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An Improvement of Multi-Scale Fusion Technique for Image Dehazing

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***Abstract*—The visibility of an outdoor imagery can be decayed by the hazy weather condition. In this paper, a modified multi-scale fusion technique is proposed to remove dense homogenous haze. The method first finds the airlight from the fused image. Then the patch-wise transmission function of the fused image is estimated by applying boundary constraints. After that a weighting function is applied on the patch-wise transmission to enhance the image structures. Using the patch-wise transmission and the weighting function, the transmission function is estimated. The dehazed image is hence recovered based on the correct estimation of both airlight and transmission function. The proposed method is then compared against the existing multi-scale fusion method by Qualitative and Quantitative evaluation. The results obtained show that the new method enhances the image visibility in dense hazy regions.**

***Index Terms*— Outdoor imagery, Dehazing, Multi-Scale fusion, Airlight, Transmission function.**

I. INTRODUCTION

The images of outdoor scenario are degraded by poor weather conditions. One such degradation factor is haze since it causes bad visibility. In such situation the light reflected from a surface is scattered in the atmosphere due to the presence of complex medium such as water droplets, fumes and dirt which can bend light from its original course of propagation as it travels from the source to the observer. Hence the image dehazing is highly desired in computer vision applications such as surveillance, remote sensing and object recognition to increase the visibility of the scene. The haze removal is a demanding problem because the haze is dependent on the unknown depth. The problem is difficult if the input is only a hazy image, because little information about the view structure is available. Early methods have been proposed by using multiple images which need additional depth information. The multi-images techniques resolve the dehazing problem by considering two or more input images taken in different atmospheric conditions. The main drawback is their learning step which in many cases is time consuming and complex to carry out [3]. Polarization based methods are based on the fact that airlight scattered by atmospheric particles is partially polarized. It removes the haze through two or more images taken with different angles of polarization. It cannot remove the haze effects, for scenes with dense haze where polarized light is not a major degradation aspect [4]. 3D geometrical models require some in depth information from user inputs.

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Their main advantage is that it's more accurate since it uses the existing Geo referenced urban models to restore hazy images [5]. In the recent past, single image dehazing has made significant progresses. Tan observes that a haze free image must have higher contrast compared to the input hazy image where haze is removed by maximizing the local contrast of the restored image but this method may not be physically valid. It is applicable for both gray and color images. The results are visually quite compelling but sometimes lead to oversaturation of colors [6]. Fattal employs a model that solves the ambiguity of airlight color, under the assumption that the surface shading and the transmission are locally uncorrelated. If the haze is dense, the color information used is not enough to estimate the transmission [7]. He *et al.* presented an approach on statistical observation of dark channel prior to estimate the object depth in hazy image. The prior assumes that at least one color channel should have small pixel value in haze free image. The prior is combined with alpha matting, which can achieve a quite compelling result and it requires additional post processing which leads to higher complexity [8].

II. IMAGING MODEL

Image degradation model (Imaging model) widely used to describe the formation of a hazy image is,

$$I(x) = J(x)t(x) + A(1-t(x)) \quad (1)$$

where ***I*** be the observed image intensity at pixel ***x***, ***J*** be the scene radiance or the desired haze free image, ***A*** be the global atmospheric light (airlight) and ***t*** is the medium transmission describing the portion of the light that is not scattered and reaches the camera. In Eq.1, the first term ***J(x)t(x)*** is called direct attenuation and the second term ***A(1-t(x))*** is called airlight. The direct attenuation describes the scene radiance and its decay in the medium and the airlight results from previously scattered light leads to the shift of the scene colors. Airlight depends on the atmospheric particles and illumination conditions. The direct attenuation is a multiplicative distortion of the scene radiance whereas the airlight is an additive one. When the haze is homogenous, the transmission ***t*** can be expressed as,

$$t(x) = e^{-\beta d(x)} \quad (2)$$

where ***β*** be the scattering coefficient of the atmosphere and ***d*** be the geometric distance. If greater the distance between the scene and the camera then lower the intensity in the transmission function. This equation indicates that the scene radiance is attenuated exponentially with the distance. The ultimate goal of haze removal is to recover ***J(x)*** from ***I(x)***. Therefore, it requires knowledge of transmission function and airlight.

$$J(x) = \frac{I(x) - A}{\max(t(x), \varepsilon)^{\delta}} + A \tag{3}$$

where ε is 0.001.

III. IMAGE DEHAZING BY MULTI-SCALE FUSION (MSF)

This section presents an image dehazing done on the basis of a fusion technique. Combining several input images into a single image is the main aim of fusion technique. Fig.1 shows the overview of the multi-scale fusion technique.

A. Generation of two input images

The input generation procedure seeks to recover optimal region visibility in at least one of the images. First the input hazy image was processed and white balance operation was done. White balancing, an important color constancy step that aims to estimate the illuminant of a scene. It enhances image appearance by discarding unwanted color casts. Here shades of grey algorithm, was adopted [9]. White balancing alone was not able to resolve the problem of visibility. It enhances visibility of the haze-free regions; therefore, to increase visible details of the hazy regions an additional input is derived. The second input was preferred to increase contrast in those regions that suffers due to atmospheric light. This can be done mathematically by computing for each pixel ***x*** by subtracting the average luminance value $(\bar{I})$ of the white balance image from the original hazy image (I) as given in Eq.4. Contrast enhancement operation amplified the visibility in hazy part, but on the other hand fine details of the image get destroyed. Hence, to eliminate this degradation a proper weight maps are defined for each derived inputs.

$$I_2(x) = 2.5 * \left(I(x) - \bar{I}\right) \tag{4}$$

B. Defining weight maps

The derived inputs were weighted by introducing three weight maps measures such as luminance, chromaticity and salience. These weight maps were calculated in a per-pixel fashion to better describe the spatial relations of degraded hazy regions. These weight maps intend to maintain the regions with good visibility.

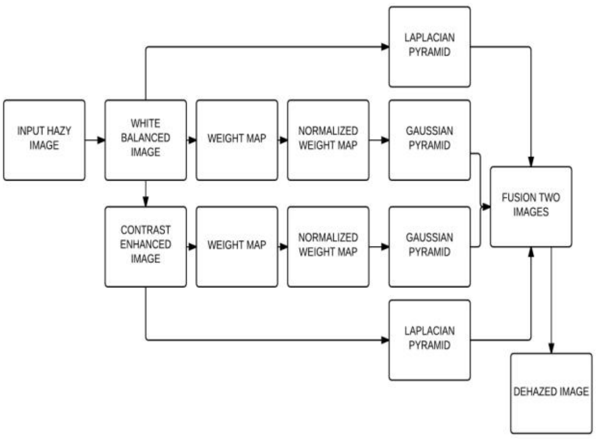

Fig. 1. Block diagram of image dehazing by multi-scale fusion

The Luminance weight map $\left(W_L^K\right)$ measured luminance gain of each pixel. This map was computed by the standard deviation between every RGB color channels and each pixel luminance *L* from input. The luminance weight map main aim was to balance the brightness of the image, but it reduces global contrast and color information.

$$W_K^L = \sqrt{\frac{1}{3}\left[\left(R_K - L_K\right)^2 + \left(G_K - L_K\right)^2 + \left(B_K - L_K\right)^2\right]} \tag{5}$$

The Chromatic weight map $\left(W_K^C\right)$ was used to control the saturation gain in the image. Also, it was used to explain the colorfulness image based on human perception. It gave high saturation to the regions with good visibility. First, convert the RGB image into HSI image. This was computed as the distance between the saturation value ***S*** of the image and max value of the saturation range $\left(S_{\max}^K\right)$.

$$W_C^K(x) = \exp\left(-\frac{S^K(x) - S_{\max}^K}{2\sigma^2}\right) \tag{6}$$

where ***k*** be the index of derived input, $S_{\max}$ be a constant and is taken as 1 and $\boldsymbol{\sigma}$ is the standard deviation (default value is 0.3). The Saliency weight map $\left(W_S^K\right)$ identifies the degree of conspicuousness with respect to the adjacent regions. This weight map had well-defined boundaries and uniformly highlighted salient regions, even at high resolution scales since it increases the global contrast in highlighted and shadowed parts.

$$W_S^K(x) = \left\| W_K^{whc} - I_K^{\mu} \right\| \tag{7}$$

where W^{whc} be the blurred version of the derived input image and I_K^{μ} be the arithmetic mean pixel value of the derived input image. The resultant weight map $\left(W^K\right)$ was computed by multiplying all three weight maps. To yield reliable results normalization is adapted.

The normalized weight map $\left(\overline{W}^K\right)$ is given by,

$$\overline{W}^K(x) = \frac{W^K(x)}{\sum_K W^K(x)} \tag{8}$$

C. Image Multi-Scale Fusion

The fundamental idea behind fusion based dehazing technique is to combine images derived from degrade image into single image by keeping only the most significant features of them. Each pixel ***x*** of the output fused image ***F*** was computed by a multi-scale pyramidal refinement strategy. Each derived input was decomposed into different pyramid levels by applying the Laplacian operator at different scales. In the same way, for each normalized weight map, a Gaussian pyramid is computed. Both pyramids must have the same number of levels. Fusion was performed at each level successively between the Laplacian inputs and a Gaussian normalized weight, yielding the fused pyramid as given in Eq.9, where ***k*** be the coefficients of the images, ***l*** represents the total number of the pyramid levels (default value ***l***=5), ***I*** be the input image, $\overline{W}^K$ be the normalized weight maps, $L\{l\}$ be the Laplacian version of the derived input and $G\{l\}$ represents the Gaussian version of the normalized weight map.

This step was performed in a bottom-up manner successively for each level of the pyramid.

$$F_l^{(i,j)} = \sum_K G_l\left\{\overline{W}_K^{(i,j)}\right\} \quad L_l\left\{I_K^{(i,j)}\right\} \tag{9}$$

The final fused image ***J*** was obtained by summing the contribution of each level of the pyramid.

$$J(x) = \sum_l F_l(x)\uparrow^d \tag{10}$$

where $\uparrow^d$ be the upsampling operator with factor $d = 2^{l-1}$.

IV. PROPOSED METHOD

The dehazed image obtained in the previous section fails to remove dense homogenous haze. So to improve the image visibility in dense region an efficient method is proposed. For this purpose, first estimate the global airlight from the fused image. After that a patch-wise transmission function of the fused image is estimated by applying boundary constraints. In order to enhance image structures, a weight function is applied to patch-wise transmission function by using a filter bank. Then scene transmission is estimated based on the patch-wise transmission from boundary constraint map and weighting function of patch-wise transmission. Final dehazed image is recovered based on the imaging model. Fig. 2 shows the modified method for haze removal.

A. Estimating the airlight

The airlight is the only illumination source of the scene. To estimate the airlight, manually identify the 'brightest pixel' in the fused image i.e., the haziest region. Thus airlight is estimated as maximum value of the observed hazy image.

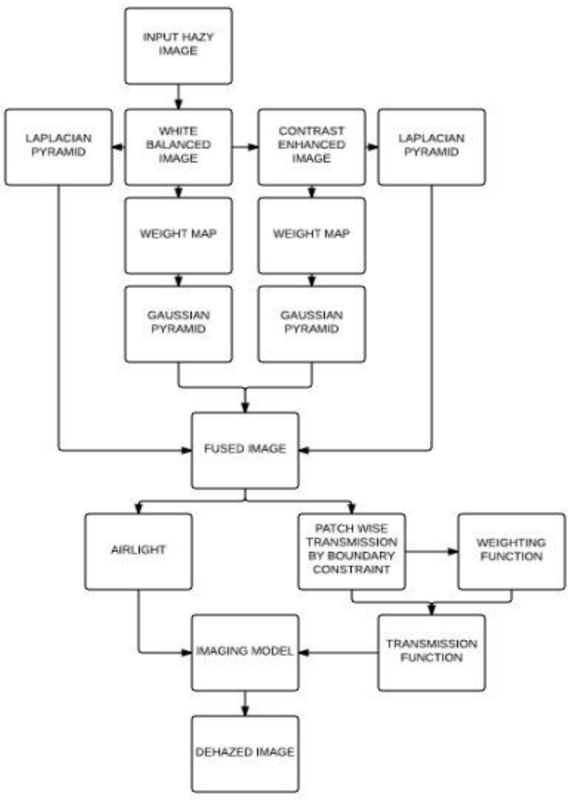

Fig. 2. Block diagram of the proposed haze removal method.

B. Estimating Transmission Function by Imposing Boundary Constraints

According to the imaging model, fused image polluted by dense haze will be pushed toward the airlight. Geometrically it means that vectors ***J(x)***, ***I(x)*** and ***A*** are coplanar and their end points are collinear in the RGB color space. By reversing the process, we can recover the clean haze free pixel. This can be done by linear extrapolation from ***A*** to ***I (x)***.

$$\frac{1}{t(x)} = \frac{\|J(x) - A\|}{\|I(x) - A\|} \tag{11}$$

For any ***x***, the linear extrapolation of the desired haze free image ***J(x)*** must be located in the radiance cube bounded by two constant vectors that are relevant to the image, and is given in Eq.12 where C_0 and C_1 are two constant vectors.

$$C_0 \le J(x) \le C_1 \tag{12}$$

Thus the extrapolation of ***J(x)*** cannot cross the boundary of the radiance cube. In turn, for each ***x***, ***J(x)*** imposes a boundary constraint on ***t(x)***, and is given by

$$0 \le t_b(x) \le t(x) \le 1 \tag{13}$$

The lower bound of transmission t(x) is the ratio of two line segments:

$$t_b(x) = \min\left\{\max_{c\in\{r,g,b\}}\left(\frac{A^c - I^c}{A^c - C_0^c}, \frac{A^c - I^c}{A^c - C_1^c}\right), 1\right\} \tag{14}$$

where ***c*** $\in$ ***{r, g, b}*** be color channel index. After that a morphological closing on is applied in order to remove artifacts. Patch-wise transmission obtained based on boundary constraint has a clear geometric interpretation.

C. Weighting function

Patch-wise transmission from the boundary constraint is based on the assumption that pixels in a local patch will share a similar depth value. This assumption fails to image patches with abrupt depth jumps so a weighting function is introduced.

$$W_j(i) = e^{-\sum_{C\in\{R,G,B\}}\left|\left(D_j \otimes I^c\right)_i\right|^2 / 2\sigma^2} \tag{15}$$

where $\otimes$ be the convolution operator, D_j be a first order differential operator, ***I*** be the index number of set of fused image pixels and W_j be the weighting matrix. Higher order differential filter bank is used to endow us with more flexibility in the use of the contextual constraint for preserving image corners and edges. This filter must have odd size to ensure the correct boundary.

D. Scene Transmission Estimation

The scene transmission function can be obtained by the combination of the patch-wise transmission derived from the boundary constraint map and weight function of patch-wise transmission. In order to optimize transmission function ***t(x)***, an optimization scheme is adopted based on variable splitting method. Basic idea of this method is to introduce various auxiliary variables and construct a sequence of simple sub problems.

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These sub problem solution finally unite to form the optimal solution of the original problem. Two optimization schemes is used such as fixing t solving u_j and fixing u_j solving t, is adopted. These optimization schemes are repeated until the whole process converges. Here optimized auxiliary variable u_j is obtained by fixing t given by,

$$u_j = \max\left(|A| - \frac{\omega}{\beta}, 0\right) sign(A) \qquad (16)$$

where ω be the local patch, β be the medium transmission coefficient, A be the airlight and ***sign (.)*** be a sign function. Final optimized transmission function is obtained by applying a 2D FFT.

$$t^* = F^{-1}\left(\frac{\lambda/\beta\, F(t) + \sum_{j\in\omega} \bar{F}(D_j) \circ F(u_j)}{\lambda/\beta + \sum_{j\in\omega} \bar{F}(D_j) \circ F(D_j)}\right) \qquad (17)$$

where F^{-1} be its inverse transform, F be the Fourier transform, $\bar{F}$ represents the complex conjugate, λ be the regularization parameter, β be the medium transmission coefficient and $\circ$ denotes the element-wise multiplication. Thus $t(x)$ is obtained which enable us to quickly dehaze images of larger sizes. Once the airlight A and the transmission $t(x)$ are estimated from the fused image, the scene radiance is obtained from Eq.3.

V. Performance Parameters

A. Database

Haze due to smoke, dust and other dry particles decreases visibility in the captured images. Similar impact is seen in fog but technically it appears as a dense cloud of water droplets close to the ground when night conditions are clear but cold. To evaluate the performance of proposed method, large dataset of different natural hazy images is used. But this dataset contains no ground-truth images. FRIDA (Foggy Road Image Database) which contain synthetic images with homogenous fog are used here [11]. To compare dehazing methods, this database contains ground-truth no-fog images as the target images.

B. Performance Parameters

The value of performance parameter evaluation metrics should be high for a good quality algorithm. The evaluation metric named structural similarity index (SSIM) is used to measure outdoor hazy image quality. The evaluation metric named Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) are used to measure synthetic hazy image quality.

1) Structural Similarity Index (SSIM)

The structural similarity (SSIM) index is a means for measuring the similarity between two images x and y. Structural information carries central information about the structure of the objects in the visual scene. These pixels have strong inter-dependencies especially when they are spatially close.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)\;\;(2\mu_x\mu_y + c_1)}{(\mu_x^2 + \mu_y^2 + c_1)\;\;(\sigma_x^2 + \sigma_y^2 + c_2)} \qquad (18)$$

where $\mu_x\,\mu_y$ denotes the mean values of original and dehazed images, $\sigma_x\,\sigma_y$ denotes the standard deviation of original and dehazed images, σ_{xy} denote the covariance value computed from the images and $c_1 c_2$ are two constants. In general, image quality MSSIM is obtained by calculating the mean of SSIM values over all windows as in Eq.21. The value of MSSIM can vary from -1 to 1.

$$MSSIM = \frac{1}{p}\sum_{j=1}^{p} SSIM_j \qquad (19)$$

2) Mean Square Error (MSE)

MSE is calculated by averaging the squared intensity of the ground image and the output image pixels as,

$$MSE = \frac{1}{NM}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} e(m,n)^2 \qquad (20)$$

where $e(m, n)$ is the difference in error between the ground and the output images. The minimum value of the MSE can be 0.

3) Peak Signal-to-Noise Ratio (PSNR)

Signal-to-noise ratio (SNR) measures image quality based on the pixel difference between ground and the output image. PSNR is defined as

$$PSNR = 10\log_{10}\frac{MAX_I^2}{MSE} \qquad (21)$$

where MAX_I be the maximum possible pixel value of the image. The PSNR value ranges from 0 to 99.

VI. RESULTS AND DISCUSSION

In order to demonstrate the robustness and effectiveness of this proposed algorithm, it has been tested on a different natural and synthetic images of maximum 600 × 800 resolution and synthetic images of 600 × 480 resolution. Firstly, this paper qualitatively evaluates the performance and secondly, quantitatively compares with parameters such as SSIM, MSE and PSNR. It is implemented using MATLAB 7.9.0 (R2009b) on i-7processor with 8-GB RAM is able to process images in approximately 30seconds.

A. Qualitative evaluation

Qualitative evaluation is used since it is difficult to obtain the corresponding ground truth data for the input outdoor hazy images. Fig. 4 gives some examples of multi-scale fusion and modified dehazing results to remove dense homogenous haze on the outdoor hazy images. If the haze is dense, then multi scale fusion technique fails. Sometimes it leads to oversaturated color in certain regions. Clearly, the results show that proposed algorithm restores dense homogenous hazy images which is more visually pleasing. The halo artifacts and noises are significantly small in our result. Fig.3 (a) shows the hazy building image. In Fig.3 (b), the building image is too dark and a few hazes still remain under the bush. In Fig.3 (c), image visibility is greatly enhanced.

B. Quantitative evaluation

In the evaluation of synthetic images good results are described by a small value for the MSE and high value for the PSNR and SSIM. The SSIM assess the structure perseveration of the ground truth image to the dehazing method output.

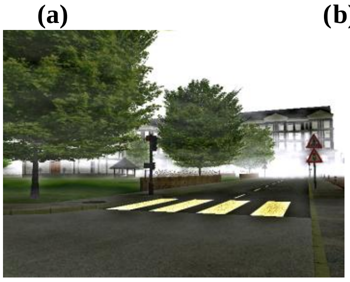
Generally the dehazed images should maintain the similar structure information to the ground truth

(a) (b) (c)

Fig. 3. Image dehazing example (a): original image. (b): Multi scale fusion's result. (c): our result.

images and the low structure similarity means the over enhancement in certain regions. Synthetic images are taken from FRIDA database. Fig.4 (a) shows a uniform fog synthetic image. In Fig.4 (b), the fused image obtained using the multi-scale fusion technique is shown. Fig.4 (c) shows the dehazed image obtained using the proposed method. Five such synthetic images taken for comparison shows that the proposed method outperforms the multi scale fusion technique and the values are shown in Table I. It is observed that the value of MSE decreases by 0.266% and the values of PSNR and SSIM increases by 6.034% and 0.019% respectively.

(a) (b)



(c)

Fig.4. Dehazing results on synthetic images (a): synthetic image with fog. (b): Multi scale fusion's result. (c): our result.

Table I. Comparison of MSE, PSNR and SSIM of synthetic images (IMG) by Multi-Scale Fusion Method (MSF) and Proposed Method (PM).

IMG	MSE		PSNR(dB)		SSIM	
	MSF	PM	MSF	PM	MSF	PM
Img_1	0.490	0.117	51.228	57.463	0.990	0.996
Img_2	0.225	0.053	54.604	60.862	0.996	0.997
Img_3	0.398	0.110	52.133	57.706	0.992	0.997
Img_4	0.458	0.153	51.523	56.279	0.989	0.994
Img_5	0.235	0.043	54.428	61.774	0.995	0.998

VII. CONCLUSION

The core of this paper is to remove dense homogenous haze from an image. Hazy imaging model taken together with fusion technique is used to restore the original image. It has been tested on a large database of natural and synthetic hazy images and resulted in visually pleasing image. In upcoming work, it is possible to test our method for videos.

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