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Multiple Fusion Based Single Image Dehazing

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Abstract

Haze is an atmospheric occurrence that notably degrades the visibility of outdoor scenes. Haze occurrence mainly due to the atmosphere particles that absorb and scatter the light that leads to the image degradation. This paper introduces a multiple fusion based novel single image approach that reduces this degradation in the visibility of images. In this method, by using white balance and contrast enhancing procedures, this approach derives from two original hazy image inputs. To blend effectively the information of the derived inputs to preserve the regions with good visibility, we filter their important features by computing three measures (weight maps): luminance, chromaticity, and saliency. To reduce artifacts introduced by the weight maps, our approach is designed in a multiscale fashion, using a Laplacian pyramid representation. This paper demonstrates the utility and effectiveness of a fusion-based technique for dehazing based on a single degraded image. The method performs in a per-pixel fashion, which is straightforward to implement. The experimental results demonstrate that the method yields results comparative to and even better than the more complex state-of-the-art techniques, having the advantage of being appropriate for real-time applications.

Keywords: Single image dehazing, outdoor images, enhancing.

Introduction

Often, the images of outdoor scenes are degraded by bad weather conditions. In such cases, atmospheric phenomena like haze and fog degrade significantly the visibility of the captured scene. Since the aerosol is misted by additional particles, the reflected light is scattered and as a result, distant objects and parts of the scene are less visible, which is characterized by reduced contrast and faded colors.

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Restoration of images taken in these specific conditions has caught increasing attention in the last years. This task is important in several outdoor applications such as remote sensing, intelligent vehicles, object recognition and surveillance. In remote sensing systems, the recorded bands of reflected light are processed in order to restore the outputs. Multi-image techniques solve the image dehazing problem by processing several input images, which have been taken in different atmospheric conditions. Another alternative is to assume that an approximated 3D geometrical model of the scene is given. In this paper of Treibitz and Schechner different angles of polarized filters are used to estimate the haze effects. In this work, the main aim is to develop a simple and fast technique and therefore, as will be shown, all the fusion processing steps are designed in order to support these important features. The main concept behind our fusion based technique is that we derive two input images from the original input with the aim of recovering the visibility for each region of the scene in at least one of them. Additionally, the fusion enhancement technique estimates for each pixel the desirable perceptual based quality (called weight maps) that controls the contribution of each input to the final result.

There are two major problems, the first one is the color cast that is introduced due to the air light influence and the second is the lack of visibility into distant regions due to scattering and attenuation phenomena. The first derived input ensures a natural rendition of the output, by eliminating chromatic casts that are caused by the airlight color, while the contrast enhancement step yields a better global visibility, but mainly in the hazy regions. However, by employing these two operations, the derived inputs taken individually still suffer from poor visibility, Therefore, to blend effectively the information of the derived inputs, filtering (in a per-pixel fashion) their important features, by computing several measures (weight maps). Consequently, in this fusion framework the derived inputs are weighted by three normalized weight maps (luminance, chromatic and saliency) that aim to preserve the regions with Good visibility.

Finally, to minimize artifacts introduced by the weight maps, our approach is designed in a multi-scale fashion, using a Laplacian pyramid representation of the inputs combined with Gaussian pyramids of normalized weights. In this technique have several advantages over previous single image dehazing methods. First, our approach performs an effective per-pixel computation, different from the majority of the previous methods that process patches. A proper per-pixel strategy reduces the amount of artifacts, since patch based methods have some limitations due to the assumption of constant airlight in every patch. In the next section, the related techniques that deal with haze removal are briefly reviewed. In Section III, some theoretical aspects of light propagation in such environments. In Section IV, introducing a new single image based dehazing technique; the details regarding our fusion technique are discussed in this section. In the next section V, the result and discussions are made, In Section VI our method is summarized.

II. Related Work

Enhancing images represents a fundamental task in many image processing and vision applications. As a particular challenging case, restoring hazy images requires specific strategies and therefore an important variety of methods have emerged to solve this problem. Firstly, several dehazing techniques have been developed for remote sensing systems, where the input information is given by a multi-spectral imaging sensor installed on the Lands at satellites. The recorded six-bands of reflected light are processed by different strategies in order to yield enhanced output images. The well-known method of Chavez is suitable for homogeneous scenes, removing the haze by subtracting an offset value determined by the intensity distribution of the darkest object.

Figure 1. Result comparison with previous work

A second category of methods employs multiples images or supplemental equipment. In practice, these techniques use several input images taken in different atmospheric conditions. Different medium properties may give important information about the hazy image regions. Such methods produce pleasing results, but their main drawback is due to their acquisition step that in many cases is time consuming and hard to carry out. Different strategies have been developed when the approximated 3D geometrical model of the scene is given. The *Deep Photo* system uses the existing georeferenced digital terrain and urban models to restore foggy images. The depth information is obtained by iteratively aligning the 3D models with the outdoor images. This method is also a single image dehazing technique. Different than previous single image dehazing approaches; This technique is built on the principle of image fusion, a well-studied topic of computational imaging that has found many useful applications such as interactive photomontage image editing ,image compositing and HDR imaging. The main idea is to combine several images into a single one, retaining only the most significant features. Even though the fusion principle has been used previously to restore hazy images, but using additionally near-infrared (NIR) image of the same scene. It is the first paper that introduces a single image dehazing technique based on the fusion principle that blends only the information existing in the input image.

III. Light Propagation

Due to the absorption and scattering, the light crossing the atmosphere is attenuated and dispersed. While in normal Conditions (clear day) the size of air molecules is relatively small compared with the wavelength of visible light, the Scattering influence might be considered insignificant. Haze is traditionally an atmospheric phenomenon where dust, smoke and other dry particles obscure the clarity of the sky. Haze reduces visibility for distant regions by yielding a distinctive gray hue in the captured images.

Based on the Koschmieder's law only a percentage of the reflected light reaches the observer causing poor visibility in such degraded scenes. The light intensity I for each pixel x, that reaches the observer is described by two main additive components: *direct attenuation* and *veiling light*, also known as *airlight*.

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

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:

$$D(x) = J(x)\,T(x).$$

The *veiling light* component V is the main cause of the color shifting, being expressed as:

$$V(x) = V_{\infty}\,(1 - T(x)).$$

IV. Fusion-Based Dehazing

In this section is presented in details of fusion technique that employs only the inputs and weights derived from the Original hazy image. The fundamental idea is to combine several input images (guided by the weights maps) into a single one, by keeping only the most significant features of them. Obviously, the choice of inputs and weights is application-dependent. By processing appropriate weight maps and inputs, this paper demonstrate that our fusion-based method is able to effectively dehaze images.

As mentioned previously, the input generation process seeks to recover optimal region visibility in at least one of the Images. In practice, there is no enhancing approach that is able to remove entirely the haze effects of such degraded inputs. Therefore, considering the constraints stated before, since the process have only one captured image of the scene, the algorithm generates from the original image only two inputs that recover color and visibility of the entire image. The first one better depicts the haze-free regions while the second derived input increases visible details of the hazy regions. The first input *I*1 is obtained by white balancing the original hazy image. By this step this paper aims a natural rendition of images, by eliminating chromatic casts that are caused by the atmospheric color, for a computationally effective dehazing approach in this paper it opted for the *shades-of-gray* color constancy technique.

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)*. the intensity measured can be modeled as:

$f(x) = \int_w e(\lambda)s(\lambda,x)\, c(\lambda)d\lambda$

Where*e(λ)* is the radiance given by the light source, *λ* is the wavelength, *s(λ, x)* denotes the surface reflectance, *c(λ)* =[*R(λ), G(λ), B(λ)*] describes the sensitivity of the sensors while *ω* is the visible spectrum. The illuminant e to be estimated is expressed as:

e = *(Re, Ge, Be)* =$\int_w e(\lambda)c(\lambda)d\lambda$.

According to the *Grey-World* assumption of Buchsbaum the average reflectance of the scene is achromatic (gray). This hypothesis is mathematically defined as follows:

$$\frac{\int s(\lambda,x)dx}{\int dx} = k$$

Where *κ* is the constant assumed to have the value 0.5.Next, by replacing *s* in equation 3 with 5, the following expression is obtained:

$$\frac{\int f(x)\,dx}{\int dx} = \frac{1}{\int dx}\iint_w e(\lambda)s(\lambda,x)c(\lambda)d\lambda dx \leftrightarrow$$

$$\frac{\int f(x)\,dx}{\int dx} = k\int_w e(\lambda)c(\lambda)d\lambda$$

As shown in *shades-of-gray* and *grey-edges* white balance can be defined based on Minkowski norm of images. *Grey-World* algorithm estimates the illumination, by stating that the average color of the entire image raised to a power *n* is achromatic (gray).

$$\left[\frac{\int f^n dx}{\int dx}\right]^{\frac{1}{n}} = ke = k(R_e, G_e, B_e)$$

For the second input we searched for a relatively complementary processing technique, capable to enhance those regions that present low contrast. Considering the air light factor from the optical model (that is both additive and multiplicative with the transmission), and since the haze is dominant in the hazy images, it is expected that the hazy regions would have a great influence over the average of the image. Moreover, due to the fact that the airlight influence increases linearly with the distance, the luminance of these regions is assumed to amplify with the distance. Mathematically, the second input computed for each pixel *x* is obtained by applying the following expression:

$$I_2(x) = \gamma(I(x) - \bar{I})$$

Where *γ* is a factor that increases linearly the luminance in the recovered hazy regions (default value is *γ* = 2.5). This default value for *γ* matches for those most cases. However, in our experiments there are few exceptions that are not satisfied. These cases are characterized by the fact that hazy regions are relatively darker than non-hazy regions.

Weight maps

Weight maps balance the contribution of each input and ensure that regions with high contrast or more saliency from a derived input, receive higher values. The *luminance weight map* measures the visibility of each pixel and assigns high values to regions with good visibility and small values to the rest. This weight map is simply computed (for each input **Ik**, with *k* indexes the derived inputs) as the deviation (for every pixel location) between the *R*,*G* and *B* color channels and the luminance *L* from the input:

$$w_L^k = \sqrt{\frac{1}{3}[(R^k - L^k)^2 + (G^k - L^k)^2 + (B^k - L^k)^2]}$$

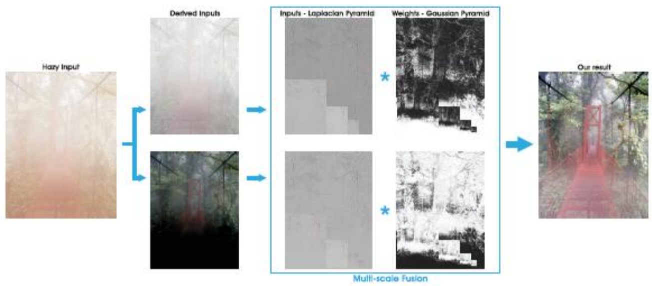

Figure 2. Dehazing flow of image

The *chromatic weight map* controls the saturation gain in the output image. This weight map is motivated by the fact that in general humans prefer images characterized by a high level of saturation. To obtain this map, for each pixel the distance between its saturation value *S* and the maximum of the saturation range is computed as following

$$w_c^k(x) = exp\left(-\frac{(s^k(x) - s_{max}^k)^2}{2\sigma^2}\right)$$

The *saliency weight map* identifies the degree of conspicuousness with respect to the neighborhood regions. This perceptual quality measure assesses that a certain object/person stands out from the rest of the image, or from nearby regions. The saliency weight at pixel position *(x, y)* of input *I k* is defined as:

$$w_s^k(x) = \|I_k^{\omega hc}(x) - I_k^{\mu}\|$$

Multi scale fusion

In the fusion process, the inputs are weighted by specific computed maps in order to conserve the most significant detected features. Each pixel *x* of the output *F* is computed by summing the inputs *Ik* weighted by corresponding normalized weight maps *W k :*

$$F(x) = \sum_{k} \hat{W}^{k}(x) I_k(x)$$

Where *Ik* symbolizes the input (*k* is the index of the inputs) that is weighted by the normalized weight map *Wk*. To prevent degradation problems, in this paper it have opted for the adapted solution that employs a classical multi-scale pyramidal refinement strategy.

Gaussian pyramid is computed. Considering that both the Gaussian and Laplacian pyramids have the same number of levels, the mixing between the Laplacian inputs and Gaussian normalized weights is performed at each level independently, yielding the fused pyramid:

$$F_l(x) = \sum_{k} G_l\left\{\hat{W}^{k}(x)\right\} L_l\{I_k(x)\}$$

Where l represents the number of the pyramid levels (default value of the number of levels is l=5) and $L\{I\}$ is the Laplacian version of the input I while $G\{W\}$represents the Gaussian version of the normalized weight map 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 contribution of the resulting inputs (levels of pyramid):

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

V. Results and Discussion

To prove the robustness of this method, the new operator has been tested on a large dataset of different natural hazy images. Haze due to dust, smoke and other dry particles reduces visibility for distant regions by causing a distinctive gray hue in the captured images. However, this technique has been successfully tested as well for a slightly different case: foggy scenes, For our problem, fog has a similar impact as haze, but technically it appears as a dense cloud of water droplets close to the ground when night conditions are clear but cold, and the heat released by the ground is absorbed during the day . It assumes that the input hazy/foggy images are color images and the images may contain achromatic objects.

Figure 3. Comparison of the recent dehazing techniques.

Besides the initial hazy images in this figure are displayed the results of Tan, Fattal, Kopf et al. and our technique. Analyzing the results of table I, in general, all the considered techniques (including our technique) yield small values of the ∑descriptor (the percentage of pixels which become completely black or completely white after the restoration). On the other hand, indicator *e* shows that most of the methods depending on the processed image remove some of the visible edges. Interestingly, only our method and He et al. technique are characterized by positive values of the indicator *e* for the considered images.

Even though the proposed method performs in general well, as the previous methods, a limitation of our algorithm may be observed for images that are characterized by nonhomogeneous haze layers. As can be seen, the other single image dehazing approaches present serious limitations while tackling this challenging case (e.g. the technique of Tarel and Hautiere yields unpleasing artifacts such as coarse edges and color distortion).Moreover, even though some enhancement may be achieved, our technique is limited to processing color images.

Table I. Result analysis

	unsharp mask			Tan [7]			Fattal [6]			Kopf [4]			He [8]			Tarel [10]			Nishino [14]			Ours		
	e	Σ	$\bar{r}$	e	Σ	$\bar{r}$	e	Σ	$\bar{r}$	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	0.05	0.00	1.42	0.06	0.0	1.42	0.07	0.0	1.88	-0.01	0.46	1.81	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	0.01	1.62	0.01	0.00	1.65	-0.01	0.0	1.87	-0.07	0.91	1.79	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	0.09	0.00	1.62	0.08	0.01	1.33	0.02	0.0	2.09	0.11	0.71	1.79	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	0.00	1.34	0.06	0.00	1.42	-0.01	0.0	2.01	0.01	1.71	1.29	0.18	0.01	1.46

Figure 4. Sample images for dehazed output.

VI. Conclusion

In this paper demonstrated that a fusion-based approach can be used to effectively enhance hazy and foggy Images. To the best of our knowledge, this is the first fusion based strategy that is able to solve such problems using only one degraded image. It shown that, by choosing appropriate weight maps and inputs, a multi-scale fusion strategy can be used to effectively dehaze images. In this paper a new technique has been tested on a large data set of natural hazy images. The method is faster than existing single image dehazing strategies and yields accurate results. In future work this method would like to test the same method on videos.

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