Thesis Reiteration Report

Yifei Liu, 9/5

Ques. 1: Description of MRP

The maximum reflectance prior (**MRP**) is a general rule based on statistics of daytime haze-free image patches, which shows, that in the most patches of a daytime haze-free image, each color channel has very high intensity at some pixels (the pixels don't have to be the same one). For the purpose of describing this prior in mathematical language, we define the maximum of pixel intensity (**MPI**) in a channel λ of the specific patch Ω_i .

$$M_\Omega^\lambda = \max_{j \in \Omega_i} I_j^\lambda$$

Where I denotes a daytime haze-free image. So, the MRP could be described as follows, and we should mention that in this term M has been normalized:

$$M_\Omega^\lambda \approx 1$$

In daytime, we can assume that incident light intensities are uniform in space and can be assumed to be fixed to value 1. Therefore, $L_J = const$, we can further deduct that:

$$M_\Omega^\lambda = \max_{j \in \Omega_i} R_j^\lambda$$

$$\max_{j \in \Omega_i} R_j^\lambda \approx 1$$

That's why it calls maximum reflectance prior.

Ques. 2: General Principle & Pseudocode

the Buildup of Nighttime Model

For the purpose of dehaze a night image, a practical model for night haze process needed to be build. The model applied for daytime haze scenes is described as follows:

$$I_i^\lambda = J_i^\lambda t_i + A^\lambda (1 - t_i)$$

What should be mentioned is that A^λ denotes the global atmospheric light, which is failed to make sense in night. According to the discussion in the Sec. 1, nighttime scene are : 1. multiple colored 2. have strongly non-uniform ambient illumination. As a result, the term A_i^λ is separated into two terms as follows:

$$A_i^\lambda \triangleq L_i \eta_i^\lambda$$

where L_i is the ambient illumination shows the distribution in space, and η_i^λ shows the color distribution in space. The final model is described as follows:

$$I_i^\lambda \triangleq L_i \eta_i^\lambda R_i^\lambda t_i + L_i \eta_i^\lambda (1 - t_i)$$

the Estimation of Ambient Illumination

Now, the aim of the dehaze process is to recover color-balanced haze free image, which is denoted as $J_i^\lambda \triangleq L_j R_j^\lambda$. The first step is to estimate ambient illumination. In other words, we need to get L_i, η_i^λ from above expression.

According to the answer of QUES.1 above, we already knows that MRP stands for:

$$M_\Omega^\lambda = \max_{j \in \Omega_i} I_j^\lambda \approx 1$$

Now let's focus on the nighttime circumstance. Based on the assumption that $L_{\Omega_i}, \eta_{\Omega_i}^\lambda, t_{\Omega_i}$ are constant in each patch, the equations in the paper could deviate the estimation of ambient illumination by (details are omitted) :

$$M_\Omega^\lambda = L_{\Omega_i} \eta_{\Omega_i}^\lambda$$

$$\eta_{\Omega_i}^\lambda = \frac{M_\Omega^\lambda}{L_{\Omega_i}}$$

In the expressions above, we let $L_{\Omega_i} = \max_{\lambda \in \{R,G,B\}} M_\Omega^\lambda$. Then, we refine $\eta_{\Omega_i}^\lambda$ by applying image guided filter. The guided image I is selected to be the grey image of original haze image. Finally, remove the color effect:

$$\hat{I}_i^\lambda \triangleq L_i R_i^\lambda t_i + L_i (1 - t_i)$$

the Estimation of Scene Transmission

In this portion, we take the same procedure above by applying the $\max$ operation and get the MPI again. Similarly, we get the L_Ω in each channel and select the maximum one as the final estimate.

$$L_{\Omega_i} = \max_{\lambda \in \{R,G,B\}} \left(\max_{j \in \Omega_i} \hat{I}_j^\lambda \right)$$

Once again, we refine the estimate to get a smooth L_i by using guided filter.

Now, the model described as:

$$\hat{I}_i^\lambda = J_i^\lambda t_i + L_i (1 - t_i)$$

Using the dark channel prior introduced in the reference paper of K. He et al, we can get the estimate of t_Ω , and refine it using guided filter.

Haze removal

Having get the detailed estimate of L_j, t_j , we can deduct the haze-free image from definition of $\hat{I}_i^\lambda$ above:

$$J_j^\lambda = \frac{\hat{I}_i^\lambda - L_j}{\max\left(t_j, t_0\right)} + L_j$$

Algorithm

input: input image I, patch size R, filter kernel size r, filter parameter ϵ

output: dehaze image J

1: calculate M_Ω^λ, $L_{\Omega_i} = \max_{\lambda \in \{R,G,B\}} M_\Omega^\lambda$, normalize $\eta_{\Omega_i}^\lambda = \frac{M_\Omega^\lambda}{L_{\Omega_i}}$ and refine $\eta_j^\lambda = f_\epsilon\left(\eta_{\Omega_i}^\lambda\right)$

2: recover: $\hat{I}_j^\lambda = \frac{I_j^\lambda}{\eta_j^\lambda}$

3: $L_{\Omega_i} = \max_{\lambda \in \{R,G,B\}}\left(\max_{j \in \Omega_i} \hat{I}_j^\lambda\right)$, refine $L_j = f_\epsilon\left(L_{\Omega_i}\right)$

4: $t_\Omega = 1 - \frac{\min_{\lambda \in \{R,G,B\}} \min_{j \in \Omega_i} \hat{I}_j^\lambda}{\min_{j \in \Omega_i} L_j}$, refine $t_j = f_\epsilon\left(t_\Omega\right)$

5: $J_j^\lambda = \frac{\hat{I}_i^\lambda - L_j}{\max\left(t_j, t_0\right)} + L_j$

/* note that $f_\epsilon\left(*\right)$ means apply a guided filter using parameter ϵ, and the guided image is the grey image of original image */

Ques. 3: Test Report

We implement the proposed algorithms using matlab (ver. 2018a) on a Laptop with Intel CORE i5-8250U (1.80GHz) and 8G memories.

The parameters are set as follows:

```
1  patchsize_x = 15;
2  patchsize_y = 15;
3  GuidedFilter_size = 32;
4  GuidedFilter_para = 0.01;
```

The time consumption based on given image set is as follows:

image	time consumption ()
Image1.bmp	
Image2.bmp	
Image3.bmp	
Image4.bmp	
Image5.bmp	