

ENHANCEMENT OF FAR-REGION HAZY IMAGE USING MULTI-EXPOSURE IMAGE FUSION

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Abstract: - Poor climate conditions can decrease visibility of images obtained outside, reducing their visual quality. The image processing task concerned about the alleviation of this impact is known as image dehazing. Many of such dehazing techniques have been introduced. However these methods cannot dehaze the far haze and high hazy images. In this work a new algorithm is designed to overcome these drawbacks. In this method, first the original hazy image is under-exposed through the sequence of gamma-correction activities. Then the resulting images with different exposure can be fused into a haze free image through a multi-scale Laplacian pyramid blending method. Experimental results on a set of foggy images determine that the proposed method better preserves the visibility of faraway hazy images and images that are highly affected by haze.

Key words: Image Dehazing, Haze Removal, Multi-Exposure Image Fusion, Gamma correction, Laplacian Pyramid.

I. **INTRODUCTION**

Usually, the atmosphere between the observer and the scene degrades the visibility of images that are captured outdoors. This phenomenon is termed as haze that attenuates the radiance, it should reach the camera. Thus, obtained images and videos are with undesirable effects such as loss of contrast and color quality degradation, reducing visibility on far away regions in the scene. The improvement of image defogging or dehazing algorithms for the restoration of image quality has turned into a task of incredible significance.

Generally, the current defog or dehaze algorithms can be divided into two groups of single and multiple-image based techniques. A single-image dehazing method doesn't take the external knowledge of the scene into consideration. But haze is a depth-dependent phenomenon, that results in the image degradation to be spatially-variant, with different areas of the image being more affected. Usually this degradation varies in accordance with depth in the imaged scene. But the lack of depth information in two-dimensional images causes ambiguity, due to which previous methods to remove haze depend on external sources of information[1,2]. However this external information usually available in generic situations. Fortunately, this unavailable depth information is typically alleviated by resorting to physical models of haze formation. Butthese models need to hold depth information, either implicitly or explicitly. As a result, most existing single-image dehazing techniques enforce prior information on the image the user expects to retain, *e.g.* an increased contrast or less attenuated colors [3, 4].

Single image haze removal is considered as a spatially varying contrast and saturation enhancement problem. In this problem different areas require distinct levels of processing. Hence, a new method is introduced to increase the visibility only on those regions. In this method the original hazy image is under-exposed through the sequence of gammacorrection activities there by generating multiple exposure images. These images contain areas with increased saturation and contrast. These images can be fused into a haze free image through a multi-scale Laplacian pyramid blending method*.* This work can be done in two steps as shown in the fig.1. First one is Multiple Exposure Fusion (MEF) removes the haze at for away regions of hazy image and second one is Contrast Limited Adaptive Histogram Equalization (CLAHE) to reduce the heavy contrast enhancement in the process of MEF.

Fig.1:Enhancement of Far-Region Hazy Image using Multi-Exposure Image Fusion.

II. **RELATED WORK**

Most existing strategies solve the bellow physical model of haze degradation, due to H.Koschmieder[5].

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

Where $I(x) = (I^R(x), I^G(x), I^B(x))$ is the degraded image, $J(x)$ is a haze-free image, $t(x)$ is the medium transmission determine the measure of light that achieves the recipient, which is inversely related todepth, and **A** will be a steady (RGB)-vector known as atmospheric light. The joined degradation of transmission and environmental light, i.e. the term $A(1-t(x))$ is typically known as airlight.

Given a hazy image **I**(x), there are number of probable solutions for **J(x)**verifying Kochsmieder's model, i.e. the reversal of eq. (1) is an under-constrained issue. When t (x) and **A**have been estimated, the above condition can be inverted:

 $J(x) = \frac{I(x) - A}{I(x)}$ $\frac{x^{3}-A}{t(x)} + A(2)$

Kochschmieder model is additionally utilized in a second group of image dehazing strategies, those in view of machine learning methods. For this situation, rather than directly estimation of $t(x)$, a mapping between a hazy image and its depth is learned from data. This can be accomplished by first making synthetic depth maps from hazy images as in [6].

In third group of image dehazing methods has the techniques considering dehazing as an image enhancement issue. These methods assume that the eq. (1) is useful to understand the relationship between haze and haze-free image. The main aim of these techniques is to produce good quality dehazed image **J(x).** This can be obtained by Fusion-based techniques like [7, 8] have different advantages than standard image dehazing techniques.

III. **PROPOSED METHOD**

The main aim of this work is to design a spatially-varyingimageenhancement method which can remove the visual effects of haze to avoid the need of evaluating transmissiont (x) and airlight**A**in eq. (1). In this work three steps are done to get a quality dehazed image. First the original hazy image divided into multi-exposure images through the gamma corrections. Second the Multi-Exposure Image Fusion (MEF) can be applied for the all exposed images. In the third step the Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to the resulting image of MEF algorithm, as shown in the flow chart of the proposed method fig. 2.

Fig. 2 Flow chart of proposed method.

A. *Exposure Modification via Gamma Correction Transforms:*

In photography, exposure is characterized as the measure of light that is permitted to enter the camera and achieve the sensors while obtaining an image [9]. Exposure can be balanced during acquisition by differing the shutter speed of the camera or on the other hand its aperture, yet it is normally difficult to accomplish a generally optimal exposure for any scene. In addition, multiple regions of the imaged scene may require completelydistinct exposures. The purpose behind this is the large dynamic range of the light achieving the camera. The difference between the brightest and darkest intensity values that a camera canregisteris called dynamic range.

In controlled brightening circumstances, a possible solution is to shed light into dark regions of the scene to diminish its dynamic range. A second approach consists of gaining multiple images of a similar scene under various exposures and combining the data on every one of these images into a single one containing sharp details both on bright and dark areas. This image processing problem is named as Multi-Exposure Image Fusion (MEF). MEF has been broadly examined in the past, and will be quickly talked about in next section.

Unfortunately, some times the user has no control on the light of the scene or the image has been already captured and stored with no option to obtain extra multiple exposure images on the same scene. In this situation the gamma correction algorithm is used to acquire different exposure images. This algorithm consists globally adjusting the intensity on an image following a power function transform:

 $I(x) \rightarrow I^{\gamma}(x)$ (3)

Where γ is real positive number. From the above equation different exposed images $\mathbf{E}_k(x) = \{\mathbf{I}^1(x), \mathbf{I}^2(x), \dots, \mathbf{I}^n(x)\}\$ are obtained.Power transform tasks were at first applied to effectively recreate luminance on CRT TVs [10].Gammacorrected advanced signals are quantized such that more extensive quantization intervals are utilized at higher luminance ranges, where changes are less noticeable. On the other hand, smaller intervals are connected for darker areas, where points of interest can be more perceptible, as showed in Fig.3, Note that, if we adapt as simple definition of image contrast for a given area Ω inside the image domain:

$$
C(\Omega) = I_{max}^{\Omega} - I_{min}^{\Omega} (4)
$$

where $\Omega = max\{I(x)\}$ and $\Omega = min\{I(x) | x\Omega \}$, at that point it can be effectively demonstrated that, e.g. for $\gamma > 1$, given area containing bright qualities like in the right side of Fig.2.b. its contrast as estimated by eq. (4), will be expanded after gamma correction.

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Fig.3: Dynamicrangeexpansion/compressionduetopowertransforms.(a): ^γ *<1Brighterintensitiesarecompressedwhiledarkerintensitiesareexpanded. (b):*γ*> 1Brighterintensitiesareassignedinawiderareaaftertransformation,whiledarkerintensitiesareplottedtoacompressedinte rval.*

B. Multi-Exposure Image Fusion (MEF):

This multiple exposure image fusion (MEF) introduced in [10], it has been largely researched. The majority of MEF algorithms can be grouped into a single-frame work to find the optimal weights W_k in the bellow equation:

$$
\mathbf{J}(x) = \sum_{k=1}^{K} \mathbf{W}_k(x) \mathbf{E}_k(x) \tag{5}
$$

Where *K* is the quantity of distinctively exposed available images $\mathbf{E}_k(x)$, and $\mathbf{J}(x)$ is a globally very much exposed image, coming about from the blend of the diverse effectively exposed regions in **E**k, which is haze-free image. Weights **W**k arenormalized so that $\sum_{k=1}$ **W**_k(x) = 1 \forall x. To calculate the weight maps of each exposed image $\mathbf{E}_k(x) = (\mathbf{E}_k^R(x)) \cdot \mathbf{E}_k^G(x)$, $\mathbf{E}_k^B(x)$), the contrast $\mathbf{C}_k(x)$ at each pixel x is estimated as the absolute value of the response to a simple Laplacian filter, while saturation $S_k(x)$ on every pixel is assessed by the standard deviation across over color channels are evaluated:

$$
\mathbf{C}_{k}(x) = \frac{\partial^{2} \mathbf{E}_{k}}{\partial x^{2}}(x) + \frac{\partial^{2} \mathbf{E}_{k}}{\partial y^{2}}(x)
$$
\n
$$
\mathbf{S}_{k}(x) = \sum_{c \in [R, G, B]} \left(\mathbf{E}_{k}^{c}(x) - \frac{\mathbf{E}_{k}^{R}(x) + \mathbf{E}_{k}^{G}(x) + \mathbf{E}_{k}^{B}(x)}{3} \right)^{2}
$$
\n(7)

Then weight map for each under-exposed image is obtained by combining multiplicatively the contrast and saturation maps:

$$
\mathbf{W}_{k}(x) = \mathbf{C}_{k}(x) \cdot \mathbf{S}_{k}(x) \quad (8)
$$

Visual artifacts occurred by directly fuse the optimal weight maps $W_k(x)$ and exposed images $E_k(x)$ as in eq.6. To avoid these visual artifacts, the multi-scale image fusion through the Laplacian and Gaussian pyramids is designed as shown in the Fig.2. To combine different scales together, first a Gaussian Pyramid is built for each weight map as:

$$
W_k^i = \text{ds}_2[W_k^{i-1}] \tag{9}
$$

where ds₂[⋅] relates to an operator that convolves an image with a Gaussian kernel, and thendownsamples it to half of its unique measurements, i is the N number of pyramid levels. Repeatingthis process N times produces a set of progressively smaller and smoother weight maps { W_k^1 , W_k^2 W_k^N }

Likewise, a Gaussian pyramid $\{E_k^1, E_k^2, \ldots, E_k^N\}$ is worked for each of the multi-exposed images E_k . At that point, a Laplacian pyramid is developed for each \mathbf{E}_k through the bellow recursive equation:

$$
\mathbf{L}_k^i = \mathbf{E}_k^i - \text{us}_2[\mathbf{E}_k^{i+1}] \tag{10}
$$

where us₂[⋅] is an administrator upsampling a image to twice its size. In the above recursion, we characterize $\mathbf{L}_{k}^{N} = \mathbf{E}_{k}^{N}$. Since $\mathbf{L}_k^i(x)$ catches the frequency content of the original image at scale i, a multi-scale combination of all $\mathbf{E}_k(x)$:

 $\mathbf{J}(x) = u s_{(m,n)} [\mathbf{L}_1^1(x) \cdot \mathbf{W}_1^1(x) + \dots \mathbf{L}_K^1(x) \cdot \mathbf{W}_K^1(x)] + u s_{(m,n)} [\mathbf{L}_1^2(x) \cdot \mathbf{W}_1^2(x) + \dots \mathbf{L}_K^2(x) \cdot \mathbf{W}_K^2(x)] + \dots + u s_{(m,n)}$ $\mathbf{L}_{1}^{N}(x) \cdot \mathbf{W}_{1}^{N}(x) + \dots \mathbf{L}_{K}^{N}(x) \cdot \mathbf{W}_{K}^{N}(x) = \sum_{i=1}^{N} \text{us}_{(m,n)}[\sum_{k=1}^{K} L_{k}^{N}(x) \cdot \mathbf{W}_{k}^{N}(x)]$ (11)

where $us_{(m, n)}$ is the administrator upsampling any given image to the measurement of E_k . The Laplacian multi-scale fusion as mention in the above is performed. This outcomes in a haze-free image integrating well contrasted areas with rich colors from each source image.

C. Contrast Limited Adaptive Histogram Equalization:

It can be tentatively confirmed that when the input hazy image contains few good contrasted areas, then the resultant image will be over-exposed producing too dark results. All together to fuse additionally contrast in the dehazed result without introducing many extra parameters in the proposed technique, a basic contrast-enhanced form of the input image can be added to the initial arrangement of under- exposed images. For this situation, the famous Contrast-Limited Adaptive Histogram Equalization (CLAHE, [11]) was chosen. This calculation relies upon the cliprange (measure of nearby contrast increment that the client chooses to permit), and it can produced the results with highly improved quality. It can be acknowledged how the local histogram equalization modifies the presence of areas in the image that were not experiencing contrast or saturation loss, primarily the zones nearer to the camera. Saturated regions coming from the midrange depth of the scene are properly added into the final result.

D. Experimental results:

The proposed method for image dehazing has few parameters that should be balanced. One of these is the amount of contrast that the client permits to be increased in the adaptive histogram equalization image that complements the under-exposed set of images, as clarified previously.

Concerning the rest of the parameters, the selected set of exposures was obtained for the values of $\gamma \in \{1, 2, 3, \ldots\}$ 4, 5} at the beginning of proposed method as shown in Fig.2. Similarly, the smoothing kernel in eq. (9) and (10) was set to a conventional separable filter given by $G = [1/16, 1/4, 3/8, 1/4, 1/16]$, and the number of levels N in the pyramid decomposition, which was consequently chosen following the recommended strategy in [12] as $L = \frac{\log(\min(\mathbb{R}^m, n))}{\log(\min(\mathbb{R}^m, n))}$ $\frac{\ln \exp(-m,n)}{\log 2}$ for

an info image of size $m \times n$.

 (a)

 (b)

 (c)

Fig. 4: Influence of the clip-range parameter c on the behaviour of the proposed technique. (a): Hazy image_City, (b): clip range c = 0.03, (c): clip range c = 0.08, (d): clip range c = 0.10, (e): clip range c = 0.15, (f): clip range c= 0.2.

With respect to scope of qualities that the adaptive histogram equalization out is permitted to expand/compress (clip range, indicated c in the accompanying), the above Fig.4 demonstrates an arrangement of cases on which the proposed method is computed with an expanding scope of clip-range values, changing from $c = 0.03$ to $c = 0.2$. It can be seen how the differentiation in the subsequent dehazed image can be continuously expanded by permitting a bigger c esteem. Unfortunately,specifying a too high value of *c* may sometimes lead to clear over-enhancing that, regardless of whether expanding visibility, may slightly distort the color distribution of the input hazy scene. It is important, however, that even for little estimations of *c* this proposed method gives great haze removal abilities. Then again, substantial estimations of *c*still offer these abilities however may modify areas that are close-by to the eyewitness and need no enhancement. A protected decision of c adjusting contrast enhancement with color safeguarding was tentatively observed to be $c = 0.10$. This esteem gives great outcomes.

 (d)

 (e)

 (f)

Fig. 5: Original hazy images (a): Train, (d): Ground, (g): City1; previous method [7] results (b), (e), (h); proposed method results (c), (f), (i).

From Fig.5: we can observe that the haze in the image can be removed with better quality by the proposed method. The (a), (d), (g)are the input hazy images, (b), (e), (h)are the output dehazed images of previous method [7], (c), (f), (i)are the output dehazed images of proposed method. From (b)-(c) we can see that the fog in the images is removed h using the proposed method compared to the previous method. From (e)-(f) and (h)-(i)we say that, the proposed method gives the better results without loss of contrast and saturation of original image, and also it removes the haze at the farregions in the hazy images. The PSNR can be calculated for different dehazed images obtained by the previous method and proposed method as shown in the Table1.

TABLE 1:

PSNR VALUES FOR DEHAZED IMAGES IN PREVIOUS AND PROPOSED METHODS.

IV.**CONCLUSIONS**

A new image dehazing technique is developed which is named as Enhancement of Far-Region Hazy Image using Multi-Exposure Image Fusion. This proposed method is developed based on the two algorithms are Multi-Exposure Image Fusion (MEF) Contrast-Limited Adaptive Histogram Equalization (CLAHE). This technique can produce images of improved quality and in a more efficient way. It exhibits a good performance for the task of image dehazing. In this approach the fog present in the far away regions of hazy images can be removed and the output dehazed image has the better visual quality. Moreover, the applied multi-scale Laplacian image fusion arrangement is a basic method within the field of multiple-exposure image fusion, and different advanced techniques could be explored to future improve performance or explore other applications.

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