Fast Single Image Dehazing Algorithm Based on Dark Channel Prior Postprint

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Abstract

To address the issue in single image dehazing algorithms based on dark channel prior theory where hazy images in certain scenes contain large bright regions (such as sky, water surface, or white-colored objects) that violate the dark channel prior assumption, resulting in poor dehazing performance, an improved single image dehazing algorithm is proposed based on this theory. First, the atmospheric light value is estimated using a statistical truncation method; then, the dark channel map is median filtered to obtain a coarsely estimated transmission map, and the transmission map of bright regions undergoes adaptive correction processing; finally, these parameters are substituted into the atmospheric scattering imaging model to complete the dehazing process. Experimental results demonstrate that, compared with the original algorithm, the proposed algorithm can accurately select pixel points from sky regions for atmospheric light estimation, effectively reducing color distortion in bright regions. Through comparative analysis of dehazing effects on hazy images captured in different outdoor scenes using different algorithms, it is evident that the proposed algorithm handles bright regions more reasonably, can better process images containing light sources, and the restored images exhibit good detail preservation with significantly improved visual effects. The proposed algorithm demonstrates excellent enhancement performance for hazy images containing large bright regions, can provide effective preprocessing for image processing tasks such as image segmentation, semantic retrieval, and intelligent analysis, and holds significant importance for research fields including traffic monitoring, video surveillance, driving video recording, and visual navigation.

Full Text

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Abstract

Existing single image dehazing algorithms based on dark channel prior theory cannot achieve satisfactory performance when images contain large bright regions (such as sky areas, water surfaces, or white objects) that violate the dark channel prior assumption. To address this problem, this paper proposes an improved single image dehazing algorithm based on dark channel prior. First, the atmospheric light value is estimated using a statistical truncation method. Then, a median filter is applied to the dark channel map to obtain a coarsely estimated transmission map, and the transmission map for bright regions is adaptively corrected. Finally, these parameters are substituted into the atmospheric scattering imaging model to complete the dehazing process.

Experimental results demonstrate that compared with the original algorithm, the proposed algorithm can accurately select pixel points from sky regions for atmospheric light estimation and effectively reduce color distortion in bright regions. Through comparative analysis of dehazing results on foggy images captured under different outdoor scenes, the proposed algorithm handles bright regions more reasonably, performs well on images with light sources, and produces restored images with good detail preservation and significantly improved visual quality. The proposed algorithm provides effective enhancement for foggy images containing large bright regions, offering a valuable preprocessing tool for image segmentation, semantic retrieval, and intelligent analysis, with important implications for traffic supervision, video surveillance, vehicle video recording, visual navigation, and related research fields.

Keywords: dehazing; dark channel prior; bright regions; atmospheric light; transmission map

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1 Dark Channel Prior Theory

1.1 Atmospheric Scattering Model

Most current single image dehazing algorithms based on physical models adopt the classic atmospheric scattering model proposed by McCartney in 1975, whose spatial model is shown in [Figure 1: see original paper]. This model can be expressed by the following mathematical formula:

$$I(p) = J(p)t(p) + A(1 - t(p))$$

where the first term is called the direct attenuation term and the second term is the atmospheric light term. Here, p represents the pixel coordinates in the image; $I(p)$ denotes the captured hazy image; $J(p)$ reflects the intensity of light directly reflected by objects, i.e., the true image after dehazing; $t(p)$ represents the transmission map (which can be expressed as $t(p) = e^{-\beta d(p)}$, where β is a scattering coefficient and $d(p)$ is scene depth), reflecting the ability of reflected light to penetrate haze along the propagation path from the object surface to the imaging device; and A is the estimated atmospheric light value, reflecting the illumination intensity at infinite distance from the imaging device.

1.2 Dark Channel Prior

Through statistical experiments on numerous outdoor haze-free images, He et al. proposed a dark channel prior theory. Previous dehazing algorithms focused on image contrast enhancement, whereas He et al. observed statistical patterns in outdoor haze-free images and discovered an objective feature inherent to images themselves: in most local regions of haze-free images, there always exist some pixels with very low intensity values in one or several color channels, approaching zero. These pixels are called dark pixels. This can be expressed as:

$$J^{dark}(p) = \min_{c \in \{R,G,B\}} \left(\min_{q \in \Omega(p)} J^c(q) \right)$$

where J^c is a color channel of image J; c represents the image color channels; and $\Omega(p)$ is a local region centered at pixel p.

1.3 Dehazing via Dark Channel Prior

In images captured under hazy weather, haze appears grayish-white, causing dark pixels with low brightness values to become grayish-white and brighter due to atmospheric light scattering. The brightness values of dark pixels in hazy images are directly related to the transmission map, so these brightness values can be used to estimate scene transmission.

First, assuming the global atmospheric light A is given, dividing both sides of Eq. (1) by A yields:

$$\frac{I(p)}{A} = \frac{J(p)}{A} t(p) + (1 - t(p))$$

Further assuming that scene depth is uniform within a local region $\Omega(p)$, a constant transmission $t(p)$ can be used within this region. Taking the dark channel of both sides of Eq. (3) gives:

$$\min_{c\in\{R,G,B\}}\left(\min_{q\in\Omega(p)}\frac{I^c(q)}{A^c}\right)=\min_{c\in\{R,G,B\}}\left(\min_{q\in\Omega(p)}\frac{J^c(q)}{A^c}\right)t(p)+(1-t(p))$$

According to the dark channel prior theory, the dark channel $J^{dark}(p)$ of haze-free images is very small and approaches 0. Atmospheric light A is a positive global constant with relatively large values. For non-bright regions in hazy images, dividing by A does not affect the dark channel' s tendency toward zero, so we can obtain:

$$\min_{c\in\{R,G,B\}}\left(\min_{q\in\Omega(p)}\frac{J^c(q)}{A^c}\right)=0$$

Substituting Eq. (5) into Eq. (4) yields a coarse transmission estimate:

$$\tilde{t}(p)=1-\min_{c\in\{R,G,B\}}\left(\min_{q\in\Omega(p)}\frac{I^c(q)}{A^c}\right)$$

To make the image appear more natural and realistic, a haze removal rate parameter ω $(0<\omega<1)$ is introduced to Eq. (6), allowing distant objects to retain some depth information. Generally, the denser the haze, the larger the value of ω. Reference [13] uses a constant value of 0.95 for this parameter. Thus, the coarse transmission map $\tilde{t}(p)$ can be approximated as:

$$\tilde{t}(p)=1-\omega\min_{c\in\{R,G,B\}}\left(\min_{q\in\Omega(p)}\frac{I^c(q)}{A^c}\right)$$

Finally, substituting the estimated atmospheric light A and transmission map $t(p)$ into Eq. (1), the haze-free image can be restored as:

$$J(p)=\frac{I(p)-A}{t(p)}+A$$

2 Proposed Method

2.1 Atmospheric Light Estimation via Statistical Truncation

In hazy video images, sky regions are typically the brightest areas, so existing algorithms often select the brightest pixels from hazy images in a certain proportion as the atmospheric light estimate. However, when images contain white objects or bright regions with light sources, the pixels used for atmospheric light estimation may fall on these bright regions rather than sky areas, causing inappropriate reference values to be used for atmospheric light estimation and resulting in significant estimation errors that substantially affect dehazing performance.

To achieve more accurate atmospheric light estimation, this paper proposes a statistical truncation-based method. Using the local mean of the brightness image as the center and local variance as the truncation interval, pixels with brightness values greater than the local mean within the truncation interval are selected as candidate pixels for atmospheric light estimation.

HSV is an intuitive color model frequently used in image processing. Since its hue and saturation components are separated from the brightness component, processing the brightness component does not affect the image' s color information. The proposed method first converts the image to HSV color space, extracts the brightness component V, and calculates its probability density function:

$$pdf(V) = \frac{v}{H \cdot V_{\max} - V_{\min}}$$

where v is a random value of V; $V_{\min}$ is the minimum value of V; and $V_{\max}$ is the maximum value of V.

Next, the average brightness value μ of the brightness image is calculated. For each pixel in the input image, pixels with brightness greater than μ are selected as candidate pixels, and the rest are removed. According to the characteristics of normal distribution, 68.26% of pixels lie within the $[\mu - \sigma, \mu + \sigma]$ interval. Therefore, among these candidate pixels, the local mean μ' and local standard deviation σ of brightness are further calculated. Pixels not satisfying $\mu' - \sigma < V < \mu' + \sigma$ are removed, and the remaining pixels serve as candidate pixels for atmospheric light estimation. This process is repeated until the ratio of candidate pixels to total image pixels falls below a preset threshold λ. Finally, the mean brightness of these pixels is calculated and used as the atmospheric light estimate A. This estimated atmospheric light value can better handle images with light sources or white objects, avoiding the selection of pixels from overly bright regions. In this paper, the threshold λ is set to 0.1.

[Figure 2: see original paper] shows the pixel statistics for atmospheric light estimation using both the proposed algorithm and He' s algorithm. The marked red pixels are the reference pixels used for atmospheric light estimation. As shown, He' s algorithm selects pixels at light source positions rather than sky regions for atmospheric light estimation, leading to inaccurate values. In contrast, the proposed algorithm successfully avoids these light source positions, with most atmospheric light estimation pixels falling in sky-containing regions, making the mean-based atmospheric light estimate more consistent with the requirements of the hazy atmospheric scattering imaging model.

[Figure 3: see original paper] displays the reference pixel statistics for atmospheric light estimation in ordinary outdoor hazy images. The marked red pixels are used for atmospheric light estimation. For ordinary outdoor hazy images without light sources, the proposed algorithm accurately selects pixels from bright sky regions while effectively avoiding surfaces with vivid color information. This demonstrates that the statistical truncation-based atmospheric light estimation algorithm can accurately estimate atmospheric light for both hazy images with and without light sources.

2.2 Transmission Map Estimation via Median Filtering and Sky Region Detection

The transmission map reflects the primary characteristics of light propagation in the atmosphere, and its estimation accuracy plays a critical role in the quality of restored images. When estimating transmission, we first assume uniform scene depth within a local region, allowing a fixed transmission value to be used within a small patch. Reference [13] applies minimum filtering to the three-channel minimum map to obtain a coarse transmission estimate, followed by "soft matting" or guided filtering for further refinement, producing transmission maps with good edge preservation and more detailed restored images. However, these methods are computationally expensive and have poor real-time performance. Reference [18] describes a simpler approach that directly uses the three-channel minimum component map as the transmission map. Although straightforward, this method produces overall dark results with unsatisfactory visual quality.

To overcome these limitations, this paper uses median filtering instead of minimum filtering, with the filtered result serving as the coarse transmission estimate. Since median filtering exhibits good edge preservation characteristics, it eliminates the need for "soft matting" or guided filtering, substantially reducing algorithmic complexity. The expression for the transmission map estimated using median filtering is:

$$\tilde{t}(p) = 1 - \omega \cdot \mathrm{med}_{q \in \Omega(p)} \left(\min_{c \in \{R,G,B\}} \frac{I^c(q)}{A^c} \right)$$

Extensive experiments reveal that dark channel prior-based dehazing methods suffer from color distortion in bright regions because the estimated scene transmission in these areas is lower than the true scene transmission. In bright regions, the three color channels R, G, and B all have large values close to the atmospheric light value, with similar brightness across channels—a pattern that holds even in hazy images. During transmission map optimization, reference [19] introduces a parameter K to determine whether pixels belong to bright regions by comparing $|I(p) - A|$ with K. When $|I(p) - A| < K$, these pixels are considered bright region pixels and their transmission values are corrected; otherwise, they remain unchanged.

However, the brightness values of the three channels at the same pixel may differ, causing inconsistent directional judgments—that is, at a given pixel, some channels may satisfy $|I(p) - A| < K$ while others satisfy $|I(p) - A| > K$. This leads to potentially different transmission values calculated across the three color channels, when in reality the transmission should be identical at a single pixel. This inconsistency is the primary cause of color distortion in sky regions.

To illustrate this issue, this paper statistically analyzes bright region pixels in eight hazy images from [Figure 2: see original paper]. The results are shown in . The table demonstrates significant differences in the number of pixels satisfying the condition across different channels of hazy images, explaining why the corrected transmission values for each color channel in reference [19] exhibit inconsistencies. Additionally, the mean number of bright region pixels in individual channels approximates the number of bright region pixels in the three-channel grayscale mean image $M(p) = \frac{1}{3}\sum_{c\in\{R,G,B\}} I^c(p)$. Therefore, this paper proposes determining bright regions by comparing the three-channel grayscale mean image $M(p)$ with threshold K. When $|M(p) - A| < K$, these pixels are considered bright region pixels and their transmission values are corrected; otherwise, they remain unchanged. The corrected transmission map is given by:

$$t^*(p) = \tilde{t}(p) \cdot |M(p) - A|$$

where $M(p)$ is the three-channel grayscale mean image of hazy image $I(p)$, and K is a preset threshold. Following reference [19], K is set to 50.

[Figure 4: see original paper] compares the transmission maps obtained by the dark channel prior algorithm and the proposed algorithm. For images containing sky regions, the dark channel prior algorithm produces transmission maps with very low brightness values in sky areas, which severely deviates from the actual transmission map of sky regions. The proposed algorithm handles sky regions more reasonably, with transmission map brightness values in sky areas being the brightest in the entire image, satisfying the dark channel prior assumption. The overall brightness values better approximate real transmission values while preserving image details more effectively.

3 Experimental Results and Analysis

To validate the effectiveness of the proposed algorithm, eight hazy images (including images with bright regions/sky areas and images with light sources) were selected and processed using different algorithms. The results are shown in [Figure 5: see original paper].

Column (a) shows the eight selected outdoor hazy images. Column (b) presents results after Adaptive Histogram Equalization (AHE). Column (c) shows results after Multi-Scale Retinex (MSR) processing (with scales of 15, 80, and 250).

Column (d) displays results using Dark Channel Prior (DCP). Column (e) shows results from the proposed improved algorithm.

The processing of the 5th and 6th images in [Figure 5: see original paper] demonstrates that the proposed algorithm achieves good results on images containing light sources, due to accurate atmospheric light estimation. For other images, adaptive histogram equalization and dark channel prior processing cause color shifts and distortion in bright regions, while multi-scale Retinex retains some haze. The proposed algorithm effectively overcomes these drawbacks, producing clear, natural results with excellent color fidelity.

For objective evaluation, this paper conducts quantitative quality analysis from the perspectives of Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Information Entropy (IE), and Average Gradient (AG). MSE measures information preservation capability (lower values indicate stronger preservation). Higher PSNR indicates better noise resistance. Information entropy reflects the amount of information contained (higher entropy means richer details). Average gradient reflects image clarity (higher values indicate better sharpness). The results demonstrate that the proposed algorithm outperforms other algorithms to some extent, achieving superior dehazing effects.

compares the processing effects of different algorithms across various metrics, showing consistent improvements.

4 Conclusion

This paper proposes an improved single image dehazing algorithm based on dark channel prior theory and the hazy atmospheric scattering imaging model. The algorithm first estimates atmospheric light using a statistical truncation method, then obtains a coarse transmission map through median filtering of the dark channel map and adaptively corrects the transmission map for bright regions. Finally, these parameters are substituted into the atmospheric scattering imaging model to complete dehazing. The algorithm demonstrates excellent performance on hazy images containing large bright regions and light sources, effectively reducing color distortion in bright regions and producing restored images with significantly improved visual quality and natural scene appearance.

The proposed algorithm provides effective preprocessing for image segmentation, semantic retrieval, intelligent analysis, and other image processing tasks, with important implications for traffic supervision, video surveillance, vehicle video recording, visual navigation, and related research fields. Future work may involve migrating the dehazing algorithm to the front-end of video image acquisition, which would be significant for reducing computational overhead and data storage requirements in back-end processing.

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