Digital Image Processing Project 1

——Dehazing

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Abstract

Nowadays, fog and hazy weathers happen from time to time due to the accompanied environmental pollution caused by the development of modern society. Under these circumstances, floating particles greatly absorb and scatter light and result in low visibility and contrast. In order to avoid the threat for computer vision and some other technologies which depend greatly on image capture, different types of image dehazing algorithms are created. As a key member of image restoration methods, Dark Channel Prior stands out for its low complexity and satisfactory effect. Some specific analysis and implementation with MATLAB about it will be covered below.

Key words: Image Dehazing, Dark Channel Prior, MATLAB

Introduction

Dehazing algorithms of image restoration are mainly based on the atmospheric scattering model. The model widely used to describe the formation of a hazy image is:

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

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 dark channel prior is based on the following observation on outdoor haze-free images: In most of the nonsky patches, at least one color channel has some pixels whose intensity are very low and close to zero. From this we can define dark channel:

$$J^{dark}(\mathbf{x}) = \min_{y \in \Omega(\mathbf{x})} \left(\min_{c \in \{r,g,b\}} J^c(\mathbf{y}) \right), \tag{2}$$

where J^c is a color channel of J and $\Omega(\mathbf{x})$ is a local patch centered at **x**.

The low intensity in the dark channel is mainly due to three factors: shadows, colorful objects or surfaces, and dark objects or surfaces. As the natural outdoor images are usually colorful and full of shadows, the dark channels of these images are really dark. According to a collection of a huge image database, most of the pixels in the dark channels have zero values, and the intensity of 90 percent of the pixels is below 25.

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. Visually, the intensity of the dark channel is a rough approximation of the thickness of the haze.

Estimating the Transmission

Assuming that the atmospheric light **A** is given. We first normalize the haze imaging equation (1) by **A**(each color channel independently):

$$\frac{I^c(\mathbf{x})}{A^c} = t(\mathbf{x})\frac{J^c(\mathbf{x})}{A^c} + 1 - t(\mathbf{x}). \tag{3}$$

We further assume that the transmission in a local patch $\Omega(\mathbf{x})$ is constant. We denote this transmission as $\tilde{t}(\mathbf{x})$. Then we calculate the dark channel on both sides of (3) and put the minimum operators on both sides:

$$\min_{\mathbf{y}\in\Omega(\mathbf{x})}(\min_c \frac{I^c(\mathbf{y})}{A^c}) = \tilde{t}(\mathbf{x}) \min_{\mathbf{y}\in\Omega(\mathbf{x})}(\min_c \frac{J^c(\mathbf{y})}{A^c}) + 1 - \tilde{t}(\mathbf{x}). \tag{4}$$

Since $\tilde{t}(\mathbf{x})$ is a constant in the patch, the dark channel of J is close to zero due to the dark channel prior, and A^c is always positive, we can simply estimate the transmission by:

$$\tilde{t}(\mathbf{x}) = 1 - \min_{\mathbf{y}\in\Omega(\mathbf{x})}(\min_c \frac{I^c(\mathbf{y})}{A^c}). \tag{5}$$

In the sky region, we have $\tilde{t}(\mathbf{x}) \to 0$. But in practice, even on clear days the atmosphere is not absolutely free of any particle. So the haze still exists when we look at distant objects. This phenomenon is called aerial perspective. If we remove the haze thoroughly, the image may seem unnatural and we may lose the feeling of depth. So, we can optionally keep a very small amount of haze for the distant objects by introducing a constant parameter ω ($0<\omega\leqslant 1$) into (5) to adaptively keep more haze for the distant objects:

$$\tilde{t}(\mathbf{x}) = 1 - \omega \min_{\mathbf{y}\in\Omega(\mathbf{x})}(\min_c \frac{I^c(\mathbf{y})}{A^c}), \tag{6}$$

where the typical value for ω is 0.95.

Soft Matting

We notice that the haze imaging equation (1) has a similar form as the image matting equation:

$$\mathbf{I} = \mathbf{F}\alpha + \mathbf{B}(1-\alpha), \tag{7}$$

where **F** and **B** are foreground and background colors, respectively, and α is the foreground opacity. A transmission map in the haze imaging equation is exactly an alpha map. Therefore, we can apply a closed-form framework of matting to refine the transmission.

Denote the refined transmission map by $t(\mathbf{x})$. Rewriting $t(\mathbf{x})$ and $\tilde{t}(\mathbf{x})$ in their vector forms as $\mathbf{t}$ and $\tilde{\mathbf{t}}$, we minimize the following cost function:

$$E(\mathbf{t}) = \mathbf{t}^{\mathrm{T}}\mathrm{L}\mathbf{t} + \lambda(\mathbf{t} - \tilde{\mathbf{t}})^{\mathrm{T}}(\mathbf{t} - \tilde{\mathbf{t}}), \tag{8}$$

where the first term is a smoothness term and λ is a weight. The matrix L is called the matting Laplacian matrix. Its (i, j) element is defined as:

$$\sum_{k|(i,j)\in\omega_k} (\delta_{ij} - \frac{1}{|w_k|})(1 + (\mathbf{I}_i - \mu_k)^{\mathrm{T}}(\textstyle\sum_k + \frac{\varepsilon}{|w_k|}\mathrm{U}_3)^{-1}(\mathbf{I}_j - \mu_k)), \tag{9}$$

where $\mathbf{I}_i$ and $\mathbf{I}_j$ are the colors of the input image **I** at pixels i and j, δ_{ij} is the Kronecker delta, μ_k and $\sum_k$ are the mean and covariance matrix of the colors in window w_k, U_3 is a 3×3 identity matrix, ε is a regularizing parameter, and $|w_k|$ is the number of pixels in the window w_k.

The optimal **t** can be obtained by solving the following sparse linear system:

$$(\mathrm{L} + \lambda\mathrm{U})\mathbf{t} = \lambda\tilde{\mathbf{t}}, \tag{10}$$

where U is an identity matrix of the same size as L. We set a small λ(typical value:10^{-4}) so that t is softly constrained by $\tilde{\mathbf{t}}$.

After solving the linear system (10), we perform a bilateral filter on t to smooth its small scale textures.

Estimating the atmospheric light

The brightest pixels in the hazy image are considered to be the most haze-opaque only when the weather is overcast and the sunlight can be ignored. In this case, the atmospheric light is the only illumination source of the scene. So, the scene radiance of each color channel considering the sunlight S is given by:

$$J(\mathbf{x}) = R(\mathbf{x})(S + A), \tag{11}$$

where $R \leqslant 1$ is the reflectance of the scene points. The haze imaging equation (1) can be written as:

$$I(\mathbf{x}) = R(\mathbf{x})St(\mathbf{x}) + R(\mathbf{x})At(\mathbf{x}) + (1 - t(\mathbf{x}))A \le A. \tag{12}$$

In this situation, the brightest pixel of the whole image can be brighter than the atmospheric light.

Recovering the Scene Radiance

With the atmospheric light and the transmission map, we can recover the scene radiance according to (1). To prevent the recovered scene radiance **J** from its prone to noise and also to preserve a small amount of haze in very dense haze regions, we restrict the transmission $t(\mathbf{x})$ by a lower bound t_0(typical value: 0.1). The final scene radiance $\mathbf{J}(\mathbf{x})$ is recovered by:

$$\mathbf{J}(\mathbf{x}) = \frac{\mathbf{I}(\mathbf{x}) - \mathbf{A}}{\max(t(\mathbf{x}), t_0)} + \mathbf{A}. \tag{13}$$

Result Analysis

Question 1&2

By using the function 'imhist', we can get the histograms for fig. H22, H26 and R1 separately as follows:

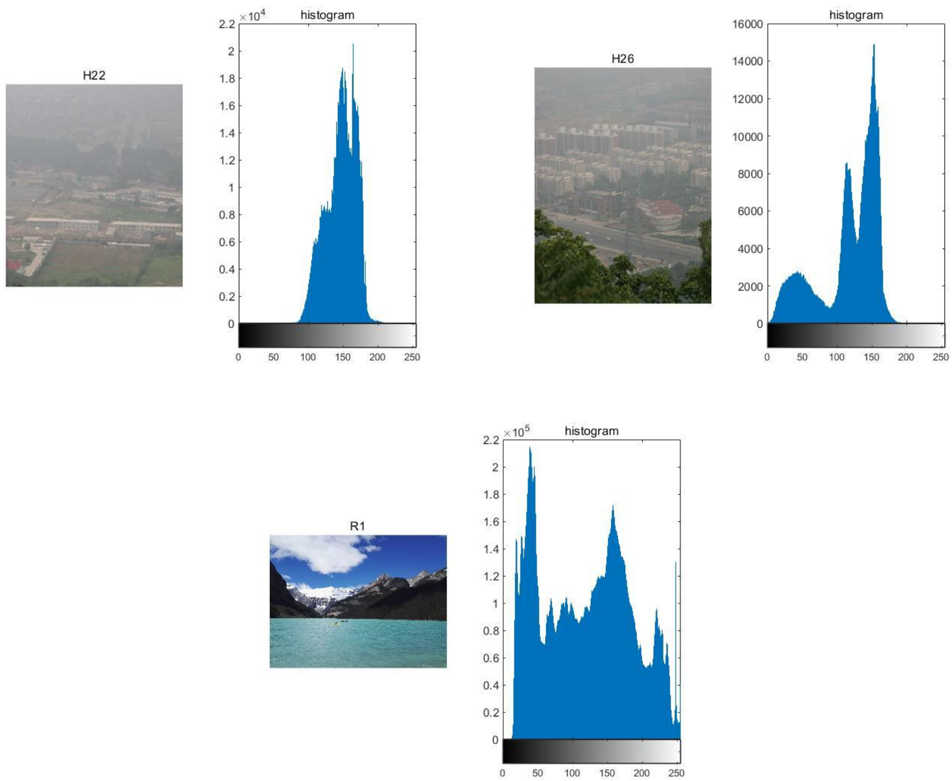

Fig.1 Histograms for hazed images and normal images

We can easily tell that the distribution of histograms for hazed images mainly concentrate on the centre, which indicates that the images are gray and low-contrast. What's more, most details are blurred. While for normal images, their histograms tend to be well-distributed, which indicates that they are bright, colorful and with high contrast.

Question 3

After reading the reference essay carefully, I was able to code and realize a simplified version of Dark Channel Prior, which means, DCP without soft matting. Later on I further adopted two more sub-functions, guided filter and box filter, to complete the algorithm and achieve better effect. Some hazed images after dehazing are showed as follows:

Fig.2 Hazed images after using dark channel prior

To get the best results, I set parameter ω to different values. For images that are relative dark and with dense fog, ω should be relatively low, and vice versa. We can easily see the function of soft matting, as it can improve the contrast and highlight more details through refining the transmission map.

For the image that takes up the least memory space(44.0KB), the program runs about 0.73 second. For the biggest one(4.07MB), the program runs about 48.43 seconds. Although we have no other data for comparison, these numbers seem not to be that efficient. But considering that the development of DCP was over a decade ago, this is fully understandable.

Some normal images after dehazing are showed as follows:

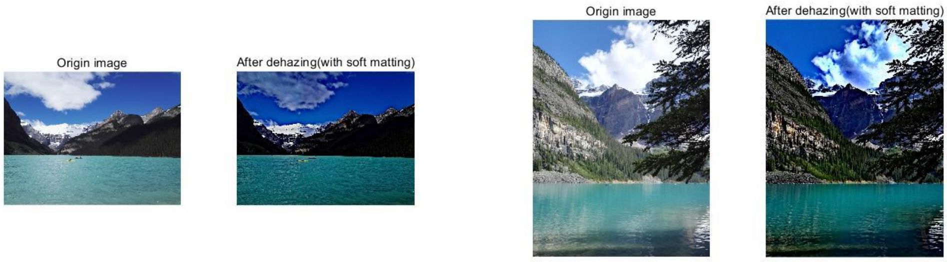

Fig.2 Normal images after using dark channel prior

In general, Dark Channel Prior can achieve a decent dehazing effect for single image. But what cannot be neglected are its several deficiencies. Firstly, most images after DCP are dim, which may requires some adjustments on their luminance for presentation purpose. Secondly, DCP may highlight edges of some objects where unnecessary. This may distort the picture slightly. Thirdly, DCP ruins the sky region to a certain extent. This include overexposure and cloud erosion. Lastly, DCP almost gives up where there is full of dense haze. This is reasonable as the algorithm hugely relies on objects that can reflect light. These issues have also emerged when editing video files. Some representative screenshots are as follows:

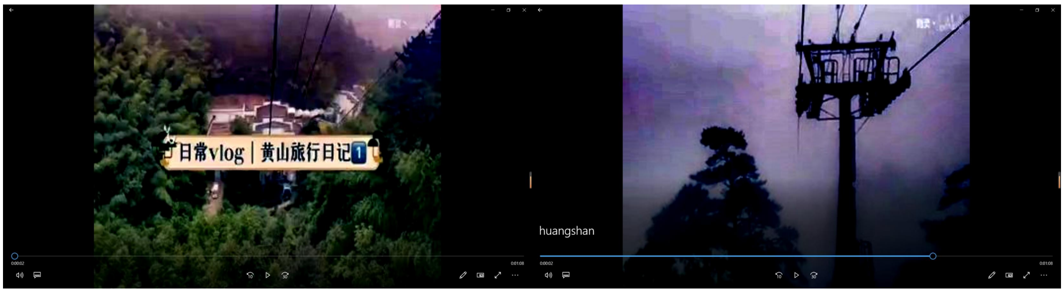

Fig.3 Screenshots of a video after using dark channel prior

For video dehazing, I used a frame-by-frame approach, which means drawing each frame and run the DCP to dehaze, then put them together to get the target video. Actually if high and stable algorithm processing speed can be ensured, we can play each frame afterwards to achieve real-time video dehazing.

Conclusion

In this work, I have implemented Dark Channel Prior programming based on my own understanding, and have summarized the algorithm in my own words. Through this process, I have laid a good foundation in image dehazing, and have deepened my understanding towards image histogram. It is worth mentioning that besides DCP, I have also tried some other methods such as histogram equalization. As they might just requires one single instruction in MATLAB, I haven’t added them into my report. Go back to DCP, it still has a long way to go, like modifying the transmission refine module in substitution of soft matting to achieve higher processing speed and better results. If we neglect the complexity, we may think of combining it with algorithms that are based on image enhancement to bring their strengths together.

References

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