An Edge-preserving Filtering Framework for Visibility Restoration

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Abstract

In this paper, we propose a new framework for edge-preserving texture-smoothing filtering to improve the visibility of images in presence of haze or fog. The proposed framework can effectively achieve strong texture smoothing while keeping edges sharp, and any low-pass filter can be directly integrated into the framework. Our experiments with three popular low-pass filters (Gaussian filter, median filter and bilateral filter) show that our framework can better preserve the contrast around edges than the original filters. The visibility restoration algorithm based on our framework outperforms existing filtering-based algorithm without losing the speed advantage compared to non-filtering-based algorithms.

1. Introduction

The presence of haze or fog in images can degrade the visibility of photographs and may hamper the performances of some image processing algorithms in computer vision applications. It is important and challenging to develop algorithms that can improve the visibility of haze images. Existing visibility restoration algorithms using multiple images [5] or scene depth information [3] are rather limited because of the acquisition of additional information. Recently, several algorithms have been proposed to solve the problem using a single haze image by introducing some assumptions or priors. Tan [7] turns the problem into an optimization problem by assuming that the visibility improved image should have better contrast and the *airlight* varies smoothly depending on the object depth in the scene. Fattal [1] solves the problem based on the assumption that object surface shading and medium transmission function of haze should be locally uncorrelated. He et al. [2] introduce a dark channel prior which comes from their observation that the minimum color component over eroded color channels of outdoor haze image turns out to be closely related to the medium transmission map of haze. They use the dark channel to estimate a rough medium

transmission map and then refine it using soft matting algorithms. However, the common disadvantage of these three algorithms are that they are too slow to fulfil the demands of real-time applications. Based on these pioneering works, Tarel et al. [8] propose a fast algorithm which treats the problem as a filtering problem and thus can achieve much faster speed. The algorithm estimates the medium transmission map based on edge-preserving smoothing, and then restores the image using the medium transmission map. The core step is the edge-preserving smoothing step, where they utilize median filtering.
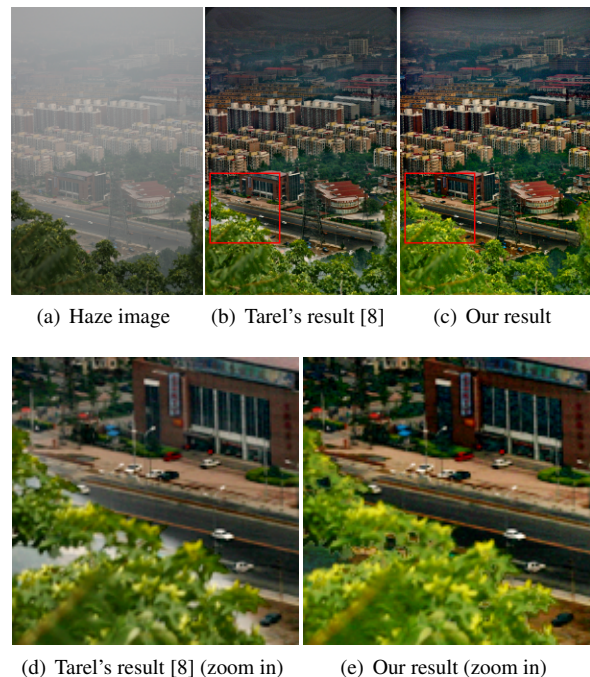

(a) Haze image   (b) Tarel's result [8]   (c) Our result

(d) Tarel's result [8] (zoom in)   (e) Our result (zoom in)

Figure 1. Visibility restoration results. Apparently, our method outperforms Tarel's algorithm [8] around large depth jumps.

The objective of using edge-preserving filtering in the visibility restoration algorithm is to smooth textured regions while preserving large scene depth discontinuities. Two popular edge-preserving filtering methods are median filtering and bilateral filtering. Unfortunately, both filtering methods cannot work well in visibility restoration. Median filter has strong smoothing ability but can blur edges, while bilateral filter with small range variance cannot achieve enough smoothing on textured regions in the visibility restoration algorithm and that with large range variance will also blur edges. Figure 1 (b) shows the restoration results of Tarel's algorithm [8] that utilizes median filtering. Note that their algorithm cannot remove haze near large scene depth discontinuities because median filtering cannot preserve edges well. In this paper, we present a new edge-preserving texture-smoothing filtering framework and show that it can generate better results in visibility restoration of haze images than existing methods.

2. Background

2.1. Edge-preserving Filtering

The main idea of the median filtering is to run through all pixels, replacing each pixel value with the median of neighboring pixel values. Bilateral filtering [9] is done by replacing the intensity value of a pixel by the average of the values of other pixels weighted by their spatial distance and intensity similarity to the original pixel. Specifically, the bilateral filter is defined a normalized convolution in which the weighting for each pixel q is determined by the spatial distance from the center pixel p, as well as its relative difference in intensity. Let I_p be the intensity at pixel p and $I_p^{\mathcal{F}}$ be the filtered value,

$$I_p^{\mathcal{F}} = \frac{\sum\limits_{q \in \Omega} G_{\sigma_{S'}}(\|p - q\|) G_{\sigma_R}(|I_p - I_q|) I_q}{\sum\limits_{q \in \Omega} G_{\sigma_{S'}}(\|p - q\|) G_{\sigma_R}(|I_p - I_q|)}, \quad (1)$$

where the spatial and range weighting functions $G_{\sigma_{S'}}$ and G_{σ_R} are often Gaussian, and σ_R and $\sigma_{S'}$ are the range and spatial variances, respectively. In this paper, the image intensities are normalized such that $I_p \in [0, 1]$ and σ_R is normally chosen between $[0, 1]$. Let the image width and height be w and h, we choose $\sigma_{S'} = \sigma_S \cdot \min(h, w)$, such that σ_S is also normally chosen between $[0, 1]$. Besides bilateral filter, we also use $\sigma_{S'}$ to represent the spatial variance of Gaussian filter and the radius of median filter in this paper.

2.2. Visibility Restoration Model

The widely adopted model for the formation of image in presence of haze or fog is as follows [4]:

$$\mathbf{I}_p = \mathbf{J}_p t_p + \mathbf{A}(1 - t_p), \quad (2)$$

where $\mathbf{I}$ is the haze image, $\mathbf{J}$ is the scene radiance (the actual appearance of the scene without haze), $\mathbf{A}$ is the atmospheric light (commonly assumed as a global constant), t_p is the medium transmission function depending on the scene depth. When the image is represented as a RGB three channels color image, $\mathbf{I}_p$, $\mathbf{J}_p$, and $\mathbf{A}$ are vectors and t_p is a scalar. The physical process of this equation can be described as follows: the actual radiance $\mathbf{J}_p$ at a point p in the scene, is attenuated by the atmosphere when passing through the haze, and shifted by an effect of atmospheric light $\mathbf{A}$ which is accumulated when the radiance passing through the haze. The first term $\mathbf{J}_p t_p$ describes the *direct attenuation* of scene radiance, while the second term $\mathbf{A}(1 - t_p)$ describes the effect of atmospheric light and is commonly called *airlight*. The goal of visibility restoration or *dehazing* algorithms is to estimate $\mathbf{J}$ given a single haze image $\mathbf{I}$. In order to estimate $\mathbf{J}$, the common way is to first estimate t_p and $\mathbf{A}$.

As can be seen from equation (2), the problem of estimating $\mathbf{J}$ using only $\mathbf{I}$ is severely ill-posed. Additional assumptions or priors need to be introduced to solve it. As mentioned in section 1, several methods have been proposed to solve it by introducing different assumptions or priors. In this paper, we follow the filtering-based method [8] and the additional assumptions and priors are hereby described explicitly as follows:

- The dark channel [2] of the haze image $\mathbf{I}$ is a rough estimation of term $(1 - t_p)$ in equation (2);
- The depth of scene objects in an image varies smoothly except over large depth jumps [7];
- All RGB color images have been white balanced, which implies that the atmospheric light $\mathbf{A}$ can be simply set to $(1, 1, 1)$ [8].

3. Our Filtering Framework

In this section, we present the details of our edge-preserving filtering framework and show how it works differently from the original filters. Given a grayscale image I as shown in Figure 3 (a) (if the input is multi-channel image, we process each channel independently), we first detect the range of the image intensity values, say $[I_{\min}, I_{\max}]$. We next sweep a family of planes at different image intensity levels $I_k \in [I_{\min}, I_{\max}], k = \{0, 1, ..., N - 1\}$ across the image intensity range space. The distance between neighboring planes is set to $\frac{I_{\max} - I_{\min}}{N - 1}$, where N is a constant. Figure 2 (b) shows such an example when $N = 5$. Smaller N results in larger quantization error while larger N increases the running time. When $N \to +\infty$ or $N = 256$ for 8-bit grayscale images, the quantization error is zero. Also, stronger smoothing usually requires smaller N.

We define the distance function of a voxel $[I(\mathrm{x}, \mathrm{y}), \mathrm{x}, \mathrm{y}]$ on a plane with intensity level I_k as the

(a) 3D view of Figure 3 (a)   (b) Established planes ($N = 5$)

(c) Distance maps $D(I_k)$ (d) Compute filtered image
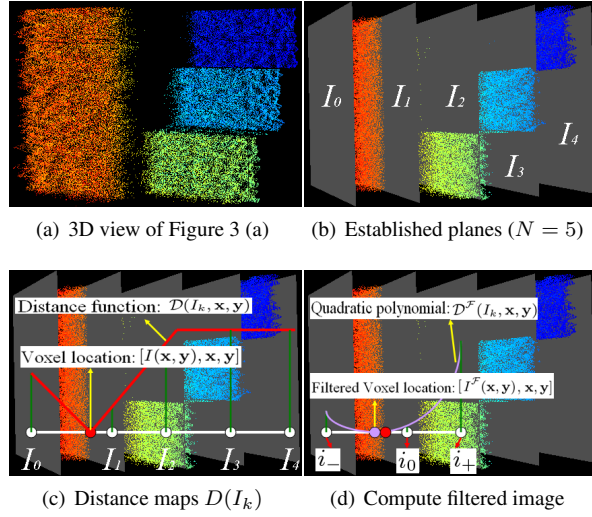
Figure 2. Our filtering framework.

(a) Original   (b) Gaussian   (c) Median   (d) Bilateral

(e) Original   (f) Our Gaussian (g) Our median (h) Our bilateral

Figure 3. Filtered results of a synthetic noisy image. (a) is the original grayscale image, and is visualized using a color map in (e) for clarity. (b)-(d): the filtered image obtained using Gaussian filter, median filter, and bilateral filter, respectively. (f)-(h): filtered images obtained using our edge-preserving filtering framework with the corresponding filters in (b)-(d).
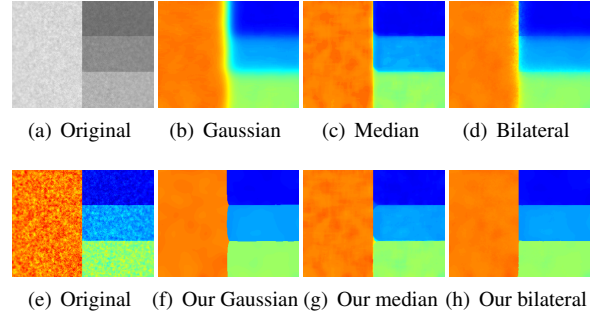
truncated Euclidean distance between the voxel and the plane (as shown in Figure 2 (c)):

$$D(I_k, \mathrm{x}, \mathrm{y}) = \min(|I_k - I(\mathrm{x}, \mathrm{y})|, \eta \cdot |I_{\max} - I_{\min}|), \tag{3}$$

where $\eta \in (0, 1]$ is a constant used to reject outliers and when $\eta = 1$, the distance function is equal to their Euclidean distance.

At each intensity plane, we obtain a 2D distance map $D(I_k)$. A low pass filter $\mathcal{F}$ is then used to smoothen this distance map to suppress noise:

$$D^{\mathcal{F}}(I_k) = \mathcal{F}(D(I_k)). \tag{4}$$

Then, the plane with minimum distance value at each pixel location $[\mathrm{x}, \mathrm{y}]$ is located by calculating

$$K(\mathrm{x}, \mathrm{y}) = \underset{k=\{0,1,...,N-1\}}{\arg\min} D^{\mathcal{F}}(I_k, \mathrm{x}, \mathrm{y}). \tag{5}$$

Let intensity levels $i_0 = I_{K(\mathrm{x},\mathrm{y})}$, $i_+ = I_{K(\mathrm{x},\mathrm{y})+1}$, $i_- = I_{K(\mathrm{x},\mathrm{y})-1}$. Assume that the smoothed distance function $D^{\mathcal{F}}(I_k, \mathrm{x}, \mathrm{y})$ at each pixel location $[\mathrm{x}, \mathrm{y}]$ is quadratic polynomial with respect to the intensity value I_k, the intensity value corresponding to the minimum of the distance function can be approximated using quadratic polynomial interpolation (curve fitting):

$$I^{\mathcal{F}}(\mathrm{x}, \mathrm{y}) = i_0 - \frac{D^{\mathcal{F}}(i_+, \mathrm{x}, \mathrm{y}) - D^{\mathcal{F}}(i_-, \mathrm{x}, \mathrm{y})}{2(D^{\mathcal{F}}(i_+, \mathrm{x}, \mathrm{y}) + D^{\mathcal{F}}(i_-, \mathrm{x}, \mathrm{y}) - 2D^{\mathcal{F}}(i_0, \mathrm{x}, \mathrm{y}))}, \tag{6}$$

which is the final filtered result of our framework at each pixel location $[\mathrm{x}, \mathrm{y}]$.

Apparently, any filter $\mathcal{F}$ can be integrated into this framework by using it to smoothen the distance map $D(I_k)$ as shown in equation (4). Figure 3 presents the experimental filtered results of our framework for a synthetic noisy image. In this experiment, the number of intensity planes N is set to 16 and $\eta = 0.1$. The parameter settings for low-pass filters are $\sigma_S = 0.05$ and as for bilateral filter, $\sigma_R = 0.2$. As can be seen in Figure 3, the use of our framework maintains the sharp intensity edges and greatly suppresses the noise inside each region.

4. Filtering-based Visibility Restoration

In Tarel's algorithm [8], they first calculate the minimum color components W of the input image **I** by

$$W_p = \min_{c \in \{r,g,b\}} (I_p^c) \tag{7}$$

where p is the location of each pixel in the image. Then they perform the following filtering on W to get B:

$$A = \mathrm{median}(W), \tag{8}$$

$$B = A - \mathrm{median}(|W - A|). \tag{9}$$

B is used to estimate the transmission map $\tilde{t}_p$ by

$$\tilde{t}_p = 1 - \min(\epsilon \cdot B_p, W_p), \tag{10}$$

where the factor ϵ in $[0, 1]$ is to control the strength of the restoration. Finally, each channel J^c of the restored image **J** can be calculated by

$$J_p^c = 1 - (1 - I_p^c)/\tilde{t}_p, \tag{11}$$

where $c \in \{r, g, b\}$ for RGB images. A followed post-processing step of tone mapping is suggested [8]

to make the color look similar to the input image.

Due to the twice median filtering (equation (8) and (9)) employed in Tarel's algorithm, it cannot remove haze near large depth jumps in the scene. On the other hand, bilateral filter can better preserve object boundaries when a small σ_R is used [9], but most of the textures are also kept thus it cannot provide enough texture smoothing in the visibility restoration algorithm. More aggressive smoothing can be achieved by increasing σ_R, but the increasing σ_R reduces the ability of the bilateral filter to preserve edges and some of the edges become blurred, as evident from Figure 3 (d). By employing our filtering framework, we modify the processing steps of visibility restoration as follows:

1) Calculate W using equation (7);
2) Get B by filtering W using our framework;
3) Estimate $\tilde{t}$ using equation (10);
4) Calculate $\mathbf{J}$ using equation (11).

5. Experimental Results

In all the experiments conducted in this paper, we use bilateral filter as the operator $\mathcal{F}$ in our filtering framework. We set the number of intensity planes N to 16, and set the parameter η in equation (3) to 0.1. The parameter ϵ in equation (10) is set to 0.95. Figure 1 (b) and (c) show the results of restoring an image using Tarel's algorithm and our algorithm, respectively. The filtering parameters for both algorithms are set to $\sigma_S = 0.05$, $\sigma_R = 0.1$ (σ_R is only for our algorithm). Compared with Tarel's algorithm, it is obvious that our algorithm can more effectively remove haze near large depth discontinuities. Figure 4 shows the result comparison of another image.

The speed of our algorithm is comparable to Tarel's algorithm, while other non-filtering-based visibility restoration algorithms mentioned in Section 1 are not comparable to our filtering-based algorithms [8]. We implement both our algorithm and Tarel's algorithm in C++. The bilateral filter in our algorithm is implemented using an $O(1)$ complexity per pixel algorithm [10] and the median filter in Tarel's algorithm is implemented by a fast $O(1)$ median algorithm [6]. Experiments show that our algorithm is only about $2.2\times$ slower than Tarel's algorithm on average. Specifically, the average running time for the image shown in Figure 4 (1024×768 pixels) are 0.78 seconds (ours) and 0.35 seconds (Tarel's) on a PC with Intel Core i7-2600 3.4GHz CPU and 4GB RAM, respectively.

6. Conclusion

We have described a filtering framework for edge-preserving smoothing, and demonstrated the benefits of using this framework when applying it to visibility restoration algorithm, where strong texture smoothing
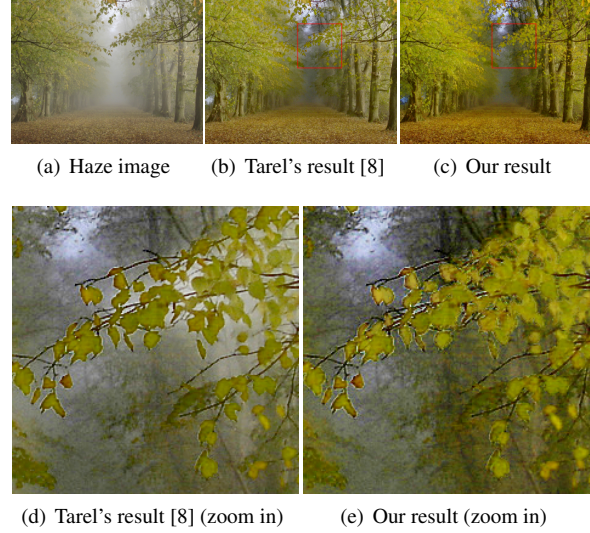

(a) Haze image   (b) Tarel's result [8]   (c) Our result

(d) Tarel's result [8] (zoom in)   (e) Our result (zoom in)

Figure 4. Visibility restoration results. Note that there is clear improvement around the leaves.

is required and the contrast around edges should be preserved. In the future, we intend to further improve our framework and apply it to other applications.

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