Single Image Dehazing Algorithm Based on Modified Dark Channel Prior

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SUMMARY Single image dehazing algorithm based on Dark Channel Prior (DCP) is widely known. More and more image dehazing algorithms based on DCP have been proposed. However, we found that it is more effective to use DCP in the RAW images before the ISP pipeline. In addition, for the problem of DCP failure in the sky area, we propose an algorithm to segment the sky region and compensate the transmission. Extensive experimental results on both subjective and objective evaluation demonstrate that the performance of the modified DCP (MDCP) has been greatly improved, and it is competitive with the state-of-the-art methods.

key words: image dehazing, dark channel prior, transmission compensation, atmospheric scattering model

1. Introduction

Single image dehazing has attracted widespread attention from scholars. Images collected under haze weather usually lose contrast and realism, causing inconvenience to computer vision applications, such as target detection, target understanding, which is due to the influence of media such as haze on the absorption and scattering of the environment light, which reduces the accuracy of the imaging device. The dehazing method based on image enhancement mainly enhances the visual effect of a hazy image by enhancing contrast. The dehazing method based on image restoration is mainly to establish an imaging model under haze weather and restore clear images through inverse calculations. The widely modeled hazing process is the Atmospheric Scattering Model (ASM) [1]. Many well-known priors are used in ASM to obtain a clear image after restoration. The most famous prior is DCP [2]. Many scholars have made many improvements based on DCP. However, DCP is not suitable for all scenarios and will fail in the sky area. The learning-based method mainly builds a dehazing neural network. The dehazing network architecture is like U-Net [3]. The learning-based method is very dependent on the data set, and it is easy to produce over-fitting on a data set.

Although the DCP-based image dehazing method has achieved great success, we have found that DCP works better in the RAW images before the ISP pipeline.

We summarize the following contributions:

• We pointed out a more effective way to use DCP and ASM for single image dehazing, that is, DCP and ASM should be used in the RAW images instead of RGB images after Image Signal Processing (ISP) pipeline.

• Aiming at the problem of DCP failure in the sky area, we propose a modified DCP (MDCP), which divides the sky area and compensates the transmission.

2. Proposed Method

In this section, we first introduce ASM and point out a more effective way to use DCP and ASM for single image dehazing. Then we propose a modified DCP (MDCP).

2.1 ASM and DCP

The atmospheric scattering model (ASM) [1] describes the formation of a hazy image:

\[ I(x) = J(x) t(x) + A (1 - t(x)), \]

where \( x \) is the pixel coordinate, \( I(x) \) represents the hazy observation, \( J(x) \) denotes the scene radiance, i.e., the haze-free image, \( A \) is the atmospheric light, \( t(x) \) is the transmission.

According to ASM, the restored scene radiance \( J(x) \) can be given by:

\[ J(x) = \frac{I(x) - A}{t(x)} + A, \]

He et al. [2] found that the pixel value of at least one of the three RGB channels of each pixel of the clear image is very low. He et al. called this prior Dark Channel Prior (DCP):

\[ J_{\text{dark}}(x) = \min_{y \in \Omega(x)} \left( \min_{r \in \{r, g, b\}} J^r(y) \right), \]

where \( c \) represents one of the RGB color channels, \( J^r \) is an intensity for an RGB channel of an image, \( \Omega(x) \) is a local
patch centered at pixel $x$. Based on DCP, $J_{dark}(x)$ is very close to zero:

$$J_{dark}(x) \approx 0,$$

(4)

So, DCP-based transmission $\tilde{t}(x)$ [2] can be expressed as:

$$\tilde{t}(x) = 1 - \min_{y \in \Omega(x)} \left( \min_{c \in \{r,g,b\}} \frac{F(y)}{A^c} \right), \quad (5)$$

where $c$ represents one of the RGB color channels, $F(y)$ represents the pixel value of the $c$ channel of the hazy image at the pixel $y$, $A^c$ represents the value of atmospheric light in the $c$ channel. It is a simple but famous prior, and many DCP-based dehazing algorithms were proposed.

2.2 A More Effective Way to Use DCP and ASM for Single Image Dehazing

ASM was proposed based on radiometric instead of RGB color image processed by the Image Signal Processing (ISP) pipeline [4]. ISP pipeline includes operations such as de-mosaicing, denoising, white balance, color correction, and gamma correction. The sensitivity of the human eye to the external light source and the input light intensity is not linear but exponential. Gamma correction in ISP pipeline is a nonlinear operation of CMOS photoelectric signals, and it is an exponential transformation to make radiometric conform to human vision. Gamma correction has changed the ratio of light intensity between radiance. Therefore, we believe that the use of ASM and DCP for image dehazing on the RGB color images processed by the ISP pipeline will greatly affect the dehazing effect. But most of the image dehazing algorithms based on DCP and ASM are making experiments on RGB color images. We believe that it should be better to use ASM and DCP for image dehazing in the RAW images before gamma correction. Experiments will verify our conjectures.

2.3 The Modified DCP (MDCP)

To use DCP and ASM more effectively, we first need to perform an inverse gamma correction on the RGB color image processing by ISP pipeline, which can be expressed as:

$$I_{raw}(x) = \frac{I(x)}{\gamma}, \quad (6)$$

where $I(x)$ represents the RGB color image after ISP pipeline processing and normalization, usually for the image in RGB mode, $\gamma$ represents the gamma values. The value of $\gamma$ is generally 1/2.2 in the ISP pipeline. $I_{raw}(x)$ represents the RAW image after inverse gamma correction. Next, all dehazing operations, including the use of ASM, the use of DCP to estimate the raw transmission, and the use of DCP to estimate atmospheric light $A$, are all based on the RAW images. Although the inverse gamma correction is a very simple operation, the improvement of the dehazing effect is obvious. We believe that DCP and ASM are more suitable for RAW images.

Second, DCP fails in the sky area [2], and it can be seen from Eq. (2) that if the transmission is not accurately estimated, it will have a great impact on the scene radiation. If the estimation of transmission of the sky area will be too small, which will result in severe color distortion. Therefore, the transmission of the sky area should be as close as possible to 1, so that the color of the sky area is less distorted during the image dehazing process. So, we propose an algorithm to segment the sky region and compensate the transmission, which can be shown in Fig. 1. The compensated transmission $\tilde{t}_{\text{sm}}(x)$ can be expressed as:

$$\tilde{t}_{\text{sm}}(x) = \tilde{t}(x) + w \times [(1 - \tilde{t}(x)) \times G(x)], \quad (7)$$

where $w$ is the compensation weight, which is set to 0.5 in this work. $G(x)$ is the gain graph, which can be expressed as:

$$G(x) = \frac{I(x) - \min(I(x))}{\max(I(x)) - \min(I(x))}, \quad (8)$$

for RAW images.

Fig. 1 Flow chart of sky area segmentation and transmission compensation algorithm.

The whole dehazing structure of MDCP can be shown...
3. Experiments

We used the recent real-world outdoor benchmark dataset BeDDE [6] for comparison experiments. BeDDE contains images with different haze levels, as well as relatively clear reference images. First, we arbitrarily selected a hazy image from the BeDDE to compare with 7 dehazing methods (FVR [7], DCP [2], CAP [8], NLD [9], MSCNN [10], DehazeNet [11], AOD-Net [12]). We use both quantitative and qualitative evaluation methods. The quantitative evaluation indicators we use are the classic evaluation indicators PSNR and SSIM [12]. As shown in Fig. 3, we surprisingly found that MDCP is the most suitable for PSNR and SSIM indicators. Visually, we can also find that MDCP achieves a good dehazing effect while also greatly reducing color distortion, especially in the sky area. Note that the reference image in BeDDE and the corresponding hazy image is collected at different times, and the content is not the same. Hence, it is necessary to comprehensively observe the visual dehazing effect from the hazy image and the reference image.

Then we compare MDCP with the state-of-the-art methods by visibility index (VI) and realness index (RI) [6] indicators for BeDDE, as shown in Table 1. From these results, we can find that MDCP achieves the best performance for RI indicator. Compared with DCP, the RI indicator has been greatly improved. For VI indicator, MDCP ranked second only to DCP. Although MDCP did not achieve the best in VI indicator, we believe that this is caused by the defects of VI indicator, for the VI indicator also uses the RGB images to calculate the transmission as a standard instead of the RAW images.

4. Discussion and Conclusions

In this letter, we mainly pointed out a more effective way to use DCP and ASM for single image dehazing. We found that the RAW images before the ISP pipeline should be used for ASM and DCP. In particular, the image dehazing operation should be performed before the gamma correction during the ISP pipeline. For future work, we will establish an image dehazing benchmark data set based on the RAW images and compare recent image dehazing algorithms through PSNR, SSIM, VI, RI and other indicators. In addition, we will study more accurate sky region seg-

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Table 1: VI and RI indicator for all images in BeDDE [6].

| Method       | VI   | RI   |
|--------------|------|------|
| FVR [7]      | 0.8054 | 0.9511 |
| DCP [2]      | 0.9111 | 0.9654 |
| BayD [13]    | 0.8294 | 0.9340 |
| CAP [8]      | 0.8507 | 0.9482 |
| NLD [9]      | 0.8278 | 0.9557 |
| MSCNN [10]   | 0.8920 | 0.9702 |
| DehazeNet [11] | 0.8902 | 0.9718 |
| AOD-Net [12] | 0.8961 | 0.9703 |
| DCPDN [14]   | 0.8940 | 0.9717 |
| GFN [15]     | 0.8659 | 0.9651 |
| DisentGAN [16]| 0.8678 | 0.9604 |
| PQC [17]     | 0.8923 | 0.9694 |
| MDCP         | 0.8994 | 0.9719 |
| Hazes images | 0.8518 | 0.9726 |

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Fig. 2  The dehazing structure of MDCP in Fig. 2.
mentation algorithms to further improve the performance of MDCP.

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