmospheric scattering model, like the single image dehazing [3] algorithm and dehazing using color-lines [4] proposed by Fattal. In the following pages, we'll introduce the defogging algorithm based on dark channel prior proposed by He [5].



(a)



(b)

Fig. 1. (a)hazy image (b)haze removed image by PhotoShop 2022

II. Atmospheric Defogging Model

When taking photos on foggy days, the light source received by the detector will be disturbed by fog, and the light source collected at this time mainly comes from two parts: the light reflected by a target that passes through particles to reach the detection system and the atmospheric light formed by scattering of particles. It can be modeled like Fig 2 expressed mathematically:

$$I(x,\lambda) = e^{-\beta(\lambda)d(x)}R(x,\lambda) + L_\infty(1 - e^{-\beta(\lambda)d(x)}) \tag{1}$$
$$= D(x,\lambda) + A(x,\lambda) \tag{2}$$

where x denotes the positions of pixels, λ denotes the light wavelength, L^∞ represents the value of atmospheric light at infinity, I is the observed foggy image and R is the haze removed image which wanted by us.

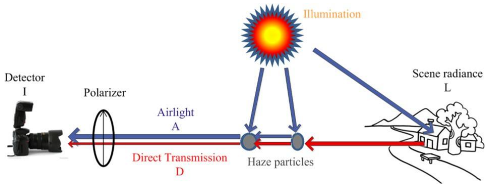


Fig. 2. Atmospheric defogging model

More generally, we let $e^{-\beta(\lambda)d(x)} = t(x)$ and it can be reduced as:

$$I(x) = R(x)t(x) + A_\infty(1 - t(x)) \tag{3}$$

III. Dark Channel Prior

He et al. found that in most of the outdoor images, there's at least one color channel that has very low intensity, and such channels are called *Dark channel*. If we put the dark channels of each pixel into one image, which means

$$J^{dark}(x) = \min_{c \in \{r,g,b\}} (\min_{y \in \Omega(x)} (J^c(y))) \tag{4}$$

where J^c is a color channel, $\Omega(x)$ is a region centered around x. In an image without fog, the intensities of J^{dark} are always low and tend to be zero except for the sky region. According to the authors, this is mainly because of three factors: (a)the shadows (b)colorful objects or surfaces (c) dark objects or surfaces. In other words, real-life landscapes rarely have off-white objects or areas except for sky, and that's why the dark channel prior is not suitable for the images that most of the areas contain sky.

In Fig 3 we can see that the dark channel for the foggy image is much brighter than the other one. However, as we said before, the dark channel prior does not work on the image with sky or any image that contains a lot of white areas like the example in Fig 4. It's obviously that the dark channels of white parts like sky and snow mountain are still light.

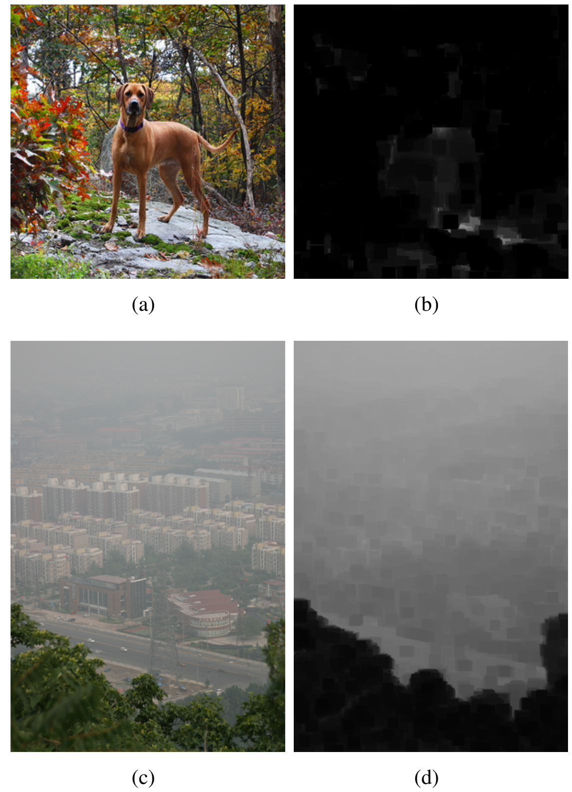


Fig. 3. (a)image without fog (b)dark channel for a (c)image with fog (d)dark channel for c

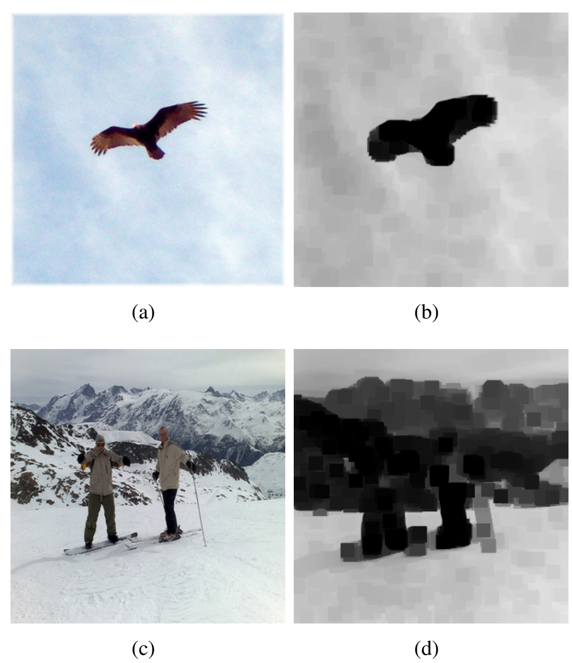


Fig. 4. (a)image contains large area of sky (b)dark channel for a (c)image with snow mountain (d)dark channel for c

IV. Defogging Using Dark Channel Prior

A. Estimating the Transmission

According to the model equation (3), there are two things to be solved: one is the transmission $t(x)$ and the other one is the atmospheric Light A.

Firstly, we take min operation for equation (3)

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

where $\tilde{t}(x)$ is the patch's transmission under the approximation that the transmission in a local patch $\Omega(x)$ is constant.

Then we divide both sides by A^c and take the min operation among three color channels on equation (5)

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

As we said before, the dark channel J^{dark} tends to be zero in the image without fog, which means

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

We don't need to do something special to the sky region as the color of the sky is usually very similar to the atmospheric light A, so that $\frac{I^c(y)}{A^c} \to 1$ and $\tilde{t}(x) \to 0$.

In real life, even the most clear weather can have a small amount of water vapor and particles, so we should preserve some of the fog. After the above derivation, we get the final expression of transmission:

$$\tilde{t}(x) = 1 - \omega \min_c(\min_{y\in\Omega(x)}(\frac{I^c(y)}{A^c})) \tag{8}$$

Moreover, if the transmission $t(x)$ tends to be zero, the first term in the equation (3) would be extremely small which might generate undesirable noise after recovering. So we also need to set a lower limit t_0 for transmission $t(x)$.

In the subsequent experiments, we set ω to 0.95, t_0 to 0.1 and the patch size to 15. It is foreseeable that there may be some problems because of the approximate transmission, and they can be refined by using some filter which will be talked about in the following part.

B. Refining the Transmission

There are already many methods to refine the transmission like *Bilateral Filtering* what we used is *Guided Filtering* and *Soft Matting*.

1) Soft matting:

In A.Levin's Soft matting method [6], we can see that, the matting equation,

$$I_i = \alpha_i F_i + (1-\alpha_i)B_i$$

has a similar form with the atmospheric defogging equation(3). And we can consider a transmission map as the alpha map of the image.

Therefore, we can apply Levin's method to refine the transmission. Let the naive transmission map be $\tilde{t}(x)$, the refined transmission map be $t(x)$. We resize them into vector form as $\tilde{\boldsymbol{t}}$ and $\boldsymbol{t}$. Then our goal is to minimize the following loss function:

$$E(t) = \boldsymbol{t}^{\boldsymbol{T}} L\boldsymbol{t} + \lambda(\boldsymbol{t} - \tilde{\boldsymbol{t}})^T(\boldsymbol{t} - \tilde{\boldsymbol{t}})$$

Where L is the Matting Laplacian matrix which can be defined as:

$$\sum_{k|(i,j)\in w_k} (\sigma_{ij} - \frac{1}{|w_k|}(1+(\boldsymbol{I}_i-\mu_k)^T(\sum_k + \frac{\varepsilon}{|w_k|}U_3)^{-1}(\boldsymbol{I}_j-\mu_k)))$$

where $\boldsymbol{I}_i$ and $\boldsymbol{I}_j$ are the colors of the input image at position i and j. μ_k and $\sum_k$ are the mean and covariance matrix of the colors in window w_k.

And we can get the refined $\boldsymbol{t}$ by solving the following equation:

$$(L + \lambda)\boldsymbol{t} = \lambda\tilde{\boldsymbol{t}}$$

Where U is an identity matrix with the same size of L, and λ is a small value to control the $\boldsymbol{t}$ by $\tilde{\boldsymbol{t}}$.

2) Guided Filtering:

Guided Filtering is proposed by He [7] in 2010. Guided filtering can not only be used in haze removal, but also noise reduction, detail smoothing/enhancement, HDR compression, image matting/feathering and joint upsampling with high efficiency.

Both simple smoothing and Gaussian smoothing have a common weakness, that is, they belong to isotropic filtering. As we know that a natural image can be seen as a combination of smooth areas and edges. Noise is usually characterized by large and similar gradients in all directions centered on it, while edge is different. Compared with the smooth region, the edge will also have a gradient change, but will only have a large gradient in its normal direction, and a small gradient in the tangential direction.

The main idea of guided filtering is to guide the image filtering by using another input image as shown in Fig 5. There is a linear relationship between the guiding image and the input image, which is set because we hope that the information provided by the guidance image is mainly used to indicate which are edges and which are smooth areas. Therefore, during filtering, if the guiding image tells us that this is a smooth area, it will be smoothed out. If the guidance diagram tells us that this is an edge, we should try to preserve that edge information in the final filtering result.

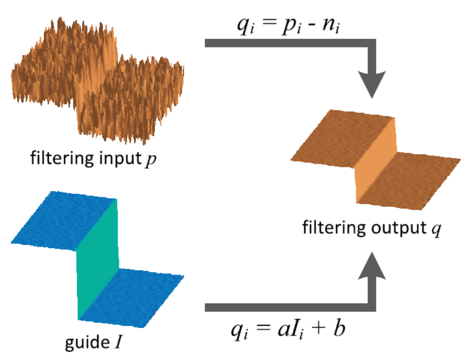


Fig. 5. Guided filtering process

It can be expressed simply as

$$q_i = a_k I_i + b_k, \forall i \in \omega_k \tag{9}$$

$$q_i = p_i - n_i \tag{10}$$

where p is the input image to be filtered, I is the guidance image and q is the output image. Here, we believe that the output image can be regarded as a local linear transformation of I, K is the midpoint of the localized window, so the pixels belonging to the window ω_k can be calculated by transforming the corresponding pixel of I through the coefficients a_k and b_k. Meanwhile, p is the image generated by q adding noise n, so we have $q = p - n$.

Next, we'll solve the coefficients. In order to keep the local linear model and make p and q as close as possible, ridge regression with regular terms is used here. As one pixel can be contained in different windows, we should calculate the average of each coefficient. Finally, we get equations like this

$$a_k = \frac{1}{|\omega|} \frac{\sum_{i \in \omega_k} I_i p_i - \mu_k \bar{p}_k}{\sigma_k^2 + \epsilon}, \tag{11}$$

$$b_k = \bar{p}_k - a_k \mu_k, \tag{12}$$

$$q_i = \frac{1}{|\omega|} \sum_{k | i \in \omega_k} (a_k I_i + b_k) \tag{13}$$

C. Estimating the Atmospheric Light

Many methods use the pixel with highest intensity to estimate the atmospheric light A like Tan [8] and Fattal [3]. However, the lightest pixel may not always means the atmospheric light but some bright objects like white cars or buildings. As mentioned before, the dark channel approximates the haze denseness well, so we can use the dark channel to estimate A. We first pick the 0.1% lightest pixels in J^{dark}, and the pixel with the highest intensity in the input image I is used as an approximate substitute for atmospheric light.

Up to here, we have already figured out every unknown term in Eq(3), but this is not the end. In order to increase the contrast of the image for a better visual effect, we add an enhancement process after recovering: lighten the brightest 1% pixels and darken the darkest 1% pixels. In the next section, we'll demonstrate our results and the difference to other methods.

V. Results

We focus on testing two given images in Fig 6.

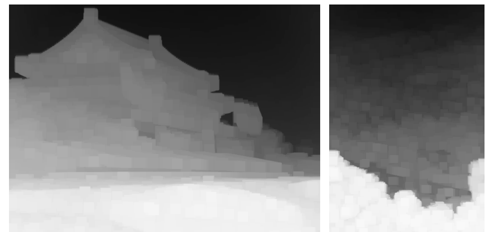
(a) (b)

Fig. 6. Two given images

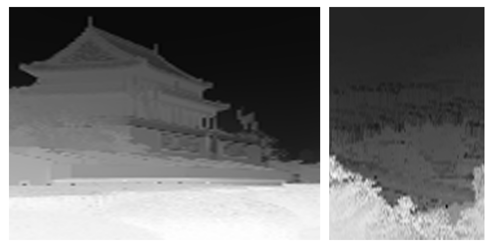
We firstly obtain their dark channels by performing the local min filter of 15×15. Then, we perform soft matting or guided filter to refine transmission. In soft matting, we down-sampled the original image to 1/9 scale, then up-sampled t after matting to original scale. In guided filter, we set the window size to 60. Fig 7 shows all the intermediate results. We can see that both soft matting and guided filter refined transmission well.

Since our estimated atmospheric light is more likely to be darker than true value, we adjusted the intensities and contrast

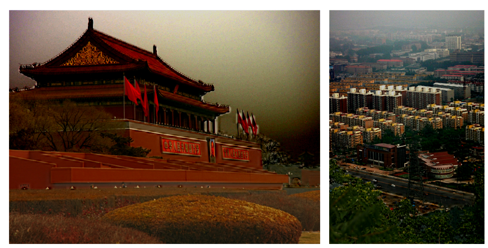
(a) dark channel



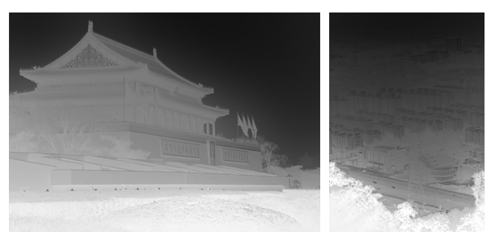
(b) transmission before matting



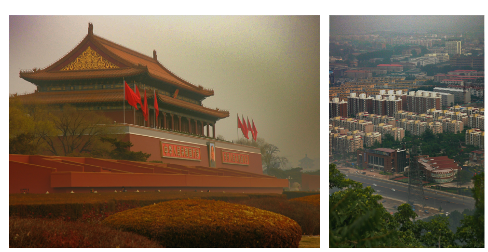
(c) transmission after soft matting



(d) restoration using soft matting t



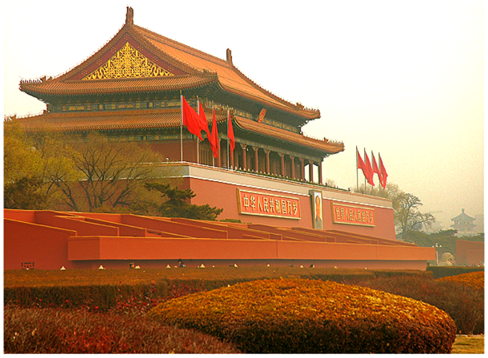
(e) transmission after guided filtering



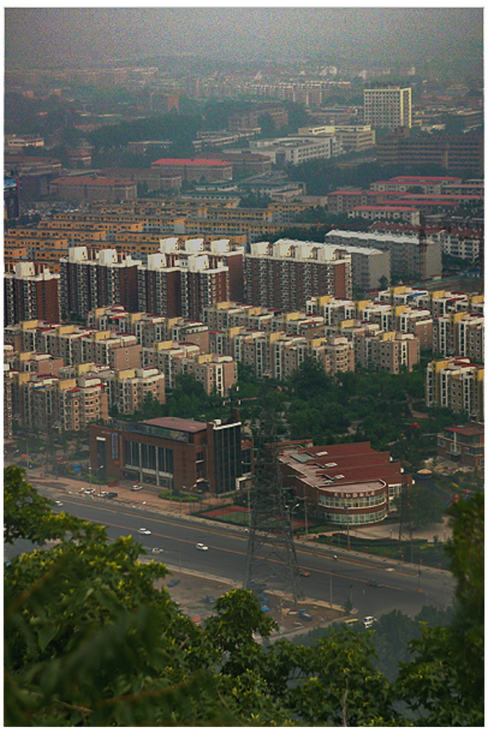
(f) restoration using guided filtered t

Fig. 7. Intermediate results

for display. In this step, both adaptive brightness enhancement and linear contrast stretching was applied. Furthermore, foggy weather and inaccuracy in matting procedure would result in lost of edge information. In order to enhance the edge, we also sharpen the results by Laplacian filter. Fig 8 shows our final results.



(a)



(b)

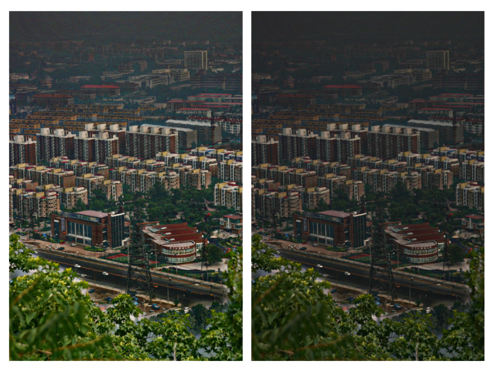
Fig. 8. Our final results

We compared our method with others, including CLAHE, homomorphic filtering, Color-lines of Fattal [4], and both 2009 [9] and 2010 [10] from Tarel's algorithm. Fig 9 and Fig 10 shows results generated by different methods.[1] We can see that results based on homomorphic filtering cannot enhance images very well. Results based on CLAHE turns to be too pale and color is unnature. Although it enhanced contrast, the effect is far from enough, and so as results from Tarel's. As for corlor-lines, the result of Fig 6(a) have a good performance, and the color contrast is even more natural than ours. However, the result of Fig 6(b) seems too light especially the nearby green plants, which shouldn't be so pale. In general, our approach has yielded the best result.

[1]Results of Fattal's colorline can be found at https://www.cs.huji.ac.il/w~raananf/projects/dehaze_cl/results/. Matlab code and results of Tarel can be found at http://perso.lcpc.fr/tarel.jean-philippe/visibility/.

(a) (b)

(c) (d)

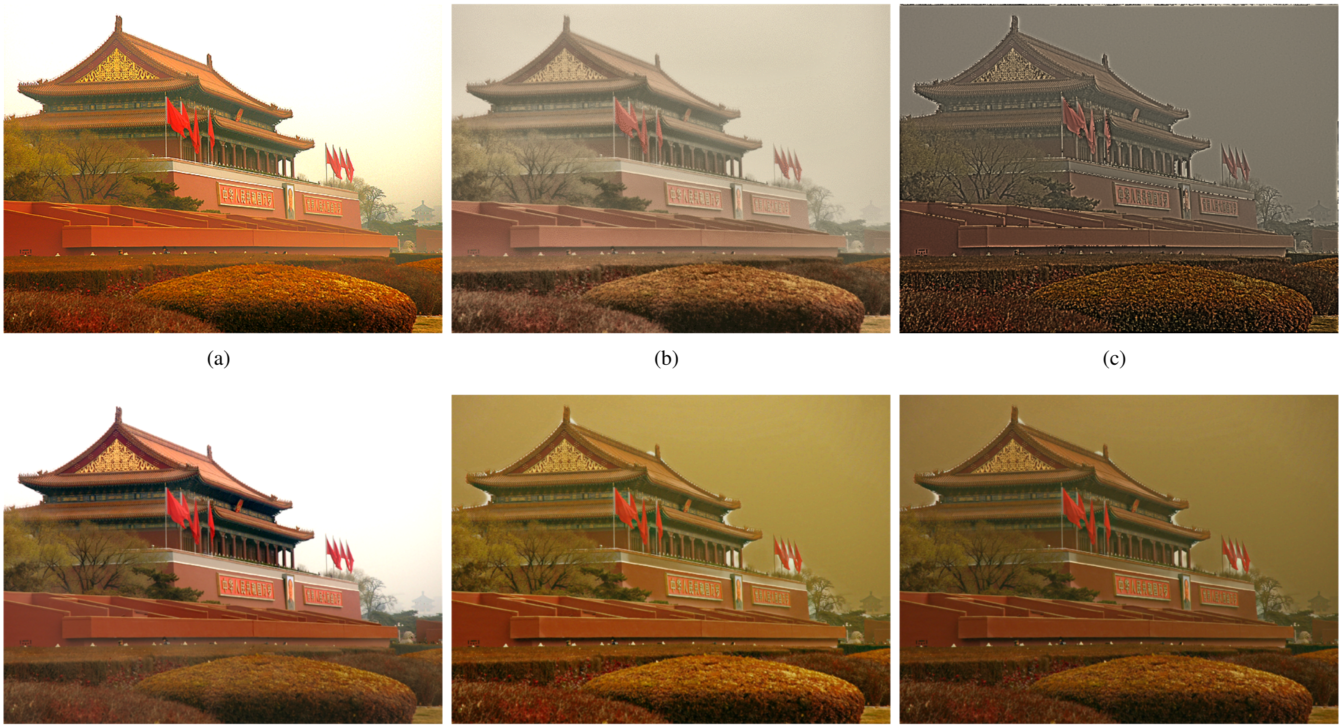


(e) (f)

Fig. 9. results of (a)ours (b)CLAHE (c)Homomorphic filtering (d)Color-lines (e)Tarel2009 (f)Tarel2010

VI. Workload Distribution

The main structure of defogging code was implemented by Yufan Feng and Bin Yang. Guided filtering was implemented by Shi Pu. Soft matting was implemented by Yufan Feng. Image enhancement after defogging was implemented by Bin



(a) (b) (c)

(d) (e) (f)

Fig. 10. results of (a)ours (b)CLAHE (c)Homomorphic filtering (d)Color-lines (e)Tarel2009 (f)Tarel2010

Yang. Project presentation was delivered by Yufan Feng. Report was credited by Shi Pu and modified by Yufan Feng and Bin Yang.

REFERENCES

[1] W. Wang and X. Yuan, "Recent advances in image dehazing.," *IEEE CAA J. Autom. Sinica*, vol. 4, no. 3, pp. 410–436, 2017.

[2] C. Ancuti, C. O. Ancuti, C. De Vleeschouwer, and A. C. Bovik, "Night-time dehazing by fusion," in *2016 IEEE International Conference on Image Processing (ICIP)*, pp. 2256–2260, IEEE, 2016.

[3] R. Fattal, "Single image dehazing," *ACM transactions on graphics (TOG)*, vol. 27, no. 3, pp. 1–9, 2008.

[4] R. Fattal, "Dehazing using color-lines," *ACM Transactions on Graphics (TOG)*, vol. 34, pp. 1 – 14, 2014.

[5] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," *IEEE transactions on pattern analysis and machine intelligence*, vol. 33, no. 12, pp. 2341–2353, 2010.

[6] A. Levin, D. Lischinski, and Y. Weiss, "A closed-form solution to natural image matting," *IEEE transactions on pattern analysis and machine intelligence*, vol. 30, no. 2, pp. 228–242, 2007.

[7] K. He, J. Sun, and X. Tang, "Guided image filtering," *IEEE transactions on pattern analysis and machine intelligence*, vol. 35, no. 6, pp. 1397–1409, 2012.

[8] R. T. Tan, "Visibility in bad weather from a single image," in *2008 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1–8, IEEE, 2008.

[9] J.-P. Tarel and N. Hautiere, "Fast visibility restoration from a single color or gray level image," in *2009 IEEE 12th international conference on computer vision*, pp. 2201–2208, IEEE, 2009.

[10] J.-P. Tarel, N. Hautiere, A. Cord, D. Gruyer, and H. Halmaoui, "Improved visibility of road scene images under heterogeneous fog," in *2010 IEEE Intelligent Vehicles Symposium*, pp. 478–485, IEEE, 2010.