Improved Single Image and Video Dehazing Using Morphological Operation

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Abstract—**In the hazy days, the contrast is reduced by the distance, which obstruct the outdoor surveillance system from working properly. In this paper, we present an effective approach for defogging the images and videos based on filtering method. We first obtain an initial atmospheric scattering light by using gray scale morphological operation and refine it using guided filter. Finally the scene radiance is corrected using the visibility restoration model. The experimental results demonstrated that this method can effectively remove the bad weather condition and enhance the contrast of the input images. The use of gray scale morphological operation of these images makes our approach faster and it takes only 80% of the time in execution as compared with the fast bilateral filter. Present algorithm, due to its speed and ability to improve visibility, can be used in many systems, ranging from tracking and navigation, surveillance, consumer electronics, intelligent vehicles to remote sensing.**

Keywords: Gray-scale, Guided filter and Bad weather condition.

I. Introduction

Haze and fog removal is a typical phenomenon, which is caused by the minute particles in the air. Haze is composed of aerosol particles suspended in gas. It occurs when the dust and smoke particles accumulate in dry air, which gives a cloudy appearance. In a foggy scene, many reactions like scattering, refraction and absorption occur. The presence of this haze leads to considerable distortion of the scene, thereby reducing its visibility drastically at times. Hence defogging and dehazing is highly required for receiving high quality performance.

Image dehazing is a quite challenging problem because the effect of haze increases with the distance [1]. Considering that the degradation of image quality is exponential in the depths point, some researchers proposed that this phenomenon can be taken advantage to get the structure information about scenes, namely depth cues, from its images. In [2, 3, 4], a haze-free image is recovered using two or more images of the same scene taken under different weather conditions. This gives good results, but its implementation is not practical as the requirements cannot always be satisfied and this makes it difficult to meet with real-time applications. Polarization-based methods [5, 6, 7] were proposed to remove the haze effects through two or more images taken with different degrees of polarization. Recently, several successful methods for single image dehazing have been proposed. The success of these approaches usually lies on using stronger prior or assumptions. Tan [8] removes haze based on an observation that clear-day images have more contrast than hazy images. Fattal [9] proposed to estimate the albedo of the scene and the medium transmission under the assumption that the transmission and the surface shading are locally uncorrelated for single image dehazing. This approach is physically sound and can usually produce impressive results. Nevertheless, it cannot well restore heavily hazy images and may fail in the cases where the assumption is invalid. He et al. [10] proposed the dark channel prior method for image deweathering, which is based on statistics of a large number of haze-free images. Combining a haze imaging model and a soft matting method, we can estimate the transmission map and achieve a significant perceptual image quality improvement. But, soft matting algorithm requires numerous data to obtain the exact transmission at discontinuous edge of depth map. Therefore, it is difficult for real time processing. To overcome these problem Tarel and Hautiere [11] proposed a novel algorithm based on median filter but this method requires many parameters for adjustment.

In this paper, an effective haze removal algorithm is presented. For the estimation of atmospheric light gray-scale erosion and dilation is used and then refined using the guided filter method. For the estimation of transmission map the dark channel prior method proposed by He et al. [10] is used. Presented algorithm, does not require any pre/post processing steps. A few halo artifacts are expected to be found in the results due to the undertaken assumptions.

This paper is organized as follows. In Section II visibility restoration model is explained. In Section III the proposed algorithm is discussed. In Section IV and V performance matrices and simulation and results are discussed. Here performance of the proposed algorithm is compared with the prior state of the art algorithms. Section VI concludes this paper.

II. Visibility Restoration Model

The widely used model for the formation of image in presence of bad weather is as follows [4, 5]:

$$I(x,y) = I_o(x,y)e^{-\beta d(x,y)} + I_\infty(1 - e^{-\beta d(x,y)}) \quad (1)$$

The apparent luminance at each pixel (x, y) is $I(x, y)$. Where, $d(x, y)$ is the distance of the corresponding object with intrinsic luminance $I_o(x, y)$, I_∞ is the luminance of the atmosphere, and β denotes the extinction coefficient. The first term is the direct attenuation of light from the object surface

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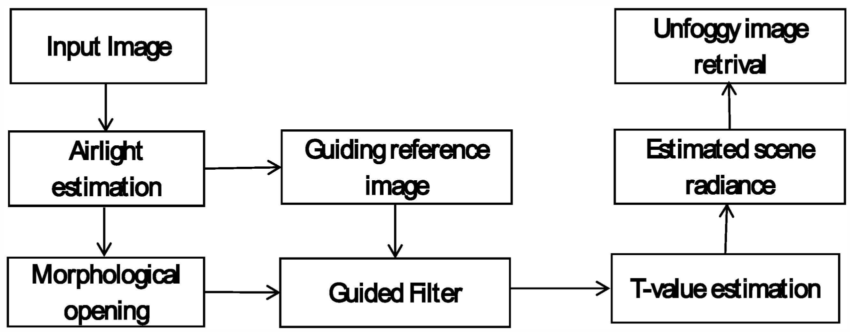

Fig. 1 *Flow chart of proposed fog removal algorithm*

and the second term is the airlight or atmospheric veil is the transmission due to scattering by the particles of the medium. When the atmosphere is homogenous, the transmission of the reflected light, which is determined by the distance between the object point and the camera is called as transmission map $T(x,y)$ and can be expressed as:

$$T(x,y) = e^{-\beta d(x,y)} \tag{2}$$

This equation shows that the transmission map is attenuated exponentially with scene depth $d(x,y)$.

III. THE PROPOSED ALGORITHM

This paper deals with the defogging and dehazing of images by using visibility restoration models and image restoration based algorithms. In this section, the proposed method will be described in detail. We will estimate atmospheric light using the gray scale morphological operation, but it contains blur edges. So we need to remove the blur edges. For this purpose, guided filter is used. The transmission map is estimated by using dark channel prior. The calculated transmission map from dark channel prior method gives good results, but it contains halos effects. So, transmission refinement is also done by using guided filter. Then finally the fog-free image is restored. The proposed method for foggy image restoration as depicted in Fig.1 consists of the following main modules:

(i) Estimate atmospheric light using the gray scale morphological operation and preserving the edges by using the guided filter method.

(ii) Estimate the transmission map using the dark channel prior method and refinement is done by using the guided filter.

(iii) Finally, estimate the scene radiance by substituting the refined transmission map through the visibility restoration model.

A. The prior knowledge of dark channel

The prior knowledge of dark channel is obtained from the observation of image without fog in outdoor condition [7]. In most of the non-sky patches, at least one color channel has very low intensity at some pixels. In other words, the minimum intensity in such a patch should has a very low value. Therefore, for an image I, dark channel is given by,

$$I^{dark}(x,y) = \min_{c\varepsilon\{r,g,b\}} \left(\min_{(x,y)\varepsilon\Omega} (I^c(\Omega)) \right) \tag{3}$$

Where, I^c is a color channel of I, $c\varepsilon\{r,g,b\}$ is color channel index and Ω is a local patch in image.

B. Estimating the atmospheric light

In most of the single image methods, the atmospheric light component A is usually estimated from the most fog-opaque pixel, such as the pixel with the max intensity value. Gray scale morphology operation is used for estimating the atmospheric light A. We first remove larger areas of white targets using the gray scale erosion and dilation operation. Then apply the gray scale opening operation for calculating the atmospheric light. The maximum value A is chosen as the candidate of the atmospheric light. The gray-scale opening operation makes the gray-scale smooth and the white target is eliminated, but it results in blurred edges. For removing the blurred edges, guided filter is used.

C. Estimating the transmission map

The transmission map is estimated as proposed by He et al. [10] using the dark channel. He et al. show that the transmission map can be estimated by:

$$\tilde{T}(x,y) = 1 - w \min_{c\varepsilon\{r,g,b\}} \left(\min_{(x,y)\varepsilon\Omega} \frac{I^c(\Omega)}{I^c_\infty} \right) \tag{4}$$

Where, w is a weighting factor and its value is application based. The parameter w is used to prevent removing the haze

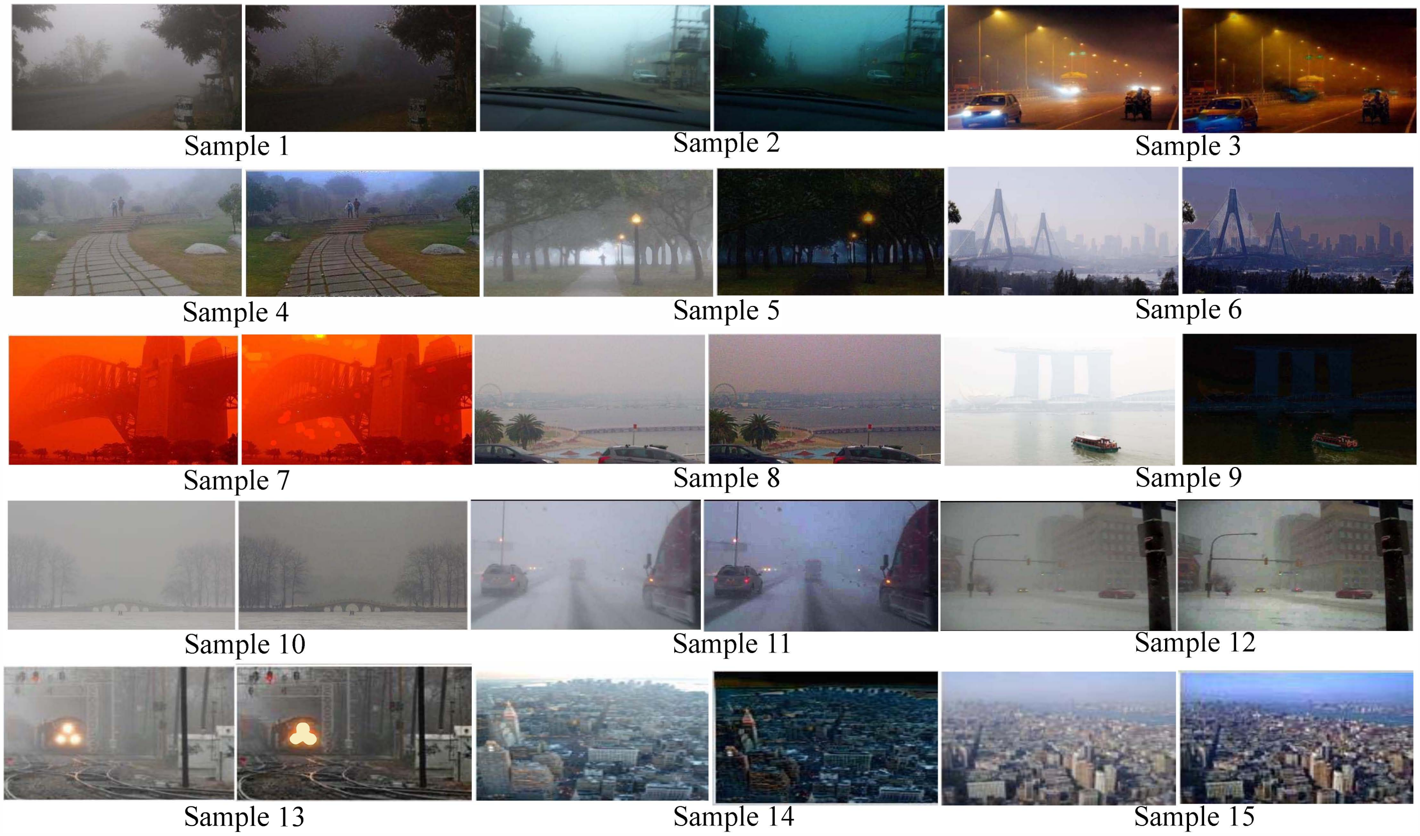

Fig. 2 *Different input images and corresponding output results*

thoroughly and keep the feeling of depth, it is set to be 0.95. The transmission obtained by equation (4) is only a coarse transmission. The recovered image using the coarse transmission contains halo artifacts. Therefore, the transmission map needs to be refined. Transmission map refinement is done by using guided filter.

D. Estimating the scene radiance

The airlight and the transmission map are estimated appropriately, the scene radiance can be obtained by solving equation (1):

$$I_o(x,y) = \frac{I(x,y) - I_\infty}{max(T(x,y), t_o)} + I_\infty \tag{5}$$

According to He et al. [7] the direct attenuation term $I_o(x,y)T(x,y)$ can be very close to zero when the transmission map $T(x,y)$ is close to zero. Since the recovered scene radiance $I_o(x,y)$ is prone to noise the transmission $T(x,y)$ is restricted to a lower bound t_o (typically 0.1) so that some amount of fog is preserved.

IV. Performance Metrices

In this section, some performance metrics like processing time, e and r value are used. Processing time is the time taken to process a particular algorithm. The time taken to process depends on the processor, the simulator and time complexity of the algorithm itself. Processing time is an important performance metric while considering a real time application. Here, we compiled the result of our approach and comparing it with the fast bilateral filter results in terms of processing time. Next, we used Hautiere method to assess the performance of the algorithms on each of the test images. The method defines the ratio e of the number of sets of new visible edges of the original image and the restored image, as well as the average gradient ratio r. They are expressed as:

$$e = \frac{n_r - n_o}{n_o} \tag{6}$$

Where, n_r and n_o are the numbers of visible edges in the original image and the restored image.

$$r = \frac{g_r}{g_o} \tag{7}$$

g_r and g_o are the average gradient of the original image and the restored image. For haze removal, the greater e and r , the better the dehazing effect.

V. Simulation and Results

In this section, the results obtained after the simulation of the proposed algorithm are analyzed and compared with the results of using fast bilateral filtering to remove the blur edges. The results are compared based on the above mentioned performance metrics. The images used for the purpose of simulating the algorithm is shown in Fig.2. The simulations were done using MATLAB R2012b (8.0.0.783) 64-bit and the

TABLE I: Algorithm processing results

Image	Size	Time (second)	e	r
Sample 1	540x960	4.461	-0.095	1.403
Sample 2	717x960	6.004	0.150	1.070
Sample 3	441x640	2.777	0.005	1.031
Sample 4	225x401	1.543	-0.236	1.469
Sample 5	367x498	2.140	0.239	1.142
Sample 6	349x620	2.329	0.480	1.479
Sample 7	230x408	1.546	-0.112	1.088
Sample 8	400x600	2.475	0.320	1.734
Sample 9	1080x1620	11.433	1.319	1.559
Sample 10	794x1247	6.960	0.191	2.424
Sample 11	360x480	2.028	0.312	1.260
Sample 12	360x480	1.947	-0.033	1.560
Sample 13	146x217	1.108	0.023	1.501
Sample 14	185x142	1.188	0.194	1.209
Sample 15	110x140	1.084	-0.05	1.432

algorithms were processed on Intel(R) Core(TM) i5-3337U CPU @ 1.80GHz along with 4GB RAM.

We had taken 15 different kinds of images so that we could get a better idea of the way the algorithm functions and for what kind of image does it works well. As can be seen from the Table I, the speed has been increased dramatically keeping the objective indicators (e and r) within appreciable limits. The green highlighted values are within the desired range. The yellow highlighted values are of tolerable range. The red highlighted values are not acceptable. The output has gone totally wrong for Sample 9. This implies that this technique is not suitable for images with too much of sky background with airlight and brightness. Table I shows that the our algorithm processing results for different input images and corresponding output results. The main contribution of our method is less processing time as compared with the fast bilateral filter. For a quantitative comparison, the speed improvement over fast bilateral filter obtained and summarized in the last columns of Table II. It is found that the proposed approach takes only 80% of the time in execution as compared with the fast bilateral filter.

After a thorough analysis of images we worked on videos. We applied two different algorithms for video processing of foggy and hazy videos, one that uses the fast bilateral filter approach and the other that makes use of the guided filter algorithm. Fig. 3 shows that the video frames results using the fast bilateral filter and guided filter. Here, first took a video and then broke it into frames. Then extracted the frames one by one and applied our algorithms on it to process the images. Then finally reconstructed the video back by combining all the frames together. The video processing was done on a predefined video. The saved video could be passed through the code and will give an output de-hazed video after a certain processing time. The real time implementation results can be seen in a live video stream with a tolerable lag of less than 0.5 seconds. From the Table III, it is clear that the proposed algorithm takes lesser processing time without compromising the video frames.

VI. Conclusion

In this paper, we proposed a faster and simpler image restoration method. The proposed method uses gray-scale morphological operation and guided filter for refinement and smoothing of atmospheric light. Our method takes less processing time as compared with the fast bilateral filtering method. Experimental results show that the proposed approach achieves dramatically high efficiency and dehazing effect as well. Our approach is giving a better result with speed improvement and

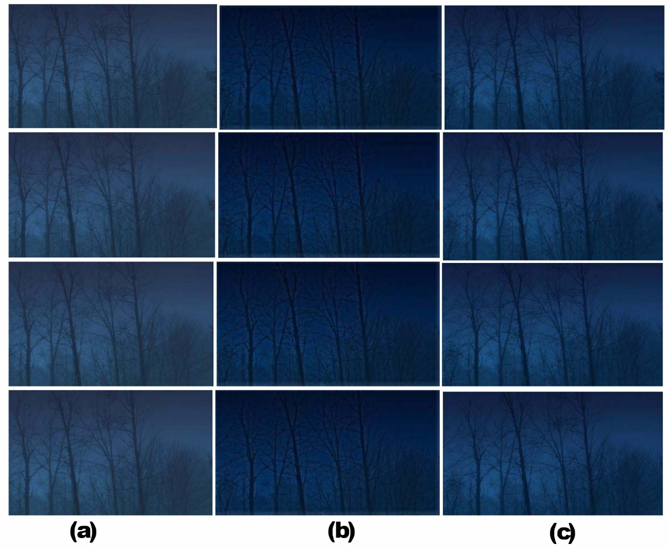

Fig. 3 *From left to right (a) video frames of original video (b) video frames of the corresponding output video using fast bilateral filter and (c) guided filter.*

TABLE II: Processing time comparison (in sec) with Fast bilateral filtering for different image sizes

Image	Size	Fast Bilateral filtering	Our	% improvement w.r.t fast bilateral filtering
Sample 1	540x960(s)	4.571	4.461	97.5
Sample 2	717x960(s)	6.112	6.004	98.2
Sample 3	441x640(s)	2.853	2.777	97.3
Sample 4	225x401(s)	1.785	1.543	86
Sample 5	367x498(s)	2.654	2.140	80.6
Sample 6	349x620(s)	2.839	2.329	82
Sample 7	230x408(s)	1.798	1.546	85.98
Sample 8	400x600(s)	2.534	2.475	97.6
Sample 9	1080x1620(s)	11.577	11.433	98.7
Sample 10	794x1247(s)	7.004	6.960	99.3
Sample 11	360x480(s)	2.145	2.028	94.5
Sample 12	360x480(s)	2.097	1.947	92.8
Sample 13	146x217(s)	1.212	1.108	91.4
Sample 14	185x142(s)	1.730	1.188	68.6
Sample 15	110x140(s)	2.355	1.084	46

TABLE III: Performance comparison results for videos

Filter used	Video size	Video length	Input size (mp4) (KB)	Output size (avi) (KB)	Time elapsed (avi file) seconds	Output Size (mp4) (KB)	Time elapsed (mp4 file) seconds
Guided video1	1280x720	4 second	1083	9066	555.238	4390	600.371
Bilateral video1	1280x720	4 second	1083	9156	696.387	4962	809.533
Guided video2	426x240	11 second	1322	2825	177.142	1173	189.624
Bilateral video1	426x240	11 second	1322	2870	242.712	1063	248.166

it is taking only 80% of the time as compared with the fast bilateral filter. The proposed approach with less processing time can be useful for many systems ranging from surveillance, intelligent vehicles, for remote sensing, etc. Next, we will focus on the hardware realization of the proposed algorithm is worth studying further.

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