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Single image dehazing via reliability guided fusion ☆

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ABSTRACT

This work addresses the shortcomings of the dark channel prior (DCP) and proposes a new and efficient method for transmission estimation. First, the accuracy of block-level and pixel-level dark channels is improved and a reliability map is generated. Then, through reliability guided fusion of block-level and pixel-level dark channels, a high-quality refined transmission map is obtained. The proposed method reduces the DCP failure probability and haloes by increasing the patch-size in an edge-preserving manner. DCP failure in the sky (bright) regions is handled by limiting the contrast boost of sky-like surfaces. This produces a more natural recovery of the sky regions. A downscaling method for fast transmission computation has also been proposed. Quantitative and qualitative comparisons show that the proposed method outperforms existing methods in terms of quality and speed. The proposed reliability guided fusion scheme is about 60 times faster than other well-known DCP based approaches.

1. Introduction

Water vapors, dust, and other airborne particles, collectively known as aerosols, scatter light from its linear path into various directions. Multiple scatterings of light across a medium create a semi-transparent veil of ambient light (atmosphere behaving like a source of light). This reduces the transmission of actual scene radiance and makes it appear hazy, thus causing difficulties in computer vision applications, such as long-ranged photography, surveillance, object detection/tracking, and scene analysis. Therefore, a robust haze removal method is highly desirable to improve the performance of these vision systems. Mathematically, image degradation in the presence of haze is expressed by the image formation model [1–7].

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

where $x = (x, y)$ is the pixel coordinate location, $I(x)$ is the hazy RGB color image captured by the camera, and $J(x)$ is the actual scene radiance or haze-free image to be recovered. The atmospheric light A describes the intensity of the ambient light for a particular scene. In several related works, it is common to assume that the aerosol reflectance properties and the dominant scene illumination are uniform across a scene [2,8–10]. This makes A constant for each color channel, hence a three dimensional vector. Transmission, $0 \leqslant t(x) \leqslant 1$, is a scalar value that represents the percentage of scene radiance $J(x)$ reaching the camera directly without being scattered. Hence $t(x)$ is inversely related to the scene's depth $d(x)$ and the opacity of the medium through which light reaches a camera. It is assumed that $t(x)$ is same for each color channel, hence it can be observed that image formation model treats each color channel independently. The first term, $J(x)t(x)$ is called "direct attenuation" that describes the percentage of the scene radiance reaching the camera. The second term $A(1 - t(x))$ is called "airlight", which represents the previously scattered light that gets trapped in the medium as ambient light leading to the shift of scene colors. The observed image is a distorted version of the actual scene radiance, where direct attenuation is a multiplicative and airlight is an additive distortion. Solving Eq. (1) is an under-constrained problem, i.e., there are a large number of possible solutions as only I is known. To constrain this indeterminacy, estimation of the transmission, or scene depth is required.

Recent research works have focused on improving single image dehazing methods as they offer a more practical solution. The majority of single image dehazing methods have focused on solving Eq. (1) by inferring depth information based on different statistical assumptions or priors. Among them, the method based on the dark channel prior (DCP) [10,11] achieves state-of-the-art performance. Despite good performance, this method has some drawbacks. It estimates patch-wise transmission that does not preserve depth edges, and dehazing as such results in haloes around the object boundaries. To reduce haloes, a transmission refinement step is necessary, which is either time-consuming [10] or less accurate [11]. Also, DCP is invalid for large bright

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surfaces [1,10]. This can make white objects over-saturated and enhance noise in the sky regions of a dehazed image. In this paper, we propose a novel single image dehazing framework that overcomes the weakness of the DCP methods in [10,11] and achieves better subjective and quantitative results than several state-of-the-art techniques. The major contributions of the proposed method are as follows:

1. To reduce the haloes caused by the local patch operation and to reduce the dehazing CPU-time, a novel transmission refinement scheme called ‘reliability guided fusion’ is developed. This method generates a high-quality refined transmission map with edge-preserving and texture smoothing properties. The accuracy of the patch-wise transmission estimate is also improved by cascading min–max operations. This strategy allows us to reduce the DCP failure probability and haloes, by increasing the patch-size in an edge-preserving manner. Quantitative and qualitative comparisons show that the proposed dehazing method outperforms existing state-of-the-art techniques in terms of quality and speed. The ‘reliability guided fusion’ scheme refines transmission about 60 times faster than the computationally expensive methods in [10,11].
2. As DCP is not valid in bright (sky) regions, we proposed a simple yet effective technique that limits the contrast boost of well-connected surfaces that closely resembles atmospheric light A, i.e. mostly sky regions. Compared to other well-known dehazing methods, this simple strategy gives a more natural dehazing of sky regions without affecting non-sky regions of the image.
3. For real-time handling of high-resolution images, we propose an efficient downscaling technique. The transmission map estimated at lower resolution is upscaled and used with the original image for recovering a haze-free image. This significantly reduces the CPU time of the dehazing process without visual degradation of the output image.

The rest of this paper is organized as follows. In Section 2, the related works of image dehazing are briefly reviewed. Our proposed method is presented in Section 3. The experimental results and analysis are shown in Section 4. Finally, the conclusions are given in Section 5.

2. Related work

Dehazing approaches can be classified into two main categories: (1) those that require additional information for estimation of $t(x)$, e.g., multiple registered images of the same scene taken under different conditions [7] or with different polarization filters [12] or near infra-red channel [13] or scene depth map [5,14,15] and (2) single image methods, that estimate $t(x)$ based on some statistical assumptions or priors [2,4,8–10,16] about the nature of a scene. The subcategories of the above approaches are methods with user assistance [5,12,14] and completely automatic methods [2,4,8–10,16].

Early work [5–7,12,14,15] on image haze removal was mostly from the first category as it relied on the use of multiple images or additional information. In the work of Kopf et al. [14], dehazing is achieved by assuming that the scene depth is already known. In [12], for the same scene, images filtered with different degrees of polarization are utilized for haze removal. Image difference based methods [6,7] utilize the difference of multiple images captured from the same scene to estimate the scene depth. 3D geographic models are used for dehazing in [15]. Although these works can produce impressive dehazing results in certain conditions, they become impractical when multiple images, depth information, user interaction, etc. is not available.

Recently, researchers have mainly focused on single image dehazing methods as they are more suitable for a general application range. In the methods [1–4,8–11,16,17], haze is removed by assuming different image priors. By assuming that the transmission and target surface shading is partially uncorrelated, Fattal [8] estimated the transmission map using the independent component analysis. Since hazy images have a low contrast, Tan et al. [9] maximized the local contrast of the recovered image to increase the visibility. However, the image recovered by this method is often oversaturated and unnatural. To overcome this, Kim et al. [3] achieved dehazing by minimizing a cost function which consisted of a contrast term and an information loss term. Tarel et al. [4] used the median filter to achieve efficient but less-accurate image dehazing. Nishino et al. [16] estimated scene depth jointly with the scene radiance in a Bayesian probabilistic framework.

Based on a statistical observation that in haze-free images, dark pixels occur frequently except in sky regions, He et al. [10] proposed the dark channel prior for image dehazing. This method achieves state-of-the-art dehazing performance. However, it has certain drawbacks, some of which were addressed and resolved recently. Carr [17] combined DCP with a piecewise planar geometry prior using the energy minimization framework. Gibson et al. [18] suggested utilizing the darkest pixel average inside each ellipsoid for image dehazing. Tang et al. [19] combined four types of haze-relevant features with Random Forest. To accelerate the transmission estimation process, a block-to-pixel interpolation method was proposed by Yu et al. in [1]. In addition to these methods, many other interesting single image dehazing algorithms have been recently proposed [2,20–22]. While these methods do produce reasonable quality results, there is still room for improvement, especially in terms of runtime. For most of these methods, runtime increases nonlinearly with image resolution, which makes them unsuitable for real-time applications.

3. New approach

In this section, we first briefly introduce the DCP and then explain our work in detail. Fig. 1 presents a flow-diagram comparison of our proposed method and the DCP methods [10,11]. The new contributions of the proposed method are separately shaded in Fig. 1(b) and can be summarized as follows: For a given input image, we limit the contrast boost of well-connected surfaces that closely resembles atmospheric light A, like sky regions. This is referred to as ‘sky handling’ (block in gray) part of our algorithm. The transmission is estimated by the reliability guided fusion scheme (blocks in blue[1]). First, the ‘block dark channel’ and the ‘pixel dark channel’ values are computed. To reduce haloes, a ‘reliability map’ of the block dark channel is generated. Then, via reliability guided fusion of block and pixel dark channels, a high-quality ‘fine dark channel’ is obtained. The final output image is recovered by using this refined transmission map. The blocks in green are optional and can be used for real-time processing of high-resolution images.

3.1. Transmission and DCP model

The majority of image dehazing methods use the image formation model in Eq. (1) to recover scene radiance. For a given image I, scene radiance J is estimated, either by first estimating the transmission [2,8,10], or together with J in a joint optimization [9,16,17]. In this work, we follow the former group of methods

[1] For interpretation of color in Figs. 1, 2, 5, and 10, the reader is referred to the web version of this article.