

Fast Hazy Image Clarity Restoration Based on Visual Perception (Postprint)

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Date: 2018-05-24T00:00:00+00:00

Abstract

Aiming at the poor visual quality of images captured under severe hazy weather conditions, this paper proposes a fast clarity restoration method for hazy images based on visual perception, which estimates two crucial parameters of the atmospheric optical physical model. First, a method combining threshold segmentation with binary tree segmentation is employed to fit a relatively accurate atmospheric light value. Subsequently, adaptive anisotropic Gaussian filtering and tone adjustment methods are utilized to optimize the transmittance. Experimental results compared with algorithms [1, 3, 5, 8] demonstrate that the dehazing results of the proposed algorithm are saturated and clear, capable of preserving clear edge details and high contrast. The algorithm exhibits high processing efficiency and can meet practical application requirements.

Full Text

Fast Fog Image Restoration Based on Visual Perception

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Abstract: Images captured under severe hazy weather conditions suffer from poor visual quality. This paper proposes a fast haze image restoration method based on visual perception that estimates two critical parameters of the atmospheric optical physical model. First, threshold segmentation combined with binary tree segmentation is employed to fit a relatively accurate atmospheric light value. Then, adaptive anisotropic Gaussian filtering and tone adjustment methods are used to optimize the transmittance. Experimental results compared with algorithms [1, 3, 5, 8] demonstrate that the proposed method produces dehazed images with saturated and clear effects, preserves sharp edge details

and high contrast, and achieves high processing efficiency that meets practical application requirements.

Keywords: visual perception; threshold segmentation; binary tree; Gaussian; tone adjustment

0 Introduction

Intelligent visual image processing systems are widely used in video surveillance, intelligent driving, and urban traffic applications. However, images acquired in foggy conditions often suffer from severe degradation, poor clarity and contrast, and are prone to distortion and color shift, which adversely affects outdoor applications of intelligent visual image processing systems. Therefore, this paper presents an image processing technique with significant practical value that is applicable to most real-world imaging devices.

In recent years, significant progress has been made in image dehazing. He et al. [1] proposed the well-known dark channel prior (DCP) assumption, which estimates transmittance based on the observation that pixel values in at least one color channel of haze-free outdoor images are close to zero. While the dark channel prior method can achieve good dehazing results, it does not handle bright regions similar to atmospheric light effectively. Many improved methods based on the dark channel approach have been proposed [2, 3], but the transmittance processed by the dark channel model is not smooth and contains significant image noise. Jiang et al. [4] constructed a one-dimensional model based on Tarel's [5] color attenuation prior and provided an equation for depth estimation; however, the form of the scattering index is not fixed and is not applicable to all images. Guo et al. [6] combined white balance strategies with supervised machine learning methods to derive transmittance. Rizzi et al. [7] proposed a method suitable for single image processing, but the dehazing results are constrained to problematic patterns—a common defect in most physics-based dehazing methods, where images under non-uniform illumination often have low overall contrast. Galdran et al. [8] provided a grayscale tone algorithm based on conventional and low-level features from Finlayson et al. [9]. A common drawback of these algorithms is their inability to eliminate defects in given parameters. In Roomi et al.'s [10] method, artificial neural networks were used to process image sets, but experiments showed that this approach fails in dense fog regions.

Inspired by the above methods, this paper proposes a novel dehazing method based on the atmospheric optical physical model, divided into two stages. In the first stage, threshold segmentation combined with binary tree segmentation is used to obtain the atmospheric light value, improving the accuracy of parameter estimation in the atmospheric optical physical model. In the second stage, adaptive anisotropic Gaussian filtering and tone adjustment are applied to process the transmittance. The improved method is efficient and produces excellent

dehazing results. Compared with existing mainstream dehazing methods, the proposed approach achieves superior visual effects and color preservation.

1 Traditional Dark Channel Prior Method

Compared with methods that consider only visual effects, the application of physical models can improve result accuracy. Therefore, the atmospheric optical physical model [11] is widely used to describe haze image characteristics and can be further divided into attenuation and scattering models, as shown in [Figure 1: see original paper] and [Figure 2: see original paper], and expressed by Equation (1):

$$V(x, y) = R(x, y)t(x, y) + A(1 - t(x, y)) \quad (1)$$

where (x, y) represents a pixel position; $V(x, y)$ denotes the observed hazy image pixel value; $R(x, y)$ represents the scene radiance of the haze-free image, indicating the reflectance of scene points from the observer's perspective; and A denotes the atmospheric light value, typically referring to points with maximum pixel values in the image.

In Equation (1), the essential factors of image degradation can be divided into two components: (a) the attenuation component $R(x, y)t(x, y)$; and (b) the scattering component $A(1 - t(x, y))$, whose attenuation degree varies with scene depth and which affects image contrast, resulting in image blur.

Equation (1) can be further expressed by Equation (2), assuming the atmospheric medium is homogeneous:

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

where $d(x, y)$ represents the distance between the scene point and imaging device (i.e., the depth value). Tarel proposed two criteria that the scattering component should satisfy: (a) the scattering component values for all image pixels should be greater than zero; and (b) the scattering component values should be less than or equal to the minimum of the RGB three-channel values of the hazy image. Combining Equations (1) and (2) reveals that the atmospheric scattering component is related to global atmospheric light and depth. Furthermore, Tarel's research shows that the atmospheric scattering component contains numerous edges; if the entire image is smoothed, the processed result will produce a "halo effect." Therefore, the characteristics of the scattering component in the atmospheric optical physical model can be described by three points: (a) the scattering component in the atmospheric model is generally smooth but becomes more pronounced at edges where depth changes abruptly; (b) pixel values of the scattering component should be greater than zero and less than

the minimum RGB three-channel values; and (c) the scattering component is directly related to atmospheric medium conditions and scene depth.

2 Threshold Segmentation for Atmospheric Light Value A

In many dehazing algorithms, estimating atmospheric light value A is often affected by specular reflection from strong visual regions. For example, reflective objects are frequently incorrectly used in estimating A . He et al. [1] used the top 1% brightest pixels in the entire image as the atmospheric light value A , but this method yields low accuracy. This paper employs threshold segmentation to obtain the approximate region of atmospheric light value A , which is then precisely determined through a binary tree method. Additionally, the efficiency of our method can be improved through adaptive Wiener filtering and morphological methods.

2.1 Locking Sky Region

The goal of threshold segmentation [12] is to separate foreground objects from the background to obtain the approximate region of atmospheric light. Therefore, the critical step in threshold segmentation is threshold selection. From prior information, sky region pixels approach values around 210. Thus, this paper adopts simple threshold segmentation to save processing time and avoid common efficiency issues in most threshold segmentation strategies. This paper uses grayscale threshold segmentation, which segments the image into foreground and background components using a given threshold. The original image is denoted as $V(x, y)$ and the segmented image as $V_1(x, y)$, with T as the set threshold. The basic calculation can be expressed as:

$$V_1(x, y) = \begin{cases} 1 & V(x, y) > T \\ 0 & V(x, y) < T \end{cases} \quad (3)$$

Setting thresholds to 150, 200, and 210, as shown in [Figure 2: see original paper], can separate the sky region s from the foreground.

2.2 Accurately Estimating Atmospheric Light Value A

To accurately obtain atmospheric light value A , this paper further employs a binary tree [13] segmentation model. The basic operation divides sky region s_1 into two equal parts, designated as s_{21} and s_{22} , then calculates the grayscale mean values of these two parts and compares them. The part with larger grayscale mean is designated as s_1^n , and the other part as s_2^n . Region s_{21} is further divided into two sub-parts using the same process. The difference d between the maximum grayscale mean and 255 is compared, and the above steps are repeated until d satisfies being less than a given threshold t . Thus, A

is obtained as the atmospheric light value, as shown in Equations (11) and (12), with the binary tree segmentation process illustrated in [Figure 3: see original paper].

Since the AC value is positive, Equation (10) can be derived as follows:

$$\|A - V(x, y)\| = t(x, y) \cdot \|A - R(x, y)\| \quad (8)$$

$$t(x, y) = \frac{\|A - V(x, y)\|_C}{\|A - R(x, y)\|_C}, \quad C \in [R, G, B] \quad (9)$$

$$\frac{1}{t(x, y)} = 1 + \frac{\|A - V(x, y)\|_C}{A_C} \quad (10)$$

In practice, transmittance $t(x, y)$ can be calculated by combining Equations (5) and (6) to eliminate one term, expressing $t(x, y)$ as:

$$t(x, y) = 1 - \min_{C \in [R, G, B]} \left(\min_{(x, y) \in \Omega(x, y)} \left(\frac{V(x, y)}{A_C} \right) \right) \quad (11)$$

To make the dehazing result more natural and preserve good effects at depth discontinuities, this paper retains a small amount of haze for distant objects. A parameter w_0 is introduced to modify Equation (11), with w_0 set to 0.95, yielding:

$$t(x, y) = 1 - w_0 \cdot \min_{C \in [R, G, B]} \left(\min_{(x, y) \in \Omega(x, y)} \left(\frac{V(x, y)}{A_C} \right) \right) \quad (12)$$

3 Anisotropic Gaussian Filtering for Transmittance Optimization

As the distance between scene objects and the observer increases, the influence of atmospheric light value A on the image also increases. From the perspective of human visual perception, this manifests as increased image brightness with increasing haze concentration. Combining the above prior knowledge of hazy images with atmospheric light value A and substituting it into the mathematical model shown in Equation (8) enables coarse estimation of $t(x, y)$. Since transmittance $t(x, y)$ changes rapidly with scene depth and varies sharply at edges, halo effects easily occur at edges during subsequent dehazing. To address this, He et al. [1] used soft matting algorithm with large matrix processing for transmittance, but this approach is computationally expensive and time-consuming. This paper employs anisotropic Gaussian filtering combined with tone adjustment to optimize transmittance.

3.1 Original Transmittance Solution

From a machine vision perspective, atmospheric light value A and $V(x, y)$ are geometrically correlated with $R(x, y)$, where transmittance $t(x, y)$ represents the ratio of two vector lines.

The dark channel prior is proposed based on extensive observation of outdoor haze-free images, revealing that at least one color channel among the three has extremely low pixel values. Based on the DCP definition, this paper assumes $R(x, y)$ is a haze-free image excluding sky regions, so its dark channel pixel values are very low and approach zero.

Research shows that low dark channel pixel values in images mainly occur in three situations: shadows (such as images of buildings or moving vehicles in cities); colorful objects or surfaces (such as green plants, red, yellow, or blue objects); and dark objects—all of which reduce dark channel pixel values.

Assuming the three channels of atmospheric light A_C are given, Equation (1) can be transformed through variable A_C to obtain Equation (8). Since pixel color channels are independent, transmittance is assumed constant within region $\Omega(x, y)$, denoted as $t(x, y)$. Calculating both sides of the dark channel equation yields:

$$R^{dark}(x, y) = \min_{C \in [R, G, B]} \left(\min_{(x, y) \in \Omega(x, y)} (R(x, y)) \right) \rightarrow 0 \quad (5)$$

$$V^{dark}(x, y) = \min_{C \in [R, G, B]} \left(\min_{(x, y) \in \Omega(x, y)} (V(x, y)) \right) \quad (6)$$

$$t(x, y) = 1 - \min_{C \in [R, G, B]} \left(\min_{(x, y) \in \Omega(x, y)} \left(\frac{V(x, y)}{A_C} \right) \right) \quad (11)$$

3.2 Anisotropic Gaussian Filtering Algorithm Mathematical Model

Both bilateral filtering and anisotropic Gaussian filtering can preserve edges and corners in images. Bilateral filtering requires weighted and mean operations, consuming excessive processing resources and resulting in low algorithm efficiency. Anisotropic Gaussian filtering offers better adaptability and robustness while preserving numerous corners and edges.

Existing Gaussian filter templates treat the origin as the core and project onto the x and y planes, forming a circle. In Equation (14), δ represents scale and θ represents direction. The traditional Gaussian filter mathematical model can be expressed as:

$$G(x, y, \delta) = \frac{1}{2\pi\delta^2} \exp\left(-\frac{x^2 + y^2}{2\delta^2}\right) \quad (14)$$

If different ratios are set for x and y , the anisotropic Gaussian filter mathematical model is obtained, projecting an ellipse onto the coordinate plane, expressed by Equation (15):

$$G(x, y, \delta_x, \delta_y) = \frac{1}{2\pi\delta_x\delta_y} \exp\left(-\frac{x^2}{2\delta_x^2} - \frac{y^2}{2\delta_y^2}\right) \quad (15)$$

Figure 4: see original paper shows the ellipse from Figure 4: see original paper rotated clockwise by angle θ along the x and y axes, converting the image from time domain to frequency domain. The coordinate transformation pattern is given by Equation (16):

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (16)$$

Substituting Equation (16) into Equation (15) yields the mathematical model for rotation by angle θ , with the anisotropic Gaussian filter operator given by Equation (17):

$$G(x, y, \delta_u, \delta_v, \theta) = \frac{1}{2\pi\delta_u\delta_v} \exp\left\{-\frac{(\cos \theta \cdot x + \sin \theta \cdot y)^2}{2\delta_u^2} - \frac{(-\sin \theta \cdot x + \cos \theta \cdot y)^2}{2\delta_v^2}\right\} \quad (17)$$

3.3 Adaptive Anisotropic Gaussian Filtering for Transmittance Optimization

This paper utilizes adaptive anisotropic Gaussian filtering [14] to optimize transmittance, enabling image smoothing while effectively preserving edge details. In Figure 4: see original paper, the long-axis scale δ_u can be determined by Equation (18):

$$\delta_u = \frac{1}{u(x, y)} = \frac{1}{t_1(x, y)} \quad (18)$$

In Equation (16), x and y are the horizontal and vertical coordinates of a pixel in the hazy image; $t_1(x, y)$ is the grayscale value of transmittance map $t(x, y)$ compressed to the range $[0,1]$ according to grayscale levels.

This paper uses the following rule to determine short-axis size δ_v : in smooth regions, the ratio of short-axis to long-axis approaches 1, while in edge regions, this ratio approaches 0. Therefore, the smoothness of the effect image is key to obtaining this ratio. The grayscale variance given by Equation (19) can indicate the smoothness of the transmittance map:

$$DC = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (t(i, j) - \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N t(i, j))^2 \quad (19)$$

In Equation (17), $M \times N$ is the selected small region; $\frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N t(i, j)$ is the grayscale mean of this region. Thus, DC in this equation can be obtained in the range 0-255. From Equation (20), the ratio between short-axis and long-axis can be obtained:

$$R = \frac{\delta_v}{\delta_u} = \frac{K}{K + DC} \quad (20)$$

In Equation (20), K is set as a scaling parameter, allowing short-axis size δ_v to be expressed as:

$$\delta_v = \delta_u \cdot R \quad (21)$$

Adaptive anisotropic Gaussian filtering requires determining direction θ and ratio K , obtained through transformation to get the perpendicular angle θ_{\perp} to direction angle θ . That is, using the Gaussian function to obtain horizontal and vertical derivatives and convolving them with the hazy image yields the vertical gradient angle θ_{\perp} at point (x, y) in the hazy image:

$$E_x(x, y) = \frac{\partial}{\partial x} G(x, y, \delta) * I(x, y) \quad (22)$$

$$E_y(x, y) = \frac{\partial}{\partial y} G(x, y, \delta) * I(x, y) \quad (23)$$

$$\theta_{\perp}(x, y) = \arctan\left(\frac{E_y(x, y)}{E_x(x, y)}\right) \quad (24)$$

The relationship between direction angle θ and perpendicular angle θ_{\perp} is given by Equation (25):

$$\theta = \theta_{\perp} + 90^{\circ} \quad (25)$$

In Equation (24), δ_u , δ_v , and perpendicular gradient angle θ_{\perp} can be obtained from the above equations. Through repeated experiments, if K is set to 20, adaptive anisotropic Gaussian filtering achieves optimal processing effects on transmittance, obtaining the optimal solution $t_1(x, y)$.

Substituting Equation (25) into Equation (15) yields:

$$G(x, y, \delta_u, \delta_v, \theta) = \frac{1}{2\pi\delta_u\delta_v} \exp\left\{-\frac{(\cos\theta_\perp \cdot x - \sin\theta_\perp \cdot y)^2}{2\delta_u^2} - \frac{(\sin\theta_\perp \cdot x + \cos\theta_\perp \cdot y)^2}{2\delta_v^2}\right\} \quad (26)$$

3.4 Clear Image Restoration

With atmospheric light value A and transmittance known, the haze-free image $R(x, y)$ can be obtained using Equation (27) based on Equation (1):

$$R(x, y) = \frac{V(x, y) - A}{\max(t(x, y), t_0)} + A \quad (27)$$

In Equation (27), t_0 is set as a lower bound value, which is empirically set to 0.1 in this paper.

3.5 Tone Adjustment of Experimental Results

In hazy environments, due to the presence and influence of atmospheric light, images captured in fog often have an overall grayish-white color tendency, and their pixel values are typically higher than those in actual conditions. Consequently, the effect images after dehazing and clarification operations have low overall brightness, as shown in Figure 7: see original paper. Performing tone adjustment on the experimental results can make the processed images have chromaticity and contrast closer to real scenes.

Tone adjustment [15] is commonly applied in high dynamic range image processing. This method first compresses high dynamic range images to be displayable on low dynamic range screens. This paper applies Drago's logarithmic method for tone adjustment, which can improve overall image brightness, detail completeness, and contrast. In this method, the mapping relationship can display the relationship between display brightness and scene brightness.

In Equation (26), L_d is display brightness, $L_{d,max}$ is maximum display brightness (set to 100), and parameter b reflects the compression degree of high-brightness region pixel values and the visibility of details in these regions. Larger b values result in more severe brightness compression. Based on the dark condition of the clarified dehazing results, this paper aims to enhance brightness and contrast in dark regions of the result image while avoiding detail loss as much as possible. Repeated experiments show that when b is in the range 1.3-1.6, the processed effects are optimal. As shown in Figure 7: see original paper, the result image processed by the algorithm alone has low overall brightness; after tone adjustment, as shown in Figure 7: see original paper, the brightness value increases, the detail range becomes more prominent, and the effect is closer to haze-free clear images in real environments.

$$L_d = \frac{L_{w,d}}{\ln(L_{w,max})} \cdot \frac{\ln(L_{w,d} + 1)}{\ln(2 + 8 \cdot (L_{w,d}/L_{w,max})^b)} \quad (26)$$

4 Experimental Results Comparison and Analysis

This paper conducted extensive experiments to verify the effectiveness of the proposed method. Both our method and comparison algorithms were implemented in MATLAB 12a on a computer with Pentium(R) D, E6700 GHz CPU and 8 GB memory. Comparison algorithms [1, 3, 5] are physics-based, while algorithm [8] is an enhancement method. All these methods have good dehazing effects. This paper created an image dataset containing 512 outdoor images obtained through web and device collection, covering rich scenes such as natural landscapes, buildings, trees, lakes, aerial photos, distant views, and close-up views.

4.1 Subjective Visual Evaluation

This paper selected different hazy images from the test set for experiments. [Figure 8: see original paper] through [Figure 12: see original paper] show hazy images with varying proportions of sky region, from small sky region proportions in [Figure 8: see original paper] to large proportions in [Figure 12: see original paper]. The following sections demonstrate dehazing effects for different scenes: pavilions (320×480), trees (420×550), building groups (550×620), buildings (480×600), and water alleys (600×720). Results from our method and four other dehazing methods [1, 3, 5, 8] are compared and analyzed for hazy images with different sky region proportions, where (a) shows the original hazy image and (b)-(f) show dehazing results.

Algorithm [1] produces dark images with varying degrees of image noise; algorithm [3] results appear whitish with halo artifacts; algorithm [5] produces blurred edge details with severe local degradation. These issues arise because the obtained transmittance is not accurate enough, which significantly amplifies image noise and color saturation. Algorithm [8] often produces color shift phenomena at the boundary between sky and non-sky regions. Our method produces bright foreground colors, retains a small proportion of haze to make the image more realistic, and emphasizes image details.

[Figure 8: see original paper] shows the smallest sky region proportion among the five test images. All methods produce visually satisfactory results, particularly our method and method [5], whose results are closer to natural states. However, our method employs tone adjustment, achieving better overall brightness and displaying more image details. As the sky proportion increases from [Figure 9: see original paper] to [Figure 12: see original paper], our method's results are closer to real scenes compared with other methods, with richer image details.

4.2 Objective Evaluation

This paper uses information entropy [16] to evaluate our method against other methods. This metric can be expressed by Equation (29):

$$IIE = 10 \cdot \log_{10}\left(\frac{FFI}{M \times N}\right) \quad (29)$$

Generally, image information entropy represents the information richness of an image. Larger IIE values indicate more saturated and clearer dehazing effects. As shown in and [Figure 8: see original paper]-[Figure 12: see original paper], our method' s IIE performance is superior to other methods because it produces lower oversaturation in sky regions without introducing much unnecessary information. demonstrates that compared with other methods, our method achieves better IIE metrics while preserving clear edge details and high contrast [17].

Table 1. Information Entropy Comparison of Different Methods

Image	Hazy	Method [1]	Method [3]	Method [5]	Method [8]	Our Method
Fig.8						
Fig.9						
Fig.10						
Fig.11						
Fig.12						

4.3 Time Complexity

To verify our method' s superiority in processing time, experiments were conducted with images of various sizes. Our method demonstrates faster speed compared with methods [1, 3, 5, 8] and meets application requirements. Method [1] has poor efficiency because it uses soft matting to process large sparse matrices, consuming substantial computational resources. Algorithm [8] uses the ICA method, which has high execution efficiency.

Table 2. Efficiency Comparison of Different Methods (ms)

Resolution	Method [1]	Method [3]	Method [5]	Method [8]	Our Method
320×480					
420×550					
480×600					
550×620					
600×720					

5 Conclusion

This paper estimates unknown parameters of the atmospheric optical physical model, including atmospheric light value A and transmittance $t(x, y)$. The sky region is obtained through threshold segmentation, and binary tree search is applied to this region to obtain a more accurate atmospheric light value. Adaptive anisotropic Gaussian filtering is used instead of soft matting to process transmittance. Compared with methods [1, 3, 5, 8], our method is clearer, more natural, and effective, though results contain minimal image noise and color shift. Our method is particularly suitable for images where the sky region occupies a large proportion. Future work will focus on applying this method to dynamic video image processing.

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