Improved Single Image Dehazing Using Guided Filter

Jiahao Pang, Oscar C. Au and Zheng Guo
The Hong Kong University of Science and Technology, Hong Kong
E-mail: jpang@ust.hk, eeau@ust.hk, zguo@alumni.ust.hk

***Abstract*—Single image dehazing is challenging because it is massively ill-posed. Haze removal based on dark channel prior is effective, but refining the transmission map with closed-form matting is computationally expensive. Recent work discovered that using guided filter to refine the transmission map is feasible. In this paper, we elaborate single image dehazing by combining dark channel prior and guided image filtering in detail. By analyzing the tradeoffs of this approach, we propose an effective scheme to adapt the parameters. Experiments and comparisons show that our method generates satisfactory dehazed results with low computation.**

(a) Input hazy image (b) Dehazed image

Fig. 1. An image before and after dehazing.

I. Introduction

Outdoor scenes, especially those distant photographs in bad weather, are usually degraded due to the presence of particles or droplets in the atmosphere. With lowered contrast, the degraded dull images lose their visual vividness and color fidelity. Consequently, image dehazing is a significant issue in many image-relevant applications.

However, single image dehazing is non-trivial because it is highly under constrained – the local transmissions, which depend on the scene depth for homogeneous atmosphere, have to be estimated. To solve this, techniques that rely on their own assumptions or priors have been come up [3, 4, 7]. Among those successful priors, the dark channel prior [4] can serve as a simple but effective guidance to estimate the local transmissions for hazy images. Unfortunately, refining the transmission map with close-form matting (soft matting in [4]) is computationally expensive. The guided filter, proposed recently in [5], filters the input by considering the content of a guidance image. Since the guided filter has close theoretical connection with the closed-form matting framework [1] and it also has O(N) time algorithm, He et al. [5] show that it is possible to apply guided filter to refine the transmission map obtained by dark channel prior, and the running time of the dehazing process can be reduced significantly. However, detailed analyses of image dehazing by combining dark channel prior and guided filter haven't been provided in [5].

In this work, we study several aspects of using guided filter to refine the coarse transmission map. Different from that in [4], we use adaptive patch size to compute the dark channel. To further improve the performance of transmission refinement, we then propose a scheme to adjust the filtering radius of the guided filter accordingly. A case of failure of this approach is also presented in this paper. Like He et al.'s work [5], we filter the coarse transmission map under the guidance of the input hazy image, this method gives a transmission map that well captures the sharp edge discontinuities of the objects.

In fact, image dehazing using dark channel prior and guided filter provides results that comparable with the state-of-the-art techniques, and its computational cost is also quite low. Therefore the insights revealed in this paper can be helpful for applications where single image dehazing is necessary. Fig. 1 presents an example of image dehazing using our method.

II. Dark Channel Prior and Image Dehazing

A. Haze Imaging Model

Although the physical mechanism of haze is rather sophisticated, the general hazy image formation model that being widely-used in computer vision and computer graphics is simple [4, 7, 8, 9]:

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

in which $\mathbf{x}$ is the pixel coordinate, $\mathbf{I}$ is the observed color, $\mathbf{J}$ is the scene radiance vector (the true color that we want to recover). And t is the transmission of the medium, which indicates the portion of light that penetrates through the haze, $\mathbf{A}$ is the global atmospheric light, which can be regarded as the global "color" of the haze.

The difficulties of single image dehazing comes from the fact that we only have the hazy observation $\mathbf{I}$, but the goal is to recover $\mathbf{J}$, $\mathbf{A}$, and $\mathbf{t}$. So the problem of haze removal is inherently under-constrained.

B. Transmission Estimation Using Dark Channel Prior

The dark channel prior is a statistics of outdoor haze-free images: for most of the non-sky patches in an outdoor haze-free image, at least one color channel contains some pixels whose intensities are very low [4]. Mathematically, the dark channel of an image $\mathbf{I}$ is given by:

$$I^{\mathrm{dark}}(\mathbf{x}) = \min_{\mathbf{y}\in\Omega(\mathbf{x})}\big(\min_{\mathrm{c}\in\{r,g,b\}} I^{\mathrm{c}}(\mathbf{y})\big), \tag{2}$$

where $\Omega(\mathbf{x})$ is a local patch centered at pixel $\mathbf{x}$, and I^{c} is a color channel of $\mathbf{I}$. For a haze-free image $\mathbf{J}$, its dark channel tends to be zero: $J^{dark} \to 0$, which is the dark channel prior proposed in [4].

According to the haze imaging model (1), with the help of the dark channel prior, He et al. [4] show that the transmission map can be estimated simply by:

$$\tilde{t}(\mathbf{x}) = 1 - \omega \min_{\mathbf{y}\in\Omega(\mathbf{x})}\big(\min_{\mathrm{c}\in\{r,g,b\}} \frac{I^{\mathrm{c}}(\mathbf{y})}{A^{\mathrm{c}}}\big), \tag{3}$$

in which $\tilde{t}(\mathbf{x})$ denotes the constant transmission in the patch $\Omega(\mathbf{x})$. The parameter ω $(0 < \omega < 1)$ in (3) is introduced to prevent removing the haze thoroughly and keep the feeling of depth, it is set to be 0.95. The global atmospheric light $\mathbf{A}$ in (3) is estimated by the technique proposed in [4], which prescreens the candidate pixels first using the dark channel of the input hazy image.

In fact, assuming constant transmission in a local patch $\Omega(\mathbf{x})$ is inappropriate. The transmission obtained by (3) is only a coarse estimation, the recovered image using the coarse transmission contains severe halo artifacts, so it is necessary to refine the transmission map and capture the depth changes at object edges. In [4], the closed-form matting framework [1] is applied to suppress the blocky artifacts in the coarse transmission map, which minimizes the following cost function,

$$E(\mathbf{t}) = \mathbf{t}^{\mathrm{T}}\mathrm{L}\mathbf{t} + \lambda(\mathbf{t} - \tilde{\mathbf{t}})^{\mathrm{T}}(\mathbf{t} - \tilde{\mathbf{t}}). \tag{4}$$

In (4), the first term (smoothness term) encodes the color line model in [1] and the second term (data term) encodes the information about the transmission, the constraint weight λ is a small value (10^{-4} in [4]). The matrix L is the N $\times$ N matting Laplacian matrix [1] for an input image with N pixels. Minimizing (4) involves computing the matting Laplacian matrix and solving a sparse linear system. This process is known as soft matting in [4] and its computational cost is very high. Notice that by implementing the local minimum filter with the fast algorithm in [6], the dark channel can be computed in O(N) time; therefore the bottleneck of the efficiency in [4] is the soft matting step. In this work, we consider using guided filter to refine the coarse transmission map and speed up the dehazing process.

III. Image Dehazing Using Guided Filter

Different from soft matting [4], after the coarse transmission map is obtained, we apply the guided filter to refine the transmission, such that the overall time complexity of the dehazing algorithm achieves O(N).

A. Guided Image Filtering

Guided filter is a type of edge-preserving smoothing operator, which filters the input image under the guidance of another image [5]. Denote the input image as p, the guidance image as I, and the filtering output as q. The local linear model of guided filter assumes that q is a linear transform of the guidance I in a window w_k centered at pixel k, so that mathematically we have:

$$q_i = a_k I_i + b_k, \forall i \in w_k, \tag{5}$$

in which the linear coefficients a_k and b_k are constant in window w_k, we also denote the radius of the window w_k as r. Guided filter seeks for coefficients (a_k, b_k) that minimizes the difference between the output q and the input p. For a window w_k, consider the cost function:

$$E(a_k, b_k) = \sum_{i\in w_k}\big((a_k I_i + b_k - p_i)^2 + \epsilon a_k^2\big), \tag{6}$$

where ϵ is a regularizer. Minimizing (6) defines a least square problem within window w_k, its solution is given by:

$$a_k = \frac{\frac{1}{|w|}\sum_{i\in w_k} I_i p_i - \mu_k \bar{p}_k}{\sigma_k^2 + \epsilon} \quad \text{and} \quad b_k = \bar{p}_k - a_k\mu_k, \tag{7}$$

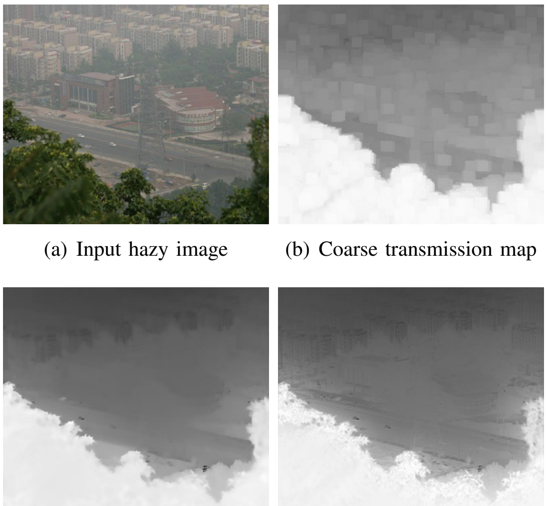
in which σ_k^2 and μ_k are the variance and mean of I in w_k, with $\bar{p}_k = \frac{1}{|w|}\sum_{i\in w_k} p_i$, and $|w|$ is the number of pixels in w_k. The final filtering output is given by:

$$q_i = \frac{1}{|w|}\sum_{k:i\in w_k}(a_k I_i + b_k) = \bar{a}_i I_i + \bar{b}_i, \tag{8}$$

where $\bar{a}_i$ and $\bar{b}_i$ are obtained with average filter: $\bar{a}_i = \frac{1}{|w|}\sum_{k\in w_i} a_k$, $\bar{b}_i = \frac{1}{|w|}\sum_{k\in w_i} b_k$. Since $(\bar{a}_i, \bar{b}_i)$ are outputs of an average filter, their gradients are quite small, so $\nabla q \approx \bar{a}\nabla I$. For RGB color guidance image, the derivations are similar [5]. As can be seen that locally, the output q captures similar details from the guidance I (by virtue of the local linear model (5)); while globally, the impression of the output q should be similar to the input p (due to the minimization of the cost function (6)).

B. Transmission Refinement Using Guided Filter

In [5], one of the application of guided filter is to refine the coarse transmission map obtained by dark channel prior. In fact, guided filter is closely related to the matting Laplacian matrix [1]. For guided filter, the guidance image I, the input p and the filtering output q play similar roles as the input image, the trimap (or the scribble constraints) and the alpha matte in the closed-form matting framework [1], respectively. In [5], the output of guided filter has proven to be one Jacobi iteration in optimizing the cost function (4). And the expected value of the constraint weight λ is 2 for guided filter, which implies that the filtering output (or the alpha matte) is loosely constrained by the input image p (or the trimap for matting). Therefore guided filter is applicable for transmission refinement in [4], since in soft matting the refined transmission map should also be loosely constrained by the coarse transmission map, which can be seen from the data term in (4).



(a) Input hazy image (b) Coarse transmission map

(c) Soft matting result (d) Guided filter output

Fig. 2. Transmission refinement using soft matting and guided filter ($r = 30$ and $\epsilon = 10^{-3}$).

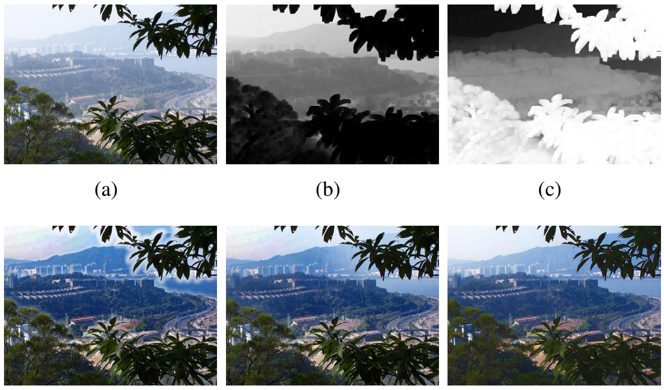
Notice that the summations in (7) and (8) can be computed with the O(N) time integral image technique [2], so the guided filter can be implemented in O(N) time (for an image with N pixels). This property is important for single image dehazing because it provides a chance to improve the efficiency of transmission refinement in [4], which reduces the complexity of the dehazing algorithm to O(N).

Fig. 2 compares the results of transmission refinement using soft matting and guided filter. The coarse transmission map (Fig. 2(b)) is obtained with patch size of 15×15. And we use Fig. 2(a) as an RGB color guidance to filter the coarse transmission map then obtain Fig. 2(d). In this case, the input image has the size of 400×330, the window radius of the guided filter is $r = 30$ and the regularizer is $\epsilon = 10^{-3}$. As can be seen that the filtering output (Fig. 2(d)) is visually similar to the refined transmission given by soft matting (Fig. 2(c)).

C. Analyses and Parameter Settings

An important parameter for computing the dark channel I^{dark} is the patch size, we denote its radius as r^{dark}. Since the computational cost in [4] is quite high, the algorithm is only suitable for small images. So in [4] the patch size is fixed as 15×15, which is relatively small. However, the complexity of our method is quite low and it is capable of processing large images with short running time, so it is not appropriate to use fixed patch size in our case. Here we adopt a simple strategy to adjust r^{dark} linearly according to the area of the image. When the number of pixels in the image exceed 5×10^6, the patch radius is fixed as $r^{\text{dark}} = 30$, preventing the patch size from growing too large; when the number of pixels in the image is less than 2×10^5, the patch radius is set to be $r^{\text{dark}} = 7$, preventing the patch size becoming too small; for images with pixel numbers in between, we interpolate the patch radius linearly. Notice that there exist a tradeoff for the patch size. When it decreases, the blocky artifacts in the coarse transmission map reduce, making it easier for the guided filter to refine the transmission; however, a smaller patch size makes the dark channel prior less appropriate, the transmission $t(\mathbf{x})$ is underestimated and the recovered scene radiance become over-saturated. Therefore the patch size should neither be too large nor too small.

For the guided filter, our experiments find that the refined transmission map is not sensitive to the regularizer ϵ, and we fix it to be 10^{-3}. But for the filtering radius r, its behavior is quite different. From the local linear model (5), a large radius r implies that the filtering output is linear to the guidance image in a large range, which helps to reduce the blocky artifacts in the coarse transmission map, so that the halo effect in the recovered image can be eliminated. However, if r is too large, the transmission map will capture too much details from the guidance (the input hazy image), making the recovered image over-saturated. Fig. 3 shows an image (with size of 896×672) recovered with different radii r. In this example, the patch size to compute the dark channel is deliberately set as 15×15. As can be seen, when $r = 8$ (corresponds to the window of 17×17, which is of similar scale as the patch size 15×15), the halo effect is quite severe (Fig. 3(d)); when $r = 800$, the halos are suppressed (Fig. 3(f)), but notice the leaves in the lower-half of the image become saturated; when $r = 80$, there're still some halos (Fig. 3(e)), but it compromises between the two extremes.



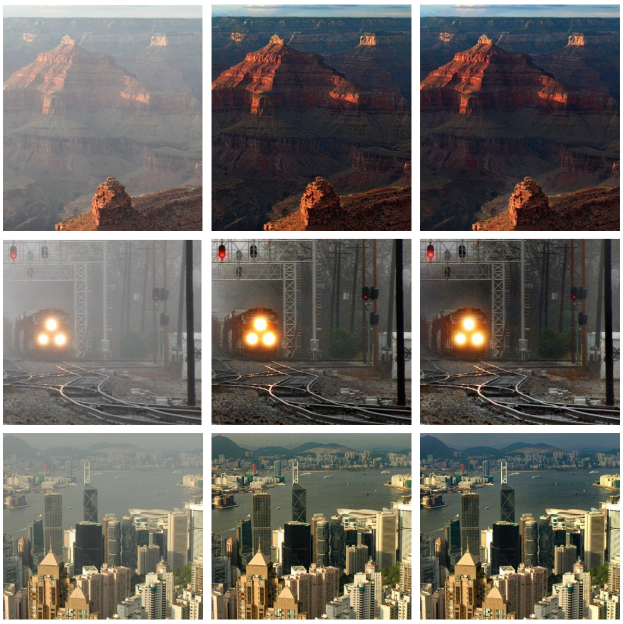
(a) (b) (c)

(d) (e) (f)

Fig. 3. Scene radiance recovery using different filtering radii r (patch size of dark channel is 15×15, $\epsilon = 10^{-3}$). (a) Input hazy image. (b) Dark channel. (c) Coarse transmission map. (d)(e)(f) Scene radiance recovered with r equals to 8, 80, and 800, respectively.

As a result, the filtering radius r of the guided filter should be much larger than the patch radius r^{dark} of the dark channel. In our implementation, we simply set $r = 5r^{\text{dark}}$, such that a good tradeoff can be achieved between halo effect and over-saturation.

After the refined transmission map $t(\mathbf{x})$ is obtained with the guided filter, the haze-free image (scene radiance) can be recovered using the haze imaging model (1). Like that in [4], in this work we also set a lower bound $t_0 = 0.1$ for the transmission to avoid noisy dehazed results.



(a) Input images (b) Results of [4] (c) Our results

Fig. 4. Dehazed results of our work and comparisons with He et al.'s work [4].

IV. Experimental Results

Compared to the work in [4], the main advantage of combining dark channel prior and guided filter to dehaze the images lies in its low computational cost. On a laptop with a 2.2 GHz Intel Core 2 Duo CPU, our C++ implementation takes about 4 seconds to process a 1-mega pixel image, but in [4], it takes about 10-20 seconds to process a 600×400 image. By virtue of its exact O(N) time complexity, the running time of our algorithm becomes tolerable for many applications.

Some dehazed results of our work and comparisons with that in [4] are shown in Fig. 4. Since the recovered haze-free images usually look quite dim, we enhance their brightness for better display. As can be seen, our approach is capable of unveiling the details for the inputs, which gives results that comparable to He et al.'s work [4].

However, guided image filtering is actually an approximation of soft matting, as proven in [5]; refining the transmission map with guided filter may not always work. Fig. 5 presents a case of failure of transmission refinement using guided filter. Firstly, the dehazed result (Fig. 5(c)) contains noticeable halos, this happens because the depth change at the object edge is too abrupt, the guided filter needs a larger filtering radius r to suppress the halos. On the other hand, in the refined transmission map (Fig. 5(b)), the details of the pedestrian are captured too well by the local linear model (5), and the transmission is under estimated, results in over-saturation in the recovered image (notice the color of the face and the jeans). This problem can be resolved by reducing the filtering radius r; however, a smaller r makes the halo effect even more severe. As a result, when the input hazy image contains discontinuities that are too abrupt, it is difficult to find an appropriate filtering radius that compromises between the halo effect and over-saturation. Therefore the low complexity of this dehazing algorithm comes with the price of some failures. To address the mentioned problem, future improvements may focus on adjusting the parameters r^{dark} and r locally within the image, at the cost of inevitable higher computation.

(a) Input image (b) Transmission map (c) Dehazed result

Fig. 5. Failure of transmission refinement using guided filter.

V. Conclusions

In this paper, we elaborate single image dehazing by combining dark channel prior [4] and guided image filtering [5], then we study several aspects of this approach. Through experiments and analyses, we propose an effective scheme to adapt the patch size of dark channel and the filtering radius of guided filter. The main benefit of using guided filter to refine the transmission lies in its low computational cost, it also generates comparable dehazed results with He et al.'s work [4]. Since guided image filtering is an approximation of soft matting in [4], this method may fail when the input image contains abrupt depth changes. Fortunately, it turns out that our work performs quite well on many hazy images, its O(N) time complexity also make it appealing for many applications.

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