Progress in Medical Devices
eISSN: 2957-5478

Review Article https://doi.org/10.61189/145362zgyopx

Research progress and applications of image defogging algorithms

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Declaration of conflict of interest: None.

Received April 25, 2023; Accepted August 28, 2023; Published September 30, 2023

Highlights

- The mainstream defogging algorithms can be classified into three categories based on their principles: image enhancement-based, physical model-based, and neural network-based.
- This paper aims to introduce and explore these categories, as well as to provide an outlook on the application and possible future development directions of defogging algorithms.

Abstract

Images taken under hazy weather conditions suffer from problems such as blurring, low contrast, and low saturation due to the scattering of atmospheric light by aerosol particles in the air, which affects the performance and judgment of image analysis equipment. With the rapid development of image processing technology and computer vision technology, researchers have proposed a large number of targeted haze removal algorithms to improve the quality of images taken under hazy weather conditions. According to the haze removal principle, mainstream haze removal algorithms can be classified into three categories: image enhancement-based, physics model-based, and neural network-based. This paper introduces and explores classic haze removal algorithms from the perspectives of principles, development, advantages, and disadvantages, and outlines the prospects for the future development and application direction of haze removal algorithms.

Keywords: Haze removal algorithm, image enhancement, physics model, neural network.

Introduction

With the rapid development of computer vision technology, image processing techniques such as object detection, classification, and tracking have become research hotspots [1, 2]. Image processing systems require high image quality, as image quality directly affects system operating efficiency and output [3]. Under special weather conditions such as haze, a large number of aerosol particles suspended in the air refract and scatter atmospheric light, making it difficult for imaging devices to obtain clear reflected light signals. The resulting images may exhibit loss of details, low contrast and saturation, color shifts, and other defects, which are not conducive to image information extraction and assessment [4]. Therefore, using image processing techniques to obtain high-quality images is of great research value.

Over the years, researchers have proposed various defogging strategies. Early defogging algorithms aimed to enhance the global contrast of images and highlight their details to achieve the defogging effect, such as histogram equalization, Retinex algorithm, and wavelet transform [5-10]. With the proposal of atmospheric scattering models, researchers have established the mapping relationship between hazy images and haze-free images by analyzing atmospheric light scattering and attenuation, and reversed this relationship to obtain dehazed images [11-14]. There are also defogging algorithms based on neural networks. With the rapid development of deep learning technology, two strategies of neural network-based defogging algorithms have emerged: one is the end-to-end model, which directly finds the mapping relationship between hazy and haze-free images

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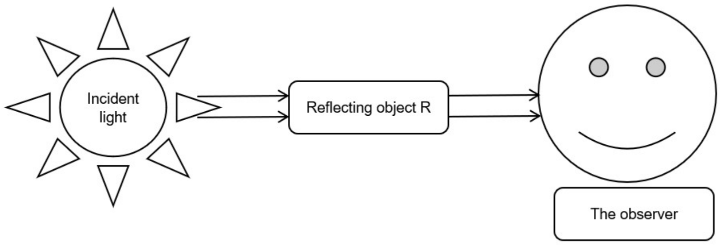

Figure 1. Theoretical model of Retinex.

through the powerful analytical capabilities of neural networks and outputs haze-free images; the other is the non-end-to-end model, which restores haze-free images by inferring key parameters of the atmospheric physical model [15-23].

Defogging algorithms have been widely used in target detection, intelligent driving, industrial image dust removal and other fields, but the application of defogging algorithm in the field of medical image is relatively simple. According to the differences in implementation principles, we divide the existing mainstream defogging methods into three categories: image enhancement-based, physical model-based and neural network-based, summarize the principles of the three defogging methods, and outline the advantages and disadvantages of the three defogging methods. In this paper, we expound the application status of defogging algorithm in industrial field and look forward to the research and development direction of defogging algorithm in medical image field.

Review of three kinds of defogging algorithms

Defogging algorithm based on image enhancement

Early haze removal algorithms aimed to enhance the global contrast of the image and highlight its details, such as histogram equalization, Retinex algorithm, and wavelet transform. The Retinex algorithm decomposes the image into an illumination component and a reflectance component, and eliminates the influence of the reflectance component according to the atmospheric scattering model to achieve haze removal. Histogram equalization stretches the image to improve its contrast and detail information, while wavelet transform enhances the image's temporal and frequency resolution, enlarging useful information to achieve haze removal [5-10].

Histogram equalization algorithm

The grayscale histogram is a graphical representation of the distribution of pixel grayscale values in an image, which can display information about the brightness, pixel values, and other characteristics of the image. The main idea of histogram equalization is to transform the distribution of the image histogram into an approximately uniform distribution through a cumulative distribution function, thereby enhancing the image contrast. To expand the brightness range of the original image, a mapping function is required to map the pixel values of the original image to the histogram in the range of (0, 255). The linear transformation process can be expressed as follows:

$$h(v) = round(\frac{s_x - s_{\min}}{N - s_{\min}} \times (L-1) \qquad (1)$$

s_x is the gray level distribution function, and L is the maximum gray level of the image. The classical global histogram equalization algorithm has good contrast enhancement and fog removal effects on images with single depth of field variations. However, it often results in the merging of low-frequency gray levels, excessive enhancement of high-frequency gray levels, and halo artifacts, leading to loss of image details.

Retinex algorithm

The Retinex theory holds that the incident light determines the dynamic range of all pixels in an image, while the inherent invariant reflection coefficient of the object itself determines the inherent properties of the image. That is, the image we perceive is formed by the light reflected off an object according to its reflection coefficient, as shown in **Figure 1** [24].

The core mathematical expression of the theory is:

$$S(x,y) = R(x,y) \times L(x,y) \qquad (2)$$

S(x,y) represents the final image result, R(x-,y) represents the reflectance function of the object to light, and L(x,y) represents the illumination function. The single-scale Retinex algorithm assumes that the final reflectance image is a smoothed image, and convolves

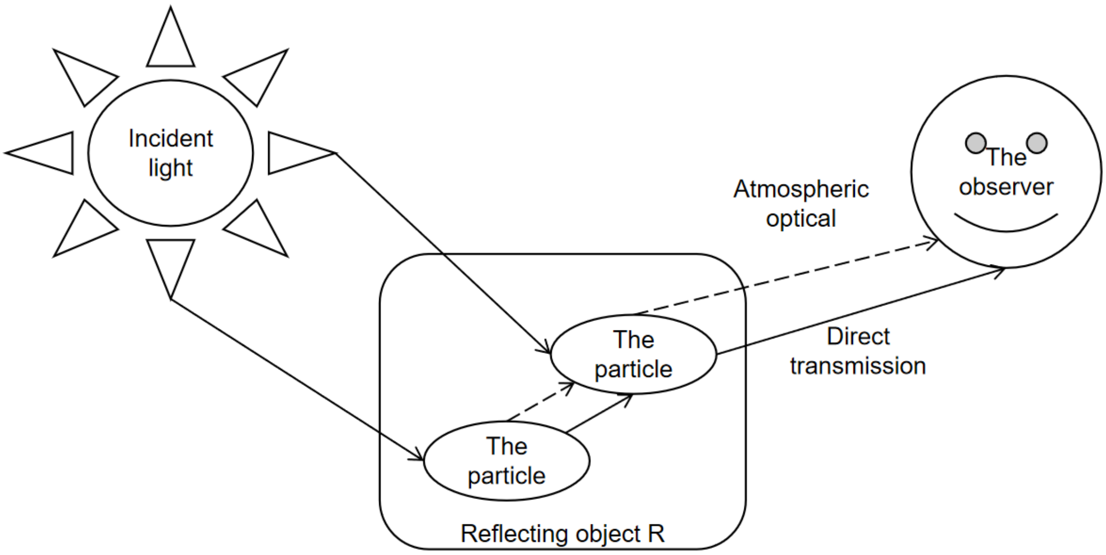

Figure 2. Atmospheric scattering model.

the original image with a Gaussian filter. It estimates the illumination changes in the image by calculating the weighted average of the pixels in the surrounding area, and finally retains the reflection properties of the object in the image, which is equivalent to performing low-pass filtering on the original image to obtain the low-pass filtered image. However, this algorithm has drawbacks such as high complexity, easy occurrence of halos, and easy distortion.

Wavelet transform algorithm

The wavelet transform algorithm decomposes the original image signals into high-frequency and low-frequency images at multiple scales. Since haze mainly affects the low-frequency part of the image, this algorithm enhances the contrast of the image by enhancing the high-frequency coefficients, thus achieving the effect of haze removal. The algorithm processes multi-channel images and merges them. However, there are issues such as possible distortion and high computational complexity.

Defogging algorithm based on physical model

Most image enhancement-based defogging algorithms propose defogging strategies from the perspectives of image brightness, contrast, saturation, etc. The defogging effect of these algorithms is often limited. In comparison, physical model-based defogging algorithms have more stable and efficient characteristics.

Atmospheric scattering model

In 1999, Narasimhan et al. proposed an atmospheric scattering model based on the theory of atmospheric scattering, as shown in **Figure 2** [25, 26]. The model assumes that the light received by the imaging system mainly comes from two parts: one is the light reflected by the target which attenuates and reaches the imaging system, and the other is the atmospheric light formed by the particle scattering of the light source.

The mathematical model for foggy image formation obtained through this physical model is as follows:

$$I(x) = J(x)t(x) + A(1 - t(x) \tag{3}$$

where I(x) is the captured foggy image, J(x) is the corresponding clear image, A is the atmospheric light intensity, and t(x) is the haze transmission rate, which can be expressed as:

$$t(x) = e^{-\beta \bullet d(x)} \tag{4}$$

where β is the atmospheric scattering coefficient, and d(x) represents the depth of field information of the pixel. Formula (3) can be divided into two parts. The first part, J(x)·t(x), represents the direct attenuation term, indicating that the reflected light of the target scene exponentially decays with the increase of depth of field. The second part, A(1-t(x)), represents the atmospheric light that enters the imaging device after being scattered by the haze. By inversely solving the atmospheric light intensity A and the transmission rate t(x) in the model, the resulting image can be defogged. Based on this, researchers have proposed three defogging strategies, which are based on additional information, image differences, and single-image, respectively.

Extra information-based defogging

In some specific situations, the key parameters in the atmospheric scattering model can be obtained by measuring the real-world haze condition, which can be used to recover a haze-free image. For example, the interactive defogging strategy proposed by Narasimhan et al. establishes a data transmission channel between the user and the system, where the user provides information such as atmospheric light intensity and sky position, and the key parameters in the model can be solved to obtain the recovered image [27]. Kopf et al. obtained the key parameters by acquiring a 3D model of the target location, which includes important information such as depth of field, from the Internet, and then used the model to generate a haze-free image [28]. Although extra information-based defogging algorithms produce good results, the acquisition of geographic and lighting information in real-world scenarios is difficult, which limits their practical application.

Image-difference-based defogging

The image-difference-based defogging algorithms estimate the model parameters by studying multiple sets of hazy or haze-free images of the same target scene, thus obtaining the haze-free image. For example, Shwartz et al. proposed a self-calibrated parameter defogging algorithm based on polarization characteristics. By installing a polarizing filter on the imaging device and using different polarization angles to capture three images with different optical characteristics, the atmospheric light intensity can be derived to obtain haze-free images [29]. Although the image-difference-based defogging algorithms perform well, they are cumbersome and expensive, which is not conducive to practical applications. Therefore, researchers have focused on single-image-based defogging algorithms.

Single-image-based defogging

The most widely used defogging algorithm based on atmospheric physics models is the dark channel prior algorithm proposed by He et al. in 2009 [30]. The authors observed the dark channel of more than 5,000 haze-free images and found that about 75% of the pixel values were 0, and 90% of the pixels had very low values [31]. They proposed the dark channel prior theory, which states that for a haze-free image, its dark channel can be represented as:

$$J_{dark} = \min_{y\in\Omega(x)}(\min_{c\in\{r,g,b\}}(J^c(y))) \qquad (5)$$

where J represents the haze-free image, J_{dark} represents the dark channel image, C represents any channel of the R, G, and B channels of the image, and Ω(x) represents the window at pixel point x. According to the dark channel prior theory, the transmission rate t(x) can be derived as:

$$J_{dark} \longrightarrow 0 \qquad (6)$$

Assuming that the transmission rate t(x) is constant, the atmospheric light intensity A can be obtained by selecting the top 0.1% brightest pixels in the dark channel image of the hazy image and locating the corresponding brightness point with the highest value in the original hazy image, as shown in Eq. (7):

$$\min_{y\in\Omega(x)}(\min_c \frac{Ic(y)}{Ac}) = t(x)\min_{y\in\Omega(x)}(\min_c \frac{Ic(y)}{Ac}) + 1 - t(x) \qquad (7)$$

According to the dark channel prior theory, the transmission rate t(x) can be derived as:

$$t(x) = 1 - \omega \min_{y\in\Omega(x)}(\min_c \frac{I^c(y)}{A^c}) \qquad (8)$$

He et al. argued that a clear sky can be regarded as a state of light fog, and depth of field information can be reflected through the density of the fog [30]. Therefore, a density factor, ω, is introduced to retain a certain degree of fog, and typically set to 0.95.

The dark channel prior defogging algorithm can restore clear, haze-free images with stability and high efficiency. However, there is a problem of distortion in defogging the sky region, leading to the emergence of a series of improved algorithms.

Defogging algorithm based on neural network

With the rapid development of deep learning technology, researchers have proposed a series of neural network-based defogging algorithms, which can be divided into two categories based on different defogging principles: non-end-to-end algorithms based on atmospheric physics models, such as the classic DehazeNet algorithm, and end-to-end defogging algorithms, such as the classic GCANet algorithm.

DehazeNet, proposed by Cai et al. in 2016, is a non-end-to-end defogging algorithm, and its network structure is shown in **Figure 3** [32]. The network consists of four parts: feature ex-

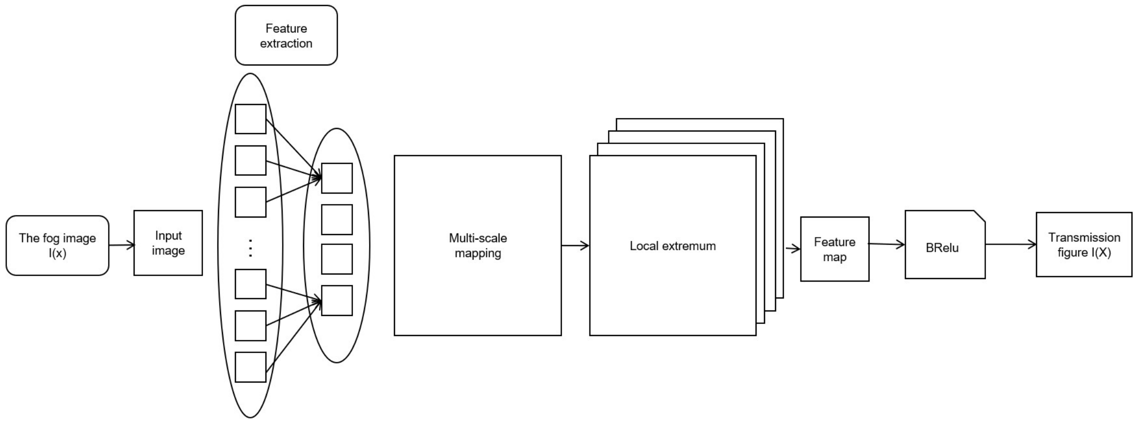

Figure 3. DehazeNet.

traction, multi-scale mapping, local extremum, and non-linear regression. Its input is a hazy image, and the output is the image's transmission rate map, which is then used to recover haze-free images based on the atmospheric physical model. Specifically, the structural design of the feature extraction layer of this algorithm combines four traditional algorithms: dark channel prior defogging algorithm, maximum contrast defogging algorithm, color attenuation prior algorithm, and defogging algorithm based on chromatic inconsistency. This fusion of neural networks and traditional algorithms leverages the powerful performance of the neural network to improve the traditional algorithms, providing new ideas for defogging algorithm research.

GCANet is an end-to-end image defogging algorithm based on the Generative Adversarial Network proposed by Chen et al. [33]. The network takes hazy images as input and directly outputs clear haze-free images. The algorithm consists of three convolutional blocks as the encoder part, one deconvolutional block, and two convolutional blocks as the decoder part. The algorithm focuses on using smooth convolution instead of dilated convolution to solve the problem of grid artifacts, and improves the defogging effect of the image by combining more contextual information and fusing different levels of features.

Current status of defogging algorithms

Based on image enhancement

To address the problem of excessive enhancement in the histogram equalization-based defogging algorithm, Kim et al. added contrast limiting modules to limit the enhancement, but leading to high algorithm complexity [34]. Soni et al. proposed an adaptive histogram equalization algorithm, which effectively improved the algorithm's efficiency and output results [35]. However, the histogram equalization-based algorithm only relies on the image's grayscale features, which are less robust and prone to additional noise.

Jobson et al. proposed a multi-scale Retinex algorithm based on the single-scale Retinex algorithm that effectively solved the halo problem but caused color distortion in the image [36]. To address this issue, researchers have proposed many improved algorithms. For example, Jobson et al. added a color restoration module based on multi-scale Retinex to propose a multi-scale Retinex with color restore algorithm, which effectively solved the color distortion problem in the defogging process [37]. The Retinex algorithm has made remarkable progress in addressing halo and color distortion problems, but with high complexity [6, 38].

Liu et al. proposed to use wavelet transform on the brightness information in the HSV space of the image, enhancing the brightness of high-frequency part of the image and suppressing that of the low-frequency part, and then restoring the color to achieve defogging [31]. This approach can reduce the algorithm's complexity. Wavelet transform has the advantage of processing images at multiple scales, and some researchers have fused wavelet transform algorithms with other algorithms for defogging. For example, Wang et al. processed foggy images with wavelet transform, sharpened the image with high-frequency signals, and then enhanced the image with server side render, effectively improving the defogging efficiency of the algorithm [39].

Histogram equalization, Retinex algorithms, and wavelet transforms, which are based on image enhancement, mainly adjust pixel values based on the image's statistical information or highlight local details in the image to achieve defogging effects. Essentially, they are all image enhancement techniques. The histogram equalization algorithm has low complexity, can enhance the image's brightness and contrast, but its robustness is poor and can easily generate additional noise. This algorithm is suitable for thin fog images that require brightness enhancement or have high resolution, but its limitations are significant when enhancing haze removal mages. Future research directions aim to enhance the algorithm's flexibility to apply to images with significant differences, but this could potentially further increase the algorithm's complexity. The Retinex algorithm and its modification algorithms are relatively comprehensive, especially the multi-scale Retinex with color restore algorithm, which performs well in haze removal, thick fog, and low light conditions and has good visual outcomes. However, the Retinex series algorithms have high complexity. Wavelet transforms depend on parameter selection, and the parameters are different under different light intensities and background conditions. This approach generally cannot be applied solely to defogging.

Based on physical models

Xiao et al. proposed a scene-aware defogging algorithm by using gamma correction based on sky segmentation, which solved the color distortion problem but could cause excessive enhancement in high-light areas [40]. Li et al. proposed a threshold-based sky region segmentation algorithm in 2021, which has good defogging effects on the sky region but has a high computational complexity [41].

Zhu et al. proposed a defogging strategy based on the color attenuation prior in 2015 [42]. The color attenuation prior theory suggests that the difference between the brightness and saturation of outdoor images is positively correlated with the haze concentration. This algorithm creates a linear model to simulate the scene depth of a hazy image and uses supervised learning methods to learn the model parameters, effectively restoring the image depth information. Then, the atmospheric scattering model is used to derive parameters such as the transmission rate to obtain a dehazed image. Yang et al. proposed using machine learning methods to derive depth-of-field information and achieve defogging effects based on the color prior theory, but the algorithm's stability is poor [43].

Defogging algorithms based on physical models rely on the imaging principles of images and atmospheric light scattering models and have some theoretical support from physics. Although defogging strategies based on additional information and image differences can achieve good defogging effects, they rely heavily on geographic information and databases, which limits their practical applications. Defogging algorithms based on the dark channel prior and color attenuation prior have less dependence on additional information. The dark channel-based defogging algorithm performs well on thin haze images, but its performance is poor in strong light, thick fog, and mist conditions. The color attenuation prior-based algorithm performs poorly on images with severe color distortion and unclear image gradient structure. Overall, defogging algorithms based on physical models have better visual outcomes, and the defogging process does not introduce additional noise, but they are severely limited by the scene.

Based on Neural network

Wang et al. proposed the STCSDN (semi training color stripping dehaze-net) defogging algorithm based on DehazeNet [44]. The algorithm assumes that convolutional neural networks have two properties in the defogging process: 1) they learn contour and shadow information faster than color information, and 2) the network is not sensitive to the concentration of haze. STCSDN uses cycle generative adversarial network and a semi-trained generator as a feature extraction module to extract haze-free grayscale images from blurry color images. The algorithm can handle haze images with different concentrations, and can effectively restore image details and enhance visual outcomes. Yang et al. proposed a hybrid iterative model that combines the dark channel prior theory and DehazeNet algorithms to better restore haze-free images that are closer to real scenes, but the algorithm is computationally complex [45]. Non-end-to-end defogging algorithms have the support of physical theory, which makes the dehazed images closer to real scenes, but they have higher parameter count and lower algorithmic simplicity.

Similarly, Engin et al. enhanced the cycle generative adversarial network formula by combining cycle consistency and perceptual loss to improve the model's ability to recover texture information, so as to obtain haze-free images with better visual outcomes [46]. Li et al. proposed the all-in-one network defogging algorithm based on convolutional neural networks, which can directly generate clear haze-free images according to the atmospheric scattering model [47]. End-to-end defogging strategies have better defogging effects, but they also suffer from issues such as more model parameters and difficulty in obtaining datasets.

Two deep learning-based defogging strategies are currently the research focus: (1) inferring certain parameters in the atmospheric scattering model using neural networks to obtain dehazed images, and (2) directly inputting hazy images and outputting haze-free images. The former can combine image enhancement algorithms with neural networks to enhance the visual outcomes of dehazing, but the parameter complexity also increases exponentially, and the stability of the algorithm is relatively poor. The latter eliminates the model's dependence on prior conditions and reduces a significant number of parameters, but the complexity increases further due to the intricate nature of real scenes and an excessive reliance on samples.

The application field of fog removal algorithm

With the thriving development of defogging algorithms based on three different strategies, defogging algorithms have been widely applied in various fields such as target detection in foggy weather, intelligent driving in foggy weather, and industrial image de-dusting. In the field of intelligent driving, autonomous driving relies on the detection of objects in the target scene. Haze can change the color of objects and weaken the brightness of the scene, affecting the performance of autonomous driving equipment. To address this issue, Ma et al. employed the Retinex algorithm to estimate the atmospheric light intensity and transmission rate based on physical properties such as color consistency in hazy images, thereby improving the road segmentation accuracy of the target scene [48]. Xu et al. replaced the soft matting process in the dark channel prior algorithm with two different filters to improve the real-time performance of dehazing, significantly improving the speed of video dehazing [49]. El-Hashash et al. also designed a real-time video defogging system based on the dark channel prior algorithm, greatly improving the performance of automatic driving in foggy weather [50].

In the field of remote sensing images, haze can cause imaging defects such as low contrast and low clarity, which are not conducive to the analysis of detailed information of images captured by devices such as drones and optical satellites. To address this issue, Huang et al. proposed an adaptive transmission rate estimation method based on the dark channel prior algorithm, according to the histogram of the dark channel image and the maximum transmission rate constraint, to obtain high-fidelity optical satellite images [51]. Li et al. proposed an end-to-end convolutional neural network defogging algorithm, which first improved the atmospheric scattering model into an end-to-end defogging model, unified multiple unknown parameters, and used a multi-scale convolutional neural network to estimate the unknown parameters, and then input the estimated values into the model to obtain haze-free images [52]. This algorithm has different degrees of improvement in visual outcomes and objective indicators for hazy remote sensing images.

In the industrial field, underground coal mine images are characterized by low illumination, high dust, and high noise intensity, which makes it difficult to extract effective image information. To address this issue, Zhang et al. enhanced the underground images using histogram equalization, obtained the dark channel image from the thumbnail image, and restored the pixel values of the image using bilinear interpolation to improve the algorithm's running speed [53]. This algorithm improved the defogging effect of underground coal mine images and increased the algorithm processing speed. Wu et al. also proposed a defogging method for degraded underground coal mine images based on the dark channel prior algorithm [54]. The algorithm weakened the influence of dust and water mist in the environment, achieving image enhancement. Similarly, researchers from Anna University implemented underwater image defogging and color correction based on the single-scale Retinex algorithm with color correction [55].

In the field of medicine, the visibility and analyzability of medical images have a great impact on the diagnosis of diseases. Defogging algorithms are often used for denoising and enhancement in the medical image field, but the application scenarios are relatively single. For example, Chen et al. combined the dark channel prior algorithm and the Retinex algorithm in a continuous sequence of medical images to achieve denoising of CT images and MRI images, effectively improving the image contrast [56]. Justin et al. proposed a local contrast mapping scheme based on the histogram equalization algorithm, achieving controllable denoising of MRI images [57].

In special scenarios, medical images may exhibit fog-like appearances. Applying physical model-based defogging algorithms to such medical images can provide critical diagnostic indicators, enabling the quantification and grading of corresponding medical features through artificial intelligence. For example, the imaging-based features of interstitial pneumonia may include ground-glass opacities, consolidations, fibrotic stripes, thickened interlobular septa, traction bronchiectasis, nodules, and reticular opacities, which appear as fog-like features [58]. By applying defogging algorithms to pneumonia CT images, the X-ray transmission rate information of the local pneumonia medium can be obtained to quantify the severity of pneumonia in this area, ultimately achieving a scientific and automatic quantification and grading definition.

Summary

Currently, there are three main approaches for foggy image restoration: image enhancement-based, physics-based, and deep learning-based methods. Image enhancement-based strategies mainly enhance image contrast and highlight details using mathematical methods to achieve the goal of defogging. Physics-based image defogging strategies are mainly based on atmospheric scattering models, in which key physical parameters are derived to obtain haze-free images by inverse calculation. Deep learning-based methods utilize powerful computational and fitting abilities of neural networks to estimate the parameters in atmospheric scattering models or directly find the mapping relationship between hazy and clear images for defogging.

The defogging strategy based on image enhancement does not require prior information and is easy to apply, yet it often introduces noise and yields constrained defogging outcomes. In contrast, the physical model-based defogging strategy is supported by physical theory. The defogging algorithm based on this model has better visual outcomes, and introduces no additional noise during the defogging process. It is more stable and efficient, but requires a lot of prior information, making it difficult to apply, and severely constraining the applicable scenes. The defogging strategy based on deep learning can enhance the visual outcome of image defogging, but how to reduce the parameters of the model and reduce the excessive dependence on the sample is an urgent problem to be solved.

All three types of defogging algorithms have significant defogging effects, but there are still some research difficulties and challenges in the development of defogging algorithms, including:

(1) High spatio-temporal complexity of algorithms. Existing algorithms have good defogging outcomes, but their high complexity poses challenges in adapting them to complex scenes such as video defogging or real-time defogging, which is not conducive to the practical application of the algorithms.

(2) Difficulties in obtaining reliable datasets. Due to the uncontrollable factors such as lighting and fog density in real-life scenes, it is difficult to obtain high-quality pairs of hazy and clear images. The robustness and stability of deep learning algorithms require high-quality datasets, which limits the development of neural network-based defogging algorithms. To address the issue of data quantity and quality, considerable human and material resources must be invested. Alternatively, transfer learning or other methods can be used to alleviate dataset limitations.

(3) Difficulty in ensuring algorithm robustness. Existing defogging algorithms have good visual outcomes when applied to one or several specific application scenarios. How to further improve the robustness of the models is the focus of future research. Combining multiple defogging algorithms for different scenarios can be a solution to increase algorithm robustness.

(4) Further expansion of application scenarios. Defogging algorithms have been applied in intelligent driving, unmanned inspection, and other fields. However, in the field of medical image processing, defogging is still at the image enhancement stage, and there has been no research on fog-like symptoms such as pulmonary pneumonia. It is possible to model based on medical imaging principles and explore methods to solve the severity grading of pneumonia.

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