

# A New Single Image Dehazing Method Based on Improved Double-area Filter and Guided Filter



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**Abstract.** When soft matting method is used to refine the transmission map, dark channel prior can provide high-quality results for most foggy images. However, this method increases image defogging algorithm complexity. Although most of improved dark channel prior algorithms can shorten the processing time, the results still suffer from white halo on the depth-edge. To overcome this problem, a novel transmission estimation method based on the improved double-area filter and guided filter is introduced in this paper. We firstly calculate the dark channel prior and coarse transmission using the median filter instated of the minimum filter, and then we utilize the improved double-area filter to filter the coarse transmission. Further, we optimize transmission by the guided filter to generate a new transmission map which includes detailed information. In addition, the atmospheric light can be estimated by the improved quadtree algorithm. Finally, we recover the free-hazy image utilizing the atmosphere attenuation model. In order to demonstrate the effectiveness of the proposed method, the experiment on several classic images was performed. Meanwhile, we compared the time consumption of our approach, He's method, Gibsion's method, Zhang's method and Zhu's method. The experimental results showed that our method not only provides better results for the depth-edge regions but also has lower complexity.

**Keywords:** dark channel prior, guided filter, image dehazing, improved double-area filter, transmission

## 1 Introduction

As it is well known, haze is a common natural phenomenon formed by suspended particles in the atmosphere (e.g., water droplets and dust). In foggy weather, the images obtained outdoors suffer from low contrast and color distortion. Therefore, these images cannot be used in computer vision applications, such as object identification and target tracking [1]. One of the main reasons why images captured outdoors exhibit the above mentioned problems is because the reflected light received by camera is attenuated. In addition, the irradiance from these objects blends with the atmospheric light scattered by particles. Thus, the effective methods must be used to remove the haze.

In recent years, a single image haze removal has exhibited remarkable progress. Tan [2] proposed a method based on the fact that haze-free images have higher contrast than degraded images and he removed the haze by maximizing the local contrast. However, that is not a physics-based method, and restored images often suffer from a halo. Fattal [3] estimated the albedo of the scene by assuming that transmission and surface shading are locally uncorrelated. The disadvantage of this estimation method is that method may fail in the case that basic assumption is not satisfied. He et al. [4] proposed a dark channel prior theory by observing a clear outdoor image, and used a soft matting technology to refine the transmission map. This prior can obtain a quite compelling clear result of very high quality. However, the

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soft matting method increases algorithm complexity. Recently, many improved image dehazing algorithms have been developed to reduce the operating time. For instance, Gibsion [5] obtained a dark channel prior using a median filter instead of a minimum filter. This method not only has a lower complexity but also does not need to refine the transmission. However, since the transmission of some pixels is overestimated, the restored images often suffer from a blackout halo. Subsequently, the dark channel prior combined with a guided filter [6] can achieve a compelling result for most haze images. However, this method may still lead to the problem of white halo on the depth-edge because estimated transmission of the depth-edge is inaccurate. Zhang et al. [7] improved the dark channel prior based on double-area filter and image fusion. Still, the restored haze-free images suffer from white halo in dense depth-edge regions. In addition, many other image dehazing methods have been proposed to improve white halo of recovered images. Zeng et al. [8] calculated the transmission of each pixel, but the depth area of restored images still contained some haze. Wang et al. [9] noticed the advantages of minimum filter and guided filter, and proposed a dehazing method based on these two filters. Ling et al. [10] estimated transmission map using a perception oriented method, but the results need to be further improved. Further, a variety of new approaches [11-16] has been proposed to remove the haze. For instance, a new kind of atmospheric scattering model was proposed in [12], and Zhu et al. introduced a new color attenuation prior to process foggy images [14]. Although these methods can provide better results, most of them have high complexity and many restrictions.

Therefore, most of the existing methods for image dehazing cannot balance between algorithm complexity and white halo. To resolve this deficiency, a new method based on improved double-area filter and guided filter is proposed in this study to remove the haze from outdoor images. Since the white halo mainly depends on transmission accuracy, our basic idea is to estimate a desirable transmission. A brief overview of proposed method is as follows. Using an original foggy image, we firstly estimate the coarse transmission map based on Gibsion's method [5]. Then the median filter is applied to transmission which is undervalued. Meanwhile, we utilize the minimum filter to filter the overestimated transmission. This step corrects the transmission that had been wrongly estimated. Subsequently, a guided filter is used to smooth the transmission map. Therefore, a desirable transmission is obtained.

In addition, time complexity is also a critical problem that needs to be considered in image hazing. In some applications, such as intelligent vehicle, remote sensing image processing, a high time complexity may make algorithm impracticable. Moreover, the traditional dark channel prior method is time consuming. However, since the minimum filter and median filter work in parallel in the improved double-region filter, our method that is based on the improved double-region filter and guide filter can provide lower time complexity.

The main contribution of this paper denotes a new efficient method with a lower time complexity, which enable a desirable transmission.

The paper is organized as follows. In section 2, we introduce the classical dark channel prior algorithm and related improved algorithms. In Section 3, we describe an image dehazing algorithm based on the improved double-area filter and guided filtering, and in Section 4 we provide results on real images obtained by proposed method. In Section 5, we give the conclusion and guidelines for our future work.

## 2 Problem Formulation

In computer vision, the most common model for image hazing [17-18] is defined by:

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

Where  $I(x)$  is the observed hazy image,  $J(x)$  is the obtained clear haze-free image,  $t(x)$  is the transmission map, and  $A$  is the global atmospheric light. The goal of image dehazing is to recover  $t(x)$ ,  $A$  and  $J(x)$  from  $I(x)$ . The multiplication  $J(x)t(x)$  denotes the direct attenuation, which indicates that light reflected from the object surface enters into the imaging system after scattering from atmospheric particles. The factor  $A(1-t(x))$  is the atmospheric veil, which results from scattering of natural light from atmospheric particles. The dark channel prior [4] is based on the fact that in most of the nonsky patches, at least one color channel contains pixels whose intensity is very low and close to zero.

Equivalently, the minimum intensity of that patch is close to zero. For a free-hazy image  $J(x)$ , its dark channel prior is given by:

$$J^{dark}(x) = \min_{y \in \Omega(x)} \left( \min_{c \in \{r, g, b\}} J^c(y) \right) \rightarrow 0. \quad (2)$$

Where  $c$  is the one-color channel ( $r, g, b$ ), and  $\Omega(x)$  is the local patch centered at  $x$ . He et al. estimated the transmission by normalization of haze imaging model (1):

$$t(x) = 1 - w \min_{y \in \Omega(x)} \left( \min_{c \in \{r, g, b\}} \frac{I^c(y)}{A^c} \right). \quad (3)$$

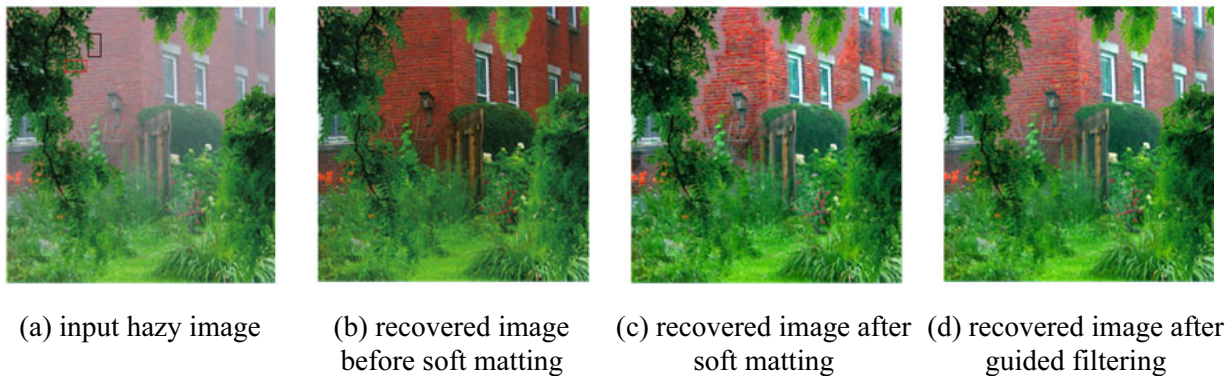
Where  $w$  is the introduced constant parameter, which is used to keep a very small amount of haze for distant objects. He et al. fixed the value of  $w$  to 0.95 for all results, and used a soft matting method to refine the transmission map. Finally, the scene radiance  $J(x)$  was recovered by:

$$J(x) = \frac{I(x) - A}{\max(t(x), t1)} + A. \quad (4)$$

Since directly recovered scene radiance  $J(x)$  is prone to the noise, He et al. restricted the transmission  $t(x)$  by a lower bound  $t1$ , whose typical value is 0.1.

As shown in Eq. (3), if we use a local minimum operation to compute transmission, we will get the same transmission in patches. Actually, the transmission changes when depth value of images changes abruptly. Thus, the transmission of pixel in the depth-edge is undervalued and restored images keep a little of haze.

In Fig. 1, an example of classical dark channel prior dehazing results is presented. As it can be seen in Fig. 1, the recovered image without soft matting suffers from a white halo. The transmission map after soft matting generates a good result, but the operation time is longer. Therefore, the recovered image after guided filtering still keeps a very small amount of haze.



**Fig. 1.** Recovered images using a dark channel

In 2011, Gibsion et al. [5] proposed a median dark channel prior, which is constructed by:

$$J^{dark}(x) = \text{med}_{y \in \Omega(x)} \left( \min_{c \in \{r, g, b\}} J^c(y) \right). \quad (5)$$

As we can see in Fig. 1(a), for a pixel which is located at the shot area whose most of local patches are depth areas, such as black box in Fig. 1(a), the transmission will be undervalued because  $I^{dark}$  and  $J^{dark}$  are overestimated. Hence, the median dark channel prior may lead to the problem of blackspot halo in clear images. In 2014, Zhang et al. [7] defined a dark region to describe a low intensity pixel of image edge area, and adopted a median filter to calculate the dark channel transmission:

$$J^{dark}(x) = \begin{cases} \text{med}_{(x,y \in w(x))} \left( \min_{c \in \{r,g,b\}} J^c(y) \right) & \text{med}_{(x \in w(x))} \left( \min_{c \in \{r,g,b\}} J^c(y) \right) \leq \min_{c \in \{r,g,b\}} J^c(y) \\ \min_{c \in \{r,g,b\}} J^c(y) & \text{med}_{(x \in w(x))} \left( \min_{c \in \{r,g,b\}} J^c(y) \right) > \min_{c \in \{r,g,b\}} J^c(y) \end{cases} \quad (6)$$

Where the minimum value of color channels  $\min_{c \in \{r,g,b\}} J^c(y)$  is defined as a dark channel, and it is used to compute the dark channel prior of dark region pixels. This method avoids blackspots and corrects transmission to the certain extent. However, as a red box in Fig. 1(a) shows, if a pixel is placed in depth region whose most of local patches are shot areas, the median dark channel prior of that pixel will be obviously small. Similarly, the transmission of that pixel will be overestimated on account of undervalued  $I^{dark}$  and  $J^{dark}$ , which will make restored images to keep a very small amount of haze. Accordingly, Zhang's method is not applicable to hazy images which contain dense places where depth changes abruptly.

### 3 A New Single Image Dehazing Method Based on Improved Double-area Filter and Guided Filter

As mentioned above, most of the existing methods for image dehazing with low complexity suffer from a white halo at image boundaries (for instance, the edges of leaves in Fig. 1). The main reason for that is variation of transmission in edge region, therefore an appropriate method should be used to estimate transmission. To achieve this goal, a new method for accurate estimation of transmission map is proposed in this paper. Firstly, using the model of median dark channel prior, a coarse estimation of transmission map is obtained. Secondly, the map is filtered by the improved double-area filter. Thirdly, a guided filter is utilized to optimize the transmission, and atmospheric light  $A$  is estimated by improved quadtree algorithm. Finally, we recover the clear images utilizing the atmosphere attenuation model.

#### 3.1 Transmission Estimation

##### 3.1.1 Coarse Transmission Estimation

In order to recover clear images and solve the white halo in the edge region, we propose a novel method to estimate the transmission map. Firstly, we obtain the median dark channel prior of degraded image using Eq. (5):

$$I^{dark}(x) = \text{med}_{y \in \Omega(x)} \left( \min_{c \in \{r,g,b\}} I^c(y) \right), \quad (7)$$

and then we calculate the coarse transmission using Eq. (1):

$$t(x) = 1 - \text{med}_{y \in \Omega(x)} \left( \min_{c \in \{r,g,b\}} \frac{I^{dark}(y)}{A^c} \right). \quad (8)$$

According to the above analysis, the coarse transmission obtained by median dark channel prior is inexact, so we propose an improved double-area filter to compute the transmission:

$$t'(x) = \begin{cases} \text{med}_{x \in \Omega(x)} t(x) & \text{med}_{x \in \Omega(x)} \left( \min_{c \in \{r,g,b\}} J^c(y) \right) > \min_{c \in \{r,g,b\}} J^c(y) \\ \min_{x \in \Omega(x)} t(x) & \text{med}_{x \in \Omega(x)} \left( \min_{c \in \{r,g,b\}} J^c(y) \right) \leq \min_{c \in \{r,g,b\}} J^c(y) \end{cases} \quad (9)$$

In Eq. (8), the coarse transmission estimated by median dark channel prior is undervalued when median dark channel prior is greater than dark channel. In order to correct transmission, we estimate transmission by applying a fast median filter to the patch. Similarly, the coarse transmission estimated by median dark channel is overestimated when the median dark channel prior is less than or equal to dark channel, so we compute the transmission by applying a minimum filter to the patch. This method solves

the deficiency of Zhang's method wherein the transmission of a pixel located in depth area, whose most of local patches are close shot areas, is overestimated. We select the patches with the same size ( $15 \times 15$ ) in improved double-area filter and median dark channel prior [4].

### 3.1.2 Refining Transmission

The guided filter [6] is defined by a local linear model. The output image can be obtained using the guidance image which can be an input to itself or another image. Guided filter can perform as an edge-preserving smoothing operator, such as popular bilateral filter, but with better behavior near the edges. Moreover, the guided filter has fast and non-approximate linear-time algorithm. In this paper, we utilize guided filter to optimize the transmission which is tackled with improved double-area filter. Because the minimal color component image (dark channel image) of original  $I(x, y)$  for each pixel  $W(x, y)$  (defined as  $W(x, y) = \min(I(x, y))$ ) includes rich edge information, we apply  $W(x, y)$  to the guidance image. The optimized  $t$  can be obtained by solving the following sparse linear system:

$$T'_i = a_k W_i + b_k, \forall i \in w_k. \quad (10)$$

where  $w_k$  is the window centered at the pixel  $k$ , with the square window radius  $r=25$  [6]. The guided filter seek the solution to Eq. (10) that minimizes the difference between  $T'$  and filter input  $W(x, y)$  to determine the linear coefficients  $a_k$  and  $b_k$ . Specifically, we minimize the following cost function in the window:

$$E(a_k, b_k) = \sum_{i \in w_k} \left( (a_k W_i + b_k - t_i)^2 + e a_k^2 \right). \quad (11)$$

Where  $t_i$  is the filter input image. The regularization parameter  $e$  is set to 0.01 [6]. According to the Least squares we can obtain the values of linear coefficients  $a_k$  and  $b_k$  by:

$$a_k = \frac{\frac{1}{|w|} \sum_{i \in w_k} W_i t_i - \mu_k \bar{t}_k}{\sigma_k^2 + e}, \quad (12)$$

$$b_k = \bar{t}_k - a_k \mu_k. \quad (13)$$

Where  $|w|$  is the number of pixels in  $w_k$ ,  $\mu_k$  is the mean of guidance image  $W(x, y)$  in  $w_k$ ,  $\sigma_k^2$  is the variance of guidance image  $W(x, y)$  in  $w_k$ , and  $\bar{t}_k$  is the mean of guidance image in  $w_k$ . The output value of the pixel is the average value of linear function which contains that pixel:

$$T'_k = \frac{1}{|w|} \sum_{k: i \in w_k} (a_k W_i + b_k) = \bar{a}_i W_i + \bar{b}_i. \quad (14)$$

## 3.2 Atmospheric Light Estimation

In Tan's work [2], the brightest pixels in the hazy image are considered as atmospheric light. However, this is true only when hazy image does not contain sky or bright-object regions. On the other hand, in He's work [4], the top 0.1 percent of the brightest pixels in the dark channel prior are picked firstly. Among these pixels, the pixels with highest intensity in the input image  $I(x, y)$  are selected as atmospheric light. Similarly, this method causes some errors when image contains a large white object. In [19], the brightest pixels of the top 95 percent of minimal color component image of the original image are considered as atmospheric light, but this method also has limitations.

In this paper, we utilize an improved quadtree algorithm to estimate the atmospheric light. The important contribution of this method is that operation time is shortened. We first divide the three-color-

component image of input hazy image into four rectangular regions. Then, we compute an average pixel intensity of each region, and divide each region with the highest average value into four sub regions. We repeat this process until the size of regions becomes smaller than a pre-specified size threshold. In each color-component image, the value of highest intensity in selected region is selected as a component of atmospheric light. The process of atmospheric light estimation is illustrated in Fig. 2, where the size threshold is set to  $20 \times 20$  [20-21].



(a) input hazy image

(b) result of  $R$ -component image segmentation

**Fig. 2.** The process of atmospheric light estimation by improved quadtree algorithm

### 3.3 Scene Radiance Recovery

As mentioned above, the overall atmospheric light  $A$  can be obtained by improved quadtree algorithm. The transmission  $T(x)$  can be estimated by improved double-region filter and guided filter. Thus, we can recover the free-hazy images by:

$$J = \frac{I - A}{\max(T(x), t1)} + A. \quad (15)$$

In this paper, the value of  $t1$  is 0.01. The proposed algorithm is based on the following steps:

**Step 1.** In the first step, the coarse transmission  $t(x)$  is estimated by median dark channel prior, and a minimum filter is utilized to tackle the transmission of pixel whose dark channel is equal to or greater than the median dark channel prior. Similarly, a median filter is used to tackle the transmission of pixel whose dark channel is less than or equal to the dark channel prior.

**Step 2.** The transmission obtained at Step 1 is optimized by the guided filter.

**Step 3.** In this step, the atmospheric light  $A$  is estimated by improved quadtree algorithm.

**Step 4.** Using the transmission obtained at Step 2 and atmospheric light obtained at Step 3, the final scene radiance  $J$  is recovered.

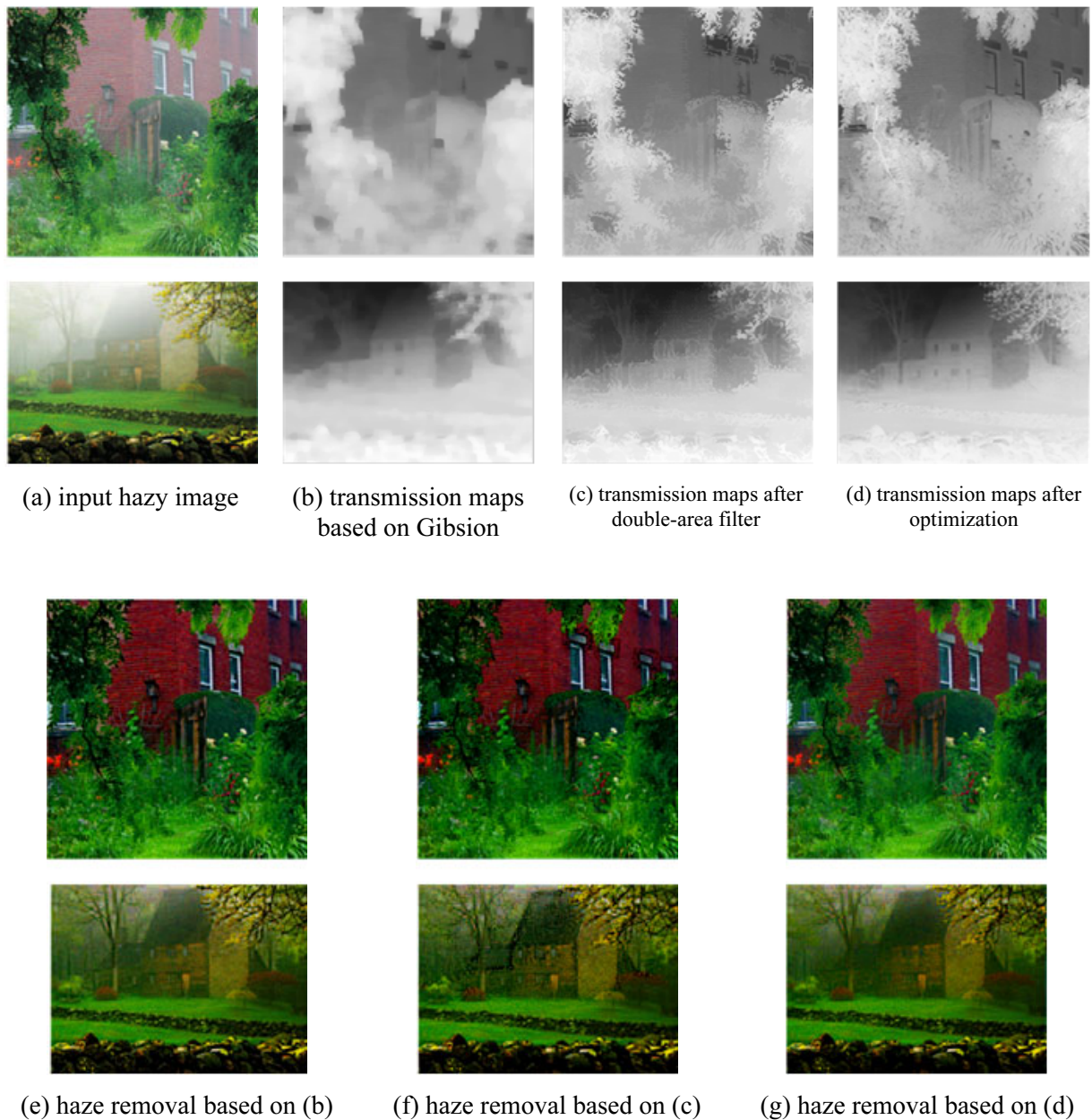
## 4 Experimental Results and Analysis

To verify the effectiveness of the proposed method, the experiment with several classic images was performed. The experiment was conducted with Matlab R2010a; the hardware platform was a desktop with 2G memory, and the operating system was Windows 7 Profession Edition. We verified the effectiveness of our method by both validation of our method and comparison of our approach with four other methods. In this article, all the image unit is pixel.

### 4.1 Method Validation

In Fig. 3, two examples of recovered scene transmission maps obtained by proposed method are illustrated. As it can be seen in Fig. 1, the transmission recovered by improved double-area filter (Fig. 3(c)) contains more information on edges, such as edges of leaves, than those recovered by median dark channel prior (Fig. 3(b)). However, the maps lose a lot of information on details. On the other hand, by filtering the transmission using the guided filter, Fig. 3(d), the generated maps contain detailed information. Further, the results obtained by the median filter (Fig. 3(e)) suffer from blackspot halo and remain a very small amount of haze. The recovered images (Fig. 3(f)) obtained by the improved double-

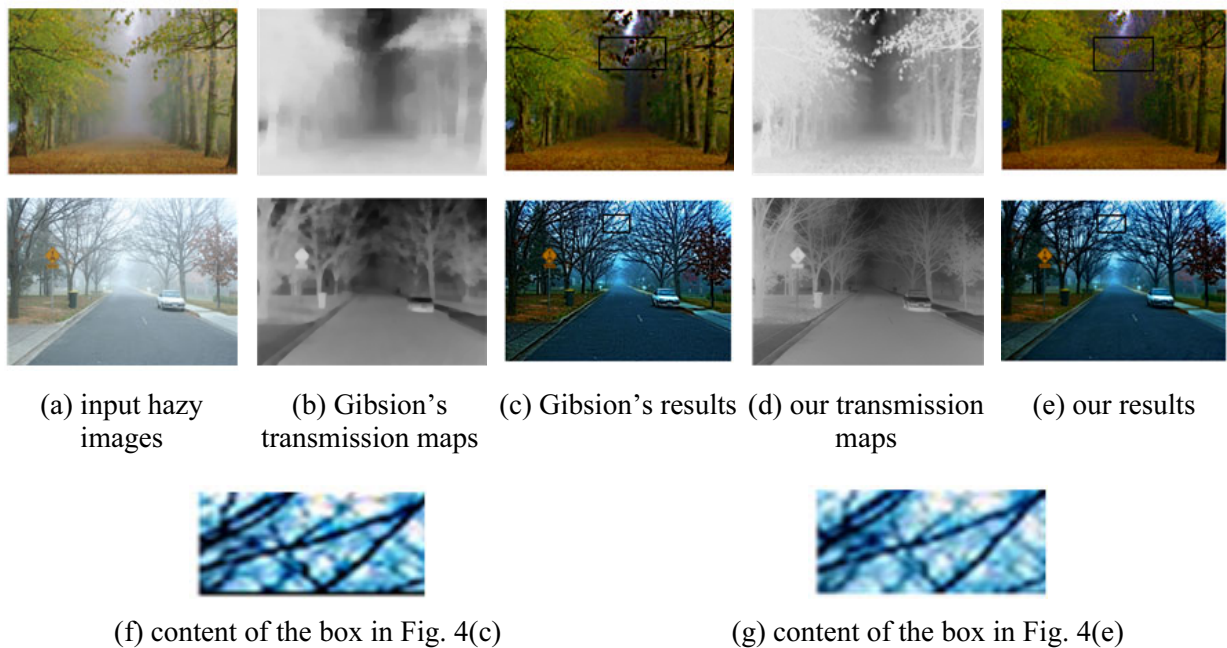
area filter still remain a few of haze in edge region. Therefore, the proposed method can provide satisfactory recover dehazing results (Fig. 3(g)) on places where depth changes abruptly.



**Fig. 3.** The obtained results

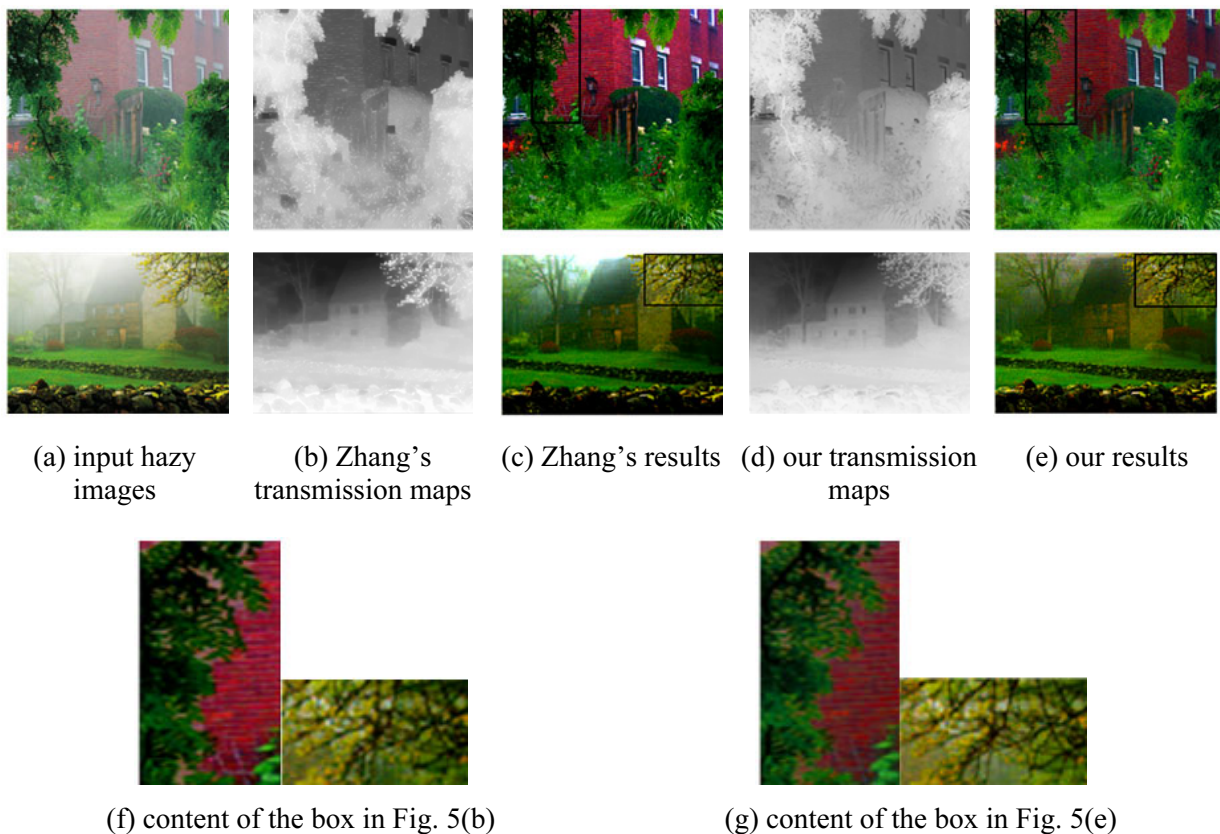
#### 4.2 Comparison of Methods

The comparison of our approach and Gibson's method is presented in Fig. 4. The Gibson's method adopts median dark channel prior to estimate the transmission. The biggest advantage of this method is that it can be implemented in real time. However, this method often tends to produce results with blackspot halo (Fig. 4(c)). In contrast, our method can improve the blackspot halo of recovered images (Fig. 4(e)). For instance, in Fig. 4(c) the leaves recovered by Gibson's method have blackspot, while the results in Fig. 4(e) are more visually pleasant.



**Fig. 4.** Comparison of our work and Gibsion's work

We also compared our approach with Zhang's et al. method and comparison results are presented in Fig. 5. Zhang's et al. estimate the transmission by defining a dark region to describe low intensity pixels of image edge area. The advantage of this method is that blackspot halo is improved, and disadvantage is that some hazy still remains in edge regions (Fig. 5(f)). However, our approach tends to generate clearer results of image details, such as jump edges and corners, as shown in Fig. 5(g).



**Fig. 5.** Comparison of our work and Zhang's work



In addition, we selected five classical foggy images containing the edge information to conduct the experiment using: our method, He’s method, Gibsion’s method, Zhang’s method and Zhu’s method. The obtained results are presented in Fig. 6. As it can be seen in Fig. 6, the images obtained by He’s method remain hazy, and Gibsion’s method often tends to recover hazy images with blackspot halo. Further, Zhang’s method has hazy in edge regions, while Zhu’s method can cause the problem of cross colors in certain areas. In contrast, our method not only has higher visual quality than four other methods, but also can remove the haze from edge regions where depth jumps abruptly.

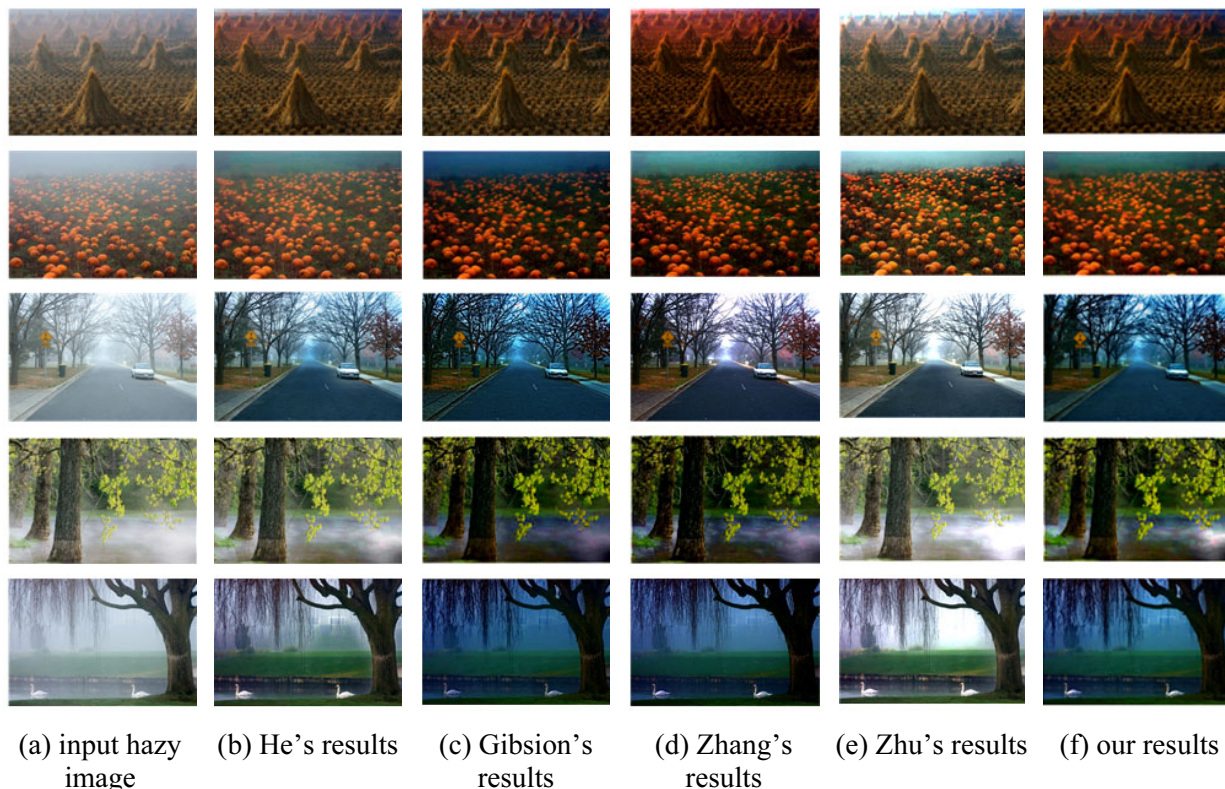


Fig. 6. Comparison of our and four other work

In this paper, the structural similarity index (SSIM) and universal quality index (UQI) are used as objective evaluations indicators of experimental results [22]. The values of quantitative evaluation indicators of dehazing of five images using all mentioned methods are presented in Table 1. As it can be seen in Table 1, all methods maintain the structural similarity with the original image but to different degrees. The UQI value obtained by He’s method is relatively high. However, our approach has higher SSIM and UQI values on the whole, thus, the images recovered by our method have higher quality.

Table 1. Values of quantitative evaluation indicators of image dehazing by different methods

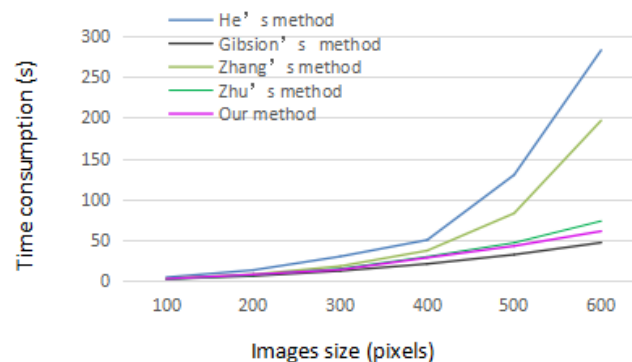
Image	He’s results		Gibsion’s results		Zhang’s results		Zhu’s results		Our results	
	SSIM	UQI	SSIM	UQI	SSIM	UQI	SSIM	UQI	SSIM	UQI
Fig. 6(1)	0.4076	0.4109	0.3634	0.6706	0.2425	0.2762	0.3827	0.3952	0.5907	0.5569
Fig. 6(2)	0.3605	0.8065	0.1874	0.3354	0.2085	0.3094	0.3355	0.8031	0.4910	0.4335
Fig. 6(3)	0.5307	0.3614	0.2450	0.3672	0.3659	0.6433	0.4931	0.4034	0.3288	0.6623
Fig. 6(4)	0.5925	0.9417	0.2112	0.3623	0.1388	0.3244	0.4161	0.9328	0.4206	0.4374
Fig. 6(5)	0.3069	0.6609	0.2742	0.2991	0.2897	0.3368	0.2944	0.3264	0.4614	0.3398

The time consumption of five methods is presented in Table 2, while its graphical representation is shown in Fig. 7. In Table 1 and Fig. 7, it can be seen that He’s method has the longest operation time. The time complexity of Zhang’s method increases rapidly with the size of image. Our method can save more operation time than Zhu’s method when the image size grows. The Gibsion’s method has the

shortest time complexity, but free-haze images recovered by this method have poor quality. Consequently, our method can achieve competitive results. Moreover, the time consumption of our approach and Gibsion's method is very close.

**Table 2.** Comparison of time consumption of different methods

Hazing image size (pixels)	He's method(s)	Gibsion's method(s)	Zhang's method(s)	Zhu's method(s)	Our method(s)
100×100	4.0736	2.0101	2.3757	1.6321	2.2119
200×200	12.9221	5.7036	7.6605	6.7078	7.4823
300×300	29.6348	11.9318	17.7523	14.6925	13.4180
400×400	49.8741	20.5543	36.7951	29.3685	28.1313
500×500	129.7327	31.8960	82.5864	46.4287	42.4984
600×600	282.5329	46.6199	196.2665	73.0636	60.6213



**Fig. 7.** Time consumption of different methods

## 5 Conclusion

In this paper, a new efficient method based on the improved double-area filter and guided filter is proposed to calculate transmission. We first obtain an initial transmission by median dark channel prior and refine it by improved double-area filter. Then, we utilize a guided filter to optimize the transmission map. Finally, the free-hazy image is restored by the atmosphere attenuation model. Experimental results showed that our method performs better than all commonly used methods, namely He's method, Gibsion's method, Zhang's method and Zhu's method. Therefore, the proposed method not only obtains better haze-free images, but also meets a real-time requirement. However, our method has a limitation. Namely, the images recovered by proposed method are dark. Therefore, in the future work, we will try to improve the proposed method in order to optimize the results.

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