Postprint: Image Dehazing Method Based on Visual Color Perception and Optical Similarity

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Abstract

To address the severe degradation of outdoor image quality caused by haze environmental effects, an image dehazing method based on visual color perception-optical similarity is proposed. By fully exploiting the visual mechanism of human color perception and combining it with the principle of image similarity, an optical similarity function is constructed, a novel image dehazing model based on visual color perception-optical similarity is established, and corresponding algorithms are designed, followed by simulation verification. Simulation experimental results demonstrate that the proposed method achieves significant effects in the process of hazy image clarification. Furthermore, through comparative analysis of dehazing performance with existing image dehazing methods in terms of subjective visual quality and objective quantitative metrics, it is shown that the proposed method obtains favorable results in hazy image processing.

Full Text

Abstract

This paper proposes an image dehazing method based on vision color perception-photometric similarity to address the severe degradation of outdoor image quality caused by haze environments. By fully utilizing the human visual mechanism for color perception and combining it with image similarity principles, we construct an optical similarity function, establish a novel image dehazing model based on vision color perception-photometric similarity, design the corresponding algorithm, and conduct simulation verification. Experimental results demonstrate that the proposed method achieves obvious effects in the process of hazy image clarification. Compared with existing image dehazing methods in terms of both subjective visual quality and objective quantitative metrics, the proposed method obtains better results in hazy image processing.

Keywords: vision color perception; image similarity; image dehazing

0 Introduction

As a critical medium for human perception of external information, images have become inseparable from human life. However, images acquired in real-world conditions suffer from quality degradation due to various factors. In particular, outdoor images are often severely degraded by frequent haze and fog weather, with many important image features obscured by fog, thereby limiting their subsequent application value [1]. In response to the practical demand for hazy image processing, numerous scholars have dedicated research efforts to image dehazing since the 1950s. Existing image dehazing methods primarily follow two research directions: one focuses on hazy image characteristics from the perspective of image contrast enhancement, while the other approaches from image restoration methods based on physical models [2].

From the contrast enhancement perspective, early research mainly employed histogram equalization methods. While such methods can improve the visual effects of dehazed images to some extent, they process the entire image uniformly, failing to adequately preserve local detail information. Consequently, Kim et al. [3] proposed a local overlapping sub-block histogram equalization method for image dehazing to enhance local details. Ai et al. [4] achieved detail restoration in dehazed images by eliminating differences between histograms of neighboring sub-blocks. Additionally, methods based on Retinex and wavelet transforms have been applied to image dehazing to enhance image contrast. For instance, improved algorithms based on single-scale Retinex [5] employ fitting functions that conform to human visual characteristics for adaptive adjustment of the single-scale Retinex function, thereby enhancing color features and expanding dynamic range in hazy images. Recognizing the low-frequency characteristics of haze information in hazy images, Cao et al. [6] further extended the Retinex algorithm in the wavelet domain, processing haze and target information at different scales to further improve dehazed image quality.

From the physical model perspective, based on the physical meaning of haze formation, dehazed images are obtained by constructing and inversely solving atmospheric physical models. Kopf et al. [7] first acquired 3D geographic information features such as scene depth and surface texture through Google Earth, then solved the atmospheric physical model to restore images. Narasimhan et al. [8] obtained such information through interactive user input to derive dehazed images. In recent years, He et al. [9] creatively proposed a dark channel prior-based image dehazing method, which demonstrates good performance for most hazy image restoration based on statistical priors from numerous outdoor images. Furthermore, He et al. [10] improved the dark channel prior method by employing guided filtering to refine the transmission map, thereby enhancing dehazing performance and reducing computational complexity. This paper proposes a vision color perception-photometric similarity-based image dehazing method that fully utilizes human visual color perception characteristics, combines them with image similarity computation models, constructs a novel vision color perception-photometric similarity-based image dehazing model, and then estimates transmission rates and atmospheric light values to restore images.

1 Methodology

1.1 Human Visual Color Perception Mechanism

1.1.1 Physiological Mechanism of Human Visual Color Perception Human color perception occurs through two primary processes: retinal photoreception and retinal neural information transmission. The first process involves the trichromatic mechanism, where cone cells produce different response channels to light stimuli of different wavelengths (long, medium, and short). The second process is the retinal neural information transmission stage, known as the opponent-process mechanism, where the three trichromatic channels interlace to form opponent color channels: black-white, red-green, and yellow-blue. The first process primarily completes the retinal response to light sources, while the second process accomplishes the fusion of opponent color channels in visual neurons. Visual system receptive field neurons interlace with each other, forming more complex color visual perception. Figures 1(a) and 1(b) [Figure 1: see original paper] illustrate the formation process of color vision in the retina and the propagation process of light sources in objects [11].

1.1.2 Human Visual Color Perception Model How the human retina perceives object colors to accomplish visual information processing has long been a hot research topic in human visual system studies, with visual color computation models serving as effective tools to elucidate this problem [12,13]. As shown in Equation (1), object color information is encoded into the three-primary-color system through three different cone cells. Considering the electrical coupling between adjacent cone cells, for input image $I_c(x, y)$, the cone cell response is given by [14]:

$$F_c(x, y) = I_c(x, y) * g(x, y; \sigma)$$

where $*$ is the convolution operator and $g(x, y; \sigma)$ is a two-dimensional Gaussian function simulating the cone receptive field:

$$g(x, y; \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

where σ is the standard deviation of the two-dimensional Gaussian function, primarily controlling its smoothing degree. In this model, based on experimental experience, σ is set to 3.0, and the sliding window size during image processing is 3×3.

1.2 Image Optical Similarity Computation Model

1.2.1 Image Similarity Reference [15] presents the similarity assumption, principle, related proofs, and image similarity computation model for two-dimensional images. Let I represent a two-dimensional image with pixel points $i \in I$, and $|I|$ denote the cardinality of set I. The image similarity computation model can be expressed by Equation (3):

$$\lim_{||I|| \to \infty} \frac{u(I)}{v(I)} = 1$$

Equation (3) indicates that the similarity of an image increases as the cardinality of its pixel set increases. In Equation (5), N_i represents the set of pixel points centered at pixel i with processing window size $d \times d$, N_0 is the set of pixel points containing the center point i, h is a weighting factor, and $v(i)$ represents the vector formed by pixel values. The weighted norm of vector $v(i)$ can be calculated as:

$$||v(i)|| = \sum_{j \in N_i} w_{i,j} \cdot ||v(j) - v(i)||$$

where the translation transformation between pixels in the image is T, i.e., $N_j = T(N_i)$, and a_k is a weighting parameter, generally represented by Euclidean norm.

1.2.2 Image Photometric Similarity Function During image acquisition, the external illumination environment directly affects image quality, particularly in space exploration or aerial photography where limited lighting conditions have more pronounced effects on acquired image quality. Furthermore, extensive research indicates that image pixel values follow a Gaussian distribution within [0,255], and within adjacent pixel sets, image pixel values also follow a Gaussian distribution in local regions. This reveals that two-dimensional images exhibit Gaussian distribution in local regions with certain similarity, providing a basis for subsequent mathematical modeling of image similarity. Simultaneously, similarity is an empirical measure summarized by humans in the process of recognizing external object characteristics, perceiving their features, and identifying key attributes of objects, forming the foundation for further discrimination and reasoning [16]. Therefore, based on the similarity of two-dimensional images and the close correlation between images and illumination environments [17], this paper establishes an image photometric similarity function (PSF) defined as follows:

$$PSF(i,j) = \sum_{q=-m}^{m} \sum_{l=-n}^{n} w_{i,j} \cdot \exp\left(-\frac{(I(i,j) - I(i+q, j+l))^2}{2\sigma_p^2}\right) \cdot \exp\left(-\frac{(I(i,j) - I_{mean})^2}{2\sigma_g^2}\right)$$

The parameter $w_{i,j}$ in Equation (7) is determined by:

$$w_{i,j} = \begin{cases} 1 & \text{if } I(i,j) \in \Omega \\ \max[255, I(i,j)] & \text{if } I(i,j) \in \Omega_{dark} \\ \text{mean}(I(x,y)) & \text{otherwise} \end{cases}$$

where $I(i,j)$ represents the pixel value in the image, the local region window size is $(2m+1) \times (2n+1)$, and σ_p and σ_g are local and global similarity factors, respectively, which can adaptively smooth the image and protect image detail information based on image similarity.

1.3 Visual Color Perception-Photometric Similarity-Based Image Dehazing Model

1.3.1 Atmospheric Scattering and Foggy Imaging Model Light propagates through the atmosphere, interacts with objects, and reflects to form images, as shown in Figure 1(b). In clear weather conditions, object reflected light is essentially unaffected by atmospheric molecules during imaging. However, in hazy environments, light propagation is affected by atmospheric aerosol particles, primarily through three mechanisms: absorption, radiation, and scattering. Absorption and radiation have relatively minor effects, while scattering significantly impacts object imaging and is considered the main cause of optical image degradation. This paper focuses on atmospheric scattering, which can be described by the atmospheric scattering mathematical model shown in Equations (9)-(11):

$$E(d, \lambda) = E_0(\lambda) \cdot e^{-\beta(\lambda)d} + E_\infty(\lambda) \cdot (1 - e^{-\beta(\lambda)d})$$

$$\beta(\lambda) \propto \lambda^{-\gamma}, \quad 0 \leq \gamma \leq 1$$

$$\beta \approx \text{constant}$$

where d is the distance between the measured target in the actual scene and the observer, $E_0(\lambda)$ is the unattenuated reflected light at zero distance from the target surface, $E_\infty(\lambda)$ is the atmospheric light at the horizon infinity, and β is the scattering coefficient, whose relationship with incident light wavelength λ is shown above.

The foggy imaging model in reference [18] indicates that images acquired in hazy environments are affected by atmospheric particles to varying degrees. Since atmospheric particle radii are typically larger than visible light wavelengths, the atmospheric light scattering coefficient has no significant effect on visible wavelengths and can be approximated as constant. Equations (9)-(11) can be simplified to the physical model of foggy image imaging:

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

where $I(x)$ is the hazy image, x represents image pixel coordinates, $J(x)$ is the attenuated reflection light image, A is the atmospheric light component, and $t(x)$ is the medium transmission function reflecting the ability of atmospheric light to pass through the transmission medium, i.e., the transmission rate.

1.3.2 Visual Color Perception-Photometric Similarity-Based Image Dehazing Model Based on the above content, we construct the visual color perception-photometric similarity-based image dehazing model as follows:

$$J_c^{dark}(x) = \min_{y \in \Omega(x)} \left(\min_{c \in \{R,G,B\}} F_c(y) \right)$$

where J_c^{dark} is the dark channel of a certain color channel among the R, G, and B channels in the original image J, F_c represents any one of the three color channels of the original image J as perceived by human vision, $\Omega(x)$ denotes a local region sliding window centered at pixel x, y is the position coordinate, and c is the color channel. According to the dark channel prior theory proposed in reference [9], we have:

$$\sum_{q=-m}^{m} \sum_{l=-n}^{n} \exp\left(-\frac{(I(i,j) - I(i+q, j+l))^2}{2\sigma_p^2} \right) \cdot \exp\left(-\frac{(I(i,j) - I_{mean})^2}{2\sigma_g^2} \right) \cdot w_{i,j} \cdot J_c^{dark}(i,j) \to 0$$

This model can effectively solve the color distortion problem in images after dehazing.

1.3.3 Transmission Rate Estimation Transforming the foggy image physical model Equation (13) for different color channels perceived by human vision yields:

$$I_c(x) = J_c(x) \cdot t(x) + A_c \cdot (1 - t(x))$$

The dark channel in each color channel is:

$$J_c^{dark}(x) = \min_{y \in \Omega(x)} \left(\min_{c \in \{R,G,B\}} J_c(y) \right)$$

According to the dark channel prior principle:

$$\min_{y\in\Omega(x)}\left(\min_{c\in\{R,G,B\}} J_c(y)\right)\to 0$$

Substituting Equation (19) into Equation (18) yields:

$$t(x)=1-\min_{y\in\Omega(x)}\left(\min_{c\in\{R,G,B\}}\frac{I_c(y)}{A_c}\right)$$

Combining with the constructed visual color perception-photometric similarity-based image dehazing model, we further improve Equation (20) to obtain the improved atmospheric transmission rate estimation model:

$$t(x)=1-\zeta\cdot\min_{y\in\Omega(x)}\left(\min_{c\in\{R,G,B\}}\frac{PSF(I_c(y))}{A_c}\right)$$

where ζ is a weighting coefficient to retain a small amount of haze and increase image realism. In this paper, the value is set to 0.96.

1.3.4 Atmospheric Light Estimation In reference [9], He et al. determined atmospheric light by selecting the brightest 10% of pixels in the dark channel map and finding the maximum values in the corresponding three color channels of the original image. Following this approach and fully incorporating the human visual color perception computation model, this paper proposes an improved atmospheric light estimation model:

$$A_c=\max_{x\in\Omega_{dark}}\left(PSF(I_c(x))\right)$$

where Ω_{dark} represents the set of pixels in the dark channel.

1.3.5 Visual Color Perception-Photometric Similarity-Based Image Dehazing Algorithm The proposed algorithm is presented below, with the flowchart shown in Figure 2 [Figure 2: see original paper].

Algorithm 1: Visual Color Perception-Photometric Similarity-Based Image Dehazing Method

Input: Hazy image $I(x,y)$ with size $M\times N$
Output: Dehazed image $J(x,y)$ with size $M\times N$

Step 1: Select pixel point $x(i,j)$ from the hazy image to be restored (i.e., from the set of $M\times N$ pixel points). (Note: $1\le i\le M$ and $0\le j\le N$)

Step 2: Initialize relevant parameters σ, σ_p, σ_g, and ζ

Step 3: Obtain the dark channel J_c^{dark} according to Equation (19)

Step 4: Obtain the atmospheric transmission map $t(x)$ according to Equation (21)

Step 5: Obtain the atmospheric light value A according to Equation (22)

Step 6: Restore the dehazed image $J(i, j)$ in the scene according to Equation (13)

2 Experimental Results

2.1 Simulation Experiment Test Platform

For the proposed visual color perception-photometric similarity-based image dehazing method, we use Matlab2017b as the simulation test platform to complete image dehazing simulation verification. Six typical test images are selected, as shown in Figure 3 [Figure 3: see original paper].

2.2 Experimental Results of the Proposed Method

The dehazing results using the proposed method are shown in Figure 4 [Figure 4: see original paper], where (a) shows the hazy images, (b) shows the transmission maps estimated during the dehazing process using the proposed method, and (c) shows the clear images after dehazing.

The experimental results demonstrate that the proposed visual color perception-photometric similarity-based image dehazing method can effectively remove haze from hazy images, significantly improve image quality, and better preserve image detail information to a certain extent. For example, in Figure 4(a), fallen leaves on the distant ground are clearly visible; in Figure 4(b), the clarity of buildings is significantly improved compared to the hazy images; in Figure 4(c), distant mountains and skies appear clearer; Figure 4(d) shows the clarified presentation of Tiananmen; Figure 4(e) demonstrates that depth information of lawns and lake water can be clearly displayed; and Figure 4(e) shows that plants can be distinctly visualized.

In summary, the proposed visual color perception-photometric similarity-based image dehazing method can significantly improve the quality of hazy images both in terms of visual effects and detail information preservation.

2.3 Comparison with Other Methods

The visual color perception-photometric similarity-based image dehazing method is compared with existing methods including the bilateral filtering-dark channel prior method [9], soft matting method [10], unoptimized transmission map method, and recent methods such as the non-local image dehazing method proposed by Berman et al. [19] at CVPR 2016 and the two-layer Gaussian regression image dehazing method proposed by Fan et al. [20] in 2017. The comparison results are shown in Figure 5 [Figure 5: see original paper].

Compared with other methods, the proposed method demonstrates certain advantages in image detail preservation, color protection, and clarity. For instance, in the first row of images in Figure 5 (forest images), the proposed method shows better dehazing effects on distant areas compared to other traditional and recent methods. In the sky portion of the second row and the lake-boundary junction in the third row, the proposed method exhibits better capability for protecting image colors.

This paper employs a no-reference sharpness evaluation algorithm (GI_F) [21] based on gradient information and human vision system (HVS) filters for quantitative evaluation of the proposed method' s effectiveness, as shown in Table 1 .

Table 1: GI_F Comparison Results Between Other Image Dehazing Methods and the Proposed Method

Method	GI_F Score
Guided Filtering and Dark Channel Prior	
Soft Matting	
Local Methods	
Berman et al. Non-Local	
Fan et al. GPR2	
Proposed Method	

3 Conclusion

This paper proposes a visual color perception-photometric similarity-based image dehazing method that fully utilizes the human visual mechanism for color perception, combines it with image similarity principles, constructs an optical similarity function, establishes a visual color perception-photometric similarity-based image dehazing model based on the dark channel prior, designs the corresponding algorithm, and conducts simulation verification. Experimental results show that the proposed method achieves obvious effects in hazy image clarification. Comparison with existing image dehazing methods further demonstrates that the proposed method obtains better results in hazy image processing. Future research will focus on further optimizing the parameters of the constructed dehazing model according to the visual characteristics of hazy images.

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