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Removing atmosphric noise using channel selective processing for visual correction

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ABSTRACT
In this paper, we propose an effective image fog removal technique from a single input image. The approach uses extraction of minimized values of statistics of the fog-free outdoor images. It is based on a key observation–most images in fog-free outdoor images contain some pixels which have low values of luminescence in at least one color channel. Using this model, we can directly estimate the effective density of fog and recover a high quality fog-free image. The parameter of calculating the effective light intensity also gives the scattering estimates of the atmospheric light, the combined Laplace of the air-light is and minimum values gives us the basic map of light spread which is further used in the restoration of intensity. The transmission of intensity between the calculated fog values in the image give the estimate for the local transition between the intensity values, this factor helps in the color restoration of the affected image and estimates the proper restoration of image after removal of dense fog particles. The visibility is highly dependent on the saturation of color values and not over saturation, which accounts for image quality improvement. Results on various images demonstrate the power of the proposed algorithm.

Keywords *-Air-light, image restoration, intensity transmission, Laplace estimation, Min. values from channels, Padding.*

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I. INTRODUCTION

Images of outdoor scenes are usually degraded by the various turbulences in the atmosphere. Fog, Rain and smoke are such forms of atmospheric noises caused due to atmospheric absorption and scattering. The visual data received by the camera from the target point is attenuated along the line of sight. Furthermore, the incoming light is blended with the air-luminescence [5] (ambient light reflected into the line of sight by atmospheric particles). The degraded images lose the contrast and color. Since the amount of light deflection depends on the distances of the projected points from the camera, the degradation is spatial-variant. Fog removal is highly desired in both consumer and computational photography and far vision applications. First, removing fog can significantly increase the visibility of the scene and correct the color shift caused by the air-light. The fog-free image is more visually pleasuring. In most computer vision algorithms, from low-level image analysis to High-level usually assume that the input image is the Radiance. The fog removal can produce depth information and benefit many vision algorithms and advanced image editing. Fog can be a useful depth clue for scene understanding. The bad fog image can be put to good use.

Improving the quality of foggy or fog image falls into two broad categories: 1) Adjusting contrast related to visibility of the image, 2) Enhancing local contrast representing details of the image.

For improving visibility of a foggy image, defogging methods exist for color images [3][4]. The defogging methods perform in the spatial domain for increasing the image contrast. However, the spatial domain adjustment of the image contrast often de-grades the details within the image because the contrast adjustment in spatial domain can control the global contrast variation but cannot take local contrast variations into account. To reduce the loss of details, we propose a method to defog fog or smog in the spatial domain first and then enhance the local contrast in the transform domain.

II. BACKGROUND

Recently, image fog removal [1][8] has made significant progress. The efficiency of the entire de-fogging algorithm is based on the estimation made during calculation of the parameters for the process. Tan [8] observes that the fog-free image must have higher contrast compared with the input fog image and he removes the fog by using the local contrast of the foggy image. In general de-hazing is formulated as:

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

Where I is the observed intensity, J is the scene radiance, A is the global atmospheric light, and t is the medium transmission describing the portion of the light that is not scattered and reaches the camera. The goal of haze removal is to recover J, A, and t from I.

The results are visually compelling but may not be physically valid. Fattal [1] estimates the albedo of the scene and then infers the medium transmission, under the assumption that the transmission and surface shading are locally uncorrelated. Fattal's approach is physically sound and can produce impressive results. The proposed method also significantly reduces ringing artifact by increasing the local contrast along edge directions. Moreover, the proposed method adjusts the local contrast in each frequency component, whereas the conventional methods adjust the contrast in frequency bands. Consequently, the enhancement performance of the proposed method yields high quality images and is more robust compared to the conventional methods.

Our approach is physically able to handle distant objects even in the heavy fog image. We do not rely on significant variance on transmission or surface shading in the input image. Like any approach using a strong assumption, our approach also has its own limitation. The minimized values of channels may be invalid when the scene object is inherently similar to the air luminescence over a large local region and no shadow is cast on the object.

III. VISIBILTY ENHANCEMENT PARAMETERS

3.1 Minimum values from Channels

The minimized value extraction is based on the following observation on fog-free outdoor images: in most of the non-sky patches, at least one color channel has very low values at some pixels. In other words, the minimum intensity in such a patch should have least value. Formally, for an image J, we define:

$J^{min}(x) = \min (\min (J^c(y)))$ (1)

$c\in\{r,g,b\}$ $y\in\Omega(x)$

Our observation says that except for the sky region, the intensity of minimum pixel is low and tends to be zero, if J is a fog-free outdoor image. We call the minimized values of J, and we call the above statistical observation or knowledge the minimized values. The low intensities in the given channel are mainly due to three factors: a) shadows. e.g., the shadows of cars, buildings and the inside of windows in cityscape images, or the shadows of leaves, trees and rocks in landscape images; b) colorful objects or surfaces. e.g., any object (for example, green grass/tree/plant, red or yellow flower/leaf and blue water surface) lacking color in any color channel will result in low values in the observed channel; c) dark objects or surfaces. As the natural outdoor images are usually full of shadows and colors, the values of pixels in these channels of these images are really low!

In practice, even in clear days the atmosphere is not absolutely free from any particle. So, the fog still exists when we look at distant objects. Moreover, the presence of fog is a fundamental cue for human to perceive depth [2, 7]. This phenomenon is called aerial perception. If we remove the fog thoroughly, the image may seem unnatural and the feeling of depth may be altered. So we have to alter them at some extent optionally, keeping a very small amount of fog for the distant objects. The nice property of this modification is that we adaptively keep more fog for the distant objects.

3.2 Calculating Intensity Transmission

Here, we first assume that the air-light A is given. We will present an automatic method to estimate the atmospheric light. We further assume that the transmission in a local patch $\Omega(x)$ is constant. We denote the intensity transmission as t(x). Taking the min operation in the local patch on the fog imaging Equation (1), we have:

$Min(I^c(y)) = t(x) \min (J^c(y)) + (1-t(x)) Ac$ (2)

$y\in \Omega(x) y\in \Omega(x)$

Notice that the min operation is performed on three colour channels independently. This equation is equivalent to:

$Min(Ic(y)) = t(x) \min (Jc(y)) + (1-t(x))$ (3)

Then, we take the min operation among three colour channels on the above equation and obtain:

$Min(\min(Ic(y))) = t(x)\min(\min(Jc(y)))$(4)

$cy\in \Omega(x)$ Ac c $y\in \Omega(x)$ $Ac + (1 - t(x))$.

The color of the sky is usually very similar to the atmospheric light A in a fog image and we have:

Min (min(Ic(y))) →1, and t(x) →0, (5)
cy∈ Ω(x) Ac

Since the sky is at infinite and tends to zero transmission, the equation (5) gracefully handles both sky regions and non-sky regions. We do not need to separate the sky regions beforehand.
T(x) = 1−ω min (min(Ic(y))), (6)
c y∈ Ω(x) Ac
The above equation estimates transition for the fog minimum values and hence a nice property of this modification is that we adaptively keep more fog for the distant objects. The value of ω is application-based. We fix it to 0.95 for all results reported. It is roughly good but contains some block effects since the transmission is not always constant in a patch. In the next subsection, we refine this map using a padding method.

3.3 Image Padding

We notice that the fog imaging Equation (1) has a similar form with the image matting equation. A transmission map is exactly an alpha map. Therefore, we apply a soft matting algorithm [6] to refine the transmission. Soft padding method has also been applied by Hsu et al. [3] to deal with the spatially variant white balance problem. In both Levin's and Hsu's works, the t is only known in sparse regions and the padding is mainly used to extrapolate the value into the unknown region. In this paper, we use the padding to refine a coarser t which has already filled the whole image.

3.4 Laplace Estimation for Foggy Image

With the transmission map, we can recover the radiance by calculating Laplace according to window size using Equation (1). But the direct attenuation term J(x)t(x) can be very close to zero when the transmission t(x) is close to zero. The directly recovered radiance J is prone to noise. Therefore, we restrict the transmission t(x) to a lower bound t0, which means that a small certain amount of fog are preserved in very dense fog regions. The final scene radiance with use of Laplace is recovered as J(x) by:
J(x) =I(x) – A (7)
Max (t(x), t_0) +A
A typical value of t_0 is 0.1%.Since the radiance is usually not as bright as the air-light, the image after fog removal looks low vibrant.

3.5 Air Light

In most of the previous image methods, the air light A is estimated from the most fog-opaque pixel. For example, the pixel with highest intensity is used as the air light in [8] and is furthered refined in [1]. But in real images, the brightest pixel could on a white car or a white building. The calculated minimized values of a fog image approximates the fog denseness well, can use the low values to improve the air light estimation. We first pick the top 0.2% brightest pixels in the value RGB channel. This simple method based on the minimized pixel extraction is more robust than the "brightest pixel" method. We use it to automatically estimate the atmospheric lights for all images.

3.6 Color Optimized Image Restoration

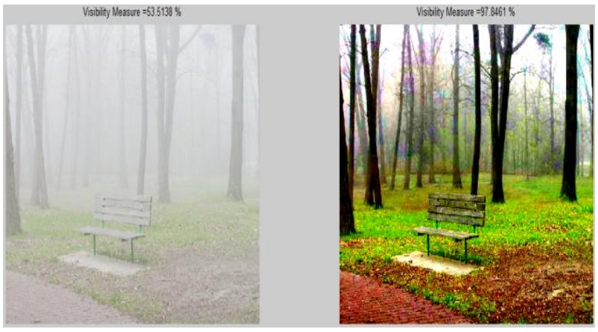
The color optimization is an algorithm that takes in a sequence of images of a constant scene taken over time and recovers the scene radiance in the absence of the visual effect of fog and a transmittance map which can be easily converted into a depth map. In this section we will see the results of this algorithm from the perspective of defogging. To account for an inaccurate assumption as movement of the direction of illumination which causes a change in the intensity of the scene radiance, we normalized each image by dividing by the average irradiance over a patch of the scene in the foreground. The reason we choose a patch of the scene in the foreground is that foreground objects are least affected by fog and therefore give us more accurate information on how the scene radiance intensity varies with changes in illumination. Further away objects would be affected greatly by fog and would therefore give inaccurate variations of scene radiance intensity.

IV. VISIBILITY ENHANCEMENT MEASURE

The metric takes as input a luminance image. The image is blurred by an 'optical' blur function and then blurred again to generate a local luminance image. These are combined pixel by pixel to form a visible contrast image.

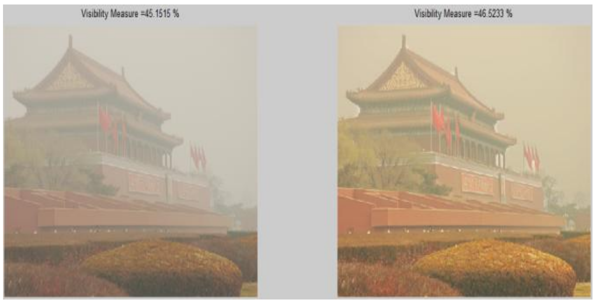
(a) Visibility = 53 % **(b)Visibility = 68 %**

Fig- 4.1 Defogging using previous technique



(c) Visibility = 53% **(d) Visibility = 97 %**

Fig- 4.2 Defogging using proposed technique



(e) Visibility = 45 % **(f) Visibility = 46 %**

Fig- 4.3 Defogging using previous technique

(g) Visibility = 45 % **(h) Visibility = 53 %**

Fig- 4.4 Defogging using proposed technique

(i) Visibility = 40 % **(j) Visibility = 49 %**

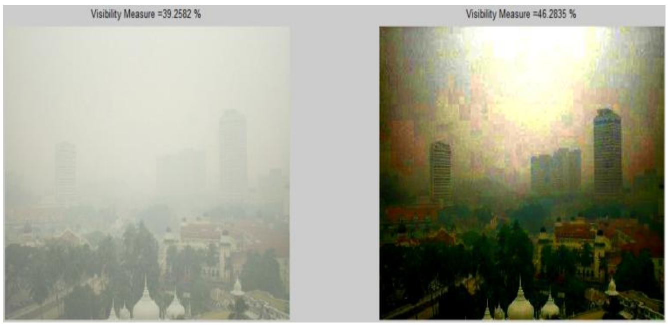
Fig- 4.5 Defogging using previous technique

(k) Visibility = 40 % **(l) Visibility = 96 %**

Fig- 4.6 Defogging using proposed technique

(m) Visibility = 39 % **(n) Visibility = 40 %**

Fig- 4.7 Defogging using previous technique



(o) Visibility = 39 % **(p) Visibility = 46 %**

Fig- 4.8 Defogging using proposed technique

The above group of images ((a) to (p))show the comparison of the improved visibility measure using the proposed and present techniques the (left side) images are the foggy original images and (the right) side images are the defogged images.

V. EXPERIMENTAL RESULTS

In our experiments, we perform the local min operator using Marcel van Herk's fast algorithm [9] whose complexity is linear to image size. Patch size is same for all images. The depth maps are computed using Equation (2) and are up to an unknown scaling parameters. The air lights in these images are automatically estimated using the method. Visibility has improved in terms of contrast and color vibrancy to a great extent as shown in figures. The colors of his result are often over saturated, since his algorithm is not physically based and may underestimate the transmission. Our method recovers the structures without sacrificing the fidelity of the colors.

VI. DISCUSSIONS AND CONCLUSIONS

The minimum value indexing is based on the statistics of the outdoor images. Applying the prior into the fog imaging model, single image fog removal becomes simpler and more effective. The limitation of most fog removal methods –is their non-preserving restoration towards saturation of color contrast for near scene objects. More advanced models [7] can be used to describe complicated phenomena near the horizon. We intend to investigate fog removal based on these models in the future.

REFERENCES

[1] R.Fattal. *Single image dehazing*.In SIGGRAPH, pages 1-9,2008.

[2] E. B. Goldstein. Sensation and perception. 1980.

[3] J.-P. Tarel and N. Hautière, "*Fast Visibility Restoration from a Single Color or Gray Level Image*", Proceedings of IEEE International Conference on Computer Vision (ICCV'09), pp.2201-2208, 2009.

[4] K. Gibson, D. V õ , and T. Nguyen, "*An investigation in de-hazing compressed images and video*", Proceedings of IEEEOCEANS Conference (OCEANS'10), Sep. 2010.

[5] H. Koschmieder. Theorie der horizontal ensichtweite. Beitr.Phys. Freien Atm., 12:171-181, 1924.

[6] A. Levin, D. Lischinski, and Y. Weiss.*A closed form solution to natural image matting*. CVPR, 1:61-68, 2006

[7] A. J. Preetham, P. Shirley, and B. Smits. A practical analytic model for daylight. In SIGGRAPH, pages 91-100, 1999

[8] R. Tan. *Visibility in bad weather from a single image.* CVPR,2008.

[9] M. van Herk. *A fast algorithm for local minimum and maximum filters on rectangular and octagonal kernels.Pattern Recogn*.Lett., 13:517-521, 1992.

Biographies and Photographs

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