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Visibility Enhancement for Roads with Foggy or Hazy Scenes

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Abstract— **Bad weather, particularly fog and haze, commonly obstruct drivers from observing road conditions. This could frequently lead to a considerable number of road accidents. To avoid the problem, automatic methods have been proposed to enhance visibility in bad weather. Methods that work on visible wavelengths, based on the type of their input, can be categorized into two approaches: those using polarizing filters, and those using images taken from different fog densities. Both of the approaches require that the images are multiple and taken from exactly the same point of view. While they can produce reasonably good results, their requirement makes them impractical, particularly in real time applications, such as vehicle systems. Considering their drawbacks, our goal is to develop a method that requires solely a single image taken from ordinary digital cameras, without any additional hardware. The method principally uses color and intensity information. It enhances the visibility after estimating the color of skylight and the values of airlight. The experimental results on real images show the effectiveness of the approach.**

I. INTRODUCTION

A considerable number of vehicle accidents are caused by poor visibility in bad weather. This is mainly due to the presence of the considerable number of atmospheric particles with significant size and distributions in the participating media. Because of these particles, light from the environment and light reflected from an object are absorbed and scattered, making the visibility not as clear as if they are not present. Some techniques have been introduced to tackle the problem [2]. Briefly, based on their techniques, they can be categorized into several classes: physics-based, heuristics and nonphysics-based solutions. While based on the sensors they use, they are grouped into: visible spectrum sensors, infrared sensors, milimeter-wave (MMW) sensors, and laser radar (LADAR) sensors.

If we investigate on the methods that work on the visible spectrum and particularly deal with foggy/hazy images solved by using physics-based solutions, there are several approaches that have been developed: first, methods that use polarizing filters [9], [5], [10]; and second, methods that use multiple images taken from foggy scenes with different densities [8], [7], [6]. Both of the approaches require that the images are multiple and taken from exactly the same point of view. While those methods can produce reasonably good results, their requirement of the specific inputs makes them impractical, particularly in real time applications, such as automatic vehicle systems. Considering their drawbacks, our goal is, therefore, to develop a method that requires solely a single image taken from an ordinary digital camera. This goal is considerably challenging, since to our best knowledge, no current method published in the literature has been proposed to tackle the goal.

Like the existing methods, our proposed method is based on the Lambert-Beer reflection model. The model is a linear combination of the direct transmission and the airlight. The direct transmission is the product of the environmental light, object reflectance, and fog/haze attenuation factor. The airlight is the product of the environmental light and the reflection of the fog/haze particles. Therefore, to enhance the visibility of foggy images, we have to estimate two crucial components, namely, the airlight and the attenuation factors. However, using only a single image as an input, mathematically, the problem is completely ill-posed. Since, from one equation we have to estimate three unknown parameters

A brief overview of our proposed method is as follows. Given an input image, we first estimate the environmental light color based on a color constancy method called inverse intensity chromaticity space (we learned that the Lambert-Beer reflection model is similar to the dichromatic reflection model). Having known the environmental light color we normalize the image so that the image looks as if lit by white illumination. Then, we obtain the airlight values based on the YIQ color space. Having estimated the intensity and airlight, the visibility enhancement can be done directly based on the physical model. The main idea of our method is to reduce the saturation, retain the hue, and increase the intensity. We consider that the method we propose is principally a physics-based solution. Note that, in this paper our goal is not to totally remove the effects of bad weather. Since, to do that is ill-posed as we shall show in the later section. Instead, our goal is to improve or enhance the visibility of images affected by fog/haze.

The rest of the paper is organized as follows: in Section II, we will discuss the basic reflection model of outdoor scenes affected by fog/haze. This model is important, since all analyses will be based on it. In Section III, we discuss a method to estimate the light color from a single image. This light color will be useful to normalize the input image, so that we can reduce the number of unknown parameters and simplify the model. Section IV will focus on the method of the visibility enhancement. We start with color analysis of the problem, and show the illposedness of it. We end the section with the explanation on the proposed solution. Section V discusses the enhancement in the max-chromaticity intensity space. To show the effectiveness of the proposed method, in Section VI we include the experimental results on real

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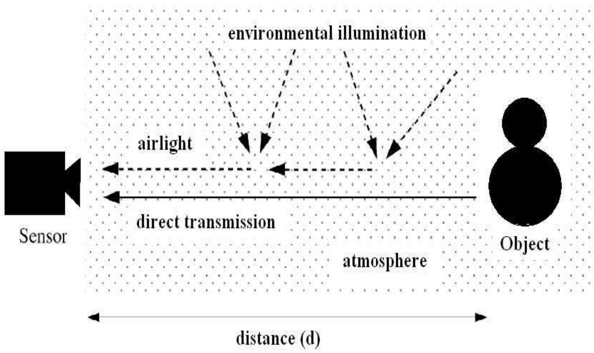

Fig. 1. *Pictorial description of the reflection of foggy or hazy scenes which is composed of the direct transmission and the airlight.*

outdoor images. Finally, we conclude the paper in Section VII.

II. Reflection Model

The exact nature of scattering is highly complex and depends on many factors including the types, orientations, sizes and distributions of particles, as well as wavelengths, polarization states and directions of the incident light [8]. To simplify the scattering of atmospheric conditions, following Narasimhan et al. [8], we model them, particularly for fog or haze, as the linear combination of direct attenuation and airlight. The direct transmission according to [8] models the way light gets attenuated as it traverses from a scene point to the observer. The airlight models how a column of atmosphere acts as a light source by reflecting environmental illumination towards an observer. Figure 1 illustrates the direct transmission and the airlight.

Mathematically, we can model the scattering of light that arrives at a digital camera and then is transformed into an image, as (for the detailed derivation refer to [8]):

$$\mathbf{E}(\mathbf{x}) = \mathbf{I}_\infty \rho(\mathbf{x}) e^{-\beta d(\mathbf{x})} + \mathbf{I}_\infty (1 - e^{-\beta d(\mathbf{x})}). \quad (1)$$

The first term in the equation represents the direct transmission, while the second term represents the airlight. $\mathbf{E}$ is the image intensity. $\mathbf{x}$ is the spatial location. $\mathbf{I}_\infty$ is the atmospheric/environmental light, which is assumed to be globally constant. ρ is the normalized radiance of a scene point, which is the function of the scene point reflectance, normalized sky illumination spectrum, and the spectral response of the camera. β is the atmospheric attenuation coefficient. d is the distance between the object and the observer. Since we assume that the model focuses on fog and haze, β in the equation is constant for different wavelengths. This assumption is common in many methods dealing with particles whose sizes are larger compared with the wavelength of light [4], such as, fog, haze, aerosol, etc. Note that, while the other parameters in the equation are scalar, $\mathbf{E}$, $\mathbf{I}_\infty$, ρ are color vectors (which have RGB values). Eq. (1) is in principle based on the Lambert-Beer law for transparent objects [3], which states that light traveling through a material will be absorbed or attenuated exponentially.

To understand the method we introduce later, Eq. (1) needs to be transformed into a chromaticity-based model. We define image chromaticity as:

$$\sigma_c = \frac{\mathbf{E}_c}{\mathbf{E}_r + \mathbf{E}_g + \mathbf{E}_b} \quad (2)$$

where σ is the image chromaticity, and index c represents the color channel (which can be either r or g or b).

If we assume that the direct transmission is not present (the object is infinitely distant), then the chromaticity will depend only on the airlight. Mathematically, $e^{-\beta d} \rightarrow 0$, in Eq.(1), since $d \rightarrow \infty$. In this case the chromaticity will depend only on the color of the environmental light. We call this light chromaticity and define it as:

$$\Gamma_c = \frac{\mathbf{I}_\infty^c}{\mathbf{I}_\infty^r + \mathbf{I}_\infty^g + \mathbf{I}_\infty^b} \quad (3)$$

where Γ is the light chromaticity.

Accordingly we can define another chromaticity, namely the chromaticity when the airlight is absent, $e^{-\beta d} = 1$:

$$\Lambda_c = \frac{\mathbf{I}_\infty^c \rho_c}{\mathbf{I}_\infty^r \rho_r + \mathbf{I}_\infty^g \rho_g + \mathbf{I}_\infty^b \rho_b} \quad (4)$$

where Λ is the object chromaticity.

Therefore, by using the chromaticity definitions, we can rewrite Eq. (1) in term of chromaticity:

$$\mathbf{E}(\mathbf{x}) = B(\mathbf{x})\Lambda(\mathbf{x}) + F(\mathbf{x})\Gamma \quad (5)$$

where:

$$B = (\mathbf{I}_\infty^r \rho_r(\mathbf{x}) + \mathbf{I}_\infty^g \rho_g(\mathbf{x}) + \mathbf{I}_\infty^b \rho_b(\mathbf{x})) e^{-\beta d(\mathbf{x})} \quad (6)$$
$$F = (\mathbf{I}_\infty^r + \mathbf{I}_\infty^g + \mathbf{I}_\infty^b)(1 - e^{-\beta d(\mathbf{x})}) \quad (7)$$

with B and F are both scalar values, while Λ and Γ are color vectors. Note that, from their chromaticity definitions, $[\sum \sigma_i = \sigma_r + \sigma_g + \sigma_b = 1]$, $[\sum \Lambda_i = \Lambda_r + \Lambda_g + \Lambda_b = 1]$, and $[\sum \Gamma_i = \Gamma_r + \Gamma_g + \Gamma_b = 1]$.

III. Light Color Estimation

In bad weather, especially in daylight, the environmental light can be assumed globally constant, since we can ignore the sunlight that directly illuminates objects appearing in the observation. This environmental light is produced by the scattering effects of the particles in the medium, which yield certain chromatic color (that is identical to the light chromaticity in Eq. (3)). In our method, to be able to enhance the visibility, we first have to estimate and then remove the light chromaticity.

The simplest way to estimate the value of the light chromaticity is by finding a patch in the input image that only has the airlight (i.e., when the distance of an object is infinite), and computing the chromaticity (by using Eq.(2)). However, to find the airlight-only patches is not trivial, and in some cases they are simply not present.

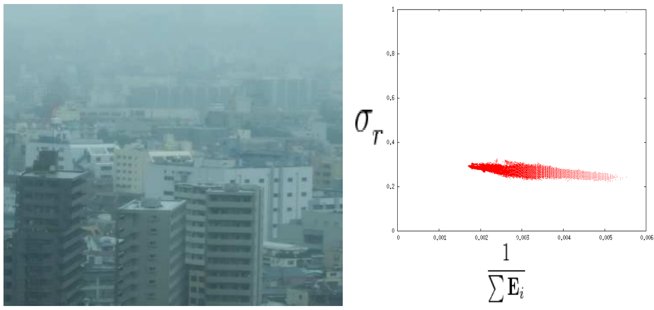

Fig. 2. *Left: input image, as can be observed the environmental light is bluish. Right: The plot of all pixels of the image into the inverse intensity chromaticity space. In this figure, we only show the chromaticity of the red channel. The other channels can be estimated independently.*

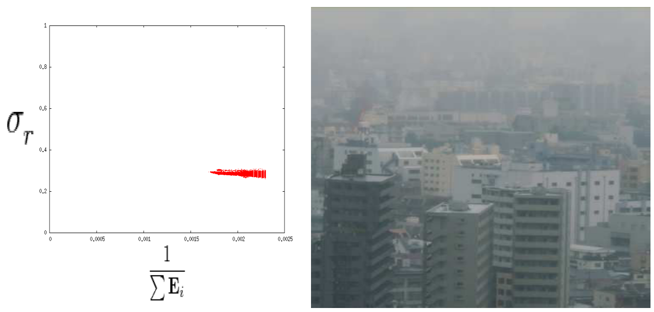

Fig. 3. *Left: the plotting after choosing 20% of the highest intensities. Right: the result of normalizing the environmental light of Figure 2.*

In this paper, we propose the estimation by using the inverse intensity chromaticity space ([11]). We found that the scattering model in Eq. (5) is similar to the dichromatic reflection model, in which Tan et al. [11] attempted to tackle in order to find the illumination chromaticity of dielectric objects that exhibit highlights.

Briefly, the explanation of the inverse-intensity chromaticity space is as follows (the detailed derivation refers to [11]). The main idea of the method is in the linear correlation between the light chromaticity and image chromaticity:

$$\sigma_c = p_c \frac{1}{\sum \mathbf{E}_i} + \Gamma_c \tag{8}$$

where $\sum \mathbf{E}_i = \mathbf{E}_r + \mathbf{E}_g + \mathbf{E}_b$. $p_c = B(\Lambda_c - \Gamma_c)$. The values of σ_c and $\sum \mathbf{E}_i$ in the equation are known, since they are computable directly from the observation.

From Eq. (8), we can create a two-dimensional space where the x-axis represents the inverse intensity ($1/\sum \mathbf{E}_i$) and the y-axis represents the image chromaticity (σ_c). By considering the equation and the space, it becomes obvious that the distribution of the points in the space will form several lines that have different gradients (p_c) but the same intercept (Γ_c). Computationally, we can use the Hough transform and a histogram-like algorithm to estimate the value of Γ_c as proposed in [11]. Figure 2.b shows the distribution of a foggy scene in the inverse-intensity chromaticity space.

In practice, since there is a possibility that the fog or haze does not cover the whole scenes in the image, we choose approximately 20% of the highest intensities in the image. The number is obtained through experimental observations (Figure 3.a). Also, in using this method, we assume that the scene is varying in the distance of the objects (as is common in outdoor scenes, particularly for road scenes).

IV. VISIBILITY ENHANCEMENT

By knowing the light chromaticity, we can remove it from the image by simply dividing the image intensity in Eq. (5) with Γ_c, which is formally described as:

$$\mathbf{E}'_c(\mathbf{x}) = \mathbf{E}_c(\mathbf{x})/\Gamma_c \tag{9}$$

$$= B(\mathbf{x})\frac{\Lambda(\mathbf{x})}{\Gamma(\mathbf{x})} + F(\mathbf{x}) \tag{10}$$

$$= B(\mathbf{x})\Lambda'(\mathbf{x}) + F(\mathbf{x}) \tag{11}$$

where Λ' is the normalized object chromaticity. E'_c is the normalized input image, whose environmental-light color is white. Figure 3.b shows the result of the normalization for Figure 2.a.

The principle idea of our method to enhance the visibility is to estimate the airlight, i.e., $F(\mathbf{x})$ in Eq. (11). Since, if we know the airlight as well as the normalized environmental light ($\mathbf{I}^r_\infty + \mathbf{I}^g_\infty + \mathbf{I}^b_\infty$) in Eq. (7), we can estimate the values of $[(\mathbf{I}^r_\infty \rho_r + \mathbf{I}^g_\infty \rho_g + \mathbf{I}^b_\infty \rho_b)\Lambda]$ in Eq. (5), which represents the scene appearance unaffected by fog/haze. However, we found that to estimate the airlight (F) from a single image is considerably intractable. Thus, before proceeding to the estimation technique, we intend to show the characteristics of foggy or hazy scenes in color analysis, particularly the hue-saturation and chromaticity analysis. The analysis has two purposes: first, we intend to show that the problem is ill-posed; second, we want to show the problem in terms of color analysis.

A. Hue and Saturation Analysis

We compute the hue and saturation values by using the following equation [1]:

$$H = cos^{-1}\left[\frac{\frac{1}{2}\left[(\mathbf{E}'_r - \mathbf{E}'_g) + (\mathbf{E}'_r - \mathbf{E}'_b)\right]}{\left[(\mathbf{E}'_r - \mathbf{E}'_g)^2 + (\mathbf{E}'_r - \mathbf{E}'_b)(\mathbf{E}'_g - \mathbf{E}'_b)\right]^{\frac{1}{2}}}\right] \tag{12}$$

$$S = 1 - \left[\frac{3}{\mathbf{E}'_r + \mathbf{E}'_g + \mathbf{E}'_b} min(\mathbf{E}'_r, \mathbf{E}'_g, \mathbf{E}'_b)\right] \tag{13}$$

Based on the hue and saturation definition, if we have two input images of an identical scene with different fog/haze density, their hue values will be exactly the same; since, the airlight in Eq. (12) will be canceled out. However, their saturation values will be different, since the airlight in Eq. (13) cannot be excluded . If we analyze the saturation values further, they will be larger if the airlight is larger, and will be smaller if the airlight is smaller. This fact leads to a conclusion that a scene with fog/haze differ to that without fog/haze only in their saturation values.

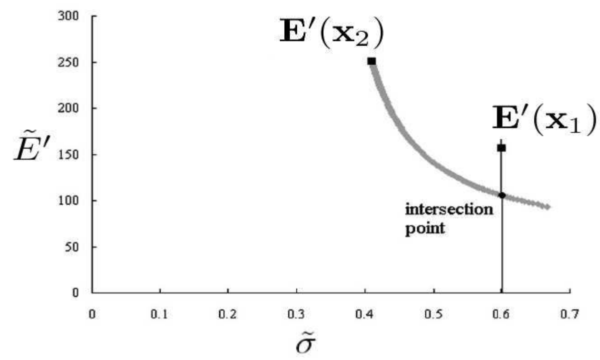

Fig. 4. *The plot of a pixel affected by fog ($\mathbf{x}_2$), and a pixel free from fog ($\mathbf{x}_1$) into the max-chromaticity intensity space*

Therefore, if we intend to enhance the visibility, particularly if we want to remove the airlight, we have to keep the hue values and to make the saturation values smaller. The problem then, is how small we should make them. This problem is not trivial and, in fact for a single input image, it is ill-posed. We will prove this mathematically below.

B. Proof of the Illposedness

For the sake of proving the illposedness, we use a two dimensional max-chromaticity intensity space. In this space, x-axis represents max-chromaticity, which is defined as:

$$\tilde{\sigma} = \frac{max(\mathbf{E}'_r, \mathbf{E}'_g, \mathbf{E}'_b)}{\mathbf{E}'_r + \mathbf{E}'_g + \mathbf{E}'_b} \tag{14}$$

where max is the maximum operator that chooses the largest values among $\mathbf{E}'_r, \mathbf{E}'_g, \mathbf{E}'_b$, so that $\tilde{\sigma}$ is, unlike σ, a scalar value. The y-axis represents $\tilde{E}'$ (=$max(\mathbf{E}'_r, \mathbf{E}'_g, \mathbf{E}'_b)$), the normalized image intensity of the color channel that is identical to that of the maximum chromaticity. $\tilde{E}'$ is also a scalar value.

Assuming that we have two normalized pixels, namely, $\mathbf{E}'(\mathbf{x}_1)$ and $\mathbf{E}'(\mathbf{x}_2)$, where $\mathbf{E}'(\mathbf{x}_1)$ is a pixel that is not affected by fog/haze (the airlight equals to zero), and $\mathbf{E}'(\mathbf{x}_2)$ is a pixel affected by fog/haze (the airlight is larger than zero), plotting those pixels into the max-chromaticity intensity space, we will find that the max-chromaticity value of the first pixel is larger than that of the second pixel (see appendix A for the proof). Figure 4 shows the plot of those pixels in the max-chromaticity intensity space. The correlation of those two pixels in the space (the curved line) can in general be formulated as (see appendix B for the detailed derivation):

$$\tilde{E}' = B(\mathbf{x})(\tilde{\Lambda}(\mathbf{x}) - 1/3)\big(\frac{\tilde{\sigma}}{\tilde{\sigma} - 1/3}(\mathbf{x})\big) \tag{15}$$

where $\tilde{\Lambda}$ is the object max-chromaticity. If we do further algebraic derivation and solely consider those two points, we have:

$$B(\mathbf{x}_2) = \frac{\tilde{E}'(\mathbf{x}_2)[3\tilde{\sigma}(\mathbf{x}_2) - 1]}{\tilde{\sigma}(\mathbf{x}_2)[3\tilde{\Lambda}'(\mathbf{x}_2) - 1]} \tag{16}$$

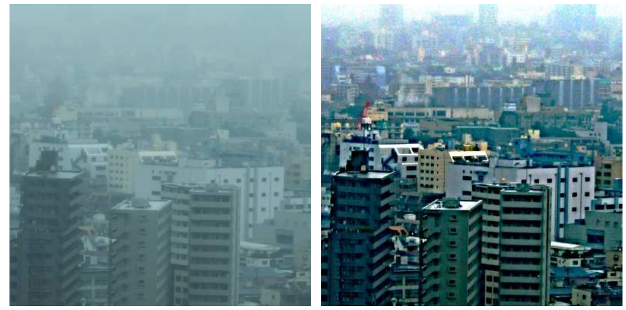

Fig. 5. *Left: input image. Right: the visibility enhancement of result.*

From the image chromaticity (Eq. (2)) and object chromaticity definition (Eq. (4)), we know that $\tilde{\Lambda}'(\mathbf{x}_1) = \tilde{\sigma}'(\mathbf{x}_1)$, since the airlight equals to zero, which then is computable from the observation. We also know from the fact that pixel 1 and pixel 2 represent the same object, which means $\tilde{\Lambda}'(\mathbf{x}_2) = \tilde{\Lambda}'(\mathbf{x}_1)$. Therefore, from the two pixels we can compute B in Eq. (16), and thus F in Eq. (11).

In the above case, we can solve the problem in a closed-form solution since we assume that there are two pixels with known object max-chromaticity ($\tilde{\Lambda}'(\mathbf{x})$). If we have only a single pixel or a single image with unknown object max-chromaticity, then we have two unknowns (B and $\tilde{\Lambda}'$) in one equation (Eq. (16)). Therefore, we can conclude that the problem of F estimation in a single image is ill-posed.

C. Intensity-based Enhancement

While we have shown that the problem of estimating F is ill-posed, fortunately in this paper our goal is not to obtain the absolute correct value of B. Our goal is to enhance the visibility, regardless of the correctness of B compared with the corresponding real world. This goal relaxes the problem, since we do not need to estimate the absolute value of F. In other words, we can approximately estimate F, as long as the visibility is enhanced.

To accomplish the goal, we compute F based on the intensity value of the YIQ color model, which is defined as:

$$Y = 0.257\mathbf{E}'_r + 0.504\mathbf{E}'_g + 0.098\mathbf{E}'_b \tag{17}$$

We assume the values of Y to be the values of F. However, the values of Y are approximated values, thus to create a better approximation, we diffuse these values by using Gaussian blur.

To have the values of $\mathbf{I}^r_\infty + \mathbf{I}^g_\infty + \mathbf{I}^b_\infty$, namely, the environmental light, we assume that the largest intensity in the image is the environmental light. Having these two values (F and $\mathbf{I}^r_\infty + \mathbf{I}^g_\infty + \mathbf{I}^b_\infty$), we can estimate the approximated values of $(1 - e^{-\beta d(\mathbf{x})})$ by using Eq. (7).

Therefore, upon knowing the approximated values of $e^{-\beta d}$ and F, we can have the following equation, which is derived from Eq. (1), to enhance the visibility of the input image:

$$\mathbf{I}_\infty(\mathbf{x})\rho(\mathbf{x}) = \big[\mathbf{E}(\mathbf{x}) - F(\mathbf{x})\Gamma\big]e^{\beta d(\mathbf{x})} \tag{18}$$

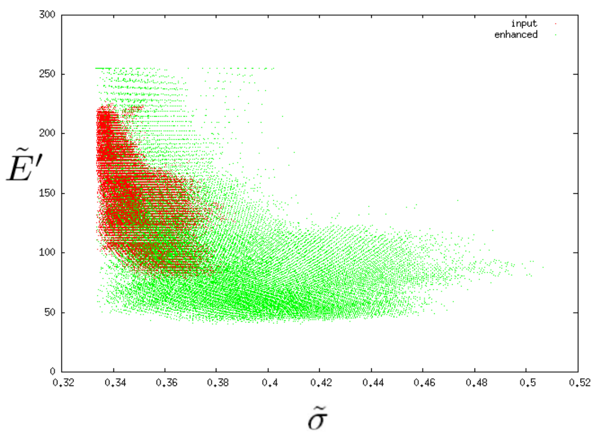

Fig. 6. *The comparison between the enhanced visibility image (green dots) and the input image (red dots) shown in Figure 5.*

where $\mathbf{I}_\infty(\mathbf{x})\rho(\mathbf{x})$ is the output whose visibility is enhanced. Figure 5 shows the enhanced visibility of Figure 2. As can be observed, the visibility is much improved in the final result.

V. Discussion

As we mentioned in Sect. III.A and B, a scene will be less foggy/hazy if the saturation values are smaller. Or, in terms of the max-chromaticity (Eq. (14)), the scene should have larger values of max-chromaticity. To show that the enhanced image in Figure 5 follows our theorem, Figure 6 show the plot of Figure 2.a and 5 in the max-chromaticity intensity space. Note that, some points still have small values of $\tilde{\sigma}$, since they are points that represent achromatic pixels (white, gray, black) of the image.

VI. Experimental Results

To demonstrate the effectiveness of our method, we used real images of outdoor scenes in our experiments. Most of these images shown in this section were taken from the internet, and the quality is considerably low.

Figure 7.a shows a typical road scene partially covered with haze and Figure 7.b shows the enhancement result. As can be observed, the contrast (and thus visibility) in Figure 7.b is more significant than Figure 7.a. Figure 8.a and Figure 9.a show examples of image with very dense fog. Figure 8.b and Figure 9.b show the enhancement. The results show considerable significant improvements of the visibility of the objects. Figure 10.a shows a typical outdoor scene whose visibility is affected by haze. The enhancement in Figure 10.b shows more contrast and clearer visualization.

VII. Conclusions

As a conclusion, we have proposed a method that is solely based on single images and can be used in real time operations, without any user interferences. To our knowledge, no current method has those useful features. Hence, we believe that many applications, such as driver assistance system, remote sensing, panoramic images, a feature of

Fig. 7. *Top: the input image. The scene is partially covered by haze. Bottom: the visibility enhancement result.*

Fig. 8. *Top: the input image. A building is covered by dense fog. Bottom: the visibility enhancement result.*

Fig. 9. *Top: the input image with dense fog. Bottom: the visibility enhancement result.*

Fig. 10. *Top: the input image. An outdoor scenery, which is partially covered by haze. Bottom: the visibility enhancement result.*

commercial digital cameras, etc, can be improved by utilizing our proposed method.

APPENDIX A

The proof that the max-chromaticity of a pixel with fog/haze is smaller than that without fog; supposing that the pixels represent an identical object.

$$\tilde{\sigma}_{fog} < \tilde{\sigma}_{nofog} \tag{19}$$

$$\frac{B\tilde{\Lambda}' + F}{B\sum \Lambda_i' + 3F} < \frac{\tilde{\Lambda}'}{\sum \Lambda_i'} \tag{20}$$

$$\frac{1}{3} < \tilde{\Lambda}' \tag{21}$$

where $\sum \Lambda_i' = 1$. The last equation shows that $[\tilde{\sigma}_{fog} < \tilde{\sigma}_{nofog}]$ is correct, since the value of any chromaticity is always bigger that $1/3$.

APPENDIX B

Derivation of the correlation between the max-chromaticity of pixels with fog and without fog in Eq. (15):

$$\tilde{\sigma} = \frac{B\tilde{\Lambda}' + F}{B\sum \Lambda_i' + 3F} \tag{22}$$

$$F = B\frac{\tilde{\Lambda}' - \tilde{\sigma}}{\tilde{\sigma} - 1/3} \tag{23}$$

$$\tilde{E}' = B(\tilde{\Lambda}' - 1/3)(\frac{\tilde{\sigma}(\mathbf{x})}{\tilde{\sigma} - 1/3}) \tag{24}$$

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