International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2015): 78.96 | Impact Factor (2015): 6.391

A Fast Single Image Haze Removal Algorithm Using Color Attenuation Prior and Pixel Minimum Channel

Shahenaz I. Shaikh[1], B. S. Kapre[2]

[1]Department of Computer Science and Engineering, Mahatma Gandhi Mission's College of Engineering, Nanded, Maharashtra, India

[2]Assistant Professor, Department of Computer Science and Engineering, Mahatma Gandhi Missions' College of Engineering, Nanded, Maharashtra, India

Abstract: ***Dehazing techniques are introduced for removing haze effects from captured images. In this paper, we use single image haze removal using Color Attenuation Prior (CAP) and later improve results by using Pixel Minimum Channel (PMC). The CAP method employs atmospheric scattering model for dehazing. The parameters like – scene depth is first learned using linear model, then transmission map is estimated from it and lastly atmospheric light is obtained. All these parameters are fed as input to atmospheric scattering model for recovering scene radiance of scene. The PMC scheme is used to relieve the problem of high computational cost. The transmission map and atmospheric light is directly estimated from PMC. Experimental results show that PMC outperforms CAP method.***

Keywords: dehazing, scene depth, transmission map, scene radiance

1. Introduction

Images are used for describing changes in the environment. When the image is vivid and without distortion, then only that changes can be learned and used in application. But in outdoor imaging, captured images are easily affected by atmospheric particles (e.g., haze, fog, mist) that absorb and scatter light as it travels from scene to the camera. The presence of such particles deteriorates quality of captured images.

Haze is defined to be an atmospheric phenomenon where dust, smoke, and other dry particles obscure the clarity of sky. Sources of haze include volcanic ashes, combustion products, sea salt, smoke, dust. Hazy images are caused due to bad weather condition. This weather condition differs mainly in the types and sizes of particles involved and their concentration. Haze tends to produce a distinctive gray or bluish hue and is certain to affect visibility. Hazy images are dim, hide true color of scene, contain less information and are certain to affect visibility. Therefore removing haze from image is vital and very important and will benefit many computer vision applications such as aerial imagery, image classification and retrieval, remote sensing, video analysis and recognition.

In this paper, we propose a novel color attenuation prior (CAP) for single image dehazing and use another dehazing technique named Pixel Minimum Channel (PMC) [2] to overcome high computational cost of CAP. The simple CAP is used for creating linear model for scene depth restoration of the hazy image. By learning the parameters of the linear model with supervised learning method, the bridge between the hazy image and its corresponding depth map is built effectively. This prior gives information about saturation, brightness and their difference in hazy image. This information is used to calculate depth of the scene. With the recovered depth information, we can easily estimate transmission map and learn the atmospheric light. These parameters of atmospheric scattering model are used for dehazing of single hazy image. An overview of the proposed CAP method is shown in Figure 1.

Figure 1: An overview of CAP method

The remainder of this paper is organized as follows: In Section 2, we review the previous dehazing methods. In Section 3, we discuss atmospheric scattering model which is widely used for image dehazing and give a concise analysis on the parameters of this model, and the proposed approach of recovering the scene depth using the color attenuation prior. In Section 4, we present another technique PMC. In Section 5, we analyses and compare the dehazing results of both the methods. Finally, we summarize this paper in Section 6.

2. Literature Survey

Image dehazing transforms images to provide better representation of the subtle details. Outdoor images taken in bad weather (e.g., foggy or hazy) usually lose contrast and fidelity, resulting from the fact that light is absorbed and scattered by the turbid medium such as particles and water droplets in the atmosphere during the process of propagation. Haze removal techniques are classified into two categories depending on number of input images used for dehazing:

1) Multiple image dehazing technique – Considers multiple images of same scene and does not depend on statistics or prior knowledge.
2) Single image dehazing technique – Considers only single image of scene and depends on statistical assumption.

Early researches used polarization-based method [3] with multiple images which are taken with different degrees of polarization. This method improves contrast of image but may fail in fog or dense haze situation. To overcome this, the next method which also deals with multiple images of same scene under different weather condition is used.

In contrast restoration of weather degraded images [4], multiple images are used to locate and compute structure of scene. Using either depth segmentation or scene structure, the contrast from any image of scene taken in bad weather is restored. The only disadvantage is it cannot handle dynamic scenes.

Recently, significant progress has been made in single image dehazing based on the physical model. He *et al*. [5] discover the dark channel prior (DCP) that, in most of the non-sky patches, at least one color channel has some pixels whose intensities are very low and close to zero. With this prior, they estimate the thickness of haze, and restore the haze-free image by atmospheric scattering model. The DCP approach is simple and effective in most cases. However, it cannot well handle the sky images and is computationally intensive.

Some improved algorithms are proposed to overcome the weakness of the DCP approach. For efficiency, Tarel et al. [6] introduced a fast dehazing approach based on the median filter, assuming that the depth of scene is continuous. Unfortunately this algorithm cannot be used on all hazy images because such a strong assumption is violated in some cases. To sum up, the limitation of the dehazing methods lies in the fact that the haze-relevant priors or heuristic cues used are not effective or efficient enough.

3. Proposed Methodology

Novel color attenuation prior is proposed for single image dehazing. This simple and powerful prior can help to create a linear model for the scene depth of the hazy image. With the recovered depth information, the haze can be easily removed from a single hazy image. The efficiency of this dehazing method is dramatically high and the dehazing effectiveness is also superior to that of prevailing dehazing algorithms. Now the atmospheric scattering model is reviewed which is widely used for image dehazing and give a concise analysis on the parameters of this model.

3.1 Atmospheric Scattering Model

The atmospheric model used for image dehazing describes the formation of hazy image and gives a concise analysis on the parameter of this model. The model is proposed by McCartney in 1976 [7], is widely used in computer vision and image processing. The model can be expressed as follows:

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

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

Where I is the hazy image, J is the scene radiance representing the haze-free image, A is the atmospheric light, *t* is the medium transmission, *ß* is the scattering coefficient of the atmosphere and *d* is the depth of scene. Since I is known, the goal of dehazing is to eliminate A and *t*, then restore J according to Equation (1).

We notice that the depth of the scene *d* is the most important information. On the one hand, since the scattering coefficient *ß* can be regarded as a constant, the medium transmission *t* can be estimated easily if the depth of the scene is given according to Equation (2). On the other hand, when the depth $d(x)$ tends to infinity, the transmission $t(x)$ tends to zero and we have:

$$I(x) = A, d(x) \to \infty \quad (3)$$

Equation (3) shows that the intensity of pixel which makes the depth tend to infinity gives the value of A. In this condition, the task of dehazing is converted into depth information recovery. However, it is a challenging task to obtain the depth map with a single hazy image

In the next section, we present a novel approach to recover the depth information directly for a single hazy image using CAP.

3.2 Color Attenuation Prior

Color attenuation means reduction in true color of scene object due to reduced reflected energy received at imaging system. As the distance of object from imaging system increases, more reflected energy gets attenuated and more airlight is added. This results into more brightness and low saturation. So image appears to be hazy.

Human brain quickly identifies hazy area from natural scenes. This inspired to conduct experiment on hazy image and seek a new prior and find new statistics. The main conclusion is that the density of the haze is positively correlated with the difference between the brightness and the saturation. We illustrate this in Figure 2. Since the haze density increases along with the change of scene depth in general, we can make an assumption that the depth of the scene is positively correlated with the density of the haze and we have:

$$d(x) \propto c(x) \propto v(x) - s(x) \quad (4)$$

Where *d* is the scene depth, *c* is the haze density, *v* is the brightness of the scene and *s* is the saturation. We regard this statistics as color attenuation prior.

Figure 2 shows how brightness and saturation varies within hazy image. In haze-free patch of hazy image, the difference between brightness and saturation is almost equal to 1. While in moderate hazy region, this difference increases and in high dense region, the difference is even higher. It seems like brightness, saturation and their difference vary regularly in a hazy image according to this observation. Although we have known that there must be link between *d*, *v*, and *s*, Equation

International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2015): 78.96 | Impact Factor (2015): 6.391

(4) is just an intuitional result and cannot ne an accurate expression.

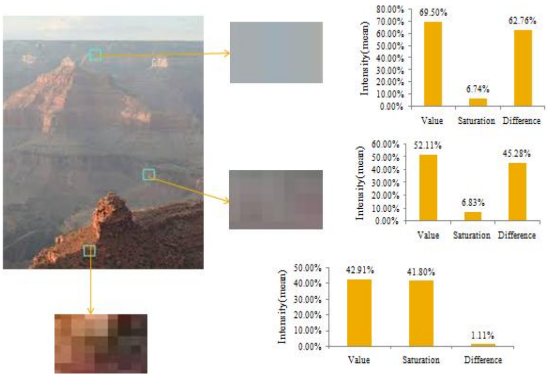

Figure 2: Relation between concentration of haze and difference between brightness and saturation.

3.3 Scene depth restoration using Linear Model

As we discovered that the difference between the brightness and saturation can approximately represent the concentration of haze, we assume that the relationship between *d*, *v*, and *s* is linear. Based on this assumption, we create a linear model as follows:

$$d(x) = \theta_0 + \theta_1 v(x) + \theta_2 s(x) \quad (5)$$

Where d is depth of scene, v is the brightness, s is the saturation and (θ_0, θ_1, θ_2) are linear coefficients. Learning linear coefficients is tedious work, for that training data is necessary. A training sample consists of a hazy image and its corresponding ground truth depth map. We use gradient descendent algorithm for this purpose. The values obtained are θ_0=0.12179, θ_1=0.959710 and θ_2=-0.780245. Once the values of coefficients are determined, they can be used for any single hazy image.

After developing relation between scene depth *d*, the brightness *v*, and the saturation *s* and estimating linear coefficients, we can recover the scene depth of the given input hazy image according to Equation (5). Here we refine initial depth map with guided filter [8] to remove blocking artifacts. In Figure 3, we show refined depth maps *d* and the transmission maps *t* can be well recovered by CAP method. With the estimated depth map, the task of dehazing is no longer difficult.

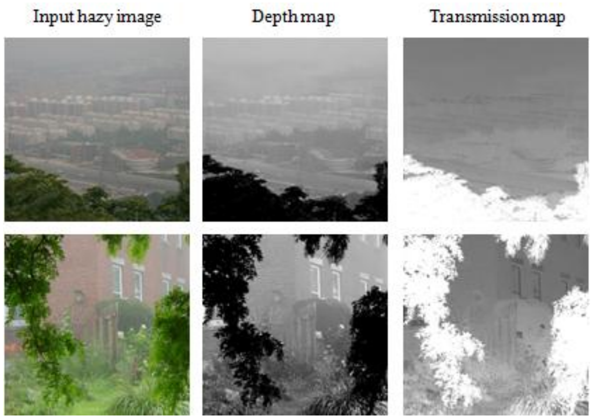

Figure 3: Results of recovering depth map and transmission map.

3.4 Estimation of the atmospheric light

As explained in atmospheric scattering model, the atmospheric light A value is taken from those pixels of hazy image I that has large depth values that is far away from observer. We pick top 0.1% brightest pixels from the depth map and select pixels with highest intensity in the corresponding hazy image I as A. Figure 4 shows position of atmospheric light.

Figure 4: Position of Atmospheric Light.

3.5 Scene radiance recovery

At this stage we have depth map *d*, transmission map t which is estimated using Equation (2) of atmospheric scattering model and atmospheric light A. So the scene radiance J can be recovered easily using Equation (1) of atmospheric scattering model. For convenience, we rewrite Equation (1) as follows

$$J(x) = \frac{I(x) - A}{t(x)} + A = \frac{I(x) - A}{e^{-\beta d(x)}} + A \quad (6)$$

Where, the scattering coefficient *ß* determine the intensity of dehazing indirectly. Its value is taken as 1. For avoiding producing too much noise, we restrict the value of the transmission *t*(*x*) between 0.1 and 0.9. So the final function used for restoring J is given below and Figure 5 shows the dehazed image.

$$J(x) = \frac{I(x) - A}{\min\{\max\{e^{-\beta d(x)}, 0.1\}, 0.9\}} + A \quad (7)$$

Figure 5: Scene radiance recovery.

The CAP scheme has satisfactory dehazing results. However, the task of restoring depth map is time consuming and as the image resolution increases, the time dehazed also increases. So we undertake another dehazing method named Pixel Minimum Channel (PMC).

3.6 Training Data Collection

In order to check effectiveness of the method, we not only dehazed naturally hazy images but also synthetic hazy images. Natural hazy images are taken from Google and for synthetic hazy image Middlebury stereo dataset [9]-[13] is used. Figure 6 shows the process of generating synthetic hazy images.

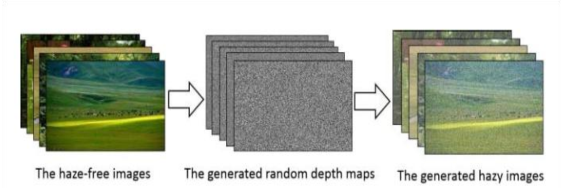

Figure 6: Process of generating synthetic hazy image using haze-free image.

Firstly, for each haze-free image, we generate a random depth map with the same size. The values of the pixels within the synthetic depth map are drawn from the standard uniform distribution on the open interval (0, 1). Secondly, we generate the random atmospheric light A (*k*, *k*, *k*) where the value of *k* is between 0.85 and 1.0. Finally, we generate the hazy image *I* with the random depth map *d* and the random atmospheric light *A* according to Equation (1) and Equation (2).

4. Pixel Minimum Channel

The PMC scheme attempts to relieve the problem of high computational cost and to handle high resolution images. Pixel minimum channel (PMC) uses the model in Equation (1) for single image dehazing. The model parameters *A* and *t*(*x*) is estimated through the PMC.

4.1 The PMC dehazing scheme

In the PMC scheme, the atmospheric light *A* and initial transmission map can be estimated directly by the PMC which comes from the 1x1 minimum filtering and then we use the guided image filter [8] to refine the initial transmission map. Given a hazy image I in RGB color space, the implementation steps of the proposed PMC scheme are described in the following steps:

Step 1.Calculate the pixel minimum channel as

$$I_{pmc}(x) = \min_{c \in \{r,g,b\}} [I^c(y)] \tag{8}$$

Step 2.Estimate atmospheric light *A* by $I_{pmc}(x)$ as

$$A = \alpha \times \max_x [I_{pmc}(x)] \tag{9}$$

Where, $0 < \alpha \leq 1$ is a scaling factor. Here $\alpha = 0.95$ is taken.

Step 3.Calculate the standard deviation of $I_{pmc}(x)$, σ

Step 4.Calculate the scaling factor *B*

$$B = \min(1.5 \times (1-\sigma), 0.75) \tag{10}$$

Step 5.Estimate the initial transmission map as

$$t(x) = 1 - B \times I_{pmc} \tag{11}$$

Step 6.Apply the guided image filter to refine the initial transmission map *t*(*x*).

Step 7.Recover the scene radiance as

$$J(x) = \frac{I(x) - A}{\max[t(x), t_0]} + A \tag{12}$$

Where, t_0 is a user-defined lower bound of *t*(*x*). Here t_0=0.1 is taken.

4.2 Estimation of Atmospheric Light and Transmission Map through PMC

We first obtained pixel minimum channel I_{pmc} by using 1x1 minimum filter on the original image. The minimum filter replaces the value of pixel by the minimum intensity level of the neighborhood of that pixel. Since the brightness of origin image is perfectly related to its PMC, we directly estimate the atmospheric light A through the maximum value of PMC with a scaling factor (Equation (9)). By refining the initial transmission map *t*(*x*) (Equation (11)) with guided filter [8], we get the final transmission map. Figure 7 shows PMC, transmission map and dehazed result using Equation (12).

Figure 7: Dehazing results of PMC method.

5. Experimental Results

In this section, we provide comparison between dehazing results of CAP and PMC method. To check effectiveness of both the methods we use qualitative measures as well. Figure 8 and 9 shows dehazing results on naturally and synthetic hazy images respectively.

Figure 8: Dehazing results on naturally hazy image Girls.

Figure 9: Dehazing results on synthetic hazy image Dolls.

Now we undertake qualitative measures to compare both the methods. We use Mean Square Error (MSE) and Structural Similarity (SSIM) [14] for comparing dehazing results on synthetic hazy image Dolls. MSE and SSIM is calculated between original image and dehazed result. Lower value of MSE means results are acceptable and higher values means unsatisfactory result. High value of SSIM means high similarity and lower SSIM value means opposite. Table1 and 2 shows MSE and SSIM between CAP and PMC respectively.

Table 1: MSE of image Dolls

Image	CAP	PMC
Dolls	0.6565	0.5665

Table 2: SSIM of image Dolls

Image	*CAP*	*PMC*
Dolls	0.96	0.92

The time complexity for CAP is O (m x n x r) and for PMC is O (m x n) for m x n image size and radius r. The time consumption for different image resolution is shown in table 3.

Table 3: Time consumption for different image resolutions

Image Size	*CAP*	*PMC*
441x450	2.5secs	1.5secs
600x450	2.9secs	1.8secs

6. Conclusion

The dehazing results of CAP and PMC are satisfactory. But the time taken for dehazing is less for PMC than for CAP. This is because CAP method first calculates depth map and then estimates transmission map and atmospheric light whereas PMC directly estimates atmospheric light and transmission map from pixel minimum channel without calculating depth map of hazy image. Also the value of scattering Coefficient *ß* cannot be regarded as constant in the atmospheric scattering model. So the dehazing algorithms which are based on the atmospheric scattering model like CAP are prone to underestimating the transmission in some cases. So more flexible model is desired.

References

[1] Qingsong Zhu, Jiaming Mai, and Ling Shao, "A Fast Single Image Haze Removal Algorithm Using Color Attenuation Prior," *IEEE Transactions On Image Processing*, vol. 24, p. 11, Nov. 2015.

[2] C. H. Hsiesh, C.Y. Chen, and Y. J. Dai, "Single image dehazing based on pixel minimum channel,' *2016 IEEE Symposium Series on Computational Intelligence (SSCI*), pp. 1-5, Athens, 2016.

[3] Y. Y. Schechner, S. G. Narasimhan, and S. K. Nayar, "Instant dehazing of images using polarization," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. I-325–I-332, 2001.

[4] S. G. Narasimhan and S. K. Nayar, "Contrast restoration of weather degraded images," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 6, pp. 713–724, Jun. 2003.

[5] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 12, pp. 2341–2353, Dec. 2011.

[6] J.-P. Tarel and N. Hautiere, "Fast visibility restoration from a single color or gray level image," in *Proc. IEEE 12th Int. Conf. Comput. Vis. (ICCV)*, pp. 2201–2208, Sep. /Oct. 2009.

[7] E. J. McCartney, *Optics of the Atmosphere: Scattering by Molecules and Particles*. New York, NY, USA: Wiley, 1976.

[8] K. He, J. Sun, and X. Tang, "Guided image filtering," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 6, pp. 1397–1409, Jun. 2013.

[9] D. Scharstein and R. Szeliski, "High-accuracy stereo depth maps using structured light," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. I-195–I-202, Jun. 2003.

[10] D. Scharstein and C. Pal, "Learning conditional random fields for stereo," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 1–8, Jun. 2007.

[11] H. Hirschmüller and D. Scharstein, "Evaluation of cost functions for stereo matching," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 1–8 Jun. 2007.

[12] D. Scharstein et al., "High-resolution stereo datasets with subpixel-accurate ground truth," in *Proc. German Conf. Pattern Recognit. (GCPR)*, pp. 31–42, 2014.

[13] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *IEEE Trans. Image Process.*, vol. 13, no. 4, pp. 600–612, Apr. 2004.