Postprint: An Adaptive Single Image Dehazing Algorithm for Reducing Color Distortion

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Abstract

Single image dehazing algorithms based on the dark channel prior represent the most efficient image dehazing techniques currently available; however, when certain scenes in an image do not fully satisfy the dark channel prior, the dehazed images frequently exhibit substantial artifacts and color distortion, thereby necessitating image-specific modifications to the method. Based on the assumption that the dark channel becomes increasingly unreliable with higher scene brightness and lower scene saturation, we redesign the dark channel confidence measure to compensate for overestimated dark channel values in scenarios where scenes do not fully comply with the dark channel prior. Furthermore, post-enhancement processing is applied to improve the visual quality of the image. The proposed algorithm was evaluated on three categories of representative hazy images. Experimental results demonstrate that, compared with related algorithms, the proposed algorithm achieves superior performance in alleviating color distortion and removing artifacts. By designing a dark channel confidence measure, the algorithm addresses the issue of overestimated dark channel values when image scenes do not fully satisfy the dark channel prior, thereby significantly enhancing the adaptability of the dark channel prior-based dehazing model to diverse hazy scenes.

Full Text

Preamble

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A Color-Preserving Self-Adaptive Single Image Dehazing Algorithm

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Abstract: The single-image haze removal algorithm based on dark channel prior is currently the most efficient image dehazing technology. However, when certain scenes in an image do not fully satisfy the dark channel prior, the processed image often exhibits significant artifacts and color distortion, necessitating method corrections based on image characteristics. This paper proposes the hypothesis that the brighter the scene, the less credible the dark channel becomes; and the lower the scene saturation, the less credible the dark channel becomes. Based on this assumption, we redesign the dark channel confidence of images to compensate for overestimated dark channel values when scenes incompletely satisfy the dark channel prior. Additionally, post-enhancement processing is applied to improve visual quality. The proposed algorithm is tested on three representative hazy images. Experimental results demonstrate that compared with related algorithms, our method performs better in alleviating color distortion and removing artifacts. By designing dark channel confidence, the algorithm overcomes the problem of overestimated dark channel values when image scenes incompletely satisfy the dark channel prior, significantly improving the adaptability of the dark channel prior dehazing model to various foggy scenes.

Keywords: image dehazing; dark channel confidence; saturation; lightness

0 Introduction

Image processing technology plays an increasingly irreplaceable role in traffic monitoring, security equipment, medical imaging, terrain surveying, intelligent driving, and photographic arts. However, outdoor image acquisition often suffers from degradation due to adverse weather conditions, with fog and haze being the most common. Since degraded images under hazy conditions lose a certain degree of contrast and color information, the performance of related vision applications is severely affected, making dehazing processing necessary.

Traditional image dehazing research can be divided into two categories: image enhancement-based algorithms and image restoration-based algorithms. In recent years, due to improved computational capabilities, some deep learning-based image dehazing algorithms have emerged [1], but these require large amounts of training data and entail high application costs. Research on traditional methods remains active [4]. Image restoration-based dehazing algorithms study the physical degradation process of images under hazy conditions, establish imaging physical models, and reflect the imaging process, making them more targeted and currently the focus of dehazing research [5].

Under hazy weather conditions, the light reaching the camera lens consists of two parts: scene radiation attenuated by atmospheric scattering during propagation, and airlight that continuously accumulates along the propagation path. Therefore, to restore the original scene radiation, estimating accurate scene depth is a common requirement for image restoration-based dehazing algorithms. However, for a single hazy image, scene depth cannot be uniquely determined, necessitating the introduction of appropriate prior conditions and assumptions.

Fattal et al. [5] estimated scene albedo and medium transmittance by assuming that transmittance and object surface shading are locally uncorrelated. This physics-based method can achieve good dehazing results, but the assumption fails when haze is severe. Tan et al. [7] assumed that local atmospheric light is constant and that haze-free images have higher contrast than hazy images, restoring images by maximizing local contrast. Although the dehazing effect is impressive, this method may be physically invalid. He et al. [8] first proposed the dark channel prior, approximating scene depth and transmittance by calculating the dark channel values of hazy images, achieving excellent dehazing results for outdoor images. However, the dark channel prior can only roughly estimate scene transmittance in hazy images and requires computationally expensive soft matting methods for optimization. Moreover, when certain scenes do not satisfy the dark channel prior, problems such as oversaturation, artifacts, overexposure, and color distortion often occur. Although this method is not perfect, the simple and efficient dark channel prior has been widely recognized, and numerous research efforts have built upon it.

To reduce the complexity of dehazing algorithms, many studies have used structurally-transformative filters with similar effects to replace soft matting methods, such as correlation filters [9], bilateral filters [10], and guided filters [11]. Tang et al. [5] used propagated filtering instead of bilateral filtering to correct the dark channel-based method. To address issues such as overexposure, artifacts, and unnatural colors caused by estimating global atmospheric light values, Xu et al. [12] proposed using bright channel prior to more reasonably estimate local atmospheric light values. To solve the problem of dark channel prior failure in certain special scenarios, Li et al. [9] proposed a method to calculate dark channel confidence based on dark channel brightness and local contrast to measure the degree to which image scenes satisfy the dark channel prior, thereby improving dehazing effects for more scene types. However, local contrast-based methods do not align well with atmospheric scattering laws and can easily lead to unreasonable over-enhancement in dehazed images. Jiang et al. [13] prevented artifacts and color distortion by suppressing transmittance at positions where scene brightness approaches atmospheric light values. However, since the algorithm is pixel-based while transmittance is calculated based on local regions, the suppression results in noticeable brightness differences within local regions, and the algorithm fails when sky and water surface brightness vary significantly. Wang et al. [14] avoided calculating the dark channel for sky regions through segmentation, but the algorithm performs poorly when boundaries between sky and scenery are blurred.

Building upon the aforementioned dark channel prior dehazing research and inspired by Li et al.' s [9] dark channel confidence method, this paper proposes a new confidence calculation method and applies post-enhancement processing to cases where restored image scene radiation is insufficient. By selecting the guided filter to replace soft matting, we achieve linear time complexity, demonstrate better performance in alleviating color distortion and removing artifacts, and significantly improve the adaptability of the dark channel prior dehazing model to different hazy scenes.

1 Related Work

In image dehazing research, the composition of hazy images is typically described using the following simplified atmospheric scattering model:

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

where $I(x,y)$ represents the observed image, $J(x,y)$ represents scene radiance, $t(x,y)$ represents medium transmittance, and A represents atmospheric light. For a color image with N pixels, Equation (1) contains $3N+3$ unknowns but only $3N$ knowns, typically requiring prior conditions or assumptions to first estimate $t(x,y)$ and A before calculating the restored haze-free image $J(x,y)$. The first term on the right side of Equation (1) is called the direct attenuation term, and the second term is called the airlight term. The direct attenuation term describes the portion of scene radiation after being continuously attenuated by the propagation medium, while the airlight term describes the portion where the atmosphere acts as a light source due to scattering, with its emitted light superimposed on the scene radiation path.

When the atmosphere is homogeneous, transmittance $t(x,y)$ can be expressed as:

$$t(x,y) = e^{-\beta d(x,y)} \tag{2}$$

where β represents the atmospheric scattering coefficient and $d(x,y)$ represents scene depth. This equation indicates that when haze concentration remains constant, transmittance is exponentially related only to scene depth.

1.1 Dark Channel Prior and Dehazing Process

The dark channel prior states that for outdoor images with sufficient lighting and abundant shadows, there universally exists a dark channel—the minimum color channel value in local regions is very small [8], defined as:

$$J_{\text{dark}}(x, y) = \min_{c \in \{r,g,b\}} \left(\min_{(i,j) \in \Omega(x,y)} J^c(i, j) \right) \tag{3}$$

where $\Omega(x, y)$ represents a local patch centered at (x, y) with radius R, and c represents a color channel of the image. Typically, for images taken in clear weather, the dark channel value is very close to 0 after removing sky regions.

Combining Equations (3), (4) with (1), we can derive the local patch transmittance:

$$\tilde{t}(x, y) = 1 - \omega \min_{c \in \{r,g,b\}} \left(\min_{(i,j) \in \Omega(x,y)} \frac{I^c(i, j)}{A^c} \right) \tag{5}$$

Since completely removing haze causes the image to lose depth perception references, a correction parameter ω is introduced to adjust transmittance. To simplify calculations, ω is typically set to 0.95. As the transmittance map obtained at this stage is a coarse estimate based on image local regions, it cannot accurately reflect scene depth changes near strong edges, often causing halos and artifacts in restored images. To incorporate scene structure information into the transmittance map, soft matting or functionally similar structurally-transformative filters such as guided filters and joint bilateral filters are used to optimize $\tilde{t}(x, y)$.

Based on the dark channel prior, He et al. [8] improved the traditional atmospheric light estimation method by first selecting pixels with the top 0.1% dark channel values from the original image, then choosing the brightest pixel value among them as the global atmospheric light value A. The final restored haze-free image is calculated as:

$$J(x, y) = \frac{I(x, y) - A}{\max(t(x, y), t_0)} + A \tag{6}$$

where t_0 is the lower bound of transmittance, typically set to 0.1 to avoid excessive noise amplification in haze-free image regions.

1.2 Dark Channel Confidence

Like most prior conditions, the dark channel prior is an empirical summary based on statistical observations that may fail in certain special scenarios. For sky regions that completely violate the dark channel prior, their transmittance is always close to 0, often resulting in severe pseudo-contours and noise in dehazed images. Additionally, for scenery with colors and brightness similar to sky regions, such as smooth water surfaces, gray-white cement roads, and building surfaces, the dark channel prior is not fully satisfied, leading to overestimated dark channel values and consequently oversaturated restored images. To address this problem, Li et al. [9] proposed the concept of dark channel confidence to correct the dark channel method by appropriately reducing the corresponding dark channel confidence for scenes that do not satisfy the prior, thereby compensating for overestimated dark channel values.

In Li' s method, dark channel confidence is defined based on two assumptions: (a) the smaller the local brightness variation, the less reliable the dark channel; (b) the higher the dark channel intensity, the lower the reliability. Accordingly, the dark channel confidence model and corrected transmittance are derived as:

$$C(x,y) = \max(C_1(x,y), C_2(x,y)) \tag{7}$$

$$\tilde{t}(x,y) = 1 - C(x,y) \min_{c\in\{r,g,b\}} \left(\min_{(i,j)\in\Omega(x,y)} \frac{I^c(i,j)}{A^c} \right) \tag{8}$$

where $C_1(x,y)$ and $C_2(x,y)$ represent dark channel confidence values measured through local contrast and dark channel brightness, respectively, with values in the interval $[0,1]$. When local regions contain detectable textures, $C(x,y)$ approaches 1, allowing complete haze removal. When regions are smooth, $C(x,y)$ decreases with increasing brightness, making the corrected transmittance larger to prevent oversaturation or artifacts in restored images caused by scenes that incompletely satisfy the dark channel prior.

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2 Proposed Algorithm

The dark channel prior holds mainly due to three types of scene elements: abundant shadows, vivid colors, and inherently dark objects [8], as shown in [Figure 1: see original paper]. Through experience and analysis, scenes satisfying the dark channel prior are precisely those with lower brightness and higher saturation in images, which is also a common characteristic of outdoor landscape and urban photography. Unfortunately, hazy images often contain large areas of high-brightness, low-saturation scenery such as sky, water surfaces, rocks, walls, and cement roads with gray-white colors, which completely or partially violate the dark channel prior. This causes dark channel-based dehazing methods to erroneously estimate haze thickness, leading to over-enhancement and resulting in varying degrees of oversaturation or even severe artifacts.

This paper designs a new method for calculating dark channel confidence based on the fundamental elements that establish the dark channel prior. The method is based on two assumptions: (a) the higher the image scene brightness, the less credible the dark channel; (b) the lower the scene saturation, the less credible the dark channel. To obtain image brightness and saturation, the original image is first converted to the HSV color space. Since dark channel confidence is proposed to refine the dark channel, its calculation should also be based on local patches. Additionally, to minimize suppression of the original dehazing effect during dark channel correction, the brightness and saturation channels of the HSV color space image are processed using minimum and maximum filters, respectively, with the same radius as used for dark channel calculation.

$$V_{\min}(x,y) = \min_{(i,j)\in\Omega(x,y)} V(i,j) \tag{9}$$

$$S_{\max}(x,y) = \max_{(i,j)\in\Omega(x,y)} S(i,j) \tag{10}$$

where $V_{\min}$ and $S_{\max}$ represent the brightness and saturation channels after minimum and maximum filtering, respectively, and V and S represent the brightness and saturation channels of the image in HSV color space. Compared with functionally similar structurally-transformative filters, the guided filter offers stronger detail preservation capability and can be implemented in linear time [11]. To incorporate the missing original image details and texture information into the calculated $V_{\min}$ and $S_{\max}$ while preserving their original intensity, this paper adopts the guided filter using the original image as the guidance image to obtain $V'_{\min}$ and $S'_{\max}$.

Based on the above analysis, we propose new confidence measures C_1 and C_2 based on brightness and saturation:

$$C_1(x,y) = 1 - \frac{1}{1+\exp\left(-k_1\left(V'_{\min}(x,y) - A\right)\right)} \tag{11}$$

$$C_2(x,y) = 1 - \frac{1}{1+\exp\left(-k_2\left(S'_{\max}(x,y) - A\right)\right)} \tag{12}$$

where A represents the mean atmospheric light value, and k_1 and k_2 are scaling coefficients for the sigmoid function curves, empirically set to 8 and 0.05, respectively. In Equation (11), A is used as a threshold because when the difference between the original image brightness I and atmospheric light value A is very small, Equation (7) divides by a very small transmittance t, causing color differences between channels and brightness differences between pixels to be amplified several times, easily creating artifacts and color distortion [13]. In Equation (12), A is used as a threshold considering that hazy images inherently have reduced scene saturation due to haze. To suppress overestimated dark channel values while minimally affecting the original dehazing effect, the final confidence is calculated as:

$$C(x,y) = \sqrt{C_1(x,y) \cdot C_2(x,y)} \tag{14}$$

Since dark channel confidence has been introduced to suppress over-enhancement, the correction parameter ω in transmittance estimation and the lower bound t_0 in image restoration are no longer needed. Equations (5) and (6) are rewritten as:

$$\tilde{t}(x,y) = 1 - C(x,y) \min_{c\in\{r,g,b\}} \left(\min_{(i,j)\in\Omega(x,y)} \frac{I^c(i,j)}{A^c} \right) \tag{15}$$

$$J(x,y) = \frac{I(x,y) - A}{\tilde{t}(x,y)} + A \tag{16}$$

In summary, the proposed algorithm measures the degree to which scenes satisfy the dark channel prior using improved dark channel confidence and employs a guided filter to optimize scene structure information in the dark channel, thereby avoiding severe color distortion and artifacts caused by inaccurate dark channel estimation.

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3 Experimental Results and Analysis

The experimental development environment was VS2017 with C++ compiler and OpenCV3.1.0 for computation. In dark channel and dark channel confidence calculations, the patch size Ω was 15×15, the guided filter window radius R was 20, and parameters ε were set to 0.1 and 10^{-2}, respectively.

Since the minimum filter and guided filter used in the dehazing process can be implemented in linear time [8, 11, 15], the overall dehazing algorithm maintains linear time complexity.

This paper selected three representative images for visual effect and quantitative evaluation, labeled as Mountain, Lake, and Gugong based on image content. To demonstrate the effectiveness of our algorithm, we compared it with methods by He et al. [8], Wang et al. [14], Li et al. [9], and Xu et al. [12] that are closely related to our approach.

3.1 Visual Dehazing Effect Analysis

The experimental results of dark channel confidence calculation using Equation (14) are shown in [Figure 2: see original paper]. From Figure 2: see original paper, we can see that confidence values are correspondingly low for sky and water regions, suppressing the problem of overestimated dark channel values. The dehazing result in Figure 2: see original paper is clear and natural.

The Mountain image (Figure 3: see original paper) represents a common heavy haze scenario with insufficient scene radiation. In such cases, restored images often suffer from low brightness, artifacts, and block effects. Results (b)-(e) all exhibit varying degrees of artifacts: (b) shows numerous artifacts in sky and dense fog areas; (c) attempts to segment sky regions for separate processing, but this is difficult when sky boundaries are not distinct; (d) uses a correlation filter that cannot accurately estimate dark channel values, resulting in restored images lacking fine scene structure information, and the post-enhancement algorithm cannot effectively improve visual quality; (e) has minimal visual distortion but still shows artifacts at sky region edges. Our algorithm, which corrects dark channel values based on original image brightness and saturation and applies brightness remapping following Li et al.' s method [16], achieves clear and naturally transitioned dehazing results, as shown in Figure 3: see original paper.

The Lake image (Figure 4: see original paper) is an actual campus photograph featuring large areas of sky and reflective water surfaces that completely violate the dark channel prior. As discussed, dark channel prior-based dehazing in such cases tends to produce numerous artifacts, color distortion, and even noise in sky and water regions. Result (b) shows extremely non-uniform brightness in sky and water areas with artifacts; (c) can better segment and process sky portions but fails for water surfaces; (d) estimates dark channel confidence through dark channel brightness and local contrast, avoiding artifacts to some extent, but the restored result is overall dark with unnatural brightness variations due to unreasonable confidence estimation; (e) also shows color distortion and artifacts in water surfaces. In contrast, our result (f) effectively avoids artifacts and color distortion while achieving dehazing, yielding the best overall performance.

The Gugong image (Figure 5: see original paper) is characterized by large areas of near-white scenes lacking surface shadows, which incompletely satisfy the dark channel prior. Dark channel prior-based dehazing in such cases often leads to color distortion. Results (b)-(d) all show varying degrees of color distortion, with originally near-white scenes appearing yellowish or even brownish; (d) also exhibits halos near strong edges (such as people) due to inaccurate scene transmittance estimation. Results (e) and (f) are relatively better, with our algorithm (f) showing slightly less color distortion than (e). However, due to inherent limitations of the dark channel prior, although our algorithm can reasonably estimate confidence to better avoid artifacts and color distortion in sky and water areas, it cannot completely avoid oversaturation in scenes that incompletely satisfy the dark channel prior while balancing dehazing effectiveness.

3.2 Quantitative Evaluation

In addition to visual evaluation, we employed two image quality assessment tools for quantitative evaluation of the processed images. The selected metrics were the blind/referenceless image spatial quality evaluator (BRISQUE) proposed by Mittal et al. [17] and the natural image quality evaluator (NIQE) [18].

The quantitative results are shown in and , where lower values indicate better quality for both metrics. BRISQUE evaluates image quality based on pixel correlation in the image space, primarily assessing the "naturalness" characteristic. Since over-dehazing introduces certain distortions to the original image, shows that all methods produce worse results than the original image, but our method still demonstrates advantages over other approaches. After proposing BRISQUE, Mittal et al. subsequently developed NIQE, which summarizes a statistical model of natural images and measures the distance between test images and this model. The Gugong image contains large light-colored areas, making Li’ s method, which suffers the most severe color distortion, paradoxically receive the highest quality score. shows that our algorithm produces relatively competitive NIQE values.

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4 Conclusion

Based on dark channel prior dehazing research, this paper addresses the problem that the dark channel prior dehazing model often causes severe artifacts and color distortion in regions that incompletely satisfy the prior (such as sky and water surfaces). By analyzing the fundamental elements that establish the dark channel prior, we more reasonably estimate dark channel confidence for hazy scenes based on brightness and saturation, significantly overcoming inherent limitations of the dark channel prior. The guided filter is selected as the structural transformation tool, achieving linear computational complexity. Additionally, for cases of insufficient scene radiation under heavy haze conditions, post-enhancement algorithms effectively improve the visibility of dark details.

Experimental comparisons demonstrate that compared with the original dark channel dehazing algorithm and related improved algorithms, our method performs better in alleviating color distortion and removing artifacts, significantly improving the adaptability of the dark channel prior dehazing model to various hazy scenes.

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Note: Figure translations are in progress. See original paper for figures.