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Multioriented Video Scene Based Image Dehazing Using Artificial Bee Colony Optimization

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Abstract:
The misty fog and hazy weather condition within the atmosphere can significantly decay the visibility of a scene. This is due to the atmospheric particles that absorb and scatter the light that travels from the scene point to the observer. This approach propose a simple and fast method for haze removal from a single input image based on image fusion. The method applies both the white balance and global contrast enhancement to the original image respectively; the method employs a bee colony optimization for accurate haze-free results. We acquire the enhanced results by determining the weight sum of the two inputs. To reduce the number of artifacts introduced by the weight maps, our method is designed in a multiscale fashion by using a Laplacian pyramid representation. This method performs in a per-pixel fashion. Experimental results demonstrate that our current method effectively removes haze, even better than the complex state-of-the-art techniques, and is sufficiently for real-time dehazing applications.

Key words: *Single image dehazing, Multi-Scale Fusion, enhancing, Artificial Bee Colony Optimization*

1. Introduction

Often the images of outdoor scenes are basically degraded by the improper weather conditions and by the presence of different particles such as fog, haze and the water droplets in the atmosphere that significantly degrade the visibility of the scene. Since the aerosol is misted by additional particles, the reflected light is scattered and as a result, distant objects and part of the scene are less visible being identified by reduced contrast and dim colors. Since restoring images degraded by haze is essential in several outdoor applications such as remote sensing, intelligent vehicles, object recognition, surveillance. In this paper we present a novel dehazing method, built on the principle of image fusion using artificial bee colony optimization. The main idea is to combine several images into a one, keeping only the most significant features. Then the inputs are weighted by normalized weight maps (luminance, chromatic and saliency) and finally combined in a multi-scale fashion, by using a laplacian pyramid representation of the original input that are combined with Gaussian pyramids of normalized weights that avoids introducing artifacts. The method is fast and being straightforward to implement Similarly, Several advantages of our technique against the previous one. First, our approach performs an effective per-pixel computation, by this; the complexity of our approach is more reduced. Secondly, our technique performs faster and being suitable for real-time applications. Fig. 1 shows the original image and the dehazing result. our technique computes a hazy image in less time and shows more accuracy.

This paper is organized as follows. In section 2, we give the optical model for atmospheric images. Then, the outline of our algorithm is presented in Section 3. In section 4 the proposed method illustrates detailedly. And, the simulation results show in section 5. Finally, the conclusions are provided. The following chapters will introduce these detailedly.

Figure 1: An example of haze removal by the proposed method. Left: original image. Right: dehazing result

2. Related Work

Enhancing image is a fundamental task in many image processing and vision applications. Restoring hazy images that require specific strategies, therefore many important methods have emerged to solve this problem. Several dehazing techniques have been applied for remote sensing system, in this system the recorded bands of reflected light are processed [1, 2] to restore the outputs. The multi-images techniques [3] solve the image dehazing problem by considering several input images taken in different atmospheric conditions, This method requires manually to identify regions that are heavily affected by haze or to provide some coarse depth information. Another alternative [4] is to assume that an approximated 3D geometrical model of the scene is given. By using [5] different angles of polarized filters the resulted images of the same scene estimates the haze effects. However the most difficult case is when only a single hazy image is used as input information. Fattal [6]
uses the Independent Component Analysis (ICA) to estimate the transmission map.
However, this method is hard to get idea result when the hazy is heavy. Also, if the ICA assumption not correct, it will get wrong result. Tan [7] calculates the maximization of local contrast to enhance the image, and then use the Markov random field (MRF) for haze removing. However this method does not consider the atmosphere light, so sometimes it leads to over-enhanced of some regions, specially the sky region. Based on the blackbody radiation theory, He et al. [8] employs a dark channel prior which assumes every local patch (15×15) in the haze-free image have an at least one-color components near zero. This assumption is sometime violated when there is no black body in some local patches. Instead of using a MRF, a soft matting algorithm is used to refine the transmission values, which is computational expensive. This prior to the haze-free image is close to black, and for hazy image become too bright. So it can be used to estimate the transmission map and the atmospheric light. Most of previous methods [6, 7, 8] that consider patches. A patch-based method has some limitations due to the assumption of a constant air light in every patch. In general, this assumption is not true and therefore, additional post processing is required (e.g. the method of, He et al. [8] needs to smooth the transmission map by alpha-matting). Kratz and Nishino [9] proposed the probabilistic method for factorizing the hazy image, and the MRF is used to estimate the energy to haze removal. This method can get the clear results, but the vision effect is not natural. In 2009, Schaul et al. [10] analyzed the visible and near-infrared light images of the same scene. The near-infrared light, with the wavelength of 700- 1100 nm, is less affected by the fog, and thus, the haze can be removed by combining the achromatic part of the visible image and the infrared image without estimating the atmospheric light or the image depth. The acquisition constraint is relatively simple, but it still cannot be used for the existing image databases. Tarel [11] proposes a bilateral filter to replace the optimization method, which improves the efficiency of algorithm and can be used in real-time. However, the dehazing result is not so good when there are discontinuous in the depth to a scene. The haze among gaps cannot be removed. The optical polarization property is exploited in [12], which use the multiple images captured the same scene with different degrees of polarization. The methods can also make good results, but they cannot be applied to dynamic scenes. It is very difficult to get depth from a single image. Some methods are proposed using multiple images [13]. The basic idea is to exploit the differences between multiple images captured for the same scene under different atmosphere conditions. The approaches can get rather good results, but it is difficult to obtained multiple images in many practical applications. A framework for analyzing the chromatic effects of the atmospheric scattering is introduced [14].

3. Optical Model

The image degradation model is based on the Koschmieder's law being generally assumed as well by the previous dehazing techniques. Due to the absorption and scattering the light crossing the atmosphere is attenuated and dispersed. Therefore only a percentage of the reflected light reaches the observer causing poor visibility in such degraded scenes. The light intensity, that reaches the observer is described by two main additive components: direct attenuation and veiling light known as well as airlight. The model is expressed as:

$$\mathbf{F = I\,J\,(x) + V_\infty\,(1 - J\,(x))} \qquad (1)$$

Where I is the scene radiance or haze-free image, Jr is the transmission along the cone of vision and V_∞ Is the veiling color constant. The optical model assumes linear correlation between the reflected light and the distance between the object and observer. The first component, direct attenuation D, represents how the scene radiance is attenuated due to medium properties: D = I J (x). The veiling light component V is the main cause of the color shifting and being expressed as:

$$\mathbf{V = V_\infty\,(1 - J\,(x))} \qquad (2)$$

The value of J depicts the amount of light that has been transmitted between the observer and the surface. Assuming a homogeneous medium, the transmission J is determined as J

(x) = e (−β d(x)) with β being the medium attenuation coefficient due to the scattering while d represents the distance between the observer and the considered surface. Practically, the problem is to estimate from the hazy input F the latent image, I when no additional information about depth and air light are provided.

4. Fusion-Based Dehazing

Most of the previous methods are computationally burdensome we searched for a different solution that processes very fast with minimum loss in accuracy. Our method is a fusion technique that employs only the inputs and weights derived from the original hazy image. And the main idea is to combine several images into a single one, keeping only the most significant features of them. By choosing appropriate weight maps and inputs, our fusion-based method is able to effectively dehaze images. However, our approach is fundamentally different since it dehazes images by simply blending the inputs weighted by several maps. Our strategy combines the input information in a per-pixel fashion minimizing the loss of the image structure.

4.1. Inputs

Our fusion method takes two inputs derived from the original image. The first inputI1 is obtained by white balancing the original hazy image. White balance step ensures the natural rendition of images by eliminating chromatic casts that are caused by the atmospheric color. Due to the fact that haze is dominating the image, an average value is computed for the entire image. The main objective of white balance algorithms, is to identify the illuminant color e(λ) or its projection on the RGB color channels (Re, Ge, Be). This steps assures that atmospheric light color constant V∞ is equal to one and the normalized image values are in the range [0, 1].

The second input the global contrast of the image becomes weaker after the attenuation of the light. To get a clear image, we will be bound to improve a global contrast of the source image. Hereon, we use histogram stretching to increase the contrast. This operation has the effect to amplify the visibility in regions degraded by haze but yielding some degradation in the rest of the image. A similar effect may be obtained by general contrast enhancing operators (e.g. gamma correction) that also amplify the visibility in the hazy parts while destroying the details in the rest of the image. However, this degradation is solved by employing proper weight maps.

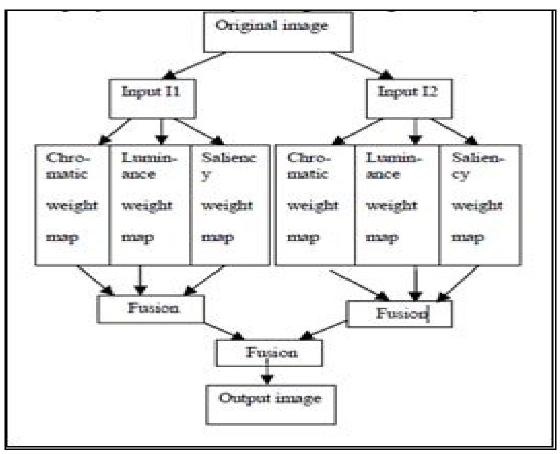

Figure 2: The outline of our algorithm

4.2. Optimal Estimation of air light map using ABC

The luminance image is divided into various subblocks and for each block air light is estimated. The air light can be estimated by improve the cost function method using a compensation that is based on the human visual model.

4.3. Restoration

The smoothed optimal airlight map is subtracted from the degraded image to restore the luminance image.

4.4. Clipped Adaptive Histogram equalization

clipped adaptive histogram Equalization can be used to restore the luminance image.. CLAHE addresses the issue of over amplification of noise that adaptive histogram equalization produces by limiting the contrast enhancement.

4.5. Weight Maps

White balance and enhancing the contrast are preliminary process to the image in RGB space. Actually the RGB model is not well adapted to explain the color for the human visual. To describe the saturation, hue and contrast of images better while observe color objects, we use the luminance weight map, chromatic weight map and saliency weight map to measure and extract more details of the input image. Then integrated into one image, we can get more accurate results. The following is the instruction of three weight maps.

4.6. Luminance Weight Map

It manages the luminance gain in the output image. This map computes the standard deviation between every R,G and B color channels and each pixel luminance L of the input. This overcomes the degradation induced by I2 in the haze-free regions ensuring a seamless transition between the inputs I1, I2. This maps also tends to reduce the global contrast and colorfulness. However, the effects are overcome by defining two additional weights: chromatic (colorfulness) and saliency (global contrast).

$$\mathbf{W}_{\mathbf{L}}^{\mathbf{k}}\sqrt{\frac{1}{3}}[(\mathbf{R}^{\mathbf{K}} - \mathbf{L}^{\mathbf{K}})^2 + (\mathbf{G}^{k} - \mathbf{L}^{k})^2 + (\mathbf{B}^{k} - \mathbf{L}^{k})^2].$$

Luminance L is computed by averaging the RGB channels

4.7. Chromatic weight map

It controls the saturation gain in the output image. To obtain this map, for every pixelis computed the distance between its saturation value Sand the maximum of the saturation range using a Gauss curve:

$$\mathbf{w}_{\mathbf{c}}^{\mathbf{k}}(\mathbf{x}) = \left(- \frac{(S^{k}(x) - S_{max}^{k})^2}{2\sigma^2}\right)$$

Where k is the derived inputs, the value of the standard deviation is σ = 0.3 and Smax is a constant that depends by the color space employed.

4.8. Saliency Weight Map

It identifies the degree of conspicuousness with respect to the neighborhood regions. In our approach is used the recent saliency algorithm of Achanta et al. [14] mainly because due to its computationally efficiency but also due to the fact that the yielded map has well-defined boundaries and uniformly highlighted salient regions even at high resolution scales. The impact of this gain is to increase the global contrast appearance since it increases the contrast in highlighted and shadowed parts.

$$\mathbf{w}_{\mathbf{S}}^{\mathbf{k}}\ (\mathbf{x}) = \left\|\mathbf{I}_{\mathbf{k}}^{\omega hc}(\mathbf{x}) - \mathbf{I}_{\mathbf{k}}^{\mu}\right\|$$

Iμ k represents the arithmetic mean pixel value of the input Ik. ωhc k is the blurred version of the same input that aims to remove high frequency such as noise.

4.9. Multi-scale Fusion

Final step, we have adopted a multi-scale image fusion In the fusion process, the inputs are weighted by specific computed maps to conserve the most significant detected features. Our approach is simplyblending the inputs weighted by several maps. Our strategy combines the input information in a per-pixel fashion minimizing the loss of the image structure. After we got the two input maps, we extract the three weight maps for each input image,they are wL _ 1， wL _ 2
（luminance weight map ） , wC _ 1 wC _ 2
（chromatic weight map）and wS _ 1 wS _ 2
（saliency weight map. In order to facilitate the subsequent weighted fusion. Each weight map must be normalized first. And the normalized value of the illuminace map of the input I1:

NwL _1 = wL _1 /(wL _1 + wL _ 2) (3)
NwL _ 2 = wL _ 2 /(wL _1 + wL _ 2) (4)

$$\mathbf{F}_{\mathbf{l}}^{(i,j)} = \sum_{\mathbf{k}} \mathbf{G}_{\mathbf{l}}\{\overline{\mathbf{W}}_{\mathbf{k}}^{(i,j)}\}\ \mathbf{L}_{\mathbf{l}}\{\mathbf{I}_{\mathbf{k}}^{(i,j)}\}$$

Where l represents the number of the pyramid levels and L {I} is the Laplacian version of the input I while G_¯Wrepresents the Gaussian version of the normalized weightmap of the ¯W . This step is performed successively for each pyramid layer, in a bottom-up manner. The final haze-free image J is obtained by summing the fussed contribution of all inputs.

$$J(x) = \sum_{l} F_l(x) \uparrow^{d}$$

where↑d is the upsampling operator with factor d = 2l−1. Normalized weight maps *k W* input *k* the fused pyramid *F*

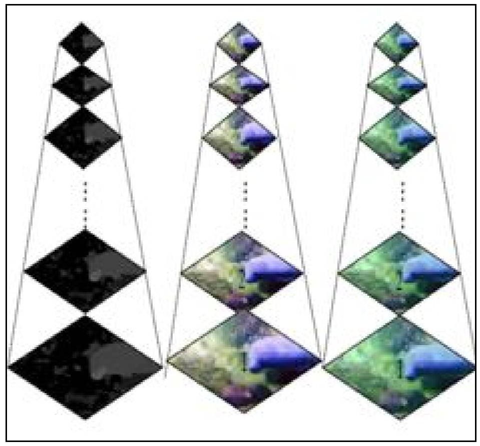

Figure 3: Pyramid Model

5. Results and Discussion

In order to prove the robustness of our method we have tested a large dataset of natural hazy images. We also considered the complete sets of images provided by the authors of the previous single image dehazing methods. As can be seen our operator is able to perform comparative with more complex methods.

	Unsharp mask			Tan[7]			Fatal[6]			Tarel[10]			ours		
	e	Σ	$\bar{r}$	e	Σ	$\bar{r}$	e	Σ	$\bar{r}$	e	Σ	$\bar{r}$	e	Σ	$\bar{r}$
Ny12	-0.09	0.72	2.57	-0.14	0.02	2.34	-0.06	0.086	1.32	0.07	0.0	1.88	0.02	0.0	1.49
Ny17	-0.10	1.28	2.29	-0.06	0.01	2.22	-0.12	0.02	1.56	-0.01	0.0	1.87	0.12	0.0	1.54
Y01	0.04	0.27	2.59	0.08	0.01	2.28	0.04	0.02	1.23	0.02	0.0	2.09	0.07	0.01	1.19
Y16	0.09	2.32	1.87	-0.08	0.01	2.08	0.03	0.00	1.27	-0.01	0.0	2.01	0.18	0.01	1.46

Table 1

However, compared with most of the existing techniques, an important advantage of our strategy is required computation time, since our method is able to processes a 600 × 800 image in approximately 2–300ms (20% for derived inputs, 35% for the weight maps while the multi-scale strategy takes approximately 45% of the entire fusion process on an Intel Core i7 CPU, 8GB RAM). In comparison, the method of Tan [7] needs more than 5 minutes per image.

6. Conclusion

The method presented on this paper is a fusion-based approach that solves the problem of single image dehazing. We have shown that by choosing appropriate weight maps and inputs, the fusion method can be used to effectively dehaze images. Our technique has been tested for a large data set of natural hazy images. The method is faster than existing single image dehazing strategies yielding accurate results. To future work, we would like to test our method for videos.

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