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Research Article

Improved Single Image Haze Removal by Multi Scale Fusion

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Abstract

The visibility of outdoor images can be degraded by the hazy weather conditions. A modified multi-scale fusion method is proposed in this paper to remove dense homogenous haze as well as fog present in an image. It is a fusion based strategy by deriving two hazy image inputs which is obtained by applying white balancing and a contrast enhancing procedure. Then filter their important features by applying weight maps which are luminance, chromaticity and saliency to preserve the important features of the derived inputs. These weight maps introduce artifacts in the images. To eliminate these artifacts we apply a multi scale fusion technique which is obtained by Gaussian and Laplacian pyramids. Then to eliminate the lightness of the image, we apply an image enhancement method. It is based on retinex theory and lightness decomposition method. The proposed method is then compared with the existing multi-scale fusion method. The results obtained shows that the new method enhances the image visibility in dense hazy regions.

Keywords: *Dehazing, Multi-scale fusion, Retinex decomposition.*

1. Introduction

As the light travels from the source to observer, the particles in the atmospheric medium cause the absorption and scattering of light. And these phenomena may lead to atmospheric degradation such as haze and fog in the outdoor scenes. But in normal conditions the size of air molecules is relatively small compared with the wavelength of visible light. Due to this the scattering influence might be considered insignificant. But in bad weather condition the size of the atmospheric particles increases. So in this condition when light travels through the atmosphere causes the absorption and scattering of the reflected light due to these particles. It reduces visibility of an image.

Haze is an atmospheric phenomenon which occurred due to the presence of dust, smoke and other dry particles reduces the clarity of the sky. By obtaining a distinctive gray hue in the captured images, for distant regions haze reduces the visibility. Fog is a dense cloud of water droplets, or cloud. Fog normally found near to ground. It is formed when the night is cold and is obtained by releasing the heat of the ground which is absorbed during day. It cools the air above ground and forms a cloud of water droplet. It is known as radiation fog.

Detection and processing of image features are the steps involved in most of the outdoor vision applications. But due to bad weather condition contrast and color of images degraded. While these conditions may be pleasing for human eyes in an artistic way, but it is necessary to remove this degradation for surveillance and other applications.

As the distance between the sensor and object increases, the effect of haze or other atmospheric phenomenon increases exponentially. General filtering techniques will not remove haze completely from the images. So finding effective methods for haze removal from the degraded images has get a lot of interest in the image processing and computer vision fields.

In this paper we introduce an enhanced method of single image haze removal method using multi scale fusion (C. O. Ancuti *et al.*, 2013) technique and retinex enhancement method.

2. Related work

Most of the existing methods use multiple images for haze removal. Chavez proposed a method (P. Chavez, 1988) for removing haze from homogeneous scenes by removing the haze by subtracting an offset value determined by the intensity distribution of the darkest object. Methods of (S. Narasimhan *et al.*, 2003, S. Narasimhan *et al.*, 2000) produce pleasing images, but these methods use multiple images. Due to acquisition steps these are more time consuming and hard to carry out. In another method (Hautire *et al.*, 2007) proposed a method for vehicle vision systems. He first estimates the weather conditions. Then according to a priori

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information about the scene structure, restore the contrast of images automatically. A more difficult problem appears when a single hazy image is available to remove the haze. Single image dehazing methods have been introduced recently. These methods can be divided into contrast-based and statistical approaches. The contrast-based enhancing approach of (J. P. Tarel *et al*., 2009) has shown to be a computationally effective technique. But in this method the depth-map should be smooth except along edges with large depth jumps. It introduces a novel algorithm for visibility restoration from a single image. The technique of (R. Fattal *et al*., 2008) is based on statistical approach and it employs a graphical model that solves the ambiguity of air light color. It assumes that image shading and scene transmission are locally uncorrelated. This method first estimates the optical transmission in hazy scenes from a single input image. Based on this estimation, the scattered light is eliminated to increase scene visibility and recover haze free scene contrasts.

3 Methodology and design

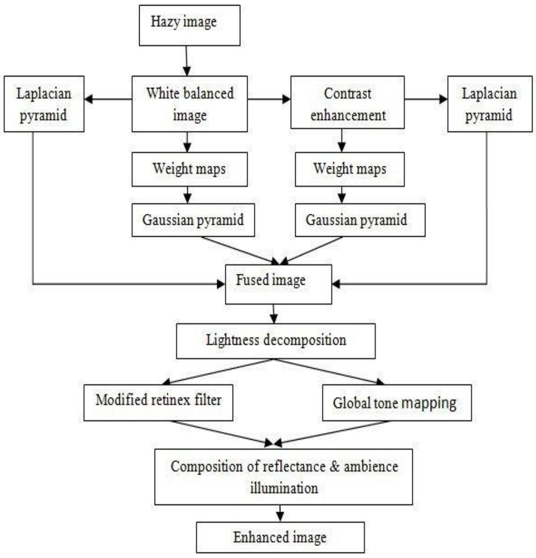

Fig.1 Block diagram of the proposed method

The proposed method introduces a single image based method which is accurately dehaze images using the original dehazed information. Image fusion is the process, which is used to blend several input images by preserving the specific features of the composite output image. Block diagram of the proposed work is shown in fig 1. It consists of two methods. One is the multi scale fusion method and second one is the image enhancement by retinex and lightness decomposition. The main concept behind the fusion based technique (C. O Ancuti *et al*., 2013) is that derive two input images from the original hazy input to recover the visibility for each region of the scene in at least one of them. And to enhance the features of the fusion method, estimate weight maps that control the contribution of each input to the final result. Then to reduce the artifacts due to the weight maps, introduces a multi scale fusion method by applying Gaussian pyramid and Laplacian pyramid. To reduce the lightness present in the dehazed image, we apply a modified retinex and lightness decomposition method.

3.1 Image Dehazing by Multi-scale Fusion

Image fusion is the process, which combines several input images by preserving only the specific features of the composite output image. The fundamental idea of image fusion is combining several input images which is obtained by calculating weight maps into a single one, and keeps the most significant features of inputs. The inputs and weights are taken according to the application. Then we apply a fusion method using Gaussian and Laplacian operator at different levels. By processing appropriate weight maps and inputs, this fusion-based method will effectively dehaze images effectively.

3.1.1 Generation of Two Input Image

To get visibility in the optimal region, derive two inputs I_1 and I_2 from the original degraded image I. The first derived input I_1 is formed by white balancing the original image which is obtained by eliminating chromatic casts. The second input was preferred to increase contrast in those regions that suffers due to atmospheric light. For the second input we used a relatively complementary processing technique, which is used to enhance those regions that has low contrast. Since the haze is dominant in the hazy regions, these hazy regions have a great influence over the average of the image. Due to the fact that the air light influence increases linearly with the distance, the luminance of these regions is also increases with the distance. Based on these, second input I_2 is obtained by subtracting the average luminance value of the entire image from the original image I. This can be expressed mathematically for each pixel x by,

$$I_2(x) = \gamma(I(x) - \bar{I}) \qquad (1)$$

where γ is a factor which increases luminance linearly in the recovered hazy regions and default value of γ is 2.5. $\bar{\mathrm{I}}$ is the average luminance value of the degraded image.

3.1.2 Weight maps

The derived inputs still suffer from low visibility in those regions with dense haze and low light conditions. The drawback of general contrast enhancement operators performs constantly the same operation across the entire image. To overcome these limitations, three weight maps are introduced. The weight maps balance the contribution of each input and also it gives higher values to the regions with high contrast or more saliency from a derived input.

Luminance weight map (W_L^k) determines the visibility of each pixel and gives higher values to the regions with good visibility and lower values to the rest. It is calculated by the following equation:

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

The luminance L is computed by averaging the RGB channels. But this map reduces the global contrast and color information. To overcome these effects we introduce two additional weight maps which are chromatic weight map and saliency weight map.

Chromatic weight map (W_C^k) controls the saturation gain of the output image. We obtain this weight map by calculating the distance between the saturation value S and the maximum of the saturation range for each pixel. This can be mathematically explained as:

$$W_C^k(x) = \exp\left(-\frac{(S^k(x) - S_{\max}^k)^2}{2\sigma^2}\right) \quad (3)$$

where k indicate the two derived inputs, the default value of the standard deviation σ = 0.3 and S_{max} is a constant that depends by the color space employed. In this method we are using HSI model. S_{max} is 1 for HSI color space.

Saliency weight map (W_s^k) estimate the contrast of image regions relative to their surroundings based on different image features such as intensity, color or orientation. Saliency weight map of each input can be obtained by,

$$W_S^k(x) = \left\| I_k^{\omega_{hc}}(x) - I_k^{\mu} \right\| \quad (4)$$

where I_k^{μ} is the arithmetic mean pixel value of the input I_k. $I_k^{\omega_{hc}}(x)$ is the blurred version of the same input to remove the high frequency noise. It is obtained by employing a $5 \times 5 \left(\frac{1}{16}[1,4,6,4,1]\right)$ binomial kernal with high frequency cut off value. Saliency is obtained in a per pixel manner after computing the blurred version of the image and arithmetic mean. Saliency map prevents introducing unwanted artifacts in the result image yielded by our fusion technique.

The resulted weight map (W^k) is obtained by multiplying all three weight maps. To get a consistent result we normalize the resulted weight map. The normalized weight map is obtained by,

$$\overline{W}^k(x) = \frac{W^k(x)}{\sum_k W^k(x)} \quad (5)$$

3.1.3 Multi scale fusion

The normalization of the weights will give the intensity scale of the result which is maintained in relatively same scale as the inputs. But these weights introduce strong halos artifacts, in the locations characterized by strong transitions of the weight maps. To avoid such degradation problems, we employ a classical multi-scale pyramidal strategy.

Each derived input is decomposed into a pyramid by applying Laplacian operator at different scales. Similarly Gaussian pyramid is computed for each normalized weight map.

Since both the Gaussian and Laplacian pyramids have the same number of levels, the Laplacian inputs and Gaussian normalized weights is mixed at each level independently, gives the fused pyramid:

$$F_l(x) = \sum_k G_l\{W^k(x)\} L_l\{I_k(x)\} \quad (6)$$

where l is the number of the pyramid levels and the default value of the number of levels is 5. L{I} is the Laplacian version of the input I and G{W} represents the Gaussian version of the normalized weight map of W. This step is performed for each pyramid layer, in a bottom-up manner. The final haze-free image is obtained by summing each level of pyramids. It is represented as,

$$J(x) = \sum_l F_l(x) \uparrow^d \quad (7)$$

where J is the final haze image $\uparrow^d$ is the upsampling operator with factor $d = 2^{l-1}$.

3.2 Image enhancement by retinex and lightness decomposition

Even after the multi scale fusion there will be some distortion in image due to the captured light in the image. This can be reduced and the image can be enhanced by the retinex and the lightness decomposition method (Bo Li *et al*., 2011) and will enhance the image by preserving the naturalness of the image. It is based on the retinex theory. First we decompose the image into reflex lightness and ambience illumination. The reflex lightness will give the details of an image and the ambience illumination will give the naturalness. After that we will apply a modified Retinex method to extract details or reflectance from reflex lightness. Then combine the reflectance and ambience illumination to obtain the enhanced image.

3.2.1 Image decomposition

The quality of an image is determined by two factors which are the detail and naturalness. And these are related to reflex lightness and ambience illumination. The dehazed image or the lightness of the image is firstly decomposed into reflex lightness ($RL_i(x,y)$) and ambiance illumination ($AI_i(x,y)$). It can be represented as,

$$L_i(x,y) = RL_i(x,y) + AI_i(x,y) \quad (8)$$

We can define ambiance illumination and reflex lightness as follows:

$$AI_i(x,y) = \alpha . L_i(x,y) \quad (9)$$

$$RL_i(x,y) = (1-\alpha)\, L_i(x,y) \quad (10)$$

$L_i(x,y)$ is the i^{th} color spectral band, and α is the weighting factor. α can be obtained by,

$$\alpha(x,y) = \frac{1}{2}\frac{L(x,y)}{L_{max}} \quad (11)$$

3.2.2. Modified retinex filter to reflex lightness

Retinex theory (Bo Li *et al*., 2011) says that the lightness is the product of reflectance and illumination. But in normal conditions, estimation of illumination is very complex. So in this modified retinex method we did not apply the retinex theory directly to the image L(x,y). We will apply retinex theory to the reflex lightness RL(x,y) which can be explained as,

$$RL_i(x,y) = R_i(x,y).F(x,y) \quad (12)$$

$R_i(x,y)$ is the reflectance of the image. $F(x,y)$ is the background illumination. Background illumination of an image is obtained by the convolution of bilateral filtering. The bilateral filter BF[.] is defined as

$$BF[L]_x = \frac{1}{W_x}\sum_{y\in s} G_{\sigma s}\left(\|x-y\|\right)G_{\sigma r}\left(\left|I_x - I_y\right|\right)I_y \quad (13)$$

where, x is the center of the local area of an image S, $\|x-y\|$ is the Euclidean distance between pixels x and y, $\left|I_x - I_y\right|$ is the intensity difference between I_x and I_y. W_x is the normalized factor. It can be obtained by,

$$W_x = \sum_{x\in s} G_{\sigma s}\left(\|x-y\|\right)G_{\sigma r}\left(\left|I_x - I_y\right|\right) \quad (14)$$

where $G_{\sigma s}$ denotes the 2D Gaussian kernel. And this can be obtained by,

$$G_{\sigma s} = \frac{1}{2\pi\sigma^2}\exp\left(\frac{-x^2}{2\sigma^2}\right) \quad (15)$$

The lightness F can be obtained by,

$$F = L_{max} * BF \quad (16)$$

$$L_i(x,y) = \max(RL_i(x,y) \quad (17)$$

where L_{max} is the maximum of three color channels. Finally from this we can obtain the reflectance $R(x,y)$ of the image by,

$$R_i(x,y) = \frac{RL_i(x,y)}{F(x,y)} \quad (18)$$

3.2.3 Global Tone Mapping of Ambience Illumination

The illumination of an image is difficult to evaluate. So we can use ambience illumination AI(x, y) for further processing. But the ambience illumination varies a lot in normal conditions. So in order to make ambience illumination smoother we will adjust AI(x,y) as follows:

$$MA(x,y) = \log(AI(x,y) + \varepsilon) \quad (19)$$

where ε is a small positive constant.

3.2.4 Composition of details and naturalness

The retinex theory says that the amount of light reaching the eye depends on the product of reflectance and illumination. Therefore, we will combine R(x, y) and MA(x, y) together by multiplication to get the enhanced image EI(x, y) :

$$EI(x,y) = R_i(x,y) * MA(x,y) \quad (20)$$

4. Results and discussion

The proposed method has been tested for a large data set which has haze as well as fog to check the robustness of the method. It is implemented by using MATLAB 2013.

First we derived two inputs from the degraded image by white balancing and contrast enhancement method. Then the two images weighted by three weight maps to enhance the details of the image. After that we obtained two normalized weight maps from the weighted images. Then applied multi scale fusion method to obtain fused dehazed image. It is done by calculating Gaussian operator for weight maps and Laplacian operator for each derived inputs. Then to enhance the dehazed image and to remove the lightness present in the image, retinex and lightness decomposition method is applied to the dehazed image. For this we first obtained the reflex lightness and ambience illumination of the image. Then calculated the reflectance using the enhanced retinex method and obtained the global tone mapped image. The enhanced image is obtained by the composition of reflectance and modified ambience illumination. The proposed method restores dense homogenous hazy images which is more visually pleasing.

The proposed method is compared with the previous dehazing method (C. O Ancuti *et al*., 2013). The output of the two fusion methods of different images are shown in fig 2. And peak signal to noise ratio (PSNR values) of two methods are compared.

Comparison of PSNR values of different images are shown in the table. From this we found that the new improved method of multi-scale fusion technique has higher PSNR value.

Input image Multi scale fusion Our result

Fig. 2 Comparison of multi scale fusion method and our result of different images

Table -1: PSNR values of different images

Image	Multi scale fusion method	Our result
Image 1	61.3	65.8
Image 2	58.2	62.6
Image 3	59.5	64.7

Conclusions

This paper proposed a new improved single image dehazing method which is done by fusion based method to remove the haze and fog present in a single image. Hazy imaging model taken together with fusion technique is used to restore the original image. This technique is based on selection of appropriate weight maps and inputs. A fusion approach is used to obtain dehazed version of hazy images. It has been tested on a large database of natural and synthetic hazy images and resulted in visually pleasing image. The experimental results show that the proposed method is an efficient enhancement technique which removes the haze from a degraded image enhances the image effectively. The method is faster than existing single image dehazing techniques and yields accurate results. In future work we would like to test this approach on underwater images and also in videos.

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