An Efficient Haze Removal Algorithm Using Chromatic Properties

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Abstract

Inclement weather conditions such as fog or haze increase traffic accident rates. Large amounts of particles and water droplets in the atmosphere absorb and scatter light, causing blurring artifacts that degrade the contrast and fidelity of outdoor images. Most intelligent automatic driving systems depend on these input images to improve driver safety. These systems are substantially limited in harsh weather conditions, to this effect. Efficient and robust algorithms are in urgent demand to benefit consumer/computational photography and computer vision applications such as stereo matching [1], segmentation[2], and recognition [3].
In this study, we began by developing a dehazing method to significantly enhance scene contrast and visibility;
haze-free images are beneficial to the stereo matching rate. Dehazing can also provide high-quality images which aid ADAS and benefit vision algorithms such as image classification and recognition. Our primary goal is eliminating the effects of inclement weather, which is a crucial task in computer vision and pattern recognition.

Index Terms— Dehazing, ADAS, chromatic properties, bilateral filter

Atmospheric Scattering Model

The following linear interpolation model proposed by McCartney [23] is widely used to describe hazy image formation:

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

where I represents observed color hazy image, x denotes pixel position in the image coordinate, J is scene radiance representing the haze-free image, A represents global atmospheric light, t denotes medium transmission ($0 \le t(x) \le 1$), β and d are atmosphere scattering coefficient and scene depth, respectively. The goal of haze removal is to recover J from I. Thus, the purpose of dehazing is to estimate A and t, then restore J according to Eq. (1). The haze-free image J(x) is recovered if we evaluate atmospheric light A and transmission t in Eq. (3). There are 3N constraints and 4N unknowns for N-pixel color image I, which thus complicates dehazing.

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

Results

Table 1

Mean squared error (MSE) comparison with He et al. [9], Meng et al. [19], and Zhu et al. [22]

Haze Image	[9]	[19]	[22]	Ours
residential	3.48	3.34	2.48	1.16
city	3.21	3.53	2.27	0.86
road	3.35	3.29	2.66	1.03
300test images	3.36±0.13	3.46±0.18	2.34±0.08	0.92±0.09

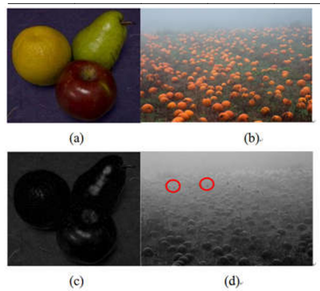

Fig.3 Fruit images; (a) Apple image with highlight; (b) Orange image with dense fog; (c) is highlight map of (a) by He et al.[] (d) is fog map of (b) via dichromatic reflection model.

Fig. 8 Heavy fog exists in Road images; (a) Foggy images of residential , city and road; (b) He et al.'s result[9](c) Meng et al.'s results [19]; (d) Zhu et al.'s results [22]; (e) Our results;(f) ground truth images

Dichromatic Reflection Model

A colorful image can be denoted as a linear combination of diffuse (Id) and specular reflections (Is) as follows:

$$I(x) = I_d(x) + I_s(x) \tag{8}$$
$$I(x) = I_{haze}(x) + I_{haze-free}(x) \tag{9}$$

Inspired by our observation, fog can be treated as specular reflections as they share similar properties. Thus Eqs. (8) is rewrote to (9) for finding foggy pixel location and atmospheric light value and medium transmission is estimated later.
The chromaticity can be described as:

$$\sigma_c = \frac{I_c}{\sum_{c \in \{r,g,b\}} I_c} \tag{10}$$

Where Ic represents colorful images with r,g,b channels. Haze-free chromaticity and image IcD (haze-free image) are defined as follows:

$$\Lambda_c = \frac{I_c^D}{\sum_{c \in \{r,g,b\}} I_c^D} \tag{11}$$

Estimating maximum dehazing chromaticity for a single image is difficult problem. So chromaticity is approximated by using based on dichromatic reflection model[24] :

$$\sigma_{\min} = \min(\sigma_r, \sigma_g, \sigma_b) \tag{12}$$
$$\lambda_c = \frac{\sigma_c - \sigma_{\min}}{1 - 3\sigma_{\min}} \tag{13}$$

The maximum component of approximate haze-free chromaticity can be computed as follows:

$$\lambda_{\max} = \max\left(\frac{\sigma_r - \sigma_{\min}}{1 - 3\sigma_{\min}}, \frac{\sigma_g - \sigma_{\min}}{1 - 3\sigma_{\min}}, \frac{\sigma_b - \sigma_{\min}}{1 - 3\sigma_{\min}}\right) \tag{14}$$

Using the approximate maximum dehazing chromaticity defined in Eq. (14), haze and haze-free image are obtained as follows:

$$I_{\text{haze(fog)}}(x) = \frac{\max_{c \in \{r,g,b\}} I_c - \lambda_{\max} \sum_{c \in \{r,g,b\}} I_c}{1 - 3\lambda_{\max}} \tag{15}$$
$$I_{\text{haze-free}}(x) = I(x) - \frac{\max_{c \in \{r,g,b\}} I_c - \lambda_{\max} \sum_{c \in \{r,g,b\}} I_c}{1 - 3\lambda_{\max}} \tag{16}$$

Conclusions

In this study, we established an efficient DRBF method by observing that fog and highlight share similar physical properties.
We can thus detect fog via dehazing reflection model to remove highlights. A fast bilateral filter was used to achieve an accurate fog map without black noise. Additionally, atmospheric light and medium transmission were easily estimated using our proposed method. This method is suitable for parallel implementation and the processing time is 1,024 KB images at a video rate on an NVIDIA Geforce 8800 GTX GPU. Experimental results show that the proposed approach achieves high efficiency and outstanding dehazing effects in both daytime and nighttime conditions.

Literature cited

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Heavy fog condition

Heavy haze images for testing are prepared via Tang et al.'s method [8], first downloading 500 road stereo images from the KITTI database- training data of city from raw data [25] and treating them as ground truth (haze-free) images. Koschmieder's law is employed via Eq.(1) to add fog to ground truth images for obtaining heavy haze images. The depth map is difficult to obtain by a single image, but by using stereo matching accurate depth information is easy to get. Then the random atmospheric light A is set between 0.85 and 0.98. The most important parameter -scattering coefficient β is set ranging from 0.9 to 1.3 in order to create heavy fog conditions. .