第十一屆台灣工業與應用數學會年會 (大學生組)   National Taiwan Normal University, Taipei, Taiwan, May 20-21, 2023

TWSIAM   國立中央大學 National Central University

Single Image Haze Removal Using Three Different Methods

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Abstract

The development of modern society is permanently accompanied by environmental pollution. Haze phenomena are becoming more and more frequent, which greatly affects our daily lives. Haze is a common atmospheric phenomenon caused by small floating particles such as dust and smoke in the air. These floating particles absorb and scatter light to a prodigious extent, leading to a decrease in the quality of captured images. Under the influence of haze, many practical applications such as image monitoring, remote sensing, and automatic driving are easily threatened, and advanced computer vision tasks such as detection and recognition are difficult to accomplish. Therefore, image dehazing has become an increasingly important technology with significant research value and a challenging task as well. In this report, I will use three different methods to remove the haze. The first method is using "Dark Channel Prior," the second method is using "Color Attenuation Prior," and the third method is using "Multilayer Perceptron."

Problem Description

Background

In computer vision and computer graphics, the model widely used to describe the formation of a haze image is as follows:

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

where I is the observed intensity, J is the scene radiance, A is the global atmospheric light, and t is the medium transmission. When the atmosphere is homogenous, the transmission t can be expressed as:

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

where β is the scattering coefficient of the atmosphere. It indicates that the scene radiance is attenuated exponentially with the scene depth d.

Method 1: Dark Channel Prior (DCP)

He et al.[1] propose a dark channel prior - a kind of statistics of the haze-free outdoor images. It is based on a key observation - most local patches in haze-free outdoor images contain some pixels which have very low intensities in at least one color channel. For an image J , we define

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

where J^c is a color channel of J and $\Omega(x)$ is a local patch centered at x. The direct attenuation $J(x)t(x)$ can be very close to zero when the transmission $t(x)$ is close to zero. The directly recovered scene radiance J is prone to noise.

Method 2: Color Attenuation Prior (CAP)

Zhu et al.[2] propose a color attenuation prior - the brightness and the saturation of pixels in a hazy image vary sharply along with the change of the haze concentration, we have:

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

where d is the scene depth, c is the concentration of the haze, v is the brightness and s is the saturation.

Create a linear model as follows:

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

where x is the position within the image, θ_0, θ_1, θ_2 are the coefficients, $\varepsilon(x)$ is a random variable representing the random error, and ε can be regarded as a random image.

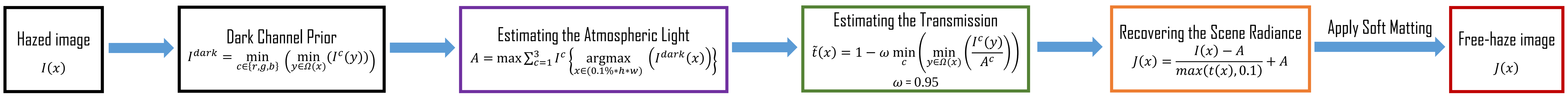
Method 3: Multilayer Perceptron (MLP)

Salazar-Colores et al.[3] propose a method used a multilayer perceptron –an artificial neural networks with at least three layers of. The main idea behind the proposed method is the strategy to estimate the accurate transmission map and the introduction of an additional step for improving the contrast image. In order to improve the contrast of the recovered image, the luminance was modified by introducing the spacecolor $L*a*b$ and a contrast stretching strategy. The multilayer perceptron is trained in terms of mean squared error using a training set of 80 images.

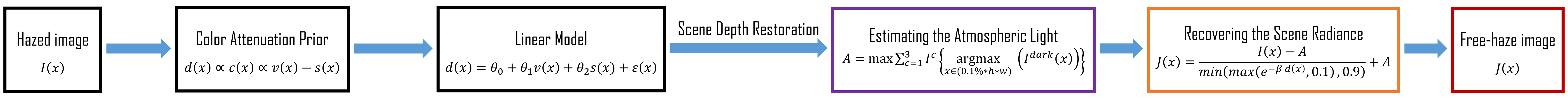
Experiment

We will use different types of images in the experiment and compare their PSNR and SSIM index. The first type is a black-and-white image with 256×256 pixels of which values decrease from 255 to 0. The second type is also a black-and-white image with 256×256 pixels of which values include merely 0 and 255. The third type are images generated by using MATLAB colormap, where colormap spring and colormap hsv are applied, respectively. The last type are real-world images, which are classic images and photos taken by myself. In this experiment, haze is added by myself using MATLAB code.

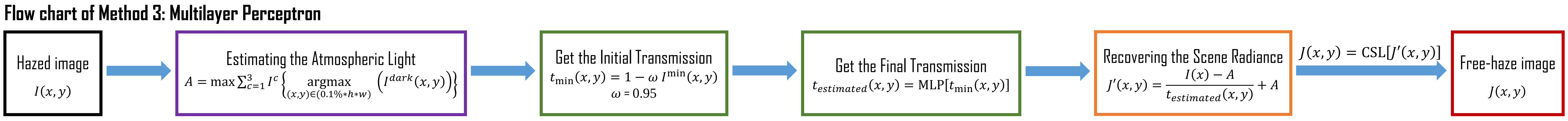
Flow chart of Method 1: Dark Channel Prior



Flow chart of Method 2: Color Attenuation Prior



Flow chart of Method 3: Multilayer Perceptron



Results and Discussion

The images from left to right are original image, hazed image, after using DCP, using CAP, and using MLP, respectively.

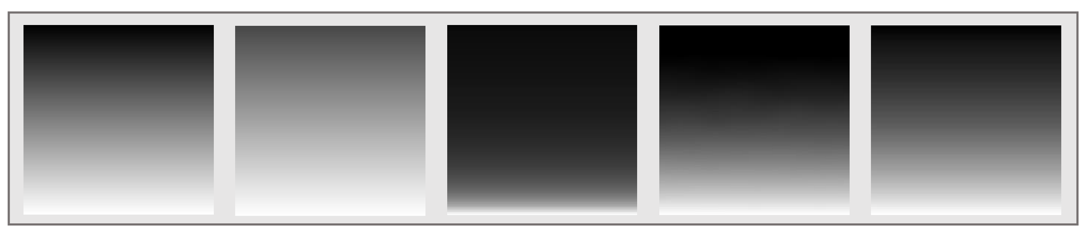


Figure 1.

The result of using DCP is the most different from the original image, and the image has an overall darker tone.

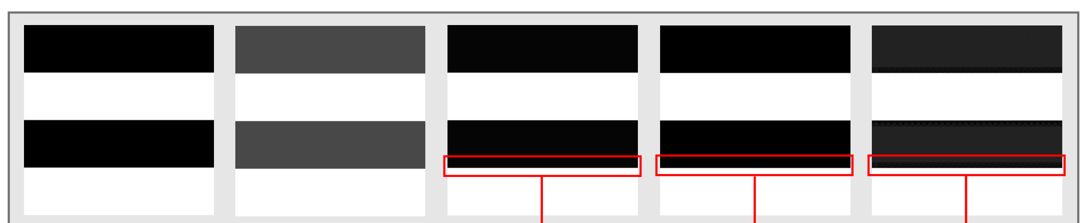
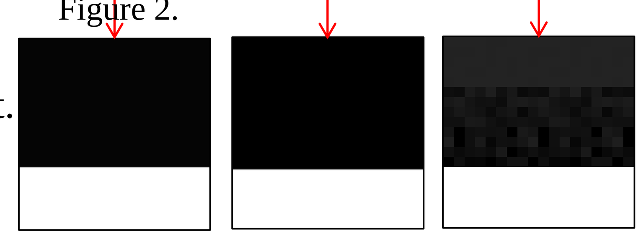


Figure 2.

The result of using MLP doesn't have a good effect. We can see many blocks in this dehazing image.



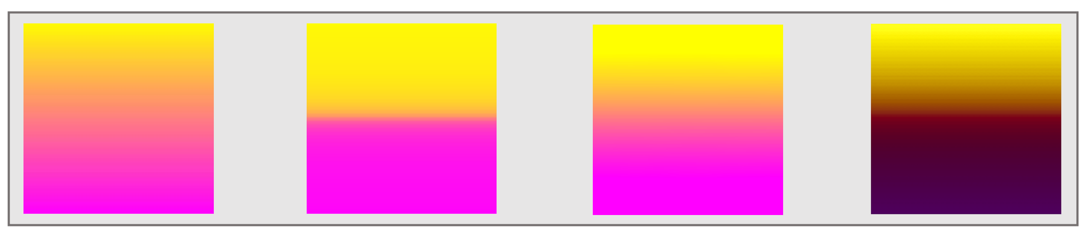


Figure 3.

The result of using MLP is changing color.

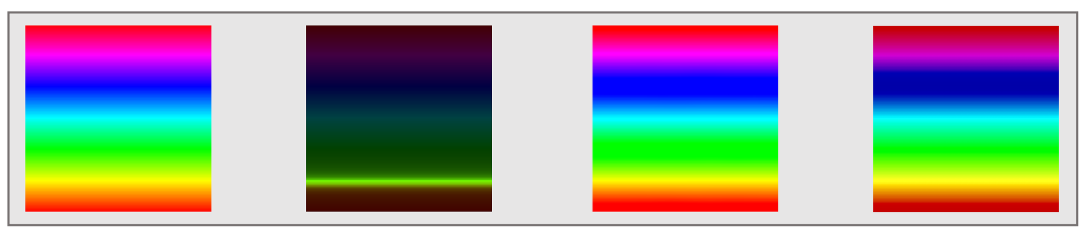


Figure 4.

Green is the only undistorted color after applying DCP.

Figure 5.

The result of using CAP looks more natural.

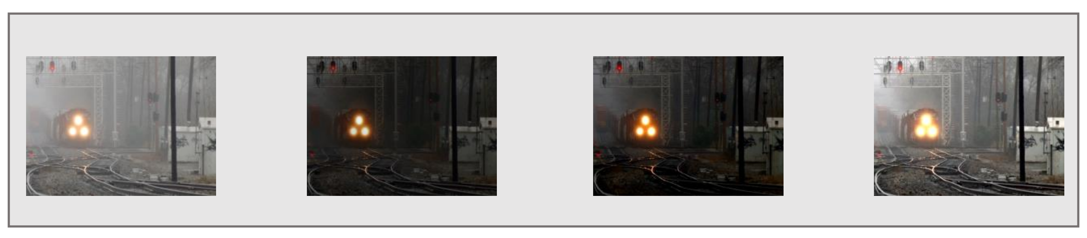


Figure 6.

The result of using DCP and CAP were faded the brightness.

Figure 7.

The result of using CAP is changing the tone of the image.

Figure 8.

The result of using DCP is overexposed.

PSNR	Figure 1.	Figure 2.	Figure 7.	Figure 8.
DCP	9.3345	37.1617	8.6280	16.2446
CAP	14.5204	Inf	17.6444	15.9018
MLP	19.2423	20.9718	19.5516	26.9425

A greater PSNR value indicates better image quality.

SSIM	Figure 1.	Figure 2.	Figure 7.	Figure 8.
DCP	0.5881	0.6358	0.4559	0.8765
CAP	0.6541	1.0000	0.5818	0.8755
MLP	0.9398	0.5374	0.8587	0.9642

A value closer to 1 indicates better image quality.

Conclusions

By observation, I noticed that MLP has a greater PSNR value and its SSIM index value is closer to 1, but CAP performs better than MLP in some particular cases. All parameter values for the experiment were held constant. It is possible that varying the parameter values would yield differing results.

Dark Channel Prior (DCP)

✕ Soft matting requires an intensive computational process. Whether the light is too bright or too dark, neither of which can be handled.

Color Attenuation Prior (CAP)

▪ By creating a linear model and learning the parameters using a supervised learning method, the depth information can be well recovered.

✕ If the concentrations of haze are the same in the image, it is hard to result in a good dehazing effect.

Multilayer Perceptron (MLP)

▪ Superior performance is achieved in terms of restoration quality compared with other dehazing methods.

✕ If the image is generated from some maps with specific colors, the result will end up with odd colors.

Future Work

To achieve the best dehazing effect, I aim to develop a suitable dehazing method that fits each particular condition, and I would like to improve the method using MLP.

References

[1] Kaiming He, Jian Sun, and Xiaoou Tang, "Single image haze removal using dark channel prior," *IEEE Transactions on Patter Analysis and Machine Intelligence*, Vol. 33, Issue 12, pp. 2341–2353, December 2011.
[2] Qingsong Zhu, Jiaming Mai, and Ling Shao, "A fast single image haze removal algorithm using color attenuation prior," *IEE Transactions on Image Processing*, Vol. 24, Issue 11, pp. 3522–3533, November 2015.
[3] Sebastián Salazar-Colores, Ivan Cruz-Aceves, and Juan-Manuel Ramos-Arreguin, "Single image dehazing using a multilayer perceptron," *Journal of Electronic Imaging*, Vol. 27, Issue 4, July 2018.