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A hierarchical airlight estimation method for image fog removal

Fan-Chieh Cheng, Chung-Chih Cheng, Po-Hsiung Lin, Shih-Chia Huang *

Department of Electronic Engineering, National Taipei University of Technology, Taipei 10608, Taiwan

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Fog phenomena result in airlight generation and degrade the visibility of the color image captured from the camera. To improve visibility, airlight estimation is necessary for image fog removal. As airlight is very bright, the traditional methods directly select bright pixels for airlight estimation. However, some bright pixels generated by light sources, such as train headlights, may interfere with the accuracy of the above-mentioned methods. In this paper, we propose a new airlight estimation method. Based on Gaussian distribution, the proposed method selects the airlight candidates in the brightest region of the input image. Moreover, the color similarity estimation is also applied to hierarchically refine the candidates. We then compute the average color from the refined candidate pixels for airlight estimation. Experimental results demonstrate that the proposed method is more accurate than other airlight estimation methods and has low time complexity.

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1. Introduction

In foggy weather, visibility degradation occurs when observers perceive object light blended with airlight due to scattering caused by a medium in the atmosphere, such as small water droplets. Degraded visibility in a foggy image then affects the effect of computer vision techniques, including motion detection (Kim and Kim, 2012), face tracking (Zou et al., 2013), license plate recognition (Wen et al., 2011), and so on. Hence, for multimedia devices, such as advanced driver assistance (Hautiere et al., 2010) and video surveillance (Yoon et al., 2012) systems, fog removal techniques play an important role for improving the visibility of the images.

According to the literature (Narasimhan and Nayar, 2003a), image defogging can be performed by modifying the distribution of the image histogram, but the effect is usually limited. As the haze formation was modeled using Koschmieder's law, numerous defogging methods based on this optical model were disclosed in the field. Basically, those methods can be divided into two groups: non-single image information methods (Narasimhan and Nayar, 2003a; Shwartz et al., 2006; Kopf et al., 2008) and single image information methods (Tan, 2008; Fattal, 2008; He et al., 2011; Gibson et al., 2012; Cheng et al., 2012; Shiau et al., 2013).

Fog removal methods using non-single image information include the use of multiple images or additional information, such as camera settings. On the other hand, fog removal methods developed using the single image require the reasonable assumption and accurate prior during image processing. However, when processing the single input image, the use of single image information is often more convenient than the use of non-single image information. Therefore, development focus concerning defogging methods in recent years has increasingly oriented towards the use of single image information.

Upon comparing the visibility of fog-free images to that of foggy images, the former visibly held local contrast, whereas the latter only faintly held local contrast. Hence, maximization of the local contrast was focused on in order to develop the visibility enhancement method (Tan, 2008). Although foggy effects of input images can be improved by enhancing the visibility, over-enhancement may occur locally.

In the fog estimation model, Fattal (2008) made an assumption that the propagation of light projected and the surface shading are partially uncorrelated. According to this assumption, mathematical statistics were utilized to estimate the albedo of a scene and infer the transmission medium, after which the fog formation in the degraded image can be removed. However, satisfactory restoration results cannot be produced via the use of Fattal's method if degraded images include heavy fog formation.

He et al. designed their fog removal method to include airlight estimation and transmission model modules (He et al., 2011). After collecting statistical information, they found that the general pixels usually feature very low luminance, with fog pixels contributed by airlight. Therefore, dark channel prior (DCP) was developed for airlight estimation, and it also transforms to the transmission model via negative computation. However, halo artifacts are usually caused by DCP that need to be further refined (He et al., 2011).

* Corresponding author.
E-mail address: schuang@ntut.edu.tw (S.-C. Huang).

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In general, airlight estimation can be performed by manual and automatic methods. The manual method directly defines image regions affected by airlight (Narasimhan and Nayar, 2003b), but it is inapplicable for realistic application due to frequent interruption. In contrast, the automatic methods are more convenient. Thus, we estimate airlight in single images automatically (He et al., 2011; Gibson et al., 2012; Cheng et al., 2012; Shiau et al., 2013). However, the traditional methods select only bright pixels as candidates of airlight regions (He et al., 2011; Gibson et al., 2012; Cheng et al., 2012; Shiau et al., 2013). This means that if bright pixels generated by light sources exist in the input images, those methods may select inappropriate candidates that result in wrong airlight estimation. In this paper, we focus solely on the challenge of accurate airlight estimation.

The remainder of this paper is divided as follows: Section 2 describes the physics-based optical model, four modern fog removal methods, and the motivation behind the proposed method. In Section 3, the proposed method is described in detail. Section 4 shows experimental results that present the comparison between ours and several other state-of-the-art defogging methods. Finally, we conclude this paper and present future work in Section 5.

2. Related works

According to Middleton (1952), the physics-based optical model can be employed for defogging. In general, object color corresponds to the light reflected from an object. The perceived object color is degraded if the reflected light partially transmits from fog to observer. Let L_0 be the reflected light of an object and L_∞ be ambient light. The presented light of object L can be formulated by

$$L = L_0 e^{-\beta d} + L_\infty (1 - e^{-\beta d}), \tag{1}$$

where $e^{-\beta d}$ is the fog factor that reveals a light reinforcement of object $L_0 e^{-\beta d}$ and airlight $L_\infty(1-e^{-\beta d})$.

In the optical model, the pixel value I can be computed using the optical model denoted by

$$I = f(L_0 e^{-\beta d} + L_\infty (1 - e^{-\beta d})). \tag{2}$$

Note that the conversion process between the incident energy on the imaging sensor and the generated pixels of the image is assumed to be linear in this form. Hence, the above formula is modified as

$$\begin{aligned} I &= f(L_0 e^{-\beta d}) + f(L_\infty (1 - e^{-\beta d})) \\ &= f(L_0) e^{-\beta d} + f(L_\infty)(1 - e^{-\beta d}) \\ &= R e^{-\beta d} + A_\infty (1 - e^{-\beta d}), \end{aligned} \tag{3}$$

When the atmosphere is homogeneous, $e^{-\beta d}$ can be represented by the transmission model t. For each pixel x, Eq. (3) is then approximated as

$$I_c(x) = R_c(x) t(x) + A_c(1 - t(x)), \tag{4}$$

where I_c is the original RGB values, R_c is the restored RGB values, A_c is the airlight values, and t is the transmission value. Note that $c = 0, 1, 2$ denotes red, green, and blue values, respectively. The fog removal methods then compute A_c and t, after which R_c can be further restored from I_c (He et al., 2011; Gibson et al., 2012; Cheng et al., 2012; Shiau et al., 2013).

We then briefly review four modern fog removal methods based on Eq. (3), including DCP, Median-DCP (MDCP), Lowest-level Channel Prior (LCP), and Edge Preservation Haze Removal (EPHR), which all include an airlight estimation module and a transmission model module. Note that DCP, MDCP, and LCP methods employ the same airlight estimation module, which is mentioned in Section 2.1.

2.1. DCP method

It is necessary to generate the dark channel of the input image before airlight estimation and transmission modeling (He et al., 2011). Let $I_{\min}$ be the minimum channel that involves the lowest color value per pixel. The minimum channel is formulated by

$$I_{\min}(x) = \min_{c \in [0,2]} (I_c(x)). \tag{5}$$

After the local patch Ω is defined, the dark channel is computed by

$$I'_{\min}(x) = \min_{p \in \Omega(x)} (I_{\min}(p)), \tag{6}$$

where p is an arbitrary pixel in the local patch. According to He et al. (2011), Ω can be 3×3, 15×15, or 31×31. However, in different cases, Ω should be manually adjusted to generate the optimized output image.

The DCP method then picks up the top 0.1% bright pixels of $I'_{\min}$ as candidates for airlight estimation. Suppose that $M(x) = 1$ for the selected candidates and $M(x) = 0$ for non-candidates; airlight color A_c can be computed by Algorithm 1.

Algorithm 1. Airlight estimation of DCP algorithm.

```
1:  (A_0, A_1, A_2) ← (0, 0, 0)
2:  for each pixel x do
3:    if M(x) = 1 then
4:      for c ← 0 to 2 do
5:        if I_c(x) > A_c then
6:          A_c ← I_c
7:        end if
8:      end for
9:    end if
10: end for
```

In addition to airlight estimation, $I'_{\min}$ is also used in the transmission model module. For each pixel x, the transmission model is formulated as follows:

$$t(x) = 1 - \omega \left(\frac{I'_{\min}(x)}{\max(I'_{\min})} \right), \tag{7}$$

where ω is a pre-defined parameter fixed by 0.95. However, Eq. (8) often generates block artifacts. Since Eq. (3) has a similar form as the image matting equation (He et al., 2011):

$$\mathbf{I} = \mathbf{F}\alpha + \mathbf{B}(1 - \alpha), \tag{8}$$

where α is the foreground opacity, $\mathbf{F}$ and $\mathbf{B}$ are foreground and background colors, respectively, and a soft matting method (Levin et al., 2008) is employed to refine t(He et al., 2011). After generating A_c and t, we can use Eq. (4) for fog removal.

2.2. MDCP method

The MDCP method directly employs the airlight estimation of DCP, but it modifies the transmission model of DCP (Gibson et al., 2012). To avoid the high computation cost of soft matting (He et al., 2011), the MDCP method uses median filter for adjusting Eq. (8). Instead of the minimum filter, the median filter is employed for processing each pixel of $I_{\min}$.

The estimated transmission t of the MDCP method is then modified from Eq. (8) and can be formulated by

$$t(x) = 1 - \omega \left(\frac{I'_{\mathrm{med}}(x)}{\max(I'_{\mathrm{med}})} \right), \tag{9}$$

where

$$I'_{\mathrm{med}}(x) = \operatorname*{med}_{p \in \Omega(x)} (I_{\min}(p)). \tag{10}$$

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