Single Image Dehazing

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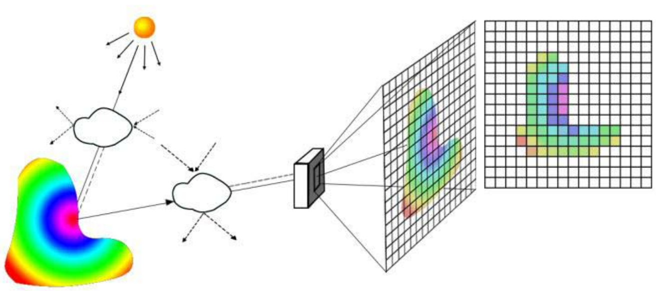
***Abstract*— Haze(or fog, mist, and other atmospheric phenomena) is a main degradation of outdoor images, weakening both colors and contrasts. Single image haze removal has been a challenging problem due to its ill-posed nature. We investigated two methods for Haze-removal, one being Color Attenuation Prior and the other being Dark Channel Prior from a single input hazy image.**

I. INTRODUCTION

The dark channel prior is a kind of statistics of outdoor haze-free images. It is based on a key observation that 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.
On the other hand for color channel prior we create a linear model for modeling the scene depth of the hazy image. Using this prior and learning the parameters of the model with a supervised learning method, the depth information can be well recovered. With the depth map of the hazy image, we can easily estimate the transmission and restore the scene radiance via the atmospheric scattering model, and thus effectively remove the haze from a single image.

II. BACKGROUND READ

Both the methods for Image Haze removal has been based on atmosphere degradation model.



Light is scattered by Haze till it reach our Imaging device, as a result we get a degraded Image recorded. If we are able to model this forward degradation process, we might probably reverse it. With this in mind we seek for some similarities in Hazy Images and also in Haze free counterparts.

$$\mathbf{I}(x) = \mathbf{J}(x)t(x) + \mathbf{A}(1 - t(x)), \tag{1}$$
$$t(x) = e^{-\beta d(x)}, \tag{2}$$

I(x) - The Received Image(Hazy)
J(x) - Scene radiance representing the haze-free image
A - Atmospheric light
t(x) - Medium transmission
β - Scattering coefficient of the atmosphere
d(x) - Depth of the scene

I, J and A are all three-dimensional vectors in RGB space. Since I is known, the goal of dehazing is to estimate A and t, then restore J according to Equation (1).

III. APPROACH

A. Color Attenuation Prior

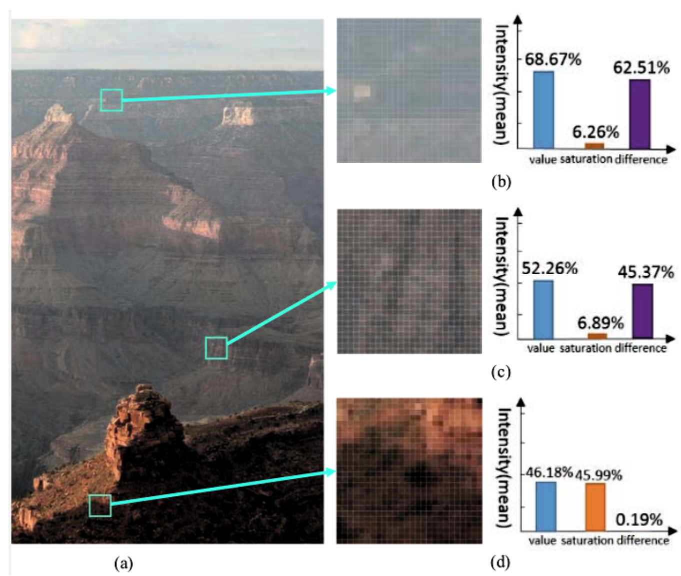
In ideal case, the range of d(x) is [0,+∞) as the scenery objects that appear in the image can be very far from the observer, and thus we have:

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

. The above equation shows that the intensity of pixel, which makes the depth tend to infinity, can stand for the value of the atmospheric light(A). Hence we define a threshold $d_{threshold}$ wherein,

$$I(x) = A, \ d(x) \geq d_{threshold}$$

. The task of dehazing can be thus converted to depth information restoration. However, it is challenging task to obtain depth-map from a single Hazy Image.



As can be seen from the above figure that concentration of Haze is positively correlated to difference between Values and Saturation. Also concentration of Haze increases along with the change of scene depth in general, we can make an assumption that the depth of scene is positively correlated with the concentration of Haze.

$$d(x) \propto v(x) - s(x)$$

. a more accurate expression was proposed:

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

where, $\theta_0, \theta_1, \theta_2$ are the unknown linear coefficients, ϵ can be regarded as a random error model. It was proposed that ϵ be Gaussian distributed with zero mean and σ^2 variance. One of the most important advantage of this model is that it has the edge-preserving property. To compute values of $\theta_0, \theta_1, \theta_2$ the system was trained on a set of Hazy Images and their corresponding ground truth Depth maps available. The values found in the reference were: $\theta_0 = 0.121779$, $\theta_1 = 0.959710$, $\theta_2 = -0.780245$, $\sigma = 0.041337$.

after putting these values in equation:

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

we get the corresponding depth-map, we then take local minimum of the obtained raw depth-map iterating over a window size of r=15. This ensures that no white area of desired scene mistaken as Atmosphere.
Consider the location of pixels with value top 1% in the Depth-map. The intensity values of the corresponding pixels in the Hazy Image are taken and maximum value among-st them is taken to be value for Atmosphere(A).

Fig: Input Hazy Image 1

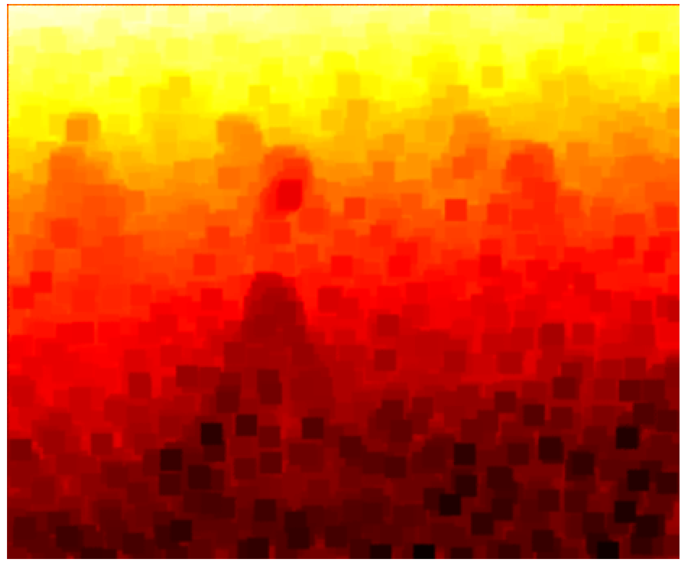


Fig: Depth Map 1

Fig: Input Hazy Image 2

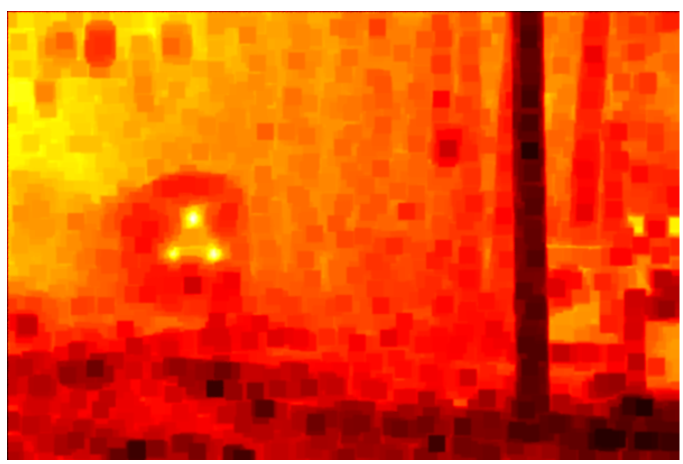


Fig: Depth Map 2

1) Guided Filter: Once we have the raw depth-map we pass it through a Guided-Filter to smooth-en out the blocky artifacts as well as preserve the edges that are there in the original Image.Guided-Filter can be described by a simple expression:

$$q_i = a_k I_i + b_k, \ \forall i \in w_k$$

where:

- w_k defines a window of size 'r'$(mask)$
- (a_k,b_k) are some linear coefficients assumed to be constant in the window w_k
- I is the guidance Image $(Depth\ map\ before\ local\ minimum)$
- q is the Output image$(Guided\ Depth\ map)$
- p is the marker image $(Depth\ map\ after\ local\ minimum)$

The cost function being :

$$E(a_k, b_k) = \Sigma_{i \in w_k}((a_k I_i + b_k - p_i)^2 + \epsilon a_k^2)$$

after solving it for minimum we get corresponding values of (a_k, b_k) to be :

$$a_k = \frac{\frac{1}{|\omega|}\sum_{i\in\omega_k} I_i p_i - \mu_k \bar{p}_k}{\sigma_k^2 + \epsilon}$$

$$b_k = \bar{p}_k - a_k \mu_k.$$

or

$$a = cov_{Ip}/(var_I + \epsilon)$$

$$b = mean_p - a.mean_I$$

using this we find an approximation to correct depth-map d(x) and the reconstruct J(x) from the equation:

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

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

The min max operation ensures that amount of noise is restricted and β is considered to be 1.0

Fig: Input Hazy Image 1

Fig: Haze Free output 1

Fig: Input Hazy Image 2

Fig: Haze Free output 2

B. Dark Channel Prior

In dark channel prior, the transmission map is obtained from the Dark channel Prior, rather than Depth-map. Moreover, it is difficult to estimate the depth map and the problem is under-constrained if the input is only a single Hazy Image.

The Dark channel prior is based on the statistics of outdoor haze-free images. In most of the local regions which do-not cover the sky, some pixels very often have very low intensity in at-least one of the color channels(RGB). In hazy images the intensity of these dark pixels in that channel is mainly contributed by the air-light. Therefore, these dark pixels can directly provide an accurate estimation of the haze transmission. Combining a haze imaging model and soft matting interpolation method, we can recover a high-quality haze-free image and produce a good depth-map.
For an arbitrary image J, its dark channel is given by:

$$J^{dark}(x) = min_{y\in\Omega(x)}(min_{c\in\{r,g,b\}}J^c(y))$$

where J^c is the color channel of J and $\Omega(x)$ is the local patch centered at x. A dark channel is outcome of two operations:

- Minimum performed on each pixel $min_{c\in\{r,g,b\}}$
- Minimum performed over the entire patch $min_{y\in\Omega(x)}$

Using the concept of a dark channel, our observation says that if J is an outdoor haze-free image, except for the sky region, the intensity of Js dark channel is low and tends to be zero:

$$J^{dark} \to 0$$

This is called as observation prior.
Due to the additive airlight, a hazy image is brighter than its haze-free version where the transmission t is low. So, the dark channel of a hazy image will have higher intensity in regions with denser haze.

$$\frac{I^c(\mathbf{x})}{A^c} = t(\mathbf{x})\frac{J^c(\mathbf{x})}{A^c} + 1 - t(\mathbf{x})$$

$$J^{\text{dark}}(\mathbf{x}) = \min_{\mathbf{y}\in\Omega(\mathbf{x})}\left(\min_{c\in\{r,g,b\}} J^c(\mathbf{y})\right)$$

$$J^{\text{dark}}(\mathbf{x}) = \min_{\mathbf{y}\in\Omega(\mathbf{x})}\left(\min_{c} J^c(\mathbf{y})\right) = 0$$

$$\min_{\mathbf{y}\in\Omega(\mathbf{x})}\left(\min_{c}\frac{J^c(\mathbf{y})}{A^c}\right) = 0$$

$$\tilde{t}(\mathbf{x}) = 1 - \min_{\mathbf{y}\in\Omega(\mathbf{x})}\left(\min_{c}\frac{I^c(\mathbf{y})}{A^c}\right)$$

Hence $transmission = 1 - Dark\ channel\ Prior$, we now perform softmax operation by using Guided Filter on this transmission map. Atmosphere is again chosen to be maximum intensity pixel in the patch of the hazy image given by location of top 1% intensity points on Depth-map.

Fig: Input Hazy Image 1

Fig: Dark Channel 1

Fig: Dehazed Image 1

Fig: Input Hazy Image 2

Fig: Dark Channel 2

Fig: Dehazed Image 2

We find that Images get oversaturated at times using Dark channel prior, especially those containing scene of atmosphere.

IV. Discussion

The key challenges faced were in obtaining the depth parameters $\theta_0, \theta_1, \theta_2$ since we did not have many images to train upon, our results varied widely from results of Jiaming Mai et. al, for demonstration purposes we have used the values of parameters as obtained by them. Another challenge worth mentioning was the choice of r (the block size) for local minimum and also in finding Dark Channel Prior. A large value for r leaded to large blocks (patches) in depth map, which even after guided filtering didn't result in a good dehazed image. The choice of r should also be chosen according to size of the image. All our codes are available to use along with reasonable documentation. You can find the code on github:

CAP(Color Attenuation Prior) -
https://github.com/TummanapallyAnuraag/ImgDehazing

DCP(Dark Channel Prior) -
https://github.com/M-ark17/Image-processing

References

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