Image Defogging Algorithm of Single Color Image Based on Wavelet Transform and Histogram Equalization

WANG Li Jun and ZHU Rong

School of Computer Science
Qufu Normal University Rizhao, Shandong 276826, China
wanglijun1942@163.com, zhurongsd@126.com

Abstract. Because of light scattered by the suspended particles in the atmosphere, photographs taken in the foggy day look gray and lack of visibility. In order to unveil the clear image’s structures and colors, we propose a image defogging algorithm of single color image based on wavelet transform and histogram equalization. Firstly, using histogram equalization to enhancement image, then to nonlinear enhancement the approximate coefficients of wavelet transform, and to distribution more uniform gray of image. A large number of experimental results show that the algorithm can enhance the image contrast and get high definition images, and outperforms in visual quality and effectively preserves texture and detail information of original images.

Keywords: Single Color Image, Image Defogging, Wavelet Transform, Histogram Equalization

1. Introduction

Haze, a common atmospheric phenomenon in our life, is light mist caused by particles such as water or dust in the air scattering and absorbing the light
reflected from an object surface before it reaches our eyes. The haze can also appear in images when taking long distant outdoor photography under this circumstance: the image will lose contrast and color fidelity, and the objects in distant region become faint. Hence, the technique for recovering a haze-free image from a real photograph is highly desired.

In many cases the images of outdoor scenes are degraded by the improper weather conditions. In such cases atmospheric phenomena like fog and haze may degrade the visibility of the scene. Haze induces its visual effect is blurring of distant objects. General contrast enhancement approaches can be applied for image defogging, such as linear or gamma correction, histogram stretching equalization, or unsharp-masking.

Recently, several single image based methods \cite{2,3,4,6,7} have been introduced. Fattal \cite{2} assumed every patch has uniform reflectance, and that the appearance of the pixels within the patch can be expressed in terms of shading and transmission. He considered the shading and transmission signals to be unrelated and used independent component analysis to estimate the appearance of each patch. The method works quite well for haze, but has difficulty with scenes involving fog, as the magnitude of the surface reflectance is much smaller than that of the air light when the fog is suitably thick.

Tan \cite{6} developed a system for estimating depth from a single weather degraded input image. Motivated by the fact that contrast is reduced in a foggy image, Tan divided the image $I$ into a series of small patches and postulated that the corresponding patch in $J$ should have a higher contrast (where contrast was quantified as the sum of local image gradients). He employed a Markov Random Field to incorporate the prior that neighboring pixels should have similar transmission values $t_i$. The method tends to produce over enhanced images in practice.

He et al. \cite{3} employed a model which assumed every local patch in the enhanced image should have at least one color component near zero. In other words, the work assumed most scenes are made up of either dark or colorful objects. The transmission $t_i$ of each patch was estimated as the minimum color component within that patch. Instead of using an MRF, the work employed a soft matting algorithm to ensure that neighboring pixels had similar transmission values.

Tarel \cite{7} proposes a bilateral filter to replace the optimization method, which improves the efficiency of algorithm and can be used in real-time. But the
defogging result is not so good when there are discontinuous in the depth of scene. The haze among gaps cannot be removed.

In this paper, we propose a image defogging algorithm of single color image based on wavelet transform and histogram equalization. Firstly, using histogram equalization to enhancement image, then to nonlinear enhancement the approximate coefficients of wavelet transform, and to distribution more uniform gray of image.

2. WAVELET TRANSFORM

The theory of wavelets provides a common framework for numerous techniques developed independently for various signal and image processing applications. For example, multiresolution image processing, used in computer vision, subband coding, developed for speech and image compression, and wavelet series expansions, developed in applied mathematics, have been recently recognized as different views of a single theory.

Since its emergence 20 years ago, the wavelet transform has been exploited with great success across the gamut of signal processing applications, in the process, often redefining the state-of-the-art performance. In a nutshell, the Discrete Wavelet Transform (DWT) replaces the infinitely oscillating sinusoidal basis functions of the Fourier transform with a set of locally oscillating basis functions called wavelets.

Wavelets are families of functions \( \psi_{s,t}(x) \) generated from a single base wavelet \( \psi(x) \) by dilations and translations:

\[
\psi_{s,t}(x) = \frac{1}{\sqrt{|s|}} \psi\left(\frac{x-t}{s}\right) \quad s \neq 0
\]  

where \( s \) is the dilation (scale) parameter, and \( t \) is the translation parameter. Wavelets must have mean zero, and the useful ones have localized support in both spatial and Fourier domains. There are orthogonal and nonorthogonal wavelet sets that span \( L^2(\mathbb{R}) \).

The set of \( \psi_{m,n}(x) \) spans \( L^2(\mathbb{R}) \) when \( s = 2^m, t = n \)

\[
\psi_{m,n}(x) = 2^{-m/2} \psi(2^{-m}(x - n))
\]  

Where \( m \) is the scale index \( (m = 0, 1, 2, \cdots) \), and \( n \) is the translation index.
The discrete wavelet transform $W(m,n)$ of a 1-D function $f(x)$ is defined as the projection of the function onto the wavelet set $\psi_{m,n}(x)$.

\[ W(m,n) = \int_{-\infty}^{\infty} dx \psi_{m,n}(x) f(x) \]  

(3)

Since the set of $\psi_{m,n}(x)$ spans the space containing $f(x)$, the reconstruction of function $f(x)$ from its wavelet transform $W(m,n)$ is possible.

\[ f(x) = \sum_{m} \sum_{n} \psi'_{m,n}(x) W(m,n) \]  

(4)

Where $\psi'_{m,n}(x)$ is the normalized dual basis of $\psi_{m,n}(x)$. For the wavelet expansion we use here, $\psi' \approx \psi$.

The wavelet transform $W(m,n)$ gives a scale-space decomposition of signals and, with simple modifications, images. It decomposes the signal into different resolution scales, with $m$ indexing the scale and $n$ indexing position in the original signal space.

In practice, we are concerned with a finite length, discrete (sampled), 1-D data set $\{f(k), k = 1,2,\cdots,N\}$, and we need appropriate discrete and finite versions of the calculations involved in the wavelet decomposition. In particular, there is a fixed limit to the resolution and, therefore, a lower bound on the scale index $m$, which we may take as $m = 1$ without loss of generality. It is useful to model this resolution limit by representing the data $f(k)$ as samples of a smoothed, or low-passed, version of a continuous signal:

\[ f(k) = \int_{-\infty}^{\infty} dx \phi(x-k)f(x) \]  

(5)

With respect to a smoothing or scaling function $\phi$. Based on this representation of the data, one may compute the wavelet coefficients in (3) by means of a purely discrete algorithm, as detailed in [6]. Beyond these considerations, there is also an effective upper limit on the scale $m$ imposed by the finite length of the signal.

### 3. Histogram Equalization

Histogram Equalization (HE) is one of the most useful forms of nonlinear contrast enhancement. When an image's histogram is equalized, all pixel values of
the image are redistributed. As a result, there are approximately an equal number of pixels for each of the user-specified output gray-scale classes (e.g., 32, 64 and 256). Contrast is increased at the most populated range of brightness values of the histogram (or "peaks"). It automatically reduces the contrast in very light or dark parts of the image, which are associated with the tails of a normally distributed histogram. Histogram equalization can also separate pixels into distinct groups if there are few output values over a wide range.

Consider a discrete grayscale subimage \{x\} and let \(n_i\) be the number of occurrences of gray level \(i\). The probability of an occurrence of a pixel of level \(i\) in the image was defined by the following Eq.(6)[7]:

\[
\Pr(i) = \frac{n_i}{n}, \quad 0 \leq i \leq L
\]  

(6)

There, \(L\) is the total number of gray levels in the image, \(n\) is the total number of pixels in the image and \(\Pr(i)\) is in fact the image’s histogram for pixel value \(i\), normalized to [0,1].

Let us also define \(\Pr(i) = \frac{n_i}{n}, \quad 0 \leq i \leq L\) the cumulative distribution function corresponding to \(\Pr\) as Eq.(7):

\[
\text{cdf}_x = \sum_{j=0}^{i} \Pr(j)
\]  

(7)

Which is also the image’s accumulated normalized histogram.

We would like to create a transformation of the form \(y = T(x)\) to produce a new image \{y\}, such that its CDF will be linearity across the value range, i.e., Eq.(8):

\[
\text{cdf}_y(i) = iK
\]  

(8)

For some constant \(K\). The properties of the CDF allow us to perform such a transform; it is defined as Eq.(9):

\[
y = T(x) = \text{cdf}_y(x)
\]  

(9)

Notice that the \(T\) maps the levels into the range [0,1]. In order to map the values back into their original range, the following simple transformation needs to be applied on the result:

\[
y' = y.(\max\{x\} - \min\{x\}) + \min\{x\}
\]  

(10)

A key advantage of histogram equalization method is that it is a fairly
straightforward technique and an invertible operator. So in theory, if the histogram equalization function is known, then the original histogram can be recovered. The calculation is not computationally intensive. A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal Acharya and Ray (2005) and Russ (2002).

In scientific imaging where spatial correlation is more important than intensity of signal, the small signal to noise ratio usually hampers visual detection. Histogram equalization often produces unrealistic effects in photographs; however it is very useful for scientific images like thermal, satellite or x-ray images, often the same class of images that user would apply false-color to (Acharya and Ray, 2005; Russ, 2002).

Image analysts should be aware that while histogram equalization often provides an image with the most contrast of any enhancement technique, it may hide much needed information. This technique groups pixels that are very dark or very bright into a very few gray scales. If one is trying to bring out information in terrain shadows, or if there are clouds in the image, histogram equalization may not be appropriate.

Duan and Qiu (2004) extended this idea to color images, but the equalized images are not visually pleasing for most cases (Duan and Qiu, 2004). When the equalization process is applied to grayscale images or the luminance component of the color images, regions with overstated contrast usually create visually annoying artifacts. In this case, the visually unsatisfactory results caused by equalization are not acceptable because they give the image an unnatural appearance.

4. Our method

After the histogram equalization, the image have a certain degree of loss of information entropy, so it is necessary to compensate for the loss of information entropy, and further enhance the boundary shape, we continue to process the histogram equalization image using wavelet transform technology. The data of the image of observation shows the area of the image boundary is encoded in the approximate coefficients, to enhance the boundary line can be distinguished on the purpose of the smooth approximation coefficients matrix multiplied by the square of each element, element is through the amplification coefficient of the edge line their areas between the coefficients of voids, so that the boundary is clearly visible.
Wavelet-based histogram equalization method to achieve the flow diagram shown in Figure 1. First the original image histogram equalization method pre-enhancement based on wavelet technology to further enhance the final result.

5. EXPERIMENTS

We have tested our approach on a large data set of natural hazy images. Figure 1 illustrates results obtained for two foggy images by our technique, compared to the methods of Tan [6], He et al. [3] and Tarel[7]. All the figures presented in this paper and supplementary material contain the original restored images provided by the authors. As can be observed, we are able to enhance the images while retaining even very fine details. Furthermore, our method accurately preserves the color of the objects in the scene.

Figure 1. Process of Wavelet-based histogram equalization method

Figure 2. Comparison between recent image defogging methods
In order to prove the robustness of our method we have tested a large dataset of natural hazy images. We also considered the complete sets of images provided by the authors of the previous single image defogging methods. As can be seen in Figure 2 our method is able to perform comparative with more complex methods.

### Table 1. Amplification and loss of contrast induced

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<tbody>
<tr>
<td>Ampl. (%)</td>
<td>0.35</td>
<td>0.22</td>
<td>1.39</td>
<td>0.33</td>
<td>1.43</td>
</tr>
<tr>
<td>Loss (%)</td>
<td>1.7</td>
<td>2.5</td>
<td>2.3</td>
<td>1.8</td>
<td>1.5</td>
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Compared with most of the existing techniques, an advantage of our method is the computation time ,and processes an image in approximately 0.35 seconds. In comparison tested a color images of 600×400, the method of Fattal [2] in approximately 35 seconds, and Tan[6] in approximately 5 minutes, and He et al.[3] in approximately 20 seconds, Tarel[7] in approximately 0.5 seconds to processing an image.

### 6. CONCLUSIONS

The method presented in this paper is a fusion-based approach that solves the problem of single image defogging. We have shown that by choosing appropriate weight maps and inputs, the fusion strategy can be used to effectively dehaze images. Our technique has been tested for a large data set of natural hazy images. Matlab experimental show that algorithm has better visual effects. To future work we would like to test our method for videos.

### REFERENCES


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