EFFICIENT SINGLE IMAGE DEFOGGING USING RADIANCE CUBE AN L1 NORM BASED REGULARIZATION

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Abstract: Cameras performance are often reduce when images were captured in bad weather conditions such as fog, smog, rain ,and dust particles .The efficient fog effect removing of single input image using regularization is ultimate goal of this paper. First estimate the intensity of light by searching the sky area in haze image. Then forming the radiance cube using boundary conditions on transmission map. The efficient algorithm is based on variable splitting is also present. Based on few general assumptions the proposed method can restore the efficient haze free image with fine image features.
Keywords: Image Deblurring; Atmospheric light; Radiance; Image depth;

I. INTRODUCTION

A distance imaging system is affected by bad atmospheric weather conditions results in blur images with poor visibility. Haze is traditionally an atmospheric phenomenon where dust, fog, smoke and other dry particles obscure the clarity of the sky. Hence captured object get blurred with loss of contrast as of surrounded fog. Though camera resolution is good these particles scatter the radiance from objects results in lowering camera performance. The observed image consists of desired image with additional noise due to effects of blurring particles. Image deblurring means removing the effects of haze particles to improve object visibility. Early methods for removing of blur depend highly on image depth or multiple observations of same image with different orientation capture. There are various methods for non-single-image deblurring.

Example polarization methods use multiple images captured at different polarization angle, depth based methods use depth information obtained elsewhere or multiple images taken at different weather conditions. While these can achieve good results but extra information required is not available hence need for more flexible methods. It's more difficult in removing blur in single image since availability of less information. Fattal proposes a refined image formation model to account for the surface shading and the scene transmission. Under the assumption that the two functions are locally statistically uncorrelated, a haze image can be broken into regions of constant albedo, from which the scene transmission can be inferred. about image structure.

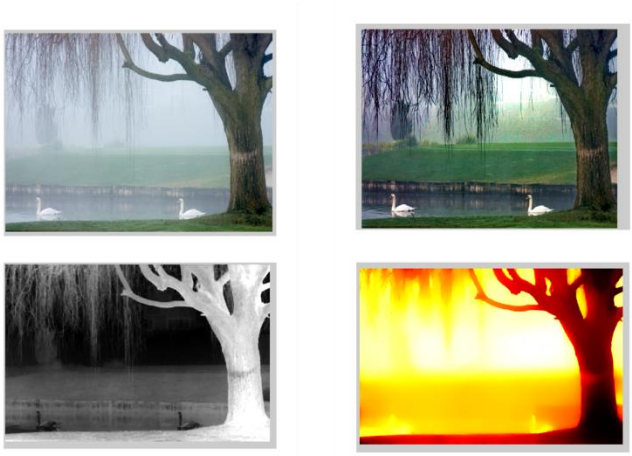


Figure 1.Image defogging from our method. From left to right(top)foggy image and defogged image.(bottom) boundary constraints and transmission map

He et al. Present an interesting image prior –darkchannel prior for single image dehazing. This prior comesfrom an observation that most local patches in haze-freeimages often contain some low intensity pixels. Our method benefits from three main contributions. Thefirst is a new constraint on the scene transmission. This simple constraint, which has a clear geometric interpretation, shows to be surprisingly effective to image defogging. Our second contribution is a new contextual regularization that enables us to incorporate a filter bank into image defogging. These filters help in attenuating the image noises and enhancing some interesting image structures, such as jump edges and corners. Our final contribution is an efficient optimization scheme, which enable us to quickly dehaze images of large sizes.

II. IMAGE DEFOGGING MODEL

A. Background

Basic model for image defogging is explained as below

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

Where I(x) is foggy observed image with pixel location x, J(x) is scene radiance i.e., the defogged image, A is global atmospheric light intensity which is assumed to be same for every pixel, and t (x) is scene transmission which is bounded in the interval $0 \leq t(x) \leq 1$ is always correlated with scene depth. Scene transmission shows how much light in the scene radiance is not scattered by haze particles and reaches the imaging system. The first term in the RHS of eq. (1) represents scene attenuation, which is how much scene information reaches the camera without scattering. Further

assuming that fog in the image is constant over the entire image (homogeneous) the transmission function can be expressed as

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

where d(x) is scene depth and β is coefficient of medium of extinction. The ultimate goal of image defogging is to get or recover J(x) from I(x) based on eq. (1). To get J(x) it requires estimate of t(x) and A. once we know both t(x) and A then we can easily recover J(x) by:

$$J(x) = \frac{I(x)-A}{[\max t(x),\varepsilon]^{\delta}} + A \quad (3)$$

The role of ε for avoiding devision by zero typically its value is 10^{-4},δ is used for fine tuning of haze effects serves as role of β in eq.2.

B. Boundary constarints.

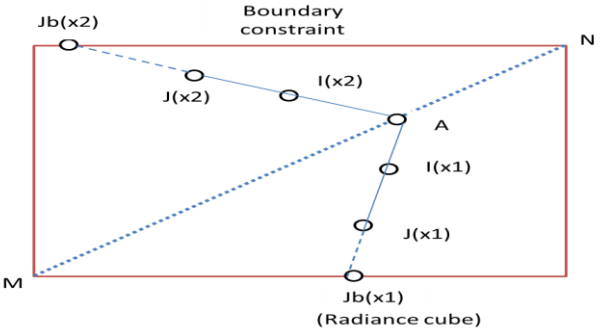


Figure 2 J(x) is the extrapolation result corresponds to each pixel x and cannot cross the boundary of radiance cube.

According to eq.1 every pixel in observed image I(x) is pushed towards global atmospheric light A as shown in fig 2. Hence we recover clear pixel J(x) from linear extrapolation from A to I(x). The appropriate amount of extrapolation is given by

$$t(x)=\frac{||I(x)-A||}{||J(x)-A||} \quad (4)$$

Scene radiance of each image is always bounded by:
M≤ J(x)≤ N
Where M and N are two vectors relevant to that figure.

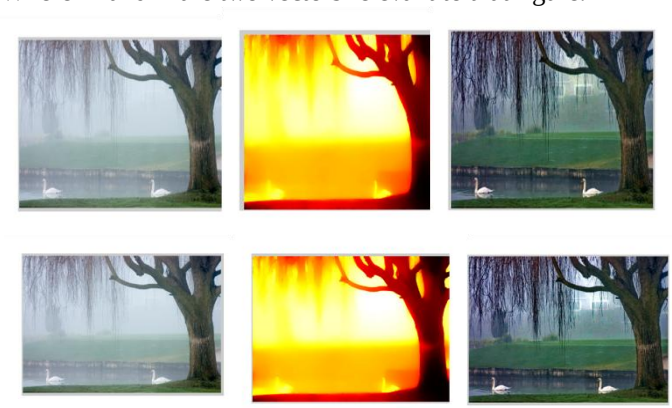


Figure 3 comparisons between dark channel method by He et al method and boundary constrains method.(top) foggy image, transmission map and cleared image of He et al method. (bottom) corresponding image of boundary constrains method.

C. Dark channel prior.

Images captured in outdoor without haze effect He et al proposed a method called dark channel prior. According to this there exists a one more color channel which has very low pixel intensity. The dark channel is defined as

$$I^{dark}(x) = min_{c\epsilon[r,g,b]}(min_{y\epsilon\Omega(x)}/I^{C}(Y)) \quad (5)$$

Where $I^{C}$is a color channel of I, and $\Omega(x)$ is local area centered at X. They examined nearly 5000 day time haze free images and found that 75% of the pixel in the dark channel had zero values and intensity of 90% of pixels were 25(maximum value was 255). They attributed that low intensity in the dark channel to three factors: shadows, colorful objects and dark objects. Reference to foggy images the dark channel is not dark. Due to added air light the foggy image is brighter than the corresponding clear image. Hence the dark channel for the dark foggy images will have higher intensity. Thus intensity of dark channel represents the fog density and object distance from the camera. Hence the dark channel method for foggy image can be illustrated as

$$I^{dark}(x) = min_{c\epsilon[r,g,b]}(max_{y\epsilon\Omega(x)}/I^{C}(Y)) \quad (6)$$

Applying above equation the boundary constraints can be shown below

$$t_b(x) = \min\{\max_{c\epsilon[r,g,b]}(\frac{A^c-I^c(x)}{A^c-M^c},\frac{A^c-I^c(x)}{A^c-N^c},1)\} \quad (7)$$

Where $t_b(x)$is the lower bound of t(x) as shown below

$$0\leq t_b(x) \leq t(x)\leq 1 \quad (8)$$

D. Weighted L1 norm based reguralization

Generally, Depth value is constant all over the pixel in the local image. Using this assumption, with help of boundary constraints we can able to derive patch wise transmission. The drawback of contextual assumption is when there is abrupt change in the image depth in the local patches which results in significant halo artifacts. Using weighting function over constrains we can overcome this problem.

$$W(m, n)\,(t(m)-t(n))\approx\approx 0 \quad (9)$$

Where m, n are neighboring pixel. W(m,n) acts as switch between constraints of m,n. when w(m,n)=0,then contextual constraints of t(x), of m, n is cancelled. Finding w (m, n) is a difficult task because it totally depends on image depth. If image depth is small between neighboring pixel is then value of w(m,n) is large so we can get t(x) and if image depth is large between two neighboring pixel w(m,n) is tending towards zero . But due to lack of depth information in single image, we cannot able to construct t(x) using depth map. Generally in a local patch, image depth jumps when there is a sudden noticeable change in the intensity value of neighboring pixel, pixel with same intensity and color share similar depth. Hence using color or intensity difference between local pixels we construct weighting function as follows.

$$w(m,n) = e^{-||I(m)-I(n)||^2/2\rho^2} \quad (10)$$

$\rho$is a prescribed parameter. Integrating weighted contextual constraints over whole image domain we obtain following contextual regularization on t(x):

$$\int_{m\epsilon\,\Omega}\int_{y\epsilon}\cdot w(m,n)|t(m)-y(y)|dmdn \qquad (11)$$

Where Ω represents image domain. On discretizing above equation we get

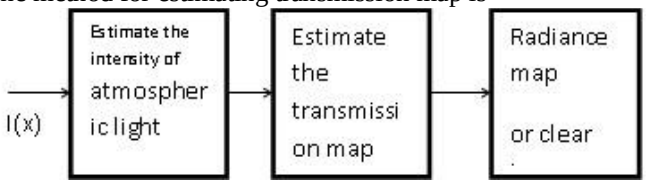
$$\sum_{i\in I}\sum_{j\in w_i} w_{ij}\,|t_i - t_j| \qquad (11)$$

Introducing set of differential operators on eq.(11)

$$\sum_{j\in w} ||W_j{}^{\circ}\left(D_j \otimes t\right)||_1 \qquad (12)$$

III. ESTIMATION OF SCENE TRANSMISSION

The method for estimating transmission map is



To compute radiance map, we require transmission map t(x) and atmospheric light(A).This method estimate A by with filtering each color channel of an input image by a minimum filter with a moving window. It gives similar same result as He et al method but perform more efficiently.

$$t^{\sim}(x) = \max_{y\epsilon w_x} t_b(y) \qquad (13)$$

The optimal transmission function t(x) by minimizing the following objective function

$$\frac{\lambda}{2}||t - t^{\sim}||^2 + \sum_{j\in w} ||W_j{}^{\circ}\left(D_j \otimes t\right)||_1 \qquad (14)$$

IV. EXPERIMENTAL RESULTS

Figure 3(below) illustrates some examples of our dehazing results and the recovered scene transmission functions. Rich details of images with vivid color information in the haze regions can recover from our method. It should be pointed out that the estimated transmissions of the right three images in the figure cannot be regarded as a scaling version of the depth map, since the hazes in the images are not homogeneous. These cases commonly occur to the captured scenes with a large area of clear sky region. Actually, the transmission function reflects the density of the hazes in the captured scene From the figure, we can see the estimated transmissions by our method are quite consistent with our intuitions.

Condition	Particle type	Radius(μm)	Concentration(cm^{-3})
Air	Molecule	10^{-4}	10^{19}
Haze	Aerosol	$10^{-2} - 1$	$10^{3} - 10$
Fog	Water droplet	1-10	100-10
Cloud	Water droplet	1-10	300-10
Rain	Water drops	$10^{2} - 10^{4}$	$10^{-2} - 10^{-5}$

Table 1 Weather particles associated particles type and concentrations

Figure 6 (top) foggy image and (bottom) corresponding defogging images

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