

Removal of Artifacts and Contrast Enhancement Using Adaptive Multiple Color Channel Prior

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To Cite this Article

Pathivada Vasavi and K.Govinda Rajulu, "Removal of Artifacts and Contrast Enhancement Using Adaptive Multiple Color Channel Prior", *International Journal for Modern Trends in Science and Technology*, Vol. 03, Issue 01, 2017, pp. 31-37.

ABSTRACT

Haze (or fog, mist, and other atmospheric phenomena) is a main degradation of outdoor images, weakening both colors and contrasts. We propose a simple but effective "Adaptive multiple color channel prior" to remove haze from a single input image. The dark channel prior is a kind of statistics of outdoor haze-free images. It is based on a key observation - most local patches in outdoor haze-free images contain some pixels whose intensity is very low in at least one color channel. Using this prior with the haze imaging model, we can directly estimate the thickness of the haze and recover a high quality haze-free image. Results on a variety of hazy images demonstrate the power of the proposed prior. Moreover, a high quality depth map can also be obtained as a by-product of haze removal. As a result, high-quality image can be recovered with lower computation complexity compared to patch-based dark channel prior. Also extracting two layers from an image where one layer is smoother than the other. This problem arises most notably in intrinsic image decomposition and reflection interference removal

KEYWORDS: multiple channel, fog removal, multiple color channel prior, interference

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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.

In poor weather conditions de haze the image is very critical issue in applications such as aerial photography, image recognition, driving assistance and visual surveillance .So dehazing the image using our method to improve contrasts of the foggy images and restores the visibility of the scene.

Hence removal of fog requires the estimation of air light map or depth map. Image enhancement and image restoration are the two techniques used in the haze removal Image.



Fig a1. Input haze image



Fig a2.haze free image

Enhancement doesn't include the cause of fog fades image value. The haze image leads to loss of information instant of using the enhancement techniques. Image refurbishes the study of the physical process of imaging in fog. Enhancement is usually used in the following three cases: noise decreases from image, contrast enhancement of the really dull and bright image, and show up the boundaries of the substance in a blurring image. Noise decrease is the Method of reducing noise forms a signal or an image. In general, images occupied with both digital camera and conventional film cameras will choose noise from a multiple of sources. It is main to removed noise for many uses of these images. Contrast enhancement is capturing clear image from side to side intensity.

Image contrast enhancement techniques have been studied in the past decades. There are various contrast enhancement methods are there, among those, histogram modification methods have received the greatest attention because of their simplicity and effectiveness . , since global histogram equalization over-enhance the image details, an alternative to this, the approaches of dividing an image histogram into several sub-intervals and modifying each sub-interval separately. The effectiveness of these sub-histogram based methods is dependent on how the image histogram is divided. The histogram of a image is obtained by using the Gaussian mixture model (GMM) and divides the histogram using the intersection points of the Gaussian components. The divided sub-histograms are then separately stretched using the estimated Gaussian parameters. Now a days technique of the color image enhancement have been found using depth [4]–[6] or stereo [7]–[9] as side information. Stereo matching algorithms and depth sensors are providing accurate depth images, and thus the use of the depth image for the color image enhancement becomes an important issue. So In this project, we propose a new contrast

enhancement algorithm that exploits the histograms of both color and depth images.

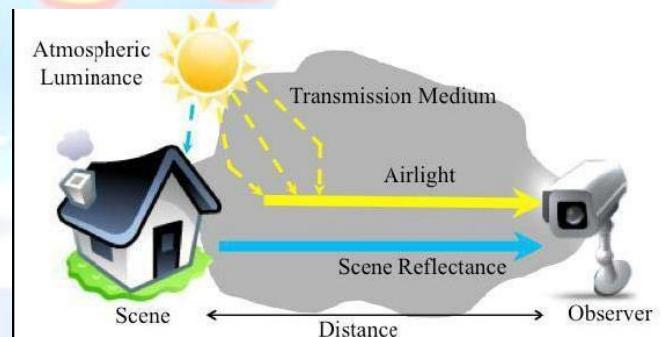
The histograms of color and depth histograms are first divided into subintervals by using Gaussian mixture model. Then the histograms of color histograms are adjusted with the similar intensity and depth values of depth image. Image obtained by [10].

II. PROPOSED WORK

Module 1:

In this paper, we propose a novel color attenuation prior for single image dehazing. This simple and powerful prior can help to create a linear model for the scene depth of the hazy image. By learning the parameters of the linear model with a supervised learning method, the bridge between the hazy image and its corresponding depth map is built effectively. With the recovered depth information, we can easily remove the haze from a single hazy image. An overview of the proposed dehazing . The efficiency of this dehazing method is dramatically high and the dehazing effectiveness is also superior to that of prevailing dehazing algorithms.

III. ATMOSPHERIC SCATTERING MODEL



where x is the position of the pixel within the image, \mathbf{I} is the hazy image, \mathbf{J} is the scene radiance representing the haze-free image, \mathbf{A} is the atmospheric light, t is the medium transmission, α is the scattering coefficient of the atmosphere and d is the depth of scene. \mathbf{I} , \mathbf{J} and \mathbf{A} are all three-dimensional vectors in RGB space. Since \mathbf{I} is known, the goal of dehazing is to estimate \mathbf{A} and t , then restore \mathbf{J} . It is worth noting that the depth of the scene d is the most important information. Since the scattering coefficient α can be regarded as a constant in homogeneous atmosphere condition , the medium transmission t can be estimated easily according to Equation if the depth of the scene is given. Moreover, in the ideal case,

the range of $d(x)$ is $[0, +\infty)$ as the scenery objects that appear in the image

IV. MULTIPLE COLOR ATTENUATOR PRIOR

To detect or remove the haze from a single image is a challenging task in computer vision, because little information about the scene structure is available. In spite of this, the human brain can quickly identify the hazy area from the natural scenery without any additional information. This inspired us to conduct a large number of experiments on various hazy images to find the statistics and seek a new prior for single image dehazing. Interestingly, we find that the brightness and the saturation of pixels in a hazy image vary sharply along with the change of the haze concentration. A natural scene to show how the brightness and the saturation of pixels vary within a hazy image. In a haze-free region, the saturation of the scene is pretty high, the brightness is moderate and the difference between the brightness and the saturation is close to zero. But it is observed the saturation of the patch decreases sharply while the color of the scene fades under the influence of the haze, and the brightness increases at the same time producing the high value of the difference in a dense-haze region, it is more difficult for us to recognize the inherent color of the scene, and the difference is even higher. It seems that the three properties (the brightness, the saturation and the difference) are prone to vary regularly in a single hazy image .

As reported in previous work, the atmospheric luminance considered to be constant in an single image and relatively high intensity in intrinsic luminance.

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

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

V. SCENE DEPTH RESTORATION

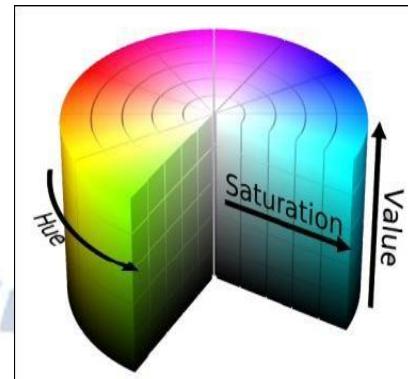
A. The Linear Model Definition

As the difference between the brightness and the saturation can approximately represent the concentration of the haze, we can create a linear model, i.e., a more accurate expression, as follows:

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

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, $\theta_0, \theta_1, \theta_2$ are the unknown linear coefficients, $\epsilon(x)$ is a random variable representing the random error of

the model, and ϵ can be regarded as a random image.



Sobel image $\nabla d = \theta_1 \nabla v + \theta_2 \nabla s + \nabla \epsilon$, where θ_1 is simply set to 1.0, θ_2 is set to -1.0, and ϵ is a random image

VI. TRAINING DATA COLLECTION

In order to learn the coefficients θ_0 , θ_1 and θ_2 accurately, the training data are necessary. In our case, a training sample consists of a hazy image and its corresponding ground truth depth map. Unfortunately, the depth map is very difficult to obtain due to the fact that there is no reliable means to measure the depths in outdoor scenes. Current depth cameras such as Kinect are not able to acquire the accurate depth information. 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 \mathbf{A} (k, k, k) where the value of k is between 0.85 and 1.0. Finally, we generate the hazy image \mathbf{I} with the random depth map d and the random atmospheric light \mathbf{A} .

VII. ESTIMATION OF THE DEPTH INFORMATION



Fig a1. depth information



Fig b1.depth information



Fig c1.depth information

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 can restore the depth map of a given input hazy image. However, this model may fail to work in some particular situations. 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 tends 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.

VIII. QUANTITATIVE COMPARISON

In order to quantitatively assess and rate the algorithms, we calculate the mean squares error (MSE) and the structural similarity (SSIM) of the result. The MSE of each result can be calculated by the following equation:

$$e = \sqrt{(1/3N\epsilon_{ce(r,g,h)} MJ^c - GC)^2}$$

where \mathbf{J} is the dehazed image, \mathbf{G} is the ground truth image, \mathbf{J}_c represents a color channel of \mathbf{J} , \mathbf{G}_c represents a color channel of \mathbf{G} , N is the number of pixels within the image \mathbf{G} , and e is the MSE measuring the difference between the dehazed image \mathbf{J} and the ground truth image \mathbf{G} . Note that \mathbf{J} and \mathbf{G} have the same size since they are corresponding with the hazy image \mathbf{I} . Given \mathbf{J} and \mathbf{G} , a low MSE represents that the dehazed

result is satisfying while a high MSE means that the dehazing effect is not acceptable.

We further show the MSEs of the results produced by different algorithms. As can be seen, Nishino et al.'s results produce the highest MSEs overall.

Module 2:

A pair of color and depth images is given as input, as shown in Fig. 1. By using Gaussian mixture model we obtain the histograms of input images. Then the algorithm modifies the histogram of the color image using the histogram of the depth image as side information. The histogram of the color image is transformed from the RGB space to the hi-saturation-intensity space. Histogram modification is then applied to the intensity channel, and then resultant color image is obtained by transforming the HIS to RGB. Figure. 2(a) and (b) show the histograms of the color and depth images with their Gaussian mixture models. Figs. 2(a) and (b)) are used to divide the histogram into sub-intervals.

Let \mathbf{c} and \mathbf{d} represent the color image and the depth image, respectively. The histograms of \mathbf{c} and \mathbf{d} are assumed to be divided into N and M sub-intervals, respectively, and the intersection points between the i^{th} and l_{i+1}^{th} sub-intervals of \mathbf{c} and \mathbf{d} . Layer labeling results of Figs. 1(a) and (b) are denoted as l_o and m_o , respectively. Using the intersection points, \mathbf{c} and \mathbf{d} can be decomposed into multiple layers.

In histogram based contrast enhancement algorithms, the mapping function for each layer is estimated such that image details in each layer can be effectively enhanced. However, histogram partitioning using only the intensity channel can assign different labels to the neighboring pixels that have similar intensity and depth values. The background region inside the dotted circle as shown in Fig. 2(c) has similar intensity and depth values as input image but different labels are cluttered in the region. Thus, if we use contrast enhancement on this background region which results unnatural images. So we propose an algorithm that adjusts the histogram partitioning such that a same label is enforced for the pixels with the similar intensity and depth values.

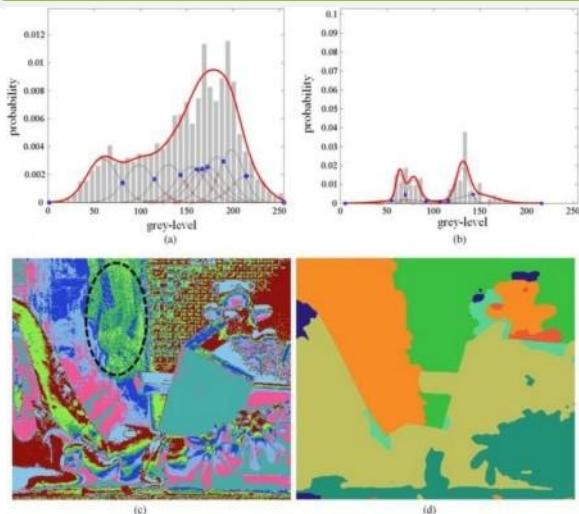


Figure 2: (a)-(b) Histogram and layer partitioning results of Figures. 1(a) and (b), respectively. (c) - (d) Layer labeling results of Figs. 1(a) and (b).

IX. CONCLUSION AND DISCUSSION

Module 1



Fig b1. Input haze image

Fig b2. haze free image



Fig c1. input haze image

Figc2 .haze free image

In this paper, we have proposed a novel linear color attenuation prior, based on the difference between the brightness and the saturation of the pixels within the hazy image. By creating a linear model for the scene depth of the hazy image with this simple but powerful prior and learning the parameters of the model using a supervised learning method, the depth information can be well recovered. By means of the depth map obtained by the proposed method, the scene radiance of the hazy image can be recovered easily. Experimental results show that the proposed approach achieves dramatically high efficiency and outstanding dehazing effects as well.

Although we have found a way to model the scene depth with the brightness and the saturation of the hazy image, there is still a common problem to be solved. That is, the scattering coefficient β in the atmospheric scattering model cannot be regarded as a constant in inhomogeneous atmosphere conditions. For example, a region which is kilometers away from the observer. Therefore, the dehazing algorithms which are based on the atmospheric scattering model are prone to underestimating the transmission in some cases. As almost all the existing single image dehazing algorithms are based on the constant assumption, a more flexible model is highly desired. To overcome this challenge, some more advanced physical models can be taken into account. We leave this problem for our future research.

Experimental Results:

In order to evaluate the performance of the proposed algorithm, the Middlebury stereo test images [14] were used in our experiment. The depth images were obtained using the stereo matching algorithm [10] as shown in Fig. 3. The pixel values of the color images were then divided by 4 to simulate low-contrast input images.

Figure 3 Experimental results corresponding to the input images in Fig. 2s. (a) -(c) the resultant image obtained by [2], (d)-(f) the resultant image obtained by the proposed algorithm, (g), (i), (k): the magnified sub regions corresponding to (a)-(c), respectively, (h), (j), (l) the magnified sub regions corresponding to (d)-(f), respectively.



Using the same histogram partitioning and mapping curve generation methods in [2], the effectiveness of the proposed algorithm can be evaluated by comparing the results obtained with and without modifying the histogram

sub-intervals, respectively. Figure 4 shows that the layer labeling result became more spatially uniform as increased. We empirically found that lambda=1000 performed well in enhancing the contrast of images. The results given here after were obtained using

$$\lambda=1$$

ACKNOWLEDGEMENT

The author would like to thank Mr.K.Govinda Rajulu, M.Tech,PhD*, Assco.Professor& Hod for his assistance in preparing this proposed model.

REFERENCES

- [1] Qingsong Zhu , Jiaming Mai and Ling Shao "A fast single image Haze Removal algorithm using color attenuation prior", *IEEE Trans. On Image Proc.*, Vol. 24 , pp- 3522-3533, Jan 2015.
- [2] Y. Luo, T. Liu, D. Tao, and C. Xu, "Decomposition based Transfer Distance Metric Learning for Image Classification", *IEEE Transactions on Image Processing*, vol. 23, no. 9, pp. 3789-3801, September 2014.
- [3] Kaiming He, Member, IEEE, Jian Sun, Member, IEEE, and Xiaou Tang, Fellow, IEEE "Guided image filtering", *IEEE Trans. Pattern Analysis and Machine Intelligence* vol.35, 2013
- [4] K.b. Gibson,D.T.Vo and T. Q. Nguyen, —An investigation of dehazing effects on image and video coding||, *IEEE Trans. Image Processing (TIP)*, vol. 12, no. 2, 2012.
- [5] K. B. Gibson, D. T. Vo and T. Q. Nguyen, "An investigation of dehazing effectss on image and video coding", *IEEE Trans. Image Processing (TIP)*, vol. 12, no. 2, 2012.
- [6] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," *IEEE Trans. Pattern Analysis and Machine Intelligence (TPAMI)*, vol. 33, no. 12, pp. 2341-2353, 2011
- [7] Andrew Adams,Jongmin Back, Myers Abraham Davis.Fast.," High -Dimensional Filtering using the permutohedral lattice|| *Journal compilation* ,vol 29(2010)
- [8] Anat levin,Dani lischinski and Yair weiss.,"A closed -form solution to natural image matting" *IEEE Transactions on pattern analysis and machine intelligence* ,vol 30,no 2,february 2008
- [9] Zhou Wang, Member, IEEE, Alan C. Bovik, Fellow, IEEEHamid R. Sheikh, Student Member, IEEE, and Eero P.Simoncelli, Senior Member IEEE, —Image Quality Assessment: From Error Visibility to Similarity"*IEEE Transactions On Image Processing*, Vol. 13, No. 4, April 2004
- [10]J. A. Stark, "Adaptive image contrast enhancement using generalizations of histogram equalization," *IEEE Trans. Image Process.*, vol. 9, no. 5, pp.889-896, May 2000