

Image Dehazing using Guided Image FilterProf. Raskar V.B¹, Mr. Tupe S.G²¹Assistant Professor, Department of E&Tc Engineering, JSPM's Imperial College of Engineering & Research, Pune²PG student, Department of E&Tc Engineering, JSPM's Imperial College of Engineering & Research, Pune

Abstract—Imaging in bad weather is frequently tarnished by dispersion due to suspended particles in the troposphere such as haze, fog and mist. It decreases scene visibility. In this paper we have proposed a haze removal algorithm using color attenuation prior model and Guided Image Filter. By creating a linear model for modelling the scene depth of the hazy image under this novel prior and learning the parameters of the model by using a supervised learning method, the depth information can be well recovered. Once depth information is recovered, it is used to estimate transmission map. We can easily restore the radiance via the atmospheric scattering model and thus perfectly remove the haze part from the image. We have implemented this algorithm by using Guided image filter and Weighted Guided Image Filter. The use of Weighted Guided Image Filter improves the performance of algorithm. The algorithm achieves high quality dehazing with high structural similarity and less mean square error.

Keywords-Dehazing, image defogging, image restoration, airlight, attenuation, scene radiance, guided image filter.

I. INTRODUCTION

Outdoor scene of image quality is degraded due to the poor weather condition such as haze, fog, mist and smoke, due to the presence of haze when the image taken from outdoor using digital camera means light gets scattered before reaching the camera due to the noise present in the atmosphere. So haze removal is critical problem. Due to absorption and scattering by atmospheric particles in haze, outdoor images have poor visibility under inclement weather. Poor visibility negatively impacts not only consumer photography but also computer vision applications for outdoor environments, such as object detection [1] and video surveillance [2]. Haze removal, which is referred to as dehazing, is considered an important process because haze-free images are visually pleasing and can significantly improve the performance of computer vision tasks.

Methods presented in earlier studies had required multiple images to perform dehazing. For example, polarization-based methods [3, 4, 5] use the polarization property of scattered light to restore the scene depth information from two or more images taken with different degrees of polarization. Similarly, in [6, 7], multiple images of the same scene are captured under different weather conditions to be used as reference. With clear weather conditions. However, these methods with multiple reference images have limitation in online image dehazing applications [6, 7] and may need a special imaging sensor [1, 2, 3]. This leads the researchers to focus the dehazing method with a single reference image. Single image based methods rely on the typical characteristics of haze-free images.



Fig 1. Hazy Image



Fig 2. Haze Free Image

Tan [8] proposed a method that takes into account the characteristic that a haze-free image has a higher contrast than a hazy image. By maximizing the local contrast of the input hazy image, it enhances the visibility but introduces blocking artifacts around depth discontinuities. Fattal [9] proposed a method that infers the medium transmission by estimating the albedo of the scene. The underlying assumption is that the transmission and surface shading are locally uncorrected, which does not hold under a dense haze.

II. Atmospheric Scattering Model

A hazy image formed as shown in Fig. 3 can be mathematically modeled as follows

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

where x indicates the position of the picture element, I is the determined hazy image, J is that the scene radiance which is haze free image that's to be rehabilitated, A is that the global atmospheric light, t is that the medium of transmission describing the portion of the light that's not scattered and reaches the camera.

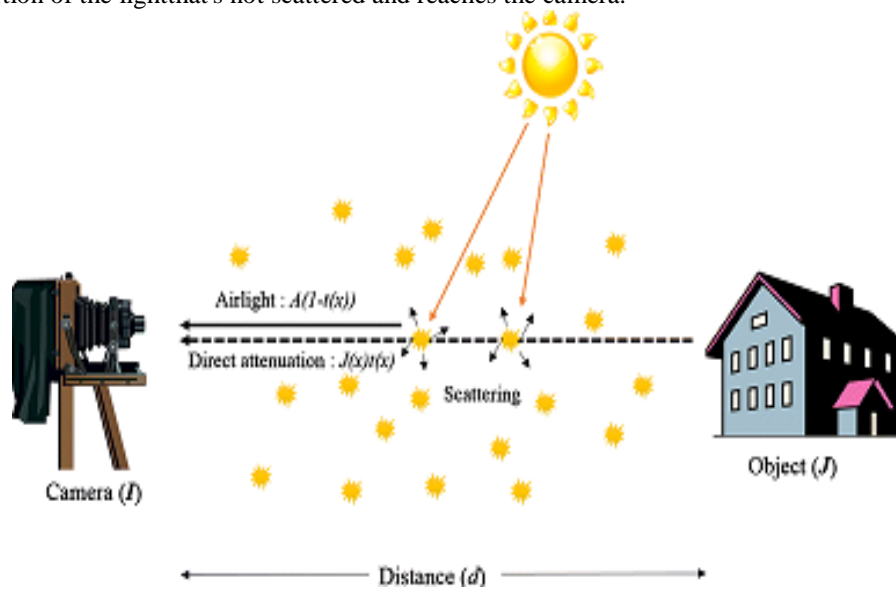


Fig 3. Hazy Image Formation

$$t(x) = e^{-\beta(\lambda)d} \quad (2)$$

In clear weather conditions, we have $\beta \approx 0$, and thus $I \approx J$. However, β becomes non-negligible for hazy images. The first term of Eq. (1), $J(x)t(x)$ (the direct attenuation), decreases as the scene depth increases. In contrast, the second term of Eq. (1), $A(1 - t(x))$ (the airlight), increases as the scene depth increases. Since the goal of image dehazing is to recover J from I , once A and t are estimated from I , J can be obtained.

III. Existing Method.

Since the concentration of the haze increases along with the change of the scene depth in general, hence

$$d(x) \propto c(x) \propto v(x) - c(x) \quad (3)$$

As the difference between the brightness and the saturation can approximately represent the concentration of the haze, a linear model is created [10],

$$d(x) = \theta_0 + \theta_1 v(x) + \theta_2 s(x) + \varepsilon(x) \quad (4)$$

where, x is the position within the image, d is the scene depth, v is the brightness component of the hazy image, s is the saturation component, θ_0 , θ_1 , θ_2 are the unknown linear coefficients, $\varepsilon(x)$ is a random variable representing the random error of the model. In order to learn the coefficients θ_0 , θ_1 , θ_2 we have used training sample which consists of a hazy image and its corresponding ground truth depth map.

Algorithm:

1. Generate random depth map.
2. Generate hazy images by using atmospheric scattering model
3. Obtain $\theta_0, \theta_1, \theta_2$ of color attenuation prior model by training of depth images and corresponding hazy images.
4. Generate depth map of input hazy images by using $d(x) = \theta_0 + \theta_1 v(x) + \theta_2 s(x) + \epsilon(x)$, where, $\theta_0 = 0.121779, \theta_1 = 0.959710, \theta_2 = -0.780245$ and $\epsilon = 0.041337$.
5. Estimate transmission map t .
6. Refine depth map and transmission map by using Guided Image Filter and Fast Guided Image Filter.
7. Estimate atmospheric light A .
8. Restore scene radiance.
9. Haze free image.

IV. Proposed Method

Let G be a guidance image and $\sigma_{G,1}^2(p')$ be the variance of G in the 3×3 window, $\Omega_1(p')$. An edge-aware weighting $r_G(p')$ is defined by using local variances of 3×3 windows of all pixels as follows:

$$r_G(p') = \frac{1}{N} \sum_{p=1}^N \frac{\sigma_{G,1}^2 + \epsilon}{\sigma_{G,1}^2 + \epsilon} \quad (5)$$

Where ϵ is a small constant. All pixels in the guidance image are used in the computation of $r_G(p')$. In addition, the weighting $r_G(p')$ measures the importance of pixel p' with respect to the whole guidance image.

The value of $r_G(p')$ is usually larger than 1 if p' is at an edge and smaller than 1 if p' is in a smooth area. Clearly, larger weights are assigned to pixels at edges than those pixels in flat areas by using the weight $r_G(p')$ in Equation (5). The GIF can be improved by incorporating these edge-aware weighting into the GIF.

The proposed weighting $r_G(p')$ in Equation (5) is incorporated into the cost function $E(a_p, b_p)$. The solution is obtained by minimizing the difference between the image to be filtered (*Depth and transmission map in our case*) and the filtering output q .

$$E(a_p, b_p) = \sum ((a_p \odot G(p) + b_p - X(p))^2 + \frac{\lambda}{r_G(p')} a_p^2) \quad (6)$$

The optimal values of a_p and b_p are computed as:

$$a_p = [\mu_{G \odot X, \zeta_1}(p') - \mu_{G, \zeta_1}(p') \mu_{X, \zeta_1}(p')] / [\sigma_{G, \zeta_1}^2(p') + \frac{\lambda}{r_G(p')}] \quad (7)$$

$$b_p = \mu_{X, \zeta_1}(p') - a_p \mu_{G, \zeta_1}(p') \quad (8)$$

where, \odot is the element-by-element product of two matrices. $\mu_{G \odot X, \zeta_1}(p')$, $\mu_{G, \zeta_1}(p')$ and $\mu_{X, \zeta_1}(p')$ are the mean values of $G \odot X$, G and X , respectively.

The final value of $q(p)$ is given as follows:

$$q(p) = \overline{a_p} + G(p) \overline{b_p} \quad (9)$$

Where, $q(p)$ is WGIF output, $G(p)$ is guidance image (Hazy Image in our case).

For easy analysis, the images X and G are assumed to be the same. Consider the case that the pixel p' is at an edge. The value of $r_{X(p')}$ is usually much larger than 1, a_p in the WGIF is closer to 1 than a_p in the GIF [11]. This implies that sharp edges are preserved better by the WGIF than the GIF. The complexity of the WGIF is $O(N)$ for an image with N pixels which is the same as that of the GIF.

V. Results

All the algorithms are implemented in the MatlabR2014a environment on a Intel Dual Core 1.80 GHz PC with 2GB RAM. The parameters used in the proposed method are initialized as follows: $r = 15, \beta = 1.0, \theta_0 = 0.121779, \theta_1 = 0.959710, \theta_2 = -0.780245$ and $\sigma = 0.041337$.

A. Estimation of the Depth.

As the relationship among the scene depth d , the brightness v and the saturation s has been established and the coefficients have been estimated, we have restored the depth map of a given input hazy image according to Equation (4).



Fig 4. Input Hazy Image

For instance, the white objects in an image are usually with high values of the brightness and low values of the saturation. Therefore, the proposed model can tend to consider the scene objects with white color as being distant. Unfortunately, this misclassification will result in inaccurate estimation of the depth in some cases. To overcome this problem, we have considered each pixel in the neighborhood. Based on the assumption that the scene depth is locally constant, we have applied minimum filter with window radius of 15 as shown in Fig. 6.

However to remove the blocking artifacts appear in the image. We have refined the depth map using guided image filtering [10] to smooth the image.



Fig 5. The raw depth map



Fig 6. The depth map with scale $r=15$

B. Estimation of the Atmospheric Light

We have picked the top 0.1 percent brightest pixels in the depth map, and select the pixel with highest intensity in the corresponding hazy image \mathbf{I} among these brightest pixels as the atmospheric light \mathbf{A} as shown in Fig 8.

C. Estimation of medium transmission

Now that the depth of the scene d and the atmospheric light \mathbf{A} are known, we can estimate the medium transmission \mathbf{t} easily according to Equation (2).

D. Scene Radiance Recovery

After estimating depth of the scene d and the atmospheric light \mathbf{A} , we have estimated the medium transmission \mathbf{t} easily according to Equation (2) and recover the scene radiance \mathbf{J} as per Equation (1).



Fig 7. The refined depth map



Fig 8. Position of the atmospheric light



Fig 9. Transmission Map



Fig 10. Haze free image

E. Mean squares error (MSE):

The MSE of each result can be calculated by the following equation:

$$e = \sqrt{\frac{1}{3N} \sum_{c \in \{r, g, b\}} \|J^c - G^c\|^2} \quad (10)$$

where, J is the dehazed image, G is the ground truth image, J^c represents a color channel of J , G^c represents a color channel of G , N is the number of pixels within the image G , and e is the MSE measuring the difference between the dehazed image J and the ground truth image G .

F. Structural similarity (SSIM):

The structural similarity (SSIM) image quality as index is introduced to evaluate the ability to preserve the structural information of the algorithms. A high SSIM represents high similarity between the dehazed image and the ground truth image, while a low SSIM conveys the opposite meaning.

Table 1 RMSE and SSIM for image cones

	GIF	FGIF	WGIF	FWGIF
RMSE	0.0285	0.0290	0.0117	0.0119
SSIM	0.94	0.93	0.99	0.985

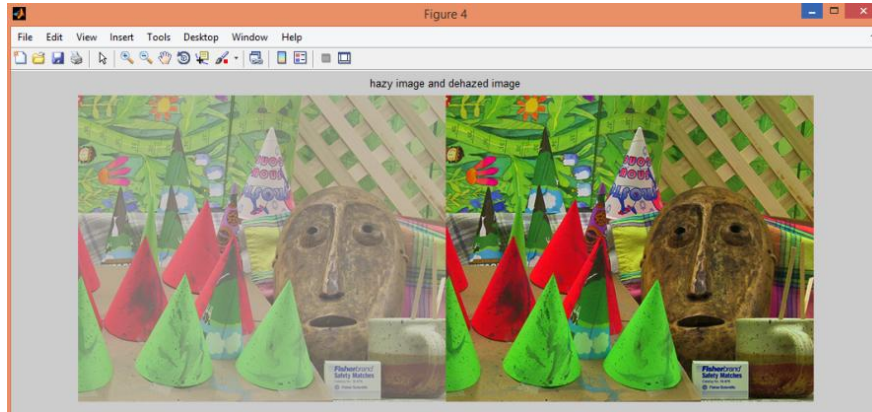


Fig.11 Output of Guided Image Filter(GIF)

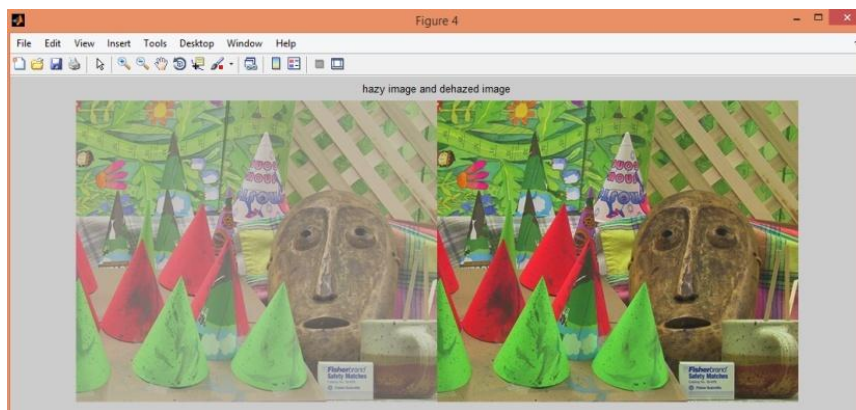


Fig 12 Output of Weighted Guided Image Filter(WGIF)

VI. Conclusion

The ill posed problem of image dehazing can be solved if Depth map of hazy image can be estimated. This depth information can be used to recover image transmission once atmospheric light is estimated. We have implemented Color Attenuation Prior algorithm by using Guided Image Filter and Weighted Guided Image Filter. Use of Weighted Guided Image Filter improves the SSIM index and decreases MSE between ground truth and dehazed image which shows that the haze layer can be removed from hazy image without loss of information in original image.

VII. References

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