ISASE-MAICS 2018

Real-Time Grayscale Dehazing Scheme For Car Vision

Zhi WANG*, Daishi WATABE* and Jianting CAO*

**Saitama Institute of Technology, FukayashiFusaiji1690, Saitama, Japan
{t7001vuk, dw, cao}@sit.ac.jp*

Abstract: To improve the safety of autonomous cars, their obstacle detection capability in bad weather must be substantially improved. Haze is a major factor that degrades outdoor images. Although various dehazing schemes have been proposed, a dehazing scheme designed to improve obstacle detection capability has not been reported. Hence, we present a dehazing algorithm that enhances the safety of an autonomous car. This algorithm should be able to work in real time, even using edge computers typically installed as car electronics. Furthermore, this algorithm should work on grayscale images, as systems dependent on color images are often unaffected by environmental color changes caused by factors such as a setting sun. We developed this algorithm based on the following three existing dehazing algorithms: dark channel prior, median dark channel prior, and the parameter tuning scheme for dark channel prior. We extend these methods based only on grayscale images. In terms of object detection capability, structural similarity index measure, and peak signal-to-noise ratio, the empirical results showed that our grayscale image-based proposed algorithm is comparable to the results of current cutting-edge methods, and operates in real time.

Keywords: *Dehazing, Object detection, Autonomous cars*

1. INTRODUCTION

Outdoor image-processing systems required for car vision or security surveillance are inevitably affected by poor weather, such as haze, fog, or smoke, which is then considered as noise. Under such conditions, photos captured outdoors often yield low contrast and appear blurred. Thus, this is an important challenge for autonomous (self-driving) car design and development, as poor visibility in bad weather conditions can lead to traffic accidents. Systems providing car vision naturally operate more effectively in good, rather than poor, weather conditions. To improve the recognition rate of object detection, it is necessary to solve the problem of visibility degradation. Therefore, we propose a fast dehazing method for car vision, and test it using Faster R-CNN [1]. In the area of object detection, the current study could prove significant, because the improvement of the obstacle detection capability of a car could allow it to effectively detect the front of obstacles and thus ensure safe driving.

However, dehazing is a challenging problem in the field of image processing. We cannot obtain the depth of haze if the input is only a single image. Several dehazing methods have been proposed to estimate the object depth by using multiple images or additional information. For example, object depth could be determined from two images of the same location taken under different weather conditions [2], or from various degrees of polarization [3], [4]. Kopf et al. [5] performed dehazing of outdoor images

by using known 3D models. These methods estimated the depth by enabling effective dehazing of images. However, these vision algorithms have limited applicability in a large number of situations when considering car vision alone.

In recent years, single-image dehazing has made great progress, as the methods have been developed as based on prior knowledge or assumptions. Tan [6] observed that haze-free images must have more contrast than hazy images. By maximizing the contrast in hazy images, the visual result was found to be better than expected. However, the restored images appear with unnatural edges. Moreover, for target recognition, these new edges are detrimental, as they compromise recognition.

Tarel [7] proposed a novel algorithm and variants for restoring scene visibility. The main advantage of this method is its speed, which enables the application of visibility restoration; the study was noted for being the first to perform this task in real time. Furthermore, the complexity of this algorithm depends only linearly on the number of image pixels.

In [8], Tarel proposed an extended algorithm as based on previous work [7]. As it was designed for the visibility enhancement of road images, this model demonstrated that a large portion of the image can be assumed as a planar view of the road, but with visibility distance above 50 m.

He et al. [9] proposed a dark channel prior (DCP) method to calculate the transmission map. The dark channel prior indicates that, in nature, haze-free outdoor

images contain some pixels that have very low intensities, or are close to zero in at least one color channel. Additionally, they implemented soft matting to reform restored images. Although the method is simple, the result proved to be quite significant. Since this time, many other algorithms based on DCPs have been adopted and improved. However, rapid processing has remained difficult to achieve in real time.

Gibson et al. [10] proposed a DCP-based method. The method uses a median filter to replace a minimum filter, and saves time in forming restored images. Although less time expensive, this method produces reconstructed images with low luminance, low peak signal-to-noise ratio (PSNR), and a low structural similarity index measure (SSIM).

Liu et al. [11] proposed a parameter that can automatically adjust the amount of haze to be removed, and can be rapidly processed; however, the restored images are often distorted in the form of pixels appearing completely white or black in the restored image.

2. METHOD

2.1 He et al. DCP-based dehazing principle

Haze Physical Model

The haze physical model has been widely implemented in computer graphics and computer vision to describe haze in images, and is based on Narasimhan's atmospheric model [12]:

$$I(x) = J(x)t(x) + A(1 - t(x)) \quad (1)$$

where $I(x)$ is defined as the observed RGB color intensities at pixel position x , $J(x)$ represents the intensities of the original image, which is viewed as the haze-free image, A is defined as the global atmospheric light, and $t(x)$ is called a transmission map. Once A and $t(x)$ are given, we obtain the haze free image $J(x)$ by solving Eq. (1).

Estimation of dark channel-based transmission map

He et al. [9] defined a dark channel of color image I as follows:

$$I^{DC}(x) = \min_{y \in \Omega(x)} \left(\min_{c \in \{R, G, B\}} I^c(y) \right) \quad (2)$$

where $I^c(y)$ represents the pixel value of channel c at coordinate y , and $\Omega(x)$ denotes a small squared region of interest of fixed size around x .

He et al. [9] developed an algorithm as based on observations of outdoor haze-free images in which at least one color channel comprised pixels with very low and close to zero intensities for most of the non-sky patches.

$$J^{DC}(x) = \min_{y \in \Omega(x)} \left(\min_{c \in \{R, G, B\}} J^c(y) \right) \approx 0 \quad (3)$$

They referred to this assumption as a DCP. Using this observation, computing the dark channel for both hand sides of Eq. (1), we have the following:

$$I^{DC}(x) \approx A(1 - t(x)) \quad (4)$$

Hence, the transmission map $t(x)$ can be obtained as

$$t(x) \approx 1 - \frac{I^{DC}(x)}{A} \quad (5)$$

Estimation of atmospheric light

He et al. [9] first selected the top 0.1% brightest pixels in the dark channel; these pixels are typically the most haze-opaque. Among these pixels, the pixels with the highest intensity A_0 in the input image I are selected as the atmospheric light.

$$A = A_0 \quad (6)$$

Haze removal parameter ω

He et al. [9][13] introduced a parameter ω ($0 \leq \omega \leq 1$) for Eq. (6) to control haze removal.

$$t(x) \approx 1 - \omega \frac{I^{DC}(x)}{A} \quad (7)$$

Note that this parameter ω is application-based and must be manually determined.

Obtaining a haze-free image

By substituting Eqs. (6) and (7) into Eq. (1), the final restored haze-free image $J(x)$ can be obtained as follows:

$$J(x) = \frac{I(x) - A_0}{t(x)} + A_0 \quad (8)$$

In order to avoid zero division, He et al. [9] introduced a small positive number t_0 to compute $J(x)$, as follows:

$$J(x) = \frac{I(x) - A_0}{\max(t(x), t_0)} + A_0 \quad (9)$$

He et al. [9] used $t_0 = 0.1$.

Refinement Restored Image

In order to improve the distortion near edges in the recovered image, He et al. [9] applied soft matching and a bilateral filter to the transmission maps. Although this process improves the recovered image, it is very time expensive.

2.2 Extending the DCP developed by He et al.

Median DCP (MDCP)

In order to increase the efficiency of the algorithm developed by He et al. [9], Gibson et al. [10] implemented a median filter instead of a minimum operation (as is shown in Eq. (2)) to omit the soft matching process; it was designated as the median dark channel. Similar to Eq. (3), Gibson et al. [10] assumed that this median dark channel of the haze-free image is near zero; the resulting assumption was referred to as the median DCP (MDCP).

$$J^{MDC} = \text{med}_{y \in \Omega(x)} \left(\min_{c \in \{R, G, B\}} J^c(y) \right) \approx 0 \quad (10)$$

Consequently, the transmission map $t(x)$ can be obtained as

$$t(x) \approx 1 - \frac{I^{MDC}(x)}{A} \quad (11)$$

The use of a median filter has the two following advantages: 1) it preserves edges while smoothing out the flat regions, and 2) it has a fast running speed owing to the omission of the soft matching process.

Estimation of parameter ω

Liu et al. [11] proposed a method that can automatically optimize the parameter ω in Eq. (7) for various images as follows:

$$\omega = pm \quad (12)$$

where m is the average of the maximum and minimum intensity values, and p is an experimentally determined value.

2.3 Proposed method

The use of grayscale images

It is known that a system dependent on color image processing is unreliable in outdoor computer vision. Because environmental colors, as is observed in a setting sun, can easily alter system performance, we aimed to develop a dehazing algorithm as solely based on grayscale images. Hence, we evaluated the resulting algorithm on grayscale images. In the preliminary experiment, we found that Gibson's method was moderately effective, even on grayscale images. Thus, we assumed the following as a starting point for the proposed method:

$$t(x) = 1 - \omega \frac{\text{med } Y(y)}{A_0} \quad (13)$$

Estimation of parameter ω

We assume ω has the following form:

$$\omega = \min(pm(m + 0.5), 0.95) \quad (14)$$

where m is the average of the maximum and minimum grayscale image intensity values. In the preliminary experiment, when the p value belongs to [1.2, 1.5], a good result is obtained. In this study, we used $p = 1.3$ in all experiments.

Mask size

We selected a 5×5 mask size for the median filter. Choosing 3×3 yields a low PSNR, whereas a mask size of 7×7 results in a degraded restored image and a low SSIM.

Restored Image Refinement

DCP method-based dehazing has the disadvantage of low luminance in the restored images. However, we solved this problem by introducing gamma correction to the transmission map.

Flow of the proposed algorithm

Figure 1 shows the flow of the proposed algorithm.

Figure 1: Flow of the proposed algorithm

Genealogy of the proposed algorithm

The genealogy of the proposed algorithm is given in Fig. 2.

Figure 2: Genealogy of the proposed algorithm

3. EXPERIMENT

To verify the effectiveness of our proposed method, we performed the following five experiments:

- First, we compared our results to those obtained via the methods proposed by Gibson et al. [10] and Liu et al. [11], because our method is an extension of their methods. Note that the comparisons were performed using benchmark images.
- Second, we compared the detection accuracy of the proposed method (softmax probability of Faster RCNN) to those of the other two methods (i.e., [10] and [11]) by using a hazy car image [12].
- Next, by using benchmark images, we compared the PSNR and SSIM of all the images, the results of which are listed in Tables I and II.
- Finally, to evaluate the processing time, we randomly selected 30 images of different sizes, and measured the processing time averaged over three trials.

4. RESULTS AND DISCUSSION

4.1 Comparison of softmax probability

Figure 3: Object detection system running on Faster RCNN. The top image is the original image, followed by the image obtained via the method proposed by Liu et al. [11], and then the method proposed by Gibson et al. [10]. The bottom-most image is obtained via the proposed method.

Figure 4: Softmax probability of car detection rate for source image obtained via the method proposed by Liu et al. [11], Gibson et al. [10], and the proposed method.

In terms of the softmax probability for true positives, a higher value is better. We first performed the dehazing operation, and then tested the recognition rate of object detection by using the Faster R-CNN-based detection system. The detection result is illustrated in Fig. 3, and the softmax probability is summarized in Fig. 4. It can be seen that our grayscale image-based method is comparable to the current state-of-the-art methods.

4.2 Comparing human visibility by using benchmark images

Some dehazing results based on benchmark images are shown in Figs. 5 and 6.

Figure 5: Comparison of dehazing results. (a) Original image and results of (b) Liu et al. [11], (c) Gibson et al. [10], and (d) the proposed method.

Figure 6: Comparison of dehazing results. (a) Original image and results of (b) Liu et al. [11], (c) Gibson et al. [10], and (d) the proposed method.

As is shown in Figs. 2 and 3, all methods removed a noticeable amount of haze in the benchmark image. However, the proposed method yields an image that is slightly brighter than those of the other methods, especially that of [10]. The amount of removed haze is slightly less than that achieved via the method proposed in [11]. In addition, due to the remaining part of the fog in the output image, we think that such a result with better authenticity. On the other hand, in the case of a grayscale image being used as the input image, because the MDC is merely a median-filtered grayscale image, the approximation given in Eq. (10) is not consistently true. This may be one reason for the slightly inferior performance in this area. However, considering that our proposed method only uses the grayscale image, the result is satisfactory.

4.3 Comparison of the PSNR and SSIM using benchmark images

Tables I and II show the verification of the PSNR and SSIM results, where the proposed method is observed to achieve the best performance. For the PSNR and SSIM, a higher value corresponds to better performance. It can be seen that our method is comparable to the conventional methods.

Table 1: PSNR results

	He[9]	Tan[6]	Tarel[7]	Tarel[8]	Gibson[10]	Proposed
ny12	14.675	11.710	16.978		13.459	15.031
ny17	17.263	12.763	13.513		12.075	15.114
y01	13.173	12.143	17.369		13.568	13.814
y16	13.568	12.403	14.510		12.398	13.992
G000	9.821	11.974	18.404	13.763	12.714	16.971
G001	9.457	10.892	16.348	12.020	11.864	16.320
G002	10.302	12.739	18.552	14.226	12.915	17.130

G003	10.326	12.387	18.572	14.290	12.793	17.022
G004	10.445	12.404	18.719	14.108	12.748	16.979
canon3	13.000				15.649	19.255
canyon2	10.019				12.050	15.417
forest1	16.652				13.807	15.384
train	13.430				12.813	13.046

Table 2: SSIM results

	He[9]	Gibson[10]	Tan[6]	Tarel[7]	Proposed
y01	82.59%	79.53%	73.73%	85.07%	85.52%
y16	89.16%	82.48%	76.41%	83.58%	91.05%
ny12	86.61%	81.76%	63.34%	85.79%	88.03%
ny17	84.96%	77.94%	77.72%	85.24%	89.47%
G000	52.58%	70.44%	67.46%	69.87%	89.82%
G001	50.89%	69.62%	60.08%	68.21%	89.62%
G002	53.63%	70.16%	70.06%	71.15%	89.68%
G003	53.78%	69.54%	68.97%	71.41%	89.41%
G004	53.94%	69.21%	68.56%	70.44%	89.29%

4.4 Processing time

The processing time results are shown in Fig. 8. Regarding hardware, a Core i5-6300HQ 2.3 GHz unit is used. The code is written by using OpenCV 2.4.9 in Visual Studio 2013. The processing speed can reach more than 70 frames per second, and the pixel and processing time are linearly related.

Figure 7: Linear relationship between processing time and pixel number

5. CONCLUSIONS AND FUTURE WORK

The current paper is an extension of [14]. Thus, in this paper, we have included a reason for the use of grayscale and new evaluation approaches based on softmax probabilities.

We proposed a dehazing algorithm that can achieve the following tasks:

- A) Work on grayscale images (unaffected by color illumination change)
- B) Operate in real time.

The empirical results indicate that our proposed algorithm is comparable to the currently implemented

algorithms [10][11] in terms of object detection capability, structural similarity index measure, peak signal-to-noise ratio, and real-time operability; the favorable performance is primarily attributed to the fact that the proposed algorithm was derived as based on only grayscale images.

The impact of this algorithm is as follows: since it can be applied to edge devices common to car electronics such as a drive image recorder in autonomous cars, and because this algorithm is based on grayscale images, which are unaffected by color illumination change, the proposed algorithm can improve car safety.

In the case of a grayscale image being used as an input image, the MDC is simply a median-filtered grayscale image. Thus, approximation of Eq. (10) is not consistently true. However, our finding is that the proposed method is applicable to various images. As the results reported here are mainly purposed to verify and validate the proposed method, the number of images used in this study may not be sufficient. Thus, future work should focus on identifying and analyzing cases in which the proposed approach does not yield adequate results.

REFERENCES

- [1].S. Ren, K. He, R. Girshick, J. Sun; Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, IEEE Transactions on Pattern Analysis and Machine Intelligence; 39(6), pp. 1137-1149, 2017.
- [2].S. G. Narasimhan, S. K. Nayar; Contrast Restoration of Weather Degraded Images, IEEE Transactions on Pattern Analysis and Machine Intelligence; 25(6), pp. 713-724, 2003.
- [3].S. Shwartz, E. Namer, and Y. Y. Schechner; Blind Haze Separation, IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), New York, 2006.
- [4].Y. Y. Schechner, S. G. Narasimhan, and S. K. Nayar; Instant dehazing of images using polarization, IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), Kauai, 2001
- [5].J. Kopf *et al.*, Deep photo: model-based photograph enhancement and viewing, ACM Transactions on Graphics; 27(5), pp. 1-10, 2008.
- [6].R. T. Tan, Visibility in bad weather from a single image, 26th IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), Anchorage, 2008.
- [7].J. P. Tarel and N. Hautiere; Fast visibility restoration from a single color or gray level image, IEEE 12th International Conference on Computer Vision (ICCV), Kyoto, 2009.
- [8].J. P. Tarel, N. Hautière, A. Cord, D. Gruyer, and H. Halmaoui; Improved visibility of road scene images under heterogeneous fog, IEEE Intelligent Vehicles Symposium, La Jolla, 2010.
- [9].K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," in IEEE Conference on Computer Vision and Pattern Recognition, 2009.
- [10].K. Gibson, D. Võ, and T. Nguyen; An investigation in dehazing compressed images and video, OCEANS 2010: MTS/IEEE Seattle, Seattle, 2010.
- [11].Q. Liu, M. Chen, and D. Zhou; Fast haze removal from a single image, 25th Chinese Control and Decision Conference, Guiyang, 2013.
- [12].S. G. Narasimhan and S. K. Nayar; Vision and the Atmosphere, International Journal on Computer Vision; 48(3), pp. 233-254, 2002.
- [13].K. He, J. Sun, and X. Tang; Single Image Haze Removal Using Dark Channel Prior, IEEE Transactions on Pattern Analysis and Machine Intelligence; 33(12), pp. 2341-2353, 2011.
- [14].Z. Wang, D. Watabe, and J. Cao; Improving visibility of a fast dehazing method, World Automation Congress (WAC), Rio Grande, 2016.