IMPLEMENTING A FAST SINGLE IMAGE HAZE REMOVAL ALGORITHM USING COLOR ATTENUATION PRIOR

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ABSTRACT

In this report, we implemented the paper "A Fast Single Image Haze Removal Algorithm Using Color Attenuation Prior" [1]. We used the color information of the image to store its depth information. On the image's depth map, we applied the atmospheric scattering model to remove the haze and restore the scene radiance.

***Index Terms*—** Dehazing, two, three, four, five

1. INTRODUCTION

Image dehazing is a problem in Image processing and computer vision domain that has been a topic of research for quite a while. We attempted to solve this problem using atmospheric scattering model. The brightness and saturation varies in a hazy image. The concentration of haze is directly dependent on the brightness (value) and saturation of the pixel. In a hazy image, the saturation of the pixel is less and the difference between value and saturation is high, and vice-versa for haze-free portions of the image. The concentration of haze increases along with the increasing depth in the image. This means that as the depth increases, the value of the image increases and saturation of the image decreases.

Using this depth map, we can restore the image via the atmospheric scattering model, which is discussed later in the paper.

2. ATMOSPHERIC SCATTERING MODEL

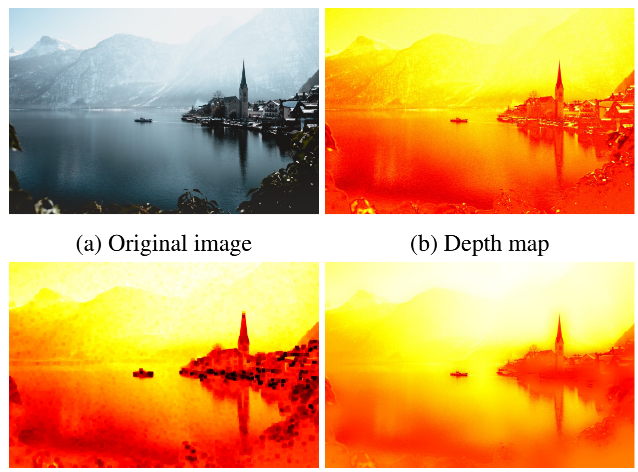
In this paper, we use atmospheric scattering model proposed by McCartney in 1976. This model describes the structure of the Hazy Image as:

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

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

Here $\mathbf{J}$ and $\mathbf{I}$ corresponds to the haze-free and hazy images respectively. t(x) is a factor that depends on t and β. $\mathbf{A}$(x) refers to the atmospheric light present at the scene. d(x) is the depth of the pixel and β is proportional amount of scattering done by the atmosphere. Increasing β will increase the strength of dehazing in the image. This effect is discussed later in the paper. In the equation all the bold quantities represent a 3D vector in RGB space whereas non-bold quantities are scalars.

We have estimated the value of **A** using the



(a) Original image (b) Depth map

(c) Depth map after min-filtering (d) Refined depth map

Fig. 1: Refinement of depth map

3. ESTIMATING ITS DEPTH INFORMATION

3.1. Calculating depth map

Assuming depth to be a function of value and saturation along with some bias and noise (additive gaussian noise), we linearly combine these terms to form the equation:

$$d(x) = \theta_0 + \theta_1 v(x) + \theta_2 s(x) + N(0, \sigma) \tag{3}$$

The can use depth maps and hazy images to actually use gradient descent to get the value of these coefficients. We used the coefficients given in the paper. Due to lack of resources and time we did not implement the linear model used to obtain the coefficients. The model was not trained due to the fact that training the model would have been computationally costly. Hazy images with depth maps are not available online so therefore we have to create our own dataset to accomplish this task. We performed the required preprocessing to generate the dataset by generating random depth maps and using haze free images to create hazy images to perform the learning.

3.2. Need for min-filtering

Depth is generated using the saturation and value of the pixels. This might cause a problem where the objects in the foreground are white. We have used the snowy lake-side image to illustrate this effect. Observe in Figure 1b, the roof tops seem to have a very high value of depth which is not really the case. To counter this effect we use min filtering with a small neighbourhood r (size of the min filter). Min filter filters out the small areas with very high depth leaving the actual high depth areas intact.

3.3. Refining the min-filtered depth map

The min-filtered depth map is blocky in nature (see Figure 1c), we cannot use this depth map to restore the scene radiance. Therefore to restore its original structure, we need to refine the obtained min filtered depth map. We tried the following two methods to do the same.

3.3.1. Gaussian blurring

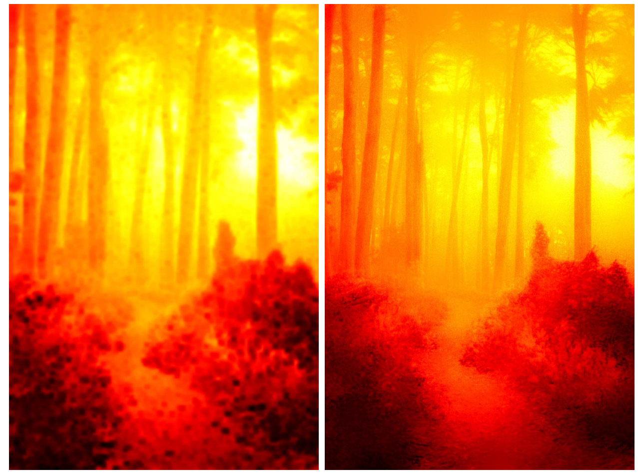
We tried Gaussian filtering as a way of removing the new found hard edges found in the image. The effect of which is shown in Figure 2a. Gaussian filter worked well with the images but an artifact was visible in the images (see Figure 2c). The algorithm dehazes the area surrounding the deep objects as well, this is due to the depth map being blurred. The *leakage* of depth is visible in the blurred depth map.

3.3.2. Guided Filtering

As suggested by the paper [1], we tried guided filtering which uses another image as a reference to perform smoothing, we used the original depth map obtained from the equation as the guide image and the min filtered depth map as the filtering image. The results can be seen in Figure 2d and 2b.

4. RESTORING THE SCENE RADIANCE

To restore the scene radiance, we need to estimate the atmospheric light. To estimate the atmospheric light, we pick the top 0.1 percent brightest pixels of the depth map and select the pixels of highest intensity in the corresponding hazy image **I** among these brightest pixels as **A** (atmospheric light)



(a) Depth map after gaussian blurring (b) Depth map after guided filtering

(c) Dehazed image after gaussian blurring (d) Dehazed image after guided filtering

Fig. 2: Gaussian blurring vs Guided filtering

Now that we have calculated the depth map and the atmospheric light, we can restore the scene radiance of the image, using the equation below:

$$\mathbf{J}(x) = \frac{\mathbf{I}(x) - A}{max(0.1, min(e^{-\beta d(x)}, 0.9))} + A \tag{4}$$

5. RESULTS

5.1. Comparing images with different scattering coefficient (β)

As explained in Section 2, β refers to the strength of atmospheric scattering. If we use a higher value of β in the algorithm, the algorithm will assume higher haze. Therefore the dehazing effect produced will be more profound. Mathematically increasing β has a similar effect to increasing

(a) Original image

(b) Result with $\beta = 0.5$

(c) Result with $\beta = 0.8$

(d) Result with $\beta = 1$

(e) Result with $\beta = 1.2$

(f) Result with $\beta = 1.5$

Fig. 3: Final results with different scattering coefficients (β)

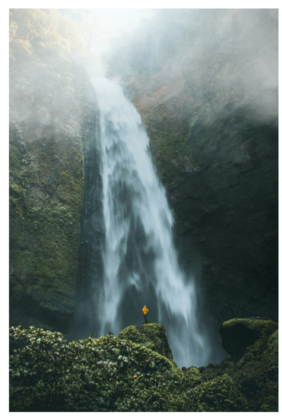
depth. Here we have a few images to demonstrate the effect of changing β on dehazing. Figure 3a shows the original image followed by the results of dehazing with varying β.

6. FUTURE WORK

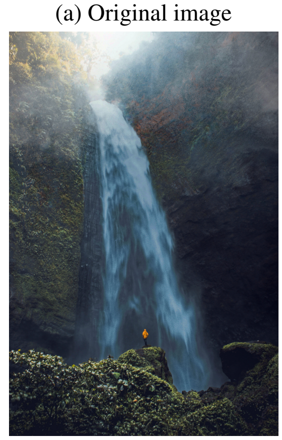
If we are able to infer more details by considering the color values of a small neighbourhood around each pixel instead of just one pixel we might be able to vary the value of beta as well. There might be a scope for this project to improve the quality and make underwater images better, instead of hazing there we'll be removing the distance based color deprecation which darkens the far off objects.

7. LIMITATIONS

Images with large low saturation areas, especially including large white objects are some of the cases where the algorithm is not able to perform well. this is due to the fact that these white depth regions are considered to be of high depth despite being rather near. For example see figure 4, here the white portion of the stream is removed by the algorithm assuming it to be haze.



(a) Original image



(b) Dehazed image

Fig. 4: Results on an image having a large white area

8. 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, no. 11, pp. 3522–3533, Nov. 2015.