A Fast Image Dehazing Algorithm for Highway Tunnel Based on Artificial Multi-exposure Image Fusion

Wenfeng Li 1*, Hongyan Wei 2, Guanqiu Qi 3, Hao Ding 1 and Ke Li 1

1 China Merchants Chongqing Communications Technology Research & Design Institute CO., LTD
2 College of Automation, Chongqing University of Posts and Telecommunications, Chongqing, 400065, China
3 Computer Information Systems Department, Buffalo State College, Buffalo, NY 14222, USA

*Corresponding author’s e-mail: liwenfeng@cmhk.com

Abstract. Single image dehazing has been a challenging problem due to its ill-posed nature. This paper proposed a fast image dehazing algorithm for highway tunnel based on artificial multi-exposure image fusion. The original blurred images are transformed into under-exposed images using a series of gamma-correction operations. Meanwhile, a multi-exposure image fusion algorithm based on two-scale decomposition is proposed. It exploits the guided filter to separate each multi-exposure image into base and detail layers. The fused base and detail layers are integrated into the fused images. Then, a linear saturation adjustment method is utilized to enhance the saturation in spatial domain. Through the above image processing steps, the final haze-free images can be obtained. In this paper, the superiority of the proposed image dehazing algorithm based on artificial multi-exposure image fusion is demonstrated through theoretical analysis and experimental verification. It can quickly improve the visibility of foggy images, and make the processed images colorful and clear.

1. Introduction

Due to the bad weather, such as haze or similar conditions in the tunnel, the monitored image is blurred, which makes it difficult to recognize the traffic status[1]. Image dehazing can eliminate the interference of haze in highway tunnel through certain image processing technology. Meanwhile, it improves the contrast and sharpness of input images. Numerous image dehazing have been put forward in recent decades. Traditional methods are divided into two categories: algorithms based on image restoration and image enhancement[2].

In the image restoration method, an atmospheric degradation model is used to evaluate and reduce the fog pattern [3]. Dark prior theory proposed by He [4] brought a major breakthrough in image recognition, and applied it to image dehazing, which provided new enlightenment for other relevant researchers. Zhu et al. [5] proposed a single image haze removal method using color attenuation prior, which creating a linear model for the scene depth of the hazy image to remove the haze. Since haze is depth-dependent phenomenon, degradation of hazy image is spatially variant. In this situation, unavailable depth information is typically alleviated by resorting to physical models of haze formation [6]. Unfortunately, even simplified physical models need to hold depth information, either implicitly or explicitly [6].
Image enhancement techniques directly improve contrast and highlight detailed features of hazy images by global or local optimization [7]. Mainstream image enhancement based dehazing techniques use histogram equalization [8], wavelet transform [9], homomorphic filtering [10] and image fusion [11] to improve image contrast and obtain clear haze-free images. Recent years, fusion-based dehazing algorithms have gradually become a hot research topic [11]. Galdran [6] exposed the hazy images using gamma-correction operations, and fused exposed images into haze-free images through a Laplacian blending scheme. Gao et al. [11] exploited a segmentation method to capture the range of global atmospheric light approximately, and an adaptive method is employed to produce several self-constructing images with different exposures. Compared with the traditional image dehazing methods, fusion-based has several advantages. The majority of methods perform an effective per-pixel computation, different from previous methods that process patches. A proper perpixel strategy reduces the amount of artifacts, since patch-based methods have some limitations due to the assumption of constant airlight in every patch [12]. Meanwhile, per-pixel computations usually more efficient and amenable to parallelization, which also can avoid costly refinement stages [13].

In this paper, a fast image dehazing algorithm for highway tunnel based on artificial multi-exposure image fusion is proposed. First, a series of gamma-correction operations are applied to original images constructed images are decomposed into the base and detail layers via the guided filter [14]. The luminance component of input images is employed to extract the exposedness features which are mapped to blending weights for base layers and detail layers though an exposedness function. Finally, the fused image is synthesized by combining the fused base and detail layers. A spatial linear saturation adjustment is performed on the fused image to obtain the final haze-free images.

The rest of this paper is organized as follows. Section II presents the proposed image dehazing method in detail. Experimental results and comparisons are presented in Section III. Finally, conclusions are given in Section IV.

2. The Proposed Image Dehazing Algorithm

This paper proposes a image dehazing framework based on artificial multi-exposure image fusion as shown in Figure 1. A hazy image I is corrected though gamma-operations, and different coefficients are set to generate under-exposure images. Then, the dehazed image H is obtained by using an artificial multi-exposure image fusion strategy on the under-exposure images.

2.1. Artificial Exposure Correction via Gamma Correction Transformation

In this paper, four different $\gamma > 1$ values (choose $\gamma = 1.2; 2; 4; 8$) are set via gamma-correction operations to obtain under-exposure images. The intensity of the globally modified image on a power function transformation is shown in eq. (1):

$$I(x) \mapsto \varepsilon \cdot I(x)^{\gamma} \quad (1)$$

where $\varepsilon$ and $\gamma$ are real positive numbers. Note that if we adopt a simple definition of image contrast for a given area $\Omega$ inside the image domain:
However, it is worth noting that gamma correction results in global increase or reduce exposure on a given image. Therefore, the following image processing steps are needed to extract the areas with good structural details from the artificially multi-exposure images in order to obtain the optimal dehazed image.

2.2. Artificial Multi-exposure Image Fusion

The blurred image is artificially transformed into under-exposure images through a series of gamma correction operations. In order to fuse image sequence better and preserve image structure details, a multi-exposure image fusion method is introduced. In this method, each multi-exposure image is segmented into a base layer and a detail layer by the guided filter. The exposure feature is extracted by the luminance component of the input multi-exposure image, which are mapped to blending weights for base layers and detail layers by an exposedness function. Then, the base and detail layers are combined to generate the final dehazed image through linear saturation adjustment in spatial domain.

2.2.1. Multi-scale Decomposition of Multi-exposure Images

The input multi-exposure image is represented as \( I_k \), \( k=1,\ldots,K \). For each input image \( I_k \), we first calculate the luminance component \( L_k \) by weighted sum of red, green and blue channels. Next, the fusion weights are obtained by using the luminance value. In our method, we employ the guided filter [18] as an effective edge-preserving smoothing filter. Each input image is divided into a smooth base layer \( B_k \) with large-scale intensity changes and a detail layer \( D_k \) with small-scale details.

2.2.2. Fusion rule of Multi-exposure Images

The process of multi-exposure image fusion is guided by the weight maps for the base and detail layers of each input image. In the proposed method, the weights are calculated using a general exposedness function \( \phi \) as illustrated in eq. (3):

\[
\phi(\varphi, \sigma) = \exp\left( -\frac{(\varphi - C)^2}{2\sigma^2} \right)
\]

(3)

Among them, \( \varphi \) represents the exposedness feature and \( \sigma \) controls the speed of the Gaussian.

In detail layer, we calculate the exposure features of each pixel position as the average luminance in a small local neighborhood. In fact, the exposure quality of image details is evaluated according to the average level of local intensity variations. Therefore, for each position \((x, y)\) in the detail layer of \( k \)th input image, the weight \( W_k^{D} \) is obtained by the exposedness function.

To obtain blending the weights of base layer, we consider the exposure quality of local and global luminance. Using the base layer itself and average luminance component as exposedness features, the local exposure weight \( W_k^{B,l} \) and global exposure weight \( W_k^{B,g} \) of the \( k \)th input image at the pixel position \((x, y)\) are obtained by the exposedness function respectively. Then, the weights \( W_k^{B,l} \) and \( W_k^{B,g} \) at each pixel position \((x, y)\) are combined to generate the weight \( W_k^{B} \).

After constructing the weights of all input images, it is normalized to have unit sum at each pixel position. Finally, the weighted average values of the base and detail layers of input images are merged into the fused image \( F \), as listed in eq. (4):

\[
F = \sum_{k=1}^{K} W_k^{B} B_k + \rho \sum_{k=1}^{K} W_k^{D} D_k
\]

(4)

Among them, \( \rho \) controls the detail intensity and thus local contrast of the resulting fused image.
2.2.3. **Spatial Linear Saturation Adjustment**
For the fused image $F$, whether to adjust the saturation is determined by the maximum and minimum components of R, G, and B channels at each pixel. Next, the saturation $S$ is adjusted in the HSL color space. After obtaining the saturation of each pixel, the same adjustment operation is performed on the three channels of the image RGB to generate the final dehazed image $H$.

3. **Experiment Results and Analysis**

3.1. **Experimental Preparation**
The following comparative experiments are carried out to prove that the proposed image dehazing algorithm has good dehazing performance in different scene images. The test images are selected from http://live.ece.utexas.edu/research/fog/fadedefade.html or we captured. This paper uses six different methods to dehaze images in different scenes respectively. These six methods are DCP [4], GPR [15], DFAD [16], WCD[17], MAMF[18] and the proposed algorithm. All of the dehazed images are generated by open source codes. All the experiments are programmed in MATLAB 2016a (MathWorks, Natick, MA, USA) on an Intel i7-7700k CPU@ 4.20-GHz desktop with 16.00 GB RAM.

For image dehazing, single evaluation index is lack of objectivity. Therefore, it is necessary to do a comprehensive analysis by using multiple evaluation indexes. In this experiment, three objective evaluation indexes were adopted to evaluate the performance of different image dehazing methods. That is, a full reference score can be used to compare the structural similarity of the hazy image as the ground truth value and the corresponding dehazed image [19]. The entropy value represents the amount of average information contained in images [20]. No-reference image quality indexes can be used to quantify the haze concentration of dehazed results for a given method [16]. Meanwhile, we record the processing time in six image dehazing methods.

3.2. **Subjective Evaluation**

In Figure 2, it shows an example of image dehazing in highway tunnel scenes. The experimental results show that the luminance of the dehazed image (b) obtained by DCP method is low. For the image (c), the dehazed image obtained by GPR method is smooth in the road. In addition, it is shown that the light area of dehazed image obtained by DEFADE method is bright. According to the dehazed image (e) obtained by WCD method, we find that the dehazed image has color distortion. There are some black blocks on the wall and white blocks on the road. Compared with the dehazed image (f) obtained by MEMF method, the proposed method performs better in whole image.
3.3. Objective Evaluation

Table 1. Evaluation of four objective indexes in image dehazing experiments. The higher values of SSIM and Entropy indexes are better, the lower value of FADE index is better.

| Method | SSIM  | Entropy | FADE  | Average Time |
|--------|-------|---------|-------|--------------|
| DCP    | 0.7808| 6.7964  | 0.5348| 1.9601       |
| GPR    | 0.7415| 0.70220 | 0.6528| 162.2043     |
| DFAD   | 0.7314| 6.9008  | 0.4895| 25.2140      |
| WCD    | 0.4369| 6.7657  | 0.6417| 2.5997       |
| MAMF   | 0.6291| 7.0620  | 0.2778| 1.9988       |
| Proposed | 0.8105| 7.1715  | 0.4561| 1.4573       |

As shown in Table 1, the performance of six image processing methods on four objective evaluation indexes is compared. Through comparative analysis of experimental data, it finds that the dehazed images obtained by proposed method have a high score in SSIM index, which retain the structural information of the original image. For the GPR method, it is found that this method consumes much time and costs in image dehazing. The DFAD method has medium scores in SSIM, FADE and entropy indexes, but its processing time is also long. Through observing the experimental data, we find that the WCD method has the lowest score on the SSIM index, that is, the similarity between the dehazed image and the original image is the lowest. Besides, the WCD method damages some image information to some extent. For the FADE index, MAMF method achieves the first result, which shows that it can effectively reduce the image haze. But for the other three indexes, the performance of this method is general. In the process of dehazing, the proposed method takes less time and has low complexity. It can effectively reduce costs and avoid waste. In brief, the proposed method can quickly achieve the purpose of dehazing. Meanwhile, it has good results in objective evaluation indexes and achieves a better human visual effect.

4. Conclusion

A fast image dehazing algorithm for highway tunnel based on artificial multi-exposure image fusion is proposed in this paper. Through a series of gamma-correction operations, the blurred images are artificially corrected to generate several under-exposure images. To fuse exposed images into high-quality images quickly, the guided filter is applied to decompose the images into the base and detail layer representations. The blending weights are efficiently computed using an exposedness function. Without any post-processing step, the computed weights are directly applied to guide the fusion process. To improve image color quality, a spatial linear saturation adjustment method is used to enhance image saturation and visibility. The experimental results show that the proposed algorithm can achieve the haze removal quickly and effectively, and the dehazed images have good human visual effects. At present, the majority of image defogging researches are based on single image. In future, extending defogging technology to video defogging will have higher practical significance and become a hot research topic.

Acknowledgments

This work is financially supported by National Key Research and Development Program of China (2017YFC08060010), the Key Technology Innovation Special of Key Industries of the Chongqing Science and Technology Bureau under Grant Nos. cstc2019jscx-fxydX0017.

References

[1] Li Y., Zhao M., Sun D. (2018) Fast enhancement algorithm of highway tunnel image based on constraint of imaging model. IET Image Processing, 12(10): 1730-1735.
[2] Wang Y.F., Wang H.Y., Yin C.L., Dai M. (2016) Biologically inspired image enhancement based on retinex. Neurocomputing, 177:373-384.
[3] Ning X., Li W., Liu W.J. (2017) A fast single image haze removal method based on human retina property. IEICE Transactions on Information and Systems, 100(1):211-214.
[4] He K.M., Jian S., Tang X.O. (2009) Single image haze removal using dark channel prior. Computer Vision and Pattern Recognition, pp.1956-1963.

[5] Zhu Q., Mai J., Shao L. (2015) A fast single image haze removal algorithm using color attenuation prior. IEEE Transactions on Image Processing, 24(11):3522-3533.

[6] Galdran A. (2018) Image dehazing by artificial multiple-exposure image fusion. Signal Processing, 149:135–147.

[7] Wang Y.F., Wang H.Y, Yin C.L., Dai M. (2016) Biologically inspired image enhancement based on retinex. Neurocomputing, 177:373-384.

[8] Thomas G., Flores-Tapia D., Pistorius S. (2011) Histogram specification: A fast and flexible method to process digital images. IEEE Transactions on Instrumentation and Measurement, 60(5):1565-1578.

[9] Li Y.C., Du L., Liu S. (2012) Image enhancement by lift-wavelet based homomorphic filtering. International Conference on Electronics, Communications and Control, pp.1623-1627.

[10] Lu Y., Liu G. (2015) A new dehazing algorithm based on overlapped sub-block homomorphic filtering. International Conference on MachineVision, 9875:1-8.

[11] Gao Y., Su Y., Li Q., Li H., Li J. (2019) Single image dehazing via self-constructing image fusion. Signal Processing, 167: 107284.

[12] Ancuti C.O. Ancuti C. Single image dehazing by multi-scale fusion. IEEE Transactions on Image Processing, 22(8):3271-3282.

[13] Chen C., Do M.N., Wang J. (2016) Robust image and video dehazing with visual artifact suppression via gradient residual minimization. European Conference on Computer Vision, pp.576-591.

[14] He K.M., Sun J., Tang X.O. (2012) Guided image filtering. IEEE transactions on pattern analysis and machine intelligence, 35(6):1397-1409.

[15] Fan X., Wang Y., Tang X.X, Gao R.J., Luo Z.X. (2016) Two-layer gaussian process regression with example selection for image dehazing. IEEE Transactions on Circuits and Systems for Video Technology, 27(12):2505-2517.

[16] Choi L.K., You J., Bovik A.C. (2015) Referenceless prediction of perceptual fog density and perceptual image defogging. IEEE Transactions on Image Processing, 24(11):3888-3901.

[17] Chiang J.Y., Chen Y.C. (2011) Underwater image enhancement by wavelength compensation and dehazing. IEEE Transactions on Image Processing, 21(4):1756-1769.

[18] Cho Y.G., Jeong J.Y., Kim A. (2018) Model-assisted multiband fusion for single image enhancement and applications to robot vision. IEEE Robotics and Automation Letters, 3(4):2822-2829.

[19] Wang Z., Bovik A.C., Sheikh H.R., Simoncelli E.P. et al. (2004) Image quality assessment: from error visibility to structural similarity. IEEE Transactions on Image Processing, 13(4):600-612.

[20] Gourab G.R., Mohammad R.K., Raabid H. (2016) Image visibility clarification and enhancement. Robotocs Project, pp.1-13.