ABSTRACT

The work in this paper presents a technique to improve the contrast of weather degraded images due to fog/haze. The proposed technique exploits guided filter to deal with the problems of color saturation and detail contrast enhancement, while maintaining the structural similarity to the input image. Experimental comparisons with state-of-the-art algorithms demonstrate that proposed approach can retrieve the contrast in detail without generating halos and avoids oversaturation in colors. Quantitative analysis also reveals the superiority of the proposed algorithm over existing schemes.

KEY WORDS

Contrast enhancement; adverse weather condition; atmospheric veil; guided filter.

1. Introduction

Outdoor vision applications such as surveillance systems, object detection and tracking, object recognition, navigation, etc., presuppose that the input photographs are captured on a clear day. However adverse weather conditions (fog, haze, mist, and rain) degrade the performance of these applications due to loss of contrast, visibility and color fidelity. This makes contrast enhancement a necessary pre-processing stage in many vision applications.

Enhancement of contrast degraded photographs from the outdoor scene is an ill-posed task because the degradation is dependent upon the unknown depth information with respect to camera. In literature various solutions have been proposed to restore the contrast. Polarization-based methods [1], [2] enhance the contrast using multiple images with different degrees of polarization. In [3], [4], [5], more constraints are obtained from multiple input images of the same scene under different weather conditions. Depth-based methods [6], [7], [8] seek additional depth information either from user inputs or from known 3D models.

Recently, single image approaches [9], [10], [11], [12] have made significant progresses. The success of these methods lies in adopting a stronger prior or assumption. Fattal [9] estimates the medium transmission and scene albedo from the single input image by assuming that transmission and surface shading are locally unrelated. Tan [10] dehaze images by amplifying the local contrast based on the observation that dehazed images have higher contrast than hazy images. Tarel et al. [11] proposed a fast algorithm for visibility restoration by assuming that small objects can have colors with low saturation. He et al. [12] use the concept of black body theory to introduce the most successful and novel prior called dark channel prior. Results of single image based approaches produces enhancement, but they are inefficient in restoring the edges that are not visible in observed image. The restored edges can be determined by adopting the learning based image enhancement/super resolution methods [13], [14] or contrast enhancement assessment methods [15].

In this paper, we proposed a technique to improve the contrast of weather degraded imagery. The proposed scheme can accurately recover hidden edges, maintains structural similarity to input image and avoid oversaturation in colors. Moreover, the algorithm is fast since the time required is linear in amount of pixels and it is applicable for both color and gray level images. Results show the effectiveness of the method to enhance the contrast of degraded images in detail without color saturation and significantly improve the visibility based on qualitative and quantitative analysis.

The remaining of this paper is organized as follows. In section 2, we briefly describe the background of optical degradation model. In section 3, frame work of proposed approach is detailed. Section 4 verifies the validity of proposed algorithm through several comparisons. Finally, in section 5, we conclude the paper.

2. Background

Adverse weather in this paper refers to the atmospheric particles such as haze, fog, and mist. These particles partially absorb and/or scatter the light from the scene and the atmosphere. In computer vision and computer graphics, the Koschmieder’s optical degradation model is widely used to approximate the formation of image as [12]:

\[ I(x) = J(x)t(x) + A(1-t(x)) \]  

where, \( x \) indicates the location of a pixel, \( I \) is the observed image, \( A \) is the global atmospheric light, \( J \) stands for the scene radiance, \( t \) is the medium
transmission. In equation (1), the first term $J(x)t(x)$ represents the transmitted component while $A(1-t(x))$ is the airlight. Pictorial depiction of the image formation in adverse weather conditions is shown in Figure 1.

\[ I(x) = J(x)e^{-\beta d(x)} + A(1-e^{-\beta d(x)}) \]  

where, $\beta$ is the atmospheric attenuation coefficient and $d$ is the scene depth. Equation (2) demonstrates that the effect of weather conditions increase exponentially with the object distance of object with respect to camera. Putting $t(x)$ in (1):

\[ I(x) = J(x)e^{-\beta d(x)} + A(1-e^{-\beta d(x)}) \]  

This indicates that the scene radiance is attenuated, exponentially with the scene depth. Supposing atmospheric veil intensity $V$ be described as [11]:

\[ V(x) = A(1-e^{-\beta d(x)}) \]  

Putting (4) into (3), we can model the observed image in terms of atmospheric veil as:

\[ I(x) = J(x) \left( 1 - \frac{V(x)}{A} \right) + V(x) \]  

Here we seek to infer the atmospheric veil out of the observed image to approach the restored image.

### 3. Proposed Enhancement Algorithm

#### 3.1 Atmospheric Light Estimation

Atmospheric light $A$ is estimated by number of ways. Most of the literary methods estimated it from the most haze-opaque pixel. The pixel with highest intensity value is taken in [10], [9] refined it by solving an optimization problem, [11] directly set $A$ to $(1, 1, 1)$ by performing the white balance, [12] picks the highest intensity pixel equals to $A$ among the top 0.1% brightest dark channel pixels. In this proposed approach, white balance is applied by assuming that atmospheric light has larger intensity than that of any other pixel.

#### 3.2 Atmospheric Veil Estimation

For an observed image $I(x)$, the atmospheric veil $V(x)$ is extracted by modifying the atmospheric veil inference proposed by Tarel et al. [11]. The non-negativity constraint on the atmospheric veil is also applicable in our proposed method. Moreover, veil being pure white cannot be larger than the image of the whiteness $D(x)$. Mathematically, these constraints can be expressed by a single inequality as $0 \leq V(x) \leq D(x)$.

When the airlight is pure white the atmospheric veil casts whiteness to the image and the amount of whiteness added depends on the depth. Besides, according to equation (4), atmospheric veil is proportional to depth. Thus, atmospheric veil can be inferred from the image of whiteness since it contains the depth information. The image of the whiteness is defined as:

For RGB image:

\[ D(x) = \min(I(x)) \]  

For gray level image:

\[ D(x) = I(x) \]  

Atmospheric veil is extracted in a robust way. Firstly, guided filter [16] is employed on $D(x)$ to obtain the filtered image of whiteness $T(x)$. We used guided filtering because it performs smoothing by preserving large jumps along edges which is necessary for the image restoration of images. In contrasted texture image portions, the absolute difference between $D(x)$ and $T(x)$ yield low values. This difference is subtracted from $T(x)$ so that $T(x)$ on these areas is not affected too much. Finally, $V(x)$ is inferred by multiplying a constant parameter $\zeta$ after obtaining the smallest entries from $S(x)$ or $D(x)$. The values of $S(x)$ do not necessarily respect the constraints on the veil and thus are thresholded. Mathematically it can be summarized as:

\[ V(x) = \zeta \left( \max(\min(S(x), D(x)), 0) \right) \]  

with \[ S(x) = T(x) - \text{guided}(|D(x) - T(x)|) \]  

and \[ T(x) = \text{guided}(D(x)) \]  

Here, $\zeta$ determines the percentage of restoration. Atmospheric veil is achieved using guided filter [16] which avoids the gradient reversal artifacts that may appear in detail enhancement. Guided filter is fast and non-approximate linear-time algorithm and it improves the accuracy of atmospheric veil in a better way. Figure 2 shows a foggy image, its corresponding modified atmospheric veil and restored result of the proposed algorithm.
3.3 Recovering Scene Radiance

With the atmospheric light and atmospheric veil, the scene radiance can be recovered as:

\[ J(x) = \frac{I(x) - V(x)}{1 - V(x)} \quad (11) \]

The scene radiance obtained after visibility restoration appears flat since the scene radiance is usually not as bright as the atmospheric light.

3.4 Visual Presentation

To make the restored image visually appealing, we employed tone mapping and contrast stretching. We apply linear mapping on log observed image and log recovered image to keep different aspects of resultant image close to the input image.

Suppose \( \mu_I \) and \( \sigma_I \) are the mean and standard deviation of the log-observed image, and \( \mu_J \) and \( \sigma_J \) denotes the mean and standard deviation of the log-recovered image. Contrast enhanced result \( C(x) \) is obtained as follows:

\[
C(x) = \frac{B(x)}{1 + \left(1 - \frac{1}{\max(B(x))}\right)B(x)}
\]

where, \( B(x) = J(x) \cdot \exp\left(\frac{\mu_I - \mu_J}{\sigma_I \sigma_J}\right) \) \quad (13)

4. Experimental Results

Proposed algorithm is controlled by following three parameters: \( \varepsilon \) which is the regularization parameter for guided filter, \( r \) is the radius of local window for guided filter and \( \zeta \) is to control the strength of restoration.

Figure 3 warrants the use of guided filter in this work. Tarel et al. [11] uses median filtering due to which the fog is not removed between the small leaves as shown in Figure 3(b). Using guided filter in Figure 3(c), we successfully recover fine details by removing the fog inside the small portions of highlighted circle and rectangle.

Figure 4. Comparison with other methods (a) Observed image (b)–(f) Results obtained by Kopf et al. [8], Fattal [9], He et al. [12], Tan [10], Tarel et al. [11] (g) Our result with \( \varepsilon = 0.01, r = 2 \) and \( \zeta = 0.9 \)
Figure 4 allows the comparison of our result with existing visibility enhancement algorithms [8], [9], [10], [11], [12]. It is apparent from the results that our algorithm significantly overcomes the dense fog on the mountains, whereas there is still a small amount of haze left to be removed using all other algorithms.

We adopted [15] to evaluate the contrast enhancement quantitatively. Here, we transform the color to gray level images and then compare gray level images by determining the three visual descriptors: rate of new visible edges (e), percentage of pixels which becomes completely black or completely white after enhancement ( ) and mean ratio of the gradients at visible edges ( ). We calculated the indicators for five approaches by Kopf et al. [8], Fattal [9], Tan [10], Tarel et al. [11], and He et al. [12] on five test images ny12, ny17, y01, y16, and stad1.

### Table 1
Rate of new visible edges

<table>
<thead>
<tr>
<th></th>
<th>Kopf et al.</th>
<th>Fattal</th>
<th>Tan</th>
<th>Tarel et al.</th>
<th>He et al.</th>
<th>Our</th>
</tr>
</thead>
<tbody>
<tr>
<td>ny12</td>
<td>0.0361</td>
<td>-0.054</td>
<td>-0.083</td>
<td>0.1451</td>
<td>0.0482</td>
<td>0.3982</td>
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<tr>
<td>ny17</td>
<td>0.0169</td>
<td>-0.106</td>
<td>-0.041</td>
<td>0.1104</td>
<td>0.0232</td>
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<td>y01</td>
<td>0.0947</td>
<td>0.0864</td>
<td>0.1219</td>
<td>0.2092</td>
<td>0.1426</td>
<td>0.4389</td>
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<tr>
<td>y16</td>
<td>0.0009</td>
<td>0.0582</td>
<td>-0.016</td>
<td>0.2406</td>
<td>0.1314</td>
<td>0.6328</td>
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<tr>
<td>stad1</td>
<td>-</td>
<td>0.2375</td>
<td>0.2947</td>
<td>0.3973</td>
<td>0.3677</td>
<td>0.6007</td>
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### Table 2
Percentage of pixels which becomes completely black or completely white after contrast enhancement

<table>
<thead>
<tr>
<th></th>
<th>Kopf et al.</th>
<th>Fattal</th>
<th>Tan</th>
<th>Tarel et al.</th>
<th>He et al.</th>
<th>Our</th>
</tr>
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<tbody>
<tr>
<td>ny12</td>
<td>0.7159</td>
<td>0.6409</td>
<td>1.8360</td>
<td>0.0</td>
<td>0.0002</td>
<td>0.0004</td>
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<td>ny17</td>
<td>0.1234</td>
<td>1.6988</td>
<td>0.7652</td>
<td>0.0001</td>
<td>0.0136</td>
<td>0.0020</td>
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<tr>
<td>y01</td>
<td>0.0194</td>
<td>0.1128</td>
<td>0.3874</td>
<td>0.0</td>
<td>0.0135</td>
<td>0.0076</td>
</tr>
<tr>
<td>y16</td>
<td>0.2835</td>
<td>0.1489</td>
<td>0.4473</td>
<td>0.0004</td>
<td>0.1521</td>
<td>0.0038</td>
</tr>
<tr>
<td>stad1</td>
<td>-</td>
<td>0.3945</td>
<td>1.9566</td>
<td>0.0</td>
<td>0.0082</td>
<td>0.0005</td>
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### Table 3
Mean ratio of the gradients at visible edges

<table>
<thead>
<tr>
<th></th>
<th>Kopf et al.</th>
<th>Fattal</th>
<th>Tan</th>
<th>Tarel et al.</th>
<th>He et al.</th>
<th>Our</th>
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<tr>
<td>ny12</td>
<td>1.4091</td>
<td>1.2875</td>
<td>2.1802</td>
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<td>ny17</td>
<td>1.6136</td>
<td>1.3546</td>
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<td>1.7057</td>
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<td>y01</td>
<td>1.6362</td>
<td>1.2152</td>
<td>2.2283</td>
<td>1.9903</td>
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<td>1.3456</td>
<td>1.2033</td>
<td>2.0602</td>
<td>1.9583</td>
<td>1.3674</td>
<td>1.9375</td>
</tr>
<tr>
<td>stad1</td>
<td>-</td>
<td>1.8673</td>
<td>4.3592</td>
<td>1.4078</td>
<td>2.1915</td>
<td>2.0249</td>
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</table>

Table 1 lists the rate of new visible edges e that evaluates the ability of the method to restore edges which are not present in the original image but are there in restored image. When compared to the state-of-the-art visibility restoration algorithms, huge improvement in the rate of restored edges is found in our algorithm. Table 2 determines the percentage of pixels that saturate in the resultant image. Compared to the others, proposed algorithm makes some pixels either completely white/black. Table 3 gives the mean ratio of the gradients at visible edges which estimate the average visibility enhancement. One can notice that most of our results are either similar or better than Kopf et al., Fattal, Tarel et al., and He et al., but less enhanced than Tan. However, it is important to note that Tan’s method faces problem of producing color oversaturation in the results.

A contrast enhancement method should provide good structural similarity (SSIM) to the contrast degraded version. Thus, we also use the method proposed in [17] to measure the SSIM between the degraded images and the restored results from the algorithm of Tan [10], Tarel et al. [11], He et al. [12], and ours. SSIM index is calculated for four test images. Figure 5 shows that SSIM indexes for our results are greater than most of the selected methods. This illuminates that our method bring less halos and artifacts when compared to popular traditional techniques.

![Figure 5. SSIM index for Tan [10], Tarel et al. [11], He et al. [12], and our results on four images](image)

Qualitative and quantitative analysis not only support each other but also verify that our algorithm can produce huge rate of new visible edges and good SSIM while avoiding oversaturation in colors.

5. Conclusion

An algorithm that improves the contrast of weather degraded color and a gray scale image is presented. Proposed method based on guided filter, can unveil the details even in heavily hazy regions without producing oversaturation in colors. Furthermore, the algorithm does not need any human intervention and its complexity is a linear function of the number of input image pixels.

### References
