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Single image haze removal using multiple scattering model for road scenes

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Abstract

Haze is one of the sources cause image degradation. Haze affects contrast and saturation of not only for the real world image, but also the road scenes. Most haze removal algorithms use an atmospheric scattering model for removing the effect of haze. Most of haze removal algorithms are based on the single scattering model which does not consider the blur in the haze image. In this paper, a novel haze removal algorithm using a multiple scattering model with deconvolution is proposed. The proposed algorithm considers blurring effect in the haze image. Down sampling of the haze image is also used for estimating the atmospheric light efficiently. The synthetic road scenes with and without haze are used to evaluate the performance of the proposed method. Experimental result demonstrates that the proposed algorithm performs better for restoring images affected by haze both qualitatively and quantitatively.

Introduction

Weather conditions such as haze or yellow dust caused by water droplets and particles in the air cause serious degradation of image quality. This degradation in image quality causes errors in various computer vision algorithms, especially object recognition, object tracking, etc. for Advanced Driver Assistance Systems (ADAS) [1]. Thus, haze removal algorithms are necessary for ADAS and drivers using screens installed in a vehicle.

Effect of the haze in captured images has been considered as a problem of contrast degradation. Researchers have founded that haze follows Koschmieder's Law [2] which means effect of haze is depend on the scene depth. Haze removal algorithms based on Koschmieder's law can be divided in two groups : single scattering model and multiple scattering model. In the case of single scattering model, the effect of haze can be expressed as:

$$I(i,j) = J(i,j)t(i,j) + A(1-t(i,j)), \tag{1}$$

where (i,j) is pixel position of the image, I is the observed image, J is the scene radiance, A is the global atmospheric light, and t is medium transmission. $t(i,j)$ can be represented as:

$$t(i,j) = exp(-\beta d(i,j)), \tag{2}$$

where $d(i,j)$ is depth of the pixel position and β denotes the atmospheric scattering coefficient.

Another approach is the multiple scattering model. This means that there is not one molecule but several molecules that affect the light acquired by the camera from an object in a haze situation, as shown in the following Fig. 1. In the multiple scattering model, light entering a pixel of the camera or image sensor captured in the form of blur by the influence of the neighborhood zones. Narasimhan *et al.* [3] defines atmospheric point spread function (APSF) for isotropic point light source as:

$$\begin{cases} I(T,u) &= \sum_{m=0}^{\infty}(g_m(T)+g_{m+1}(T))P_m(\mu) \\ g_m(T) &= I_0 e^{-\beta_m T - \alpha_m \log T} \\ \alpha_m &= m+1 \\ \beta_m &= \dfrac{2m+1}{m}(1-q^{(m-1)}), \end{cases} \tag{3}$$

where T is optical thickness and q is forward scattering parameter. These two values are assigned differently for clear, hazy and foggy weather condition. The images obtained under the multiple scattering model can be expressed as:

$$\begin{aligned} I_{blurred}(i,j) =& I(i,j) \otimes APSF \\ =& ((J(i,j)t(i,j) + A(1-t(i,j)) \otimes APSF, \end{aligned} \tag{4}$$

where $\otimes$ means convolution operation. The modeling of the image degraded by the multiple scattering model is expressed as an ill-posed problem with three unknown unknowns of $APSF$, $t(i,j)$, and A as shown in (4).

Proposed method

Based on the above analysis, we propose a method to remove the effect of haze on road scenes using a multiple scattering model. First, we estimates a blur kernel to remove blurness for each region respectively. Second, distance between the target to the camera is determined. Finally the global atmospheric light is estimated and restores the original scene radiance J. The flowchart of the proposed algorithm is shown in Fig. 2.

Estimation of APSF

In the proposed method, the APSF is estimated in consideration of the characteristics of the road scenes. Conventional methods estimate the kernel of APSF based on the type of weather

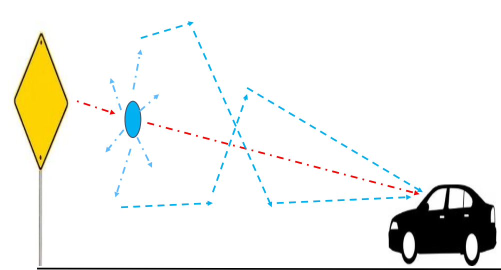

Figure 1. *Image fomation for road scenes based on multiple scattering model.*

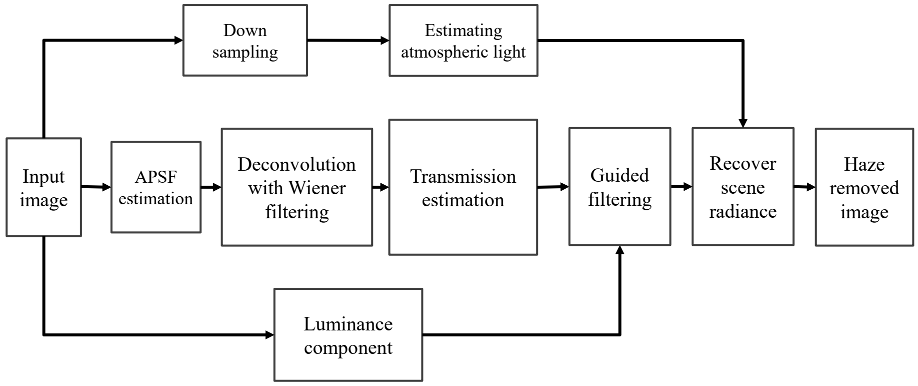

Figure 2. *The flowchart of the proposed method.*

and the thickness of the haze. However, using the same APSF kernel for the entire image can cause problems for areas that are less affected by haze. As can be seen in the Fig. 3 below, the use of APSF kernel and deconvolution causes artifacts in the area where haze density is low. R. Wang *et al.* [4] suggested that the APSF kernel can be approximated by a generalized Gaussian distribution (GGD). The probability density function of GGD is expressed as:

$$GGD(x) = \frac{\eta}{2\psi\Gamma(\frac{1}{\eta})} \exp^{(\frac{-|x-\mu|}{\psi})^{\eta}}, \tag{5}$$

where μ is the mean, Γ means gamma function, η and ψ are parameters that determine shape and scale of GGD. The blur kernel at the pixel position (i, j) in two-dimensional image using GGD and APSF can be expressed as:

$$GGD(i,j)\,|(m,n) = \frac{\eta}{2\psi\Gamma(\frac{1}{\eta})} \exp^{(\frac{-|i-u|}{\psi})^{\eta}+(\frac{-|j-v|}{\psi})^{\eta}} \tag{6}$$

$$h_{APSF}(i,j)\,|(m,n) = \frac{GGD(i,j)}{\sum_{k=-m/2}^{m/2}\sum_{l=-n/2}^{n/2} GGD(k,l)}, \tag{7}$$

where m, n are mask size, u, v are center pixel of each mask, and h_{APSF} is normalized kernel at pixel position (i, j). GGD changes its distribution according to the η and ψ values. By changing the values of η and ψ, it is possible to approximate the (3) which set the values of T and q differently according to weather conditions. Choi *et al.* [5] proposed several features to measure the density of haze in an image. One of the feature is the contrast energy. As haze density increases, the contrast energy of the region is decreased. If specific region has more detail information, the contrast energy is also high, and we can determine the density of haze is low. In the proposed method, we use local variance as a feature to measure the contrast energy of the region. The relationship between local variance, ψ, and η can be defined as follows:

$$\psi = \varepsilon_1 \cdot \sigma^2_{n\times n} \tag{8}$$

$$\eta = \varepsilon_2 \cdot \sigma^2_{n\times n}, \tag{9}$$

where, $\sigma^2_{n\times n}$ is local variance size of n by n, ε_1 is constant larger than 1 and ε_2 is constant between 0 and 1. In the proposed method, (7) and APSF are used to resotre blur due to haze. As in the conventional method [4], we used Wiener filter to restore blurness. The restored image with Wiener filter can be expressed as:

$$I_{restored} = deconv(I_{blurred}, h_{APSF}) = deconv \\ (J(i,j)t(i,j) + A(1-t(i,j)) \otimes h_{APSF}, h_{APSF}), \tag{10}$$

where *deconv* means deconvolution operation.

Estimation of transmssion

In the proposed method, the transmission is estimated based on the dark channel prior (DCP) proposed by He *et al.* [6]. Even though the dehaze problem is an ill-posed problem, $t(i, j)$ can be estimated using dark channel prior. The dark channel is defined as:

$$J^{dark}(i,j) = \min_{(i,j)\in\Omega} \min(J^c(i,j)), c \in \{r,g,b\}, \tag{11}$$

where J^{dark} is the dar channel, Ω is a local patch, and c is the color channels in RGB color space. In this paper, we set size of Ω as 15×15. Then, $t(i, j)$ can be estimated using dark channel prior as:

$$\tilde{t}(i,j) = 1 - w \cdot \min_{(i,j)\in\Omega} \min_{c}(\frac{I^c(i,j)}{A^c}), \tag{12}$$

(a) (b)

Figure 3. *Result with APSF deconvolution in low density haze area: (a) haze image; (b) artifact in haze removed image.*

where $\bar{t}(i,j)$ is estimated depth at (i,j) and w is applicative parameter which set 0.95. This estimated transmission is called coarse transmission. Using coarse transmission causes blocking artifacts at the boundary between blocks. He *et al.* [6] used soft matting to remove artifacts. However, soft matting process requires a lot of source and time. To overcome the limitations, haze removal algorithms using guided filter [7] or bilateral filter [8] are proposed. In the proposed method, guided filtering is used for smoothing the coarse transmission. Since the transmission is obtained through the minimum of R, G, and B channels, coarse transmission is a single channel image. Thus, we use luminance component of the input image as a guide image for filtering. The filtered transmission can be represented as:

$$t_{filtered} = guide(\bar{t}, I_{luminance}), \tag{13}$$

where $guide$ means guided image filtering and $I_{luminance}$ is luminance component of the input image.

Estimate A and recover scene radiance

From the equation of single scattering model or multiple scattering model, A can be estimated when depth is ∞ as t goes to 0. He *et al.* first picked 0.1% highest pixels from dark channel image, and estimate A as the highest value among those pixels [6]. This process sorts the whole image, which requires a lot of time and cost. Since the value of A is determined by only one pixel, in the proposed method, we down samples the input image and determines the maximum value of image as the value of A with the He's method [6]. Since the sky-region occupies most of the road scenes, down sampling the input image to $\frac{1}{8}$ times does not affect to the estimation of A. We can restore the haze free image J by using the values $I_{resotred}$, A, and $t_{filtered}$. The haze free image, scene radiance, is expressed as:

$$J(i,j) = \frac{I_{restored}(i,j) - A}{\max(t_{filtered}(i,j), t_0)} + A, \tag{14}$$

where t_0 is a typical value for preventing denominator goes to 0.

Experimental results

In this section, we compare the proposed algorithm with several haze removal algorithms to evaluate its performance. Since the haze removal method is proposed for the driver assiatantce systems, the road-environment image is used as the experimental image. In order to accurately measure the performance of the proposed method, both the reference image and the image containing the haze are required, but it is impossible to actually obtain the pair image. We use synthetic image pairs using graphics to compare performance of the proposed method with other conventional methods. Tarel *et al.* created a FRIDA dataset [1] for visibility enhancement. Also Gaidon *et al.* provided a Virtual KITTI dataset, a photo-realisitic synthetic video dataset [9].

In this paper, we use these two datasets to compare the results of the proposed method with conventional methods. The conventional methods which used are DCP [6], GDCP [7], CAP [10], DEFADE [5], and Tarel *et al.* [1]. The results of the conventional methods and the propsoed method with one of the images in FRIDA dataset are shown in Fig. 4. The results show that the DCP-based haze removal algorithms are more effective in restoring haze affected image. Tarel *et al.* proposed utilizes the position of the camera mounted on the vehicle, so color distortion occurs near traffic sign. In the case of CAP and DEFADE, stable results are obtained, but performs little restoration in areas with high haze density. Result with the proposed algorithm, removes haze more thoroughly using multiple scattering model.

For the objective quality assessment for the proposed method, we used metrics to evaluates the performance of algorithms. Also, since the FRIDA dataset provides the original image without the haze, it is possible to measure how the haze removed image is the same as the original image. For contrast, we use Naturalness Image Quality Evaluator(NIQE) [11] and for similarity we use structural similarity index(SSIM) [12]. Also, to measure how much the haze density has decreased, we used Fog Aware Density Evaluator (FADE) [5]. The results are shown in Table 1.

The smaller value of NIQE metric means that the image has better perceptual quality. For the SSIM, the value goes near 1 as the haze removed image is same as the original image. The smaller value of FADE means the image contains lower haze density. The best value for each metric denoted as bold. Among the conventional haze removal algorithms DEFADE show satisfactory results for three metrics.

For the Virtual KITTI dataset, we compare our proposed method with DEFADE. For the subjective quality assessment, the results are shown in Fig. 5. Also, the results for quantative quality are shown in Table 2. For the Virtual KITTI dataset, haze density with FADE is the lowest at original haze image. This happens because the metric, FADE is proposed from the actual images, not virtual images. The virutality of the dataset also affects the absolute value of SSIM, even though the proposed method shows the highest value among haze images and DEFADE algorithm. As

Table 1. Quantitative measurement results of FRIDA dataset

Methods/Metrics	NIQE	SSIM	FADE
Haze image	4.441	0.603	1.966
DCP	4.748	0.619	0.719
GDCP	4.894	0.557	0.668
CAP	4.958	0.669	0.939
DEFADE	3.922	0.670	1.356
Tarel	5.934	0.479	0.404
Proposed	**3.302**	**0.678**	**0.389**

Table 2. Quantitative measurement results of Virtual KITTI dataset

Methods/Metrics	NIQE	SSIM	FADE
Haze image	3.922	0.267	**0.438**
DEFADE	3.771	0.242	0.765
Proposed	**3.679**	**0.358**	0.866

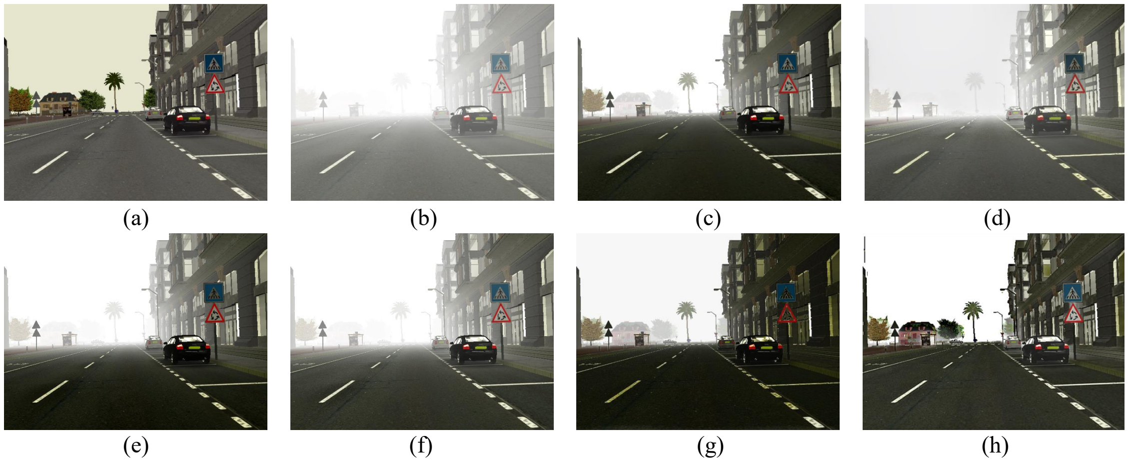

Figure 4. *Comparison with conventional methods: (a) original image; (b) haze image; (c) DCP; (d) GDCP; (e) CAP; (f) DEFADE; (g) Tarel et al.; (h) proposed method.*

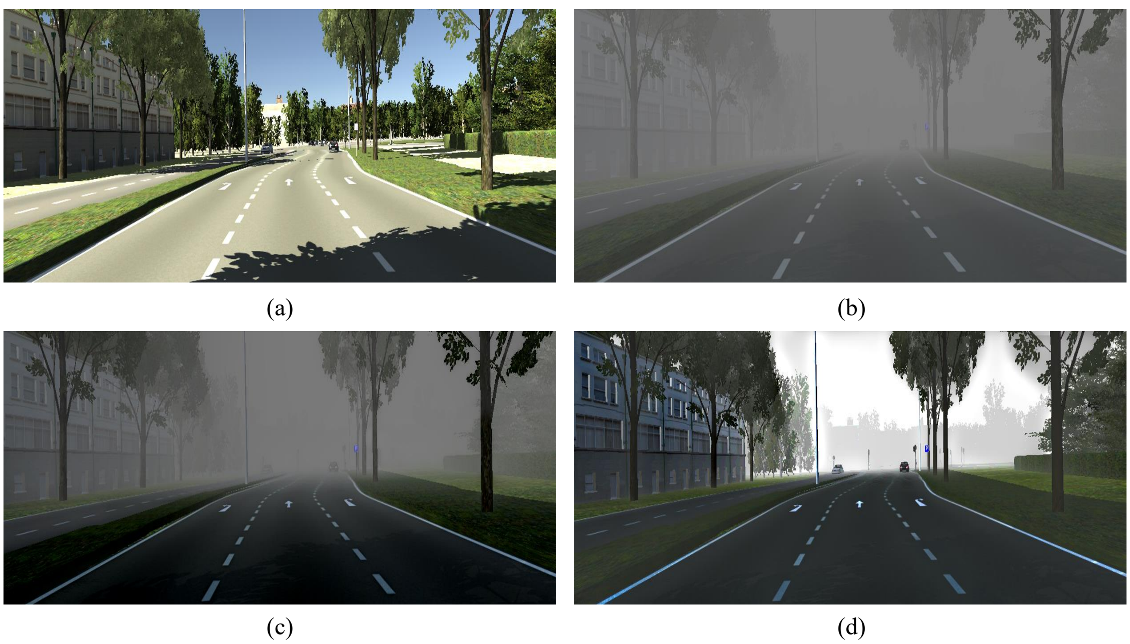

Figure 5. *Comparison with conventional methods: (a) original image; (b) haze image; (c) DEFADE; (d) proposed method.*

shown in Table 1 and 2, the proposed method performs well for most haze road scenes.

Concolusion

This paper presents the single image based haze remvoal algorithm using multiple scattering model. The proposed algorithm applies different APSF at each region according to their spatial characteristics. Also, by using down sampling, the proposed method reduces resource and time consuming for calculating atmospheric light. The proposed method can be applied not only to road scenes but also to another real world haze images. The results show that the proposed method performs well for synthetic road images with haze than the conventional algorithms.

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