HAZE REMOVAL USING GRADIENT FUSION STRATEGY

M. Ramesh Kanthan
Research and Development Centre,
Bharathiar University Coimbatore, India

Dr. S. Naga Nandini Sujatha
Dept of Computer Science, Govt. Arts College for Women,
Nilakottai, Tamil Nadu, India

ABSTRACT

The goal of Haze Removal algorithms is to recover and enhanced the scene from foggy image. Many applications need accurate Haze Removal algorithms. The de-fog feature works through a complex algorithm which based on the fog destiny of the scene, then analyses the atmospheric light and sharpness adjustments to produce image enhancement. In contrast with existing technology the proposed method focus on image enhancement based on Adaptive contrast Histogram equalization, and image edge strengthened Gradient model. The fusion strategy is driven by the intrinsic properties of the original image and is highly dependent on the choice of the inputs and the weights. Then the output haze free image has reconstructed using fusion methodology. In order to increase the accuracy, interpolation method has used in the output reconstruction. A promising retrieval performance is achieved especially in particular examples.

Key words: Single Image, Fusion, Dehazing, Multi–Scale Fusion, Interpolation, Weight Maps.


http://www.iaeme.com/ijgm/issues.asp?JType=IJGM&VType=7&IType=2

1. INTRODUCTION

Haze is a maddening factor when it shows up in the image. If it causes poor visibility, hazy image created major problems in some applications in the field of computer vision, such as surveillance, object recognition, etc. Fog, mist and some other particles that degrade the scene image are the results of atmospheric absorption and light scattering.[19] In order to obtain the clear images, haze removal is inevitable.
The classical methods for image enhancement are histogram equalization, homomorphic filter, curvelet transform, Retinex algorithm, fast median filter and so on. The image restoration methods focus on the degradation process of the hazed image, aim at establishing the degradation model, deducing the degradation process and compensating the distortion during the degradation to get the undisturbed original image or its best estimation. In image fusion technology [1] combines the image features from various inputs. But the extracted features only depend on the enhanced results of the input foggy image. Some of the algorithm based on the atmospheric light estimation [2][3] for fog or haze detection. The best restoration algorithms are mostly based on polarizing filter [15], user interaction [13], known 3D models [12] or multiple images [8]. Although these methods can significantly enhance the visibility, the user-interaction or strict requirement on the inputs limits their applications. Recently, haze removal from a single image has made great progress. Many dehazing algorithms [7, 8] based on single image have been developed since Fattal [2]. All these works are based on the assumptions, physically or empirically.

In this paper, a novel algorithm is proposed to enhance hazy image based on a single image dehazing fusion technique. Our method has built based on fusion principle which shown utility in several applications such as multispectral video enhancement [12], underwater image enhancement and intelligent transport system [FRIDA-database]. The image fusion is a technology that combines multiple images into an enhanced picture to offering added values to the observers. In contrast to the existing dehazing methods and fusion-based enhancement methods, our proposed algorithm does not require multiple images or physical model. It derives the inputs and the weights functions only from the original degraded image.

2. PROPOSED METHOD

The main concept behind fusion based dehaze technique is that 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. In order to derive the images that fulfill the visibility assumptions (good visibility for each region in at least one of the inputs) required for the fusion process. The first input derived from the Adaptive Histogram Equalized method. And the other input derived based on Gradient edge strengthen energy function [11]. The proposed algorithm consists of three main steps: Inputs assignment (derivation of the inputs from the original hazy image), Defining weight measures (Luminance, Chromaticity and saliency) and using multi-scale fusion of the inputs and weight measures output reconstruction with interpolation in addition to pyramidal reconstruction in order to increase the sharpness of the output image. The block diagram of proposed method is shown in figure 1.

This novel system adopts the study and analysis of haze removal and concentrates in the development of processing steps addressing the issues of the transmission estimate using weighted function. The fusion technique proposed in this paper derives two different inputs of the given input hazy image. Those images guided by the weights maps of derived input images, using only the most significant features. Obviously, the choice of inputs and weights are application-dependent. Fusion-based method is able to effectively de-haze the image since weight map depend on the most significant features.
Derived inputs

One of the simplest and the most often used assumptions about the color constancy is called Gray World Theory (GWT). The majority of all visual scenes in the world can be integrated to the gray, i.e. average of R, G and B. The most direct solution for automatic correction of the white is to calculate the mean values for each color channel of the captured image. Let denote a full-color image of size \( n \times n \) as \( RGB(x;y) \), where \( x \) and \( y \) denote the indices of the pixel position. The individual red, green, and blue color components are \( R(x;y), G(x;y), \) and \( B(x;y) \), respectively. If the three values are identical, the image already satisfies the gray world assumption and no further adjustment is necessary.

\[
\begin{align*}
R_{avg} &= \frac{1}{n^2} \sum_{x=1}^{n} \sum_{y=1}^{n} R(x, y) \\
G_{avg} &= \frac{1}{n^2} \sum_{x=1}^{n} \sum_{y=1}^{n} G(x, y) \\
B_{avg} &= \frac{1}{n^2} \sum_{x=1}^{n} \sum_{y=1}^{n} B(x, y)
\end{align*}
\]

(1)

2.2. Adaptive Histogram Equalization

Histogram equalization employs a monotonic, non-linear mapping which re-assigns the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities (i.e. a flat histogram). This technique is used in image comparison processes (because it is effective in detail enhancement) and in the correction of non-linear effects introduced by, say, a digitizer or display system.

Figure 1 Proposed Process diagram
Haze Removal Using Gradient Fusion Strategy

The histogram processing methods discussed above are global in the sense that they apply a transformation function whose form is based on the intensity level distribution of an entire image. Although this method can enhance the overall contrast and dynamic range of an image, there are cases in which enhancement of details over small areas is desired. The solution in these cases is to derive a transformation based upon the intensity distribution in the local neighbourhood of every pixel in the image.

The histogram processes described above can be adapted for local enhancement. The procedure involves defining a neighbourhood around each pixel and, using the histogram characteristics of this neighbourhood, to derive a transfer function which maps that pixel into an output intensity level. This is performed for each pixel in the image. Local enhancement may also define transforms based on pixel attributes other than histogram, e.g. intensity mean to control variance and variance to control contrast are common.

Gradient Edge Strengthen Energy

Edges are places in the image with strong intensity contrast. Since edges often occur at image locations representing object boundaries, edge detection is extensively used in image segmentation. Representing an image by its edges has the further advantage that the amount of data is reduced significantly while retaining most of the image information. Since edges correspond to strong illumination gradients, it can be highlight by calculating the derivatives of the image.

\[
\frac{df(i)}{d(i)} = f(i +) - f(i)
\]  

(2)

The position of the edge can be estimated with the maximum of the 1st derivative or with the zero-crossing of the 2nd derivative. For a discrete one-dimensional function \( f(i) \), the first derivative can be approximated by differential equation. Calculating the formula in equation (2) is equivalent to convolving the function with \([-1 \ 1]\). Similarly the 2nd derivative can be estimated by convolving \( f(i) \) with \([1 \ -2 \ 1]\). Gradient edge detection is the more widely used technique. Here, the image is convolved with only two kernels, one estimating the gradient in the x-direction, \( G_x \), the other the gradient in the y-direction, \( G_y \). The absolute gradient magnitude is then given by
In many implementations, the gradient magnitude is the only output of a gradient edge detector. The figure 3 shows the various results obtained from local as well as global enhancement techniques of Contrast enhancement and colour enhancement (WB- White balance, GC-Gamma correction, HE- Histogram equalization, CLAHE-Contrast limited Adaptive Histogram Equalization,CE- Contrast Enhancement).

Input Image WB GC HE CLAHE CE

**Figure 3** First input - Intermediate Results – for comparison

### 2.4. Image Interpolation Techniques

Interpolation is the process of determining the values of a function at positions lying between its samples. It achieves the unknown pixel density by fitting a continuous function through the discrete input samples. The numerical accuracy and computational cost of interpolation algorithms are directly tied to the interpolation kernel. The simplest interpolation from a computational standpoint is the nearest neighbor, where each interpolated output pixel is assigned the value of the nearest sample point in the input image. This technique is also known as point shift algorithm and pixel replication. The interpolation kernel for the nearest neighbor algorithm is defined as

\[ h(x) = \begin{cases} 1 & 0 \leq |x| < 0.5 \\ 0 & 0.5 \leq |x| \end{cases} \]  

(5)

The frequency response of the nearest neighbor kernel is 

\[ H(\omega) = \text{sinc}(\omega) \]  

(6)

The kernel and its Fourier transform are shown in the following Figure.

**Figure 4** Kernel nearest neighbor – Fourier transform

Convolution in the spatial domain with the rectangle function \( h \) is equivalent in the frequency domain to multiplication with a sinc function. Due to the prominent side lobes and infinite extent, a sinc function makes a poor low-pass filter. This technique achieves magnification by pixel replication and minification by sparse point sampling. For large-scale changes, nearest neighbor interpolation produces images with blocky effects.
3. MULTI SCALE FUSION STRATEGY

This proposed approach is based on the fusion strategy and it has been derived from the original hazy image inputs by applying an adaptive histogram equalization and edge gradient energy function. The fusion enhancement technique estimates perceptual based qualities known as the weight maps for each pixel in the image. 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 \( I(k) \) weighted by corresponding normalized weight maps \( W_k \). where \( I(k) \) symbolizes the input \( k \) is the index of the inputs) that is weighted by the normalized weight maps \( W_k \).

The design of the weight measures needs to consider the desired appearance of the restored output. Since image restoration is tightly correlated with the color appearance, so the measurable values such as haze density, salient features. The fusion process should preserve all relevant information of the input imagery in the composite image. The images are first decomposed using a Laplacian Pyramid decomposition of the original image into a Hierarchy of images such that each level corresponds to a different band of image frequencies. The next step is to compute the Gaussian pyramid of the weight map. Blending is then carried out for each level separately.

\[
F(x) = \sum_{k} I(k) W_k(x)
\]

![Input](image1.png) ![Adaptive Histogram equalized](image2.png) ![Intermediate Result](image3.png) ![Output](image4.png)

**Figure 5** Sample image of smoke affected in Singapore
(Courtesy: onenewpage.us & asiasociety.org)

4. EXPERIMENTAL RESULT

Haze due to dust, smoke and other dry particles reduce visibility for distant regions by causing a instinctive gray hue in the captured images. However, our technique has been successfully tested as well for a slightly different case: foggy scenes .For example the algorithm works well for haze due to smoke. The experimental results shows the smoke image obtain from Singapore.
The experiments continue with the haze due to fog. That yields good results for standard test images. The result comparisons are shown below with the literature survey method. The time factor also depends on the size of the image. If the size of the image increases then, the time period has also increases. It has shown in chart1.

![Sample image](http://www.iaeme.com/ijgm/index.asp)

**Figure 6** Output of Sample image Taken from standard test images

**Table 1** Performance of proposed Algorithm

<table>
<thead>
<tr>
<th>Image</th>
<th>Size</th>
<th>Processing time (sec)</th>
<th>MSE</th>
<th>PSNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sweden Road</td>
<td>600X400</td>
<td>1.26</td>
<td>0.054</td>
<td>12.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.013</td>
<td>18.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.016</td>
<td>19.7</td>
</tr>
<tr>
<td>Forest</td>
<td>462X609</td>
<td>1.06</td>
<td>0.01</td>
<td>17.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.05</td>
<td>13.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.16</td>
<td>7.9</td>
</tr>
<tr>
<td>Lake</td>
<td>558X373</td>
<td>0.8</td>
<td>0.1163</td>
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</tr>
</tbody>
</table>

**Chart 1** PSNR and MSE comparison
The term **peak signal-to-noise ratio (PSNR)** is an expression for the ratio between the maximum possible value (power) of a signal and the power of distorting noise that affects the quality of its representation. Image enhancement or improving the visual quality of a digital image can be subjective. It is necessary to establish quantitative/empirical measures to compare the effects of image enhancement algorithms on image quality. The MSE represents the average of the squares of the "errors" between our actual image and our noisy image. It is calculated using the formula in equation 7.

\[
MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2
\]  
\[
PSNR = 20 \log_{10} \left( \frac{\text{MAX} f}{\sqrt{\text{MSB}}} \right)
\]

If the dB value approximated with 30 then the accuracy of the image is high, otherwise relatively low. The results show that the fog removal accuracy is accepted to above average performance.

5. CONCLUSION

The proposed algorithm used the pixel-based operation and, it is straightforward to solve the depth discontinuities of the scenes which, in the input image. Then the input patches are smoothening by interpolation method as post processing in order to get smooth output resultant image. The multi-scale fusion strategy can be used to effectively dehaze images by choosing appropriate weight maps and inputs. Our 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. This algorithm can be applied for any type of light haze. The future focus of the algorithm will be the extension of this method to apply for dense haze.

REFERENCES


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