SINGLE IMAGE DEHAZING BASED ON CONTRAST ENHANCEMENT

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ABSTRACT

A simple and adaptive single image dehazing algorithm is proposed in this work. Based on the observation that a hazy image has low contrast in general, we attempt to restore the original image by enhancing the contrast. First, the proposed algorithm estimates the airlight in a given hazy image based on the quad-tree subdivision. Then, the proposed algorithm estimates the transmission map to maximize the contrast of the output image. To measure the contrast, we develop a cost function, which consists of a standard deviation term and a histogram uniformness term. Experimental results demonstrate that the proposed algorithm can remove haze efficiently and reconstruct fine details in original scenes clearly.

Index Terms— Image enhancement, image restoration, contrast enhancement, and single image dehazing.

1. INTRODUCTION

The quality of a captured image in bad weather is usually degraded by the presence of haze in the atmosphere, since the incident light to a camera is attenuated and the image contrast is reduced. Dehazing is the process to remove haze effects in captured images and reconstruct the original colors of natural scenes. Recently, lots of efforts have been made to develop efficient dehazing algorithms. In general, dehazing algorithms estimate scene depths and compute the thickness of haze accordingly.

There have been several approaches to estimate scene depths using multiple images or additional information. For example, scene depths are estimated from two or more images of the same scene that are captured in different weather conditions [1, 2] or using different polarization filters [3, 4]. Also, prior knowledge of geometry information is used to estimate the scene structure in [5]. These methods can estimate scene depths and hence haze thickness effectively, but it is not always possible to obtain multiple images or additional information in some applications.

In order to overcome the drawback of multiple image dehazing algorithms, single image dehazing algorithms have been investigated as well. Tan [6] used the contrast maximization technique, assuming that a dehazed image should have high contrast. However, this algorithm often generates halo artifacts and overstretches contrast. He *et al.* [7] proposed a dehazing algorithm based on the dark channel prior, which means that at least one color channel should have almost zero pixel values within a window in a haze-free image. Their algorithm yields impressive results, but the color tone might be modified due to inaccurate estimation of airlight. Oakley and Bu [8] assumed all pixels in an entire image have similar depth values and subtracted the same offset from all pixel values. Their algorithm is computationally very simple, but it cannot adaptively remove haze when a captured image has variable scene depths.

In this work, we propose a simple and adaptive single image dehazing algorithm based on contrast enhancement. An airlight is first estimated based on the quad-tree subdivision of a given hazy image. Then, the optimal transmission is estimated to maximize the contrast of the restored image. To measure the contrast, we use the standard deviation term and the histogram uniformness term. Moreover, to reflect space-varying scene depths, we extend the transmission estimation scheme to a locally adaptive block-based scheme. Experimental results demonstrate that the proposed algorithm achieves promising dehazing results at low computational complexity.

This paper is organized as follows. Section 2 introduces the haze modeling equation. Section 3 describes the proposed dehazing algorithm, and Section 4 extends it to the locally adaptive scheme. Section 5 presents simulation results. Finally, Section 6 concludes the paper.

2. HAZE MODELING

The observed brightness of a capture image in the presence of haze can be modeled based on the atmospheric optics [1, 2, 9] via

$$I_p = t_p \cdot J_p + (1 - t_p) \cdot A, \tag{1}$$

where J_p and I_p denote the original color and the observed color at pixel position p, respectively, and A is the airlight that represents the ambient light in the atmosphere. Also, $t_p \in [0, 1]$ is the transmission of the light reflected by the object. Since the light traveling a longer distance is more attenuated, we have

$$t_p = e^{-\beta d_p}, \tag{2}$$

where β is the attenuation coefficient determined by the weather condition and d_p is the scene depth from the camera. Thus, the reflected object color J_p is attenuated by t_p, whereas the airlight A is weighted by $(1 - t_p)$ and plays a more important role if the object is farther from the camera.

3. GLOBAL DEHAZING

To remove haze using a single image, additional constraints are required. For example, Oakely and Bu assumed that the same level of

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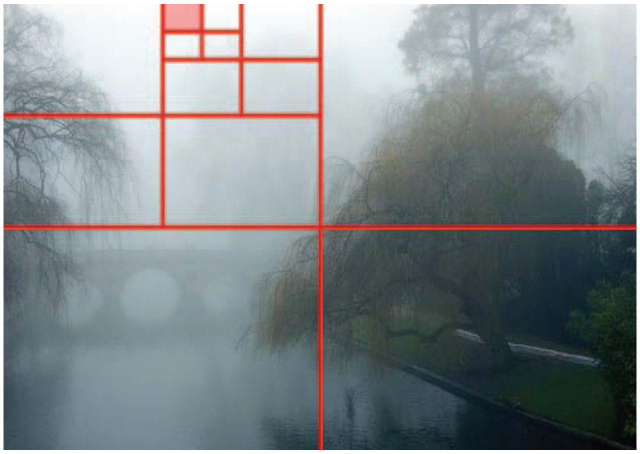


Fig. 1. Airlight estimation. By recursively dividing block into smaller sub-blocks and choosing the brightest sub-block, we locate the region that are hazed most densely and then estimate the airlight.

brightness is added to all pixels in a hazy image [8]. Similarly, in the global dehazing, we also assume that a captured image consists of pixels with similar depths. Thus, we approximate the transmission as a constant for all pixels. Note that, in the next section, we will extend the algorithm to estimate a space-varying transmission map.

Based on the constant transmission assumption, the haze modeling equation in (1) can be rewritten as

$$J_p = \frac{I_p - A}{t} + A. \quad (3)$$

Then, the original color J_p can be recovered from the observed color I_p by estimating the airlight A and the transmission t. Let us describe how to estimate the airlight and the transmission subsequently.

3.1. Airlight Estimation

Airlight is the ambient light in atmosphere, which is often estimated as the brightest color in an observed image. However, in such a case, too bright objects in an image may cause undesirable selection of the airlight. To estimate the airlight more reliably, we propose a hierarchical searching method based on the quad-tree subdivision.

As shown in Fig. 1, an input image is first divided into four blocks. The average pixel value of each block is computed, and then the brightest block with the largest average is selected to be divided again into four smaller blocks. This process is repeated until the size of a block is less than a pre-specified threshold. In Fig. 1, the red block is finally selected. Let (r_i, g_i, b_i) be the color vector of the ith pixel in the selected block. Then, the airlight is chosen as the color vector that minimizes the distance $\|(r_i, g_i, b_i) - (255, 255, 255)\|$. By minimizing the distance from the pure white vector $(255, 255, 255)$, we attempt to choose the airlight that is as bright and white as possible.

3.2. Transmission Estimation

After estimating the airlight A, the dehazed value J_p in (3) depends on the selection of the transmission t. We determine t so that the dehazed image has the maximum contrast. To measure the contrast of an image, we employ two criteria: standard deviation and histogram uniformness.

The first criterion is the standard deviation of the luminance components of the dehazed values J_p's. More specifically, we have the standard deviation

$$\sqrt{\frac{1}{N}\sum_{p=1}^{N}(J_{p,Y} - \bar{J_Y})^2}, \quad (4)$$

where N is the number of pixels in the image, $J_{p,Y}$ denotes the luminance component of J_p, and $\bar{J_Y}$ denotes the average of $J_{p,Y}$. Then, the standard deviation can be rewritten as a function of t using the formula in (3), given by

$$f_{\mathrm{std}}(t) = \frac{\sqrt{\frac{1}{N}\sum_{p=1}^{N}\left(I_{p,Y} - \bar{I_Y}\right)^2}}{t}, \quad (5)$$

where $I_{p,Y}$ is the luminance component of I_p and $\bar{I_Y}$ is the average of $I_{p,Y}$. Without truncation, the standard deviation $f_{\mathrm{std}}(t)$ is a monotonically decreasing function of the transmission t. However, after the dehazing using (3), some color values are smaller than 0 or larger than 255, which are truncated to 0 and 255, respectively. If we take into account this truncation procedure, $f_{\mathrm{std}}(t)$ has a concave shape in general, as illustrated in Fig. 2. In this example, if t is less than 0.4, too many pixel values are mapped to 0 or 255, thus the standard deviation rather decreases as t gets smaller.

The second criterion for measuring the contrast is the uniformness of the histogram. Note that a high contrast image tends to have a widely and uniformly distributed histogram, whereas the histogram values of a low contrast image are concentrated to a small range. Let h denotes the histogram of the dehazed image. More specifically, let $h_i(t)$ be the number of pixels that have luminance i in the dehazed image, when the transmission is set to t. Then, the uniformness or flatness of the histogram can be defined as

$$f_{\mathrm{uniform}}(t) = \sqrt{\sum_{i=0}^{255}\left(\frac{1}{256} - \frac{h_i(t)}{N}\right)^2}. \quad (6)$$

A smaller f_{uniform} indicates that the histogram h is more uniform.

Notice that a high contrast image has a large f_{std} but a small f_{uniform}. Therefore, we determine the transmission t to minimize the cost function

$$f_{\mathrm{cost}}(t) = -f_{\mathrm{std}}(t) + f_{\mathrm{uniform}}(t). \quad (7)$$

Fig. 2 shows $f_{\mathrm{std}}(t)$, $f_{\mathrm{std}}(t)$, and $f_{\mathrm{cost}}(t)$ for a test image. In this example, the transmission is estimated to be about 0.65.

4. LOCAL DEHAZING

The proposed global dehazing algorithm in Section 3 requires a low computational complexity, since the transmission is assumed to be a constant over an entire image. However it may not produce faithful results when scene depths vary complicatedly within an image, for example, when the depth differences between foreground objects and the background are very large.

Therefore, we also develop a local dehazing algorithm, which estimates space-varying transmission values. We first divide an input image into multiple blocks, and then estimate the optimal transmission for each block that maximizes the block contrast in a similar way to the global dehazing algorithm. We set the block size to

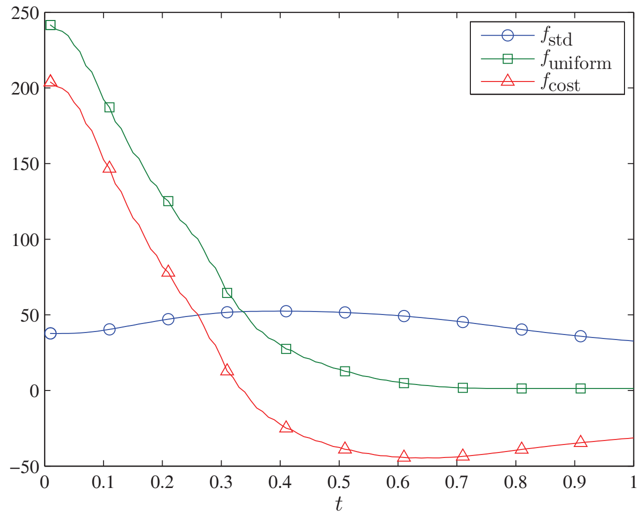
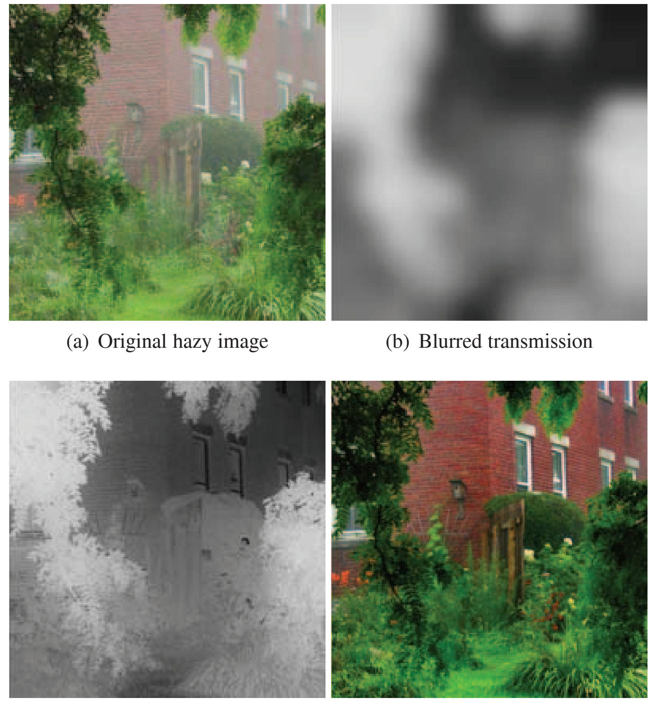


Fig. 2. The transmission t is set to minimize the cost function $f_{\mathrm{cost}}(t) = -f_{\mathrm{std}}(t) + f_{\mathrm{uniform}}(t)$, where f_{std} and f_{uniform} are the standard deviation term and the uniformness term.



(a) Original hazy image (b) Blurred transmission

(c) Refined transmission (d) Dehazed image

Fig. 3. Estimation of space-varying transmission for the local dehazing algorithm.

40×40 experimentally as a tradeoff between the accuracy and the reliability. More specifically, as the block size becomes smaller, the local depth variation can be estimated more accurately, but the estimated information is less reliable since a smaller number of pixels are employed in the cost function formulation.

Blocking artifacts may occur, since the transmission is estimated for each block independently of the other blocks. To alleviate those artifacts, we blur the blockwise transmission map using a Gaussian smoothing filter, as shown in Fig. 3(b). After the blurring, the transmission map still may not reflect the depth variation within a block faithfully. Therefore, we refine the transmission map more accurately using the edge information of the original image, since discontinuities in the depth map coincide with edges in the color image in general. To this end, edge preserving filters, such as the guided filter [10] or the cross bilateral filter [11], can be employed. In this work, we use the guided filter. Fig. 3(c) shows the refined transmission map, which faithfully reconstructs detailed edge structures.

5. EXPERIMENTAL RESULTS

The performance of the proposed single image dehazing algorithm is evaluated on various test images. In this section, we use test images, which have complicated depth structures. Thus, we provide the results of the local dehazing algorithm only.

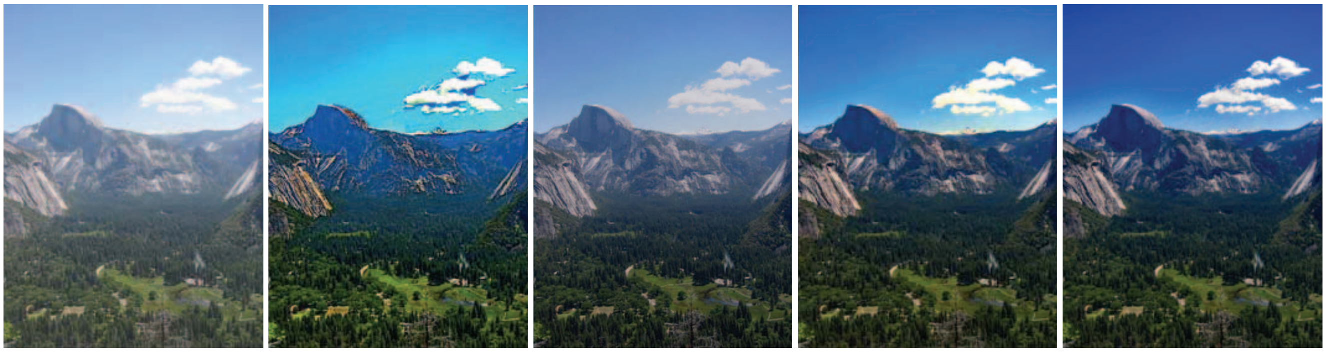
In Fig. 3, we see that the proposed algorithm removes haze in the input image and reconstruct the fine details of grass and trees clearly.

Fig. 4 compares the proposed algorithm with the conventional algorithms [6, 7, 8]. The Tan's algorithm [6] overstretches the contrast, yielding halo effects, as observed in the mountain and sky regions in Fig. 4(b). The Oakley and Bu's algorithm [8] estimates a global offset for an entire image and subtracts it from all pixel values. Thus, the overall brightness of the output image is reduced in Fig. 4(c). Moreover, [8] cannot reflect the space-varying depth information. The He *et al.*'s algorithm [7] provides superior performance to the other conventional algorithms, as shown in Fig. 4(d). However, we see that the proposed algorithm provides even better performance in Fig. 4(e). Notice that the clouds are more faithfully reconstructed. Fig. 5 shows another set of comparison results. It exhibits similar tendency to Fig. 4.

We also compare the complexity of the proposed algorithm to those of the conventional algorithms. The proposed algorithm is implemented in the MATLAB language, and a personal computer with a 2.5GHz Core Quad processor is employed in the test. The proposed algorithm takes about $20 \sim 30$ seconds to dehaze a 600×400 image, while the Tan's algorithm, the Oakley and Bu's algorithm, and the He *et al.*'s algorithm take about 300, 15, and 60 seconds, respectively. The proposed algorithm is not optimized yet. After the optimization, the processing speed of the proposed algorithm is expected to improve significantly.

6. CONCLUSIONS

In this paper, we proposed a simple adaptive dehazing algorithm using a single image, which is based on contrast enhancement. The proposed algorithm first estimates the airlight in a given hazy image based on the quad-tree subdivision. Then, the proposed algorithm estimates the optimal transmission to maximize the contrast. To measure the contrast, we developed the cost function, which consists of the standard deviation term and the histogram uniformness term. Furthermore, we extended the proposed algorithm to estimate a space-varying transmission map to dehaze an image with a com-



(a) Original hazy image (b) Tan [6] (c) Oakley and Bu [8] (d) He *et al.* [7] (e) Proposed algorithm

Fig. 4. Comparison of the proposed algorithm and the conventional algorithms on a test image.

(a) Original hazy image (b) Tan [6] (c) Oakley and Bu [8] (d) He *et al.* [7] (e) Proposed algorithm

Fig. 5. Comparison of the proposed algorithm and the conventional algorithms on another test image.

plicated depth structure more faithfully.

This work can be generalized to a video dehazing algorithm. Since video dehazing requires a huge amount of computing power, it is essential to develop a low complexity algorithm. The complexity of the proposed algorithm depends mainly on the edge preserving filtering, which consumes about 70% of the total computing time. Hence, one of the future research issues is to design an efficient filter, which uses the edge information to refine the transmission map accurately but at low computational complexity.

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