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A Survey of Image Dehazing Algorithms

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Abstract

Image dehazing, as an important aspect in the field of image processing, is mainly aimed at restoring image details, improving image contrast, and improving recognizability. This paper mainly starts from two aspects: traditional defogging methods and deep learning dehazing methods. Traditional algorithms mainly include image enhancement algorithm and physical model algorithm, while deep learning dehazing algorithm mainly includes convolutional neural network based dehazing algorithm and generative adversative network dehazing algorithm. According to the developed algorithms, the advantages and disadvantages of each algorithm will be discussed and the future prospects will be pointed out.

Keywords

Image Dehazing; Histogram Equalization; Dark Channel Prior; Atmospheric Scattering Model; Convolutional Neural Network; Generative Adversarial Network.

1. Introduction

Based on the different principles used, the image dehazing algorithm is generally divided into traditional dehazing algorithm and deep learning defogging algorithm. The traditional defogging algorithm includes dehazing based on physical model and defogging based on image enhancement. Image dehazing algorithm based on physical model. This algorithm is based on atmospheric scattering model, combined with assumptions and a priori information to achieve dehazing effect. It has strong pertinence for fog removal, and has a good effect on image detail restoration and color contrast restoration. The traditional dehazing based on image enhancement takes the fog in the image as a general image denoising to enhance the image and highlight the image details. This kind of algorithm has wide applicability., Based on the method of deep learning, this kind of algorithm has two principles. The first is the dehazing algorithm based on convolutional neural network (CNN), which uses the combination of CNN and atmospheric scattering model to infer some parameters to achieve the purpose of dehazing. The second method does not require the existence of prior information or assumptions, but mainly uses the direct image translation through neural network or the continuous training of data to learn its characteristics to achieve the transformation between foggy and non foggy images. This method has natural effect, stronger universality and easy to be popularized.

2. Traditional Image Dehazing Algorithm

In the traditional image dehazing algorithm, the precondition of image dehazing algorithm based on atmospheric scattering model is generally to select atmospheric light value and scene depth, and then the effect is different according to the selected characteristics or prior knowledge, such as contrast, color attenuation and dark channel prior. There are also a small number of image dehazing based on image enhancement. This method ignores the imaging reasons of fog map, processes fog as ordinary noise, and obtains a clear fog free image by exploring the original information of fog map and improving its contrast and sharpness.

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2.1 Atmospheric Scattering Model

The mathematical model established by Srinivasa g. Narasimhan[1] et al. Explains the elements and imaging process of fog imaging. Due to the absorption and scattering of suspended particles in the atmosphere, the energy of reflected light of the object is reduced, and the object is affected by the target light formed by the scattering of various ambient light, resulting in blurred imaging results and brightness Imaging with low contrast will result in poor quality. G. Mie obtains the strict solution of elastic scattering incident on spherical particles of arbitrary size and material through Maxwell equation. The atmospheric scattering model illustrates that the formation of a fog map is usually affected by two aspects: on the one hand, the incident light passes through the process of scattering and absorption before reaching the target; on the other hand, the scattering of various ambient lights makes it also participate in the imaging light, that is, atmospheric light. Its model is shown in Figure 1. The formula is shown in (1).

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

Where X represents the pixel points of the image, I (x) is the final fog map, J (x) represents the clear image waiting to be recovered, and T(x) represents the transfer function, that is, the part where the particles arrive at the imaging equipment without scattering,

$$T(x) = e^{-\beta d(x)} \tag{2}$$

β is the atmospheric scattering coefficient, and d(x) is the distance between the equipment and the target. The larger the distance d(x) in the image, the smaller the transmission rate T(x). And the formula (2)shows that if $d(x) \to \infty$, $T(x) \to 0$,combined with formula (1), formula can be obtained:

$$I(x) = A, d(x) \to \infty \tag{3}$$

However, in real life, d(x) cannot approach infinity, so in order to represent d(x) →∞, the smaller t0 is generally used as transmittance T(x). At this time, a is represented by the maximum value of pixels in the image at this time. As follows:

$$A = \max_{y \in \{x | T(x) \le t_0\}} I(y) \tag{4}$$

In order to restore a clear image, it is necessary to combine equation (1) and equation (4), so that the value of atmospheric light intensity A can be deduced from the accurate estimation of transmittance T(x) by equation (4), and then a fog free image can be obtained. Therefore, in the dehazing research of this model, the most important thing is to accurately estimate the transmittance T(x).

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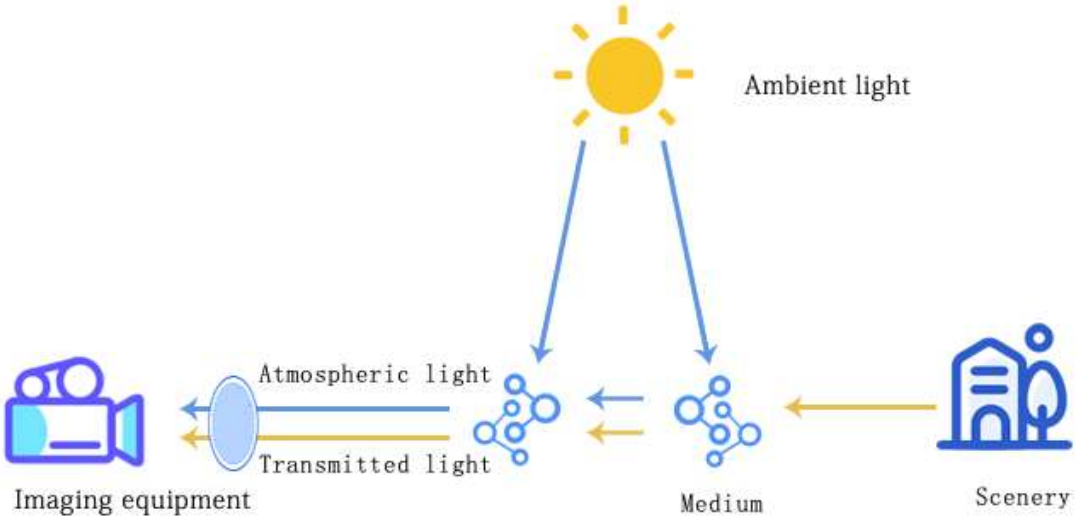

Figure 1. atmospheric scattering model

2.2 Dehazing Algorithm based on Physical Model

A large number of experiments have proved that the contrast of fog free image is higher than that of fog image. Tan et al. [2] found that the transmittance in the image changes with the change of depth, estimated the atmospheric light according to the observation results that the change of local atmospheric light basically tends to be smooth, and developed a function based on Markov random field framework to solve the problem of multiple input images of the previous scene, This algorithm only needs one image input to achieve the purpose of dehazing, and can enhance the image contrast and clarity, but it also has shortcomings: the model is easy to generate images with high saturation because it does not restore the radiation problem of the original scene. He et al.[3]proposed a dark channel prior (DCP), that is, there will be some pixels in almost all outdoor non sky fog free areas. Almost all of these pixels will have at least one-color channel close to zero, which is combined with the atmospheric scattering model to obtain a fog free image. Its expression:

$$J^{dark(x)} = \min_{y\in\Omega(x)}(\min_{C\in(R,G,B)} J^{C(y)}), J \to 0 \tag{5}$$

Where C represents one of the three channels R, G and B. JC (y) is the brightness, Jdark(x) is the dark channel of fog map, and Ω (x) is the rectangular area centered on pixel points (x, y). Generally, the minimum gray value in the area is taken to replace the value of (x, y). In the actual outdoor non sky fog free area, a large number of research facts show that the gray value of dark channel pixels is low, which is generally treated as 0. The dark channel priori is the dehazing algorithm. Although it makes the image defogging simple and easy to operate, the effect is not ideal for dense fog or fog images containing sky or water surface. There will be unnatural distortion of sky color transition and brightness reduction, and image processing also consumes a lot of computing resources. Zhu et al. [4] is similar to the dark channel a priori, and uses the atmospheric scattering model as the basis for dehazing. In this paper, the scene depth is estimated by brightness saturation, and then the obtained depth map is combined with the physical model to achieve the effect of dehazing. This method is called cap. The effect and speed of image restoration by cap method are good, but there will be color deviation.

2.3 Image Enhancement Method Dehazing

Histogram equalization is a common method of image enhancement, which mainly includes global and local equalization. As shown in the figure below, Figure 2 shows the fog map after local equalization and global histogram equalization, and Figure 3 shows their corresponding histograms.

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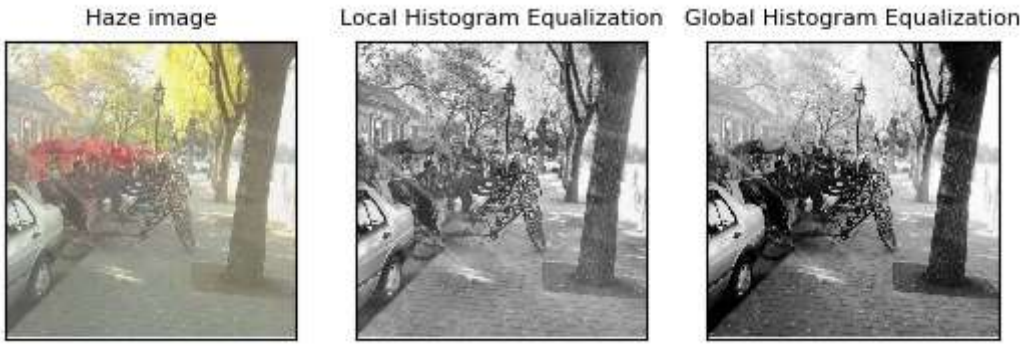

Figure 2. fog map, local equalization and global equalization

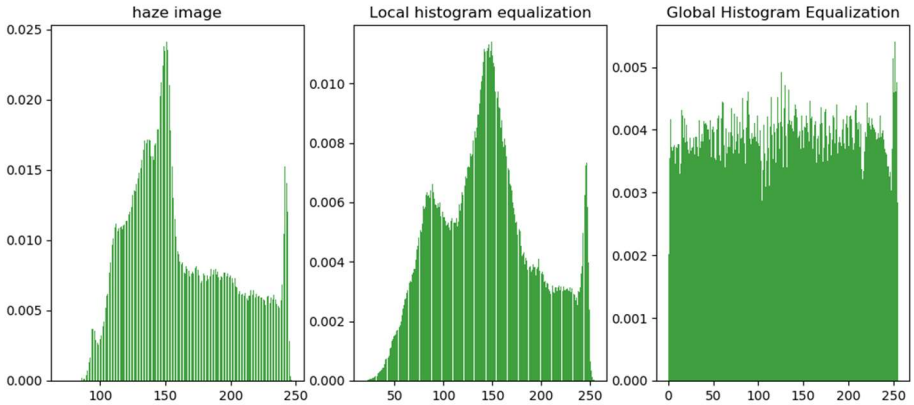

Figure 3. fog map and histogram after local and global equalization

The principle of equalization is to make the histogram distribution in a picture uniform, so as to enhance the contrast of the picture. The contrast of each pixel can be equalized by the histogram, but the contrast of each pixel can be enhanced by the general fog. Of course, as shown in the figure, local histogram equalization can also enhance the contrast of local areas. Pizer et al.[5] proposed an adaptive histogram equalization algorithm to overcome the problems of excessive noise and slow dehazing speed, focusing on the improvement of image contrast to achieve the purpose of defogging. This method has not been well processed in image details. In order to overcome the strong saturation problem of histogram equalization before, stark[6] proposed to block the input image, and then use histogram equalization for each part to strengthen it. Homomorphic filtering enhances the image by removing multiplicative noise to achieve brightness labeling and increasing contrast. Li et al.[7] proposed pixel replacement to maintain the image information as similar as possible before and after denoising in view of the loss of information such as noise free area details when homomorphic filtering removes noise. However, because it focuses on the frequency domain information of the image and considers less spatial features, the dense fog removal effect is not very good in most cases. Different from homomorphic filtering, wavelet transform[8] links the spatial and frequency domain information together, which is very effective for noise suppression, which enhances the expression ability of the algorithm and strengthens the details of the image while improving the contrast. The Retinex based image enhancement algorithm[9] believes that the reflection ability of the object to the wave determines the color of the object, and the uneven illumination will not affect the color of the object. This algorithm can improve the image contrast.

In traditional defogging, the dehazing based on physical model often has some disadvantages, such as color bias, color distortion and large consumption of computing resources. Although image

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enhancement and dehazing can also improve the image detail and contrast to a certain extent, and the efficiency and implementation are relatively easy, this method ignores the imaging reasons of the fog image. Therefore, while improving the image contrast, the image color distortion is also serious.

3. Image Dehazing Algorithm based on Deep Learning

With the increasing development of deep learning, convolutional neural network based on deep learning has attracted more and more attention from researchers because of its strong extraction ability, adaptive ability and processing speed far better than traditional networks, and began to try to use various networks for image dehazing algorithms. It can be roughly divided into defogging method based on convolutional neural network and defogging method based on Countermeasure network.

3.1 Dehazing Algorithm based on Convolutional Neural Network

The main principle is based on the scattering model, taking the paired fog map and the picture containing projection map and atmospheric light label as the data set, combined with convolutional neural network to remove fog. Dehaze-Net of CAI et al.[10] estimates the projection information of the foggy image in the input convolution, then combines the obtained information with the scattering model, and uses the proposed bilateral rectification linear unit to obtain the Fogless image more accurately.

Zhang et al.[11]used the countermeasure network as the basis and added the scattering model to the generator to remove fog. For the smooth transition problem in the dehazing map, they used the boundary perception loss function to solve it. Although good results have been achieved, its parameter adjustment is a difficulty. The Single image dehazing via multi-scale convolutional neural networks (MSCCN) proposed by Ren et al.[12] is improved because of manual features such as dark channels. For the restrictions of color difference and contrast on defogging, the coarse-scale network is used to estimate the input projection map, and then the fine-scale network is used to optimize the local area. Compared with the traditional dehazing method, this method is relatively fast, but it can't defog the fog map at night. Although AOD-Net proposed by Li et al.[13] also relies on the scattering model, it establishes an input adaptive module model through constant deformation to reduce the loss of parameter estimation, and then combines it with another image generation module to obtain a fog free image.

Equation (6) is obtained from equation (1) and (2) image model formula in 2.1 atmospheric scattering model. When T(x) and A are in the same formula, the reconstruction error of pixels is reduced to the greatest extent.

$$J(x) = K(x)I(x) - K(x) + b \tag{6}$$

Here:

$$K(x) = \frac{\frac{1}{t(x)}(I(x) - A) + (A - b)}{I(x) - 1} \tag{7}$$

The Multi-Scale Boosted Dehazing Network with Dense Feature Fusion（MSDBN-DFF）proposed by Dong et al.[14] is based on the U-Net architecture. An enhancement module is added to the decoder to better recover the fog free image. In order to better extract the features, a network module based on back projection technology is added in the U-Net coding stage to better retain the spatial information of high-resolution features, Compared with other similar networks, this network model recovers more parameter details on various data sets. However, due to the huge amount of network parameters, it also brings some difficulties to the training.

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3.2 Dehazing Algorithm based on Generated Countermeasure Network

Of course, with the brilliance of generative confrontation network (GAN) in image translation, scholars everywhere have tried to use GAN based network model to carry out dehazing experiments. Cycle-Dehaze[15] inputs unpaired fog map and non fog map. Based on the two generators and two discriminators of Cycle-GAN, the pre training model of vgg16 network is used to extract picture features, and the fog map is compared with non fog map, so as to add cyclic perceptual consistent loss to the original loss function to further improve the dehazing effect. FD-GAN proposed by Dong et al.[16] obtains image low-frequency information based on Gaussian filter and Laplace obtains high-frequency components, and the low-frequency components mainly represent smooth regions, and the high-frequency components mainly represent abrupt regions such as texture information and edges. A discriminator for distinguishing the difference between high-frequency and low-frequency of fog image is constructed to strengthen the texture, hue and other information of the generated image. GFN-Net[17] designed by Ren et al. First preprocesses the image: including using white balance (WB) to solve the color problem caused by atmospheric light projection, and using gamma transform (GC) and contrast enhancement (CE) to reduce the problem of too dark visual effect during transmission.

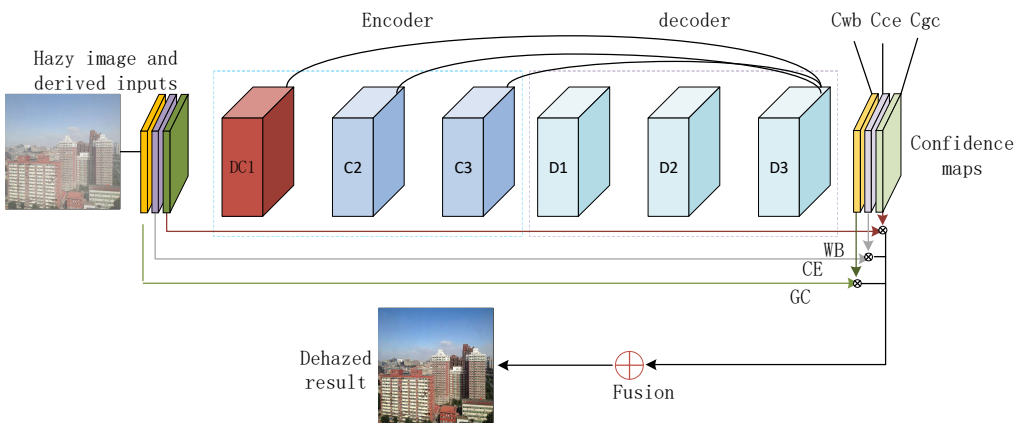

Figure 4. GFN-dehazed basic network structure

The image is input into a neural network with U-Net structure composed of encoder and decoder, but the difference is that the size of all characteristic images of the u-net network remains unchanged, and in order to increase the acceptance domain, extended convolution (DC) is used in the encoder to input the original image into the network after the three preprocessing mentioned above. Then, the image confidence map, and are obtained in the deconvolution layer. Finally, the obtained confidence graph is multiplied by the derived graph of the original input to obtain the fog free output graph J, which is represented by equation (8).

$$J = C_{\mathrm{wb}} * I_{wb} + C_{ce} + I_{ce} + C_{gc} * I_{gc} \tag{8}$$

To sum up, the end-to-end defogging network based on deep learning has great advantages over the traditional network in computational performance, and the convolution neural network dehazing method based on the physical model still has some errors in color contrast and saturation of the defogged image due to the existence of parameter errors in the model, Although the end-to-end generation countermeasure network model overcomes the shortcomings of error and improves the image quality to a certain extent, the training problems such as over fitting of the model will still lead to incomplete or excessive fog removal.

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4. Conclusion

The traditional dehazing based on image enhancement treats the fog in the image as a general image denoising, which leads to the distortion and unnaturalness caused by the lack of the internal mechanism of fog. However, the traditional dehazing method based on physical model depends on a priori knowledge, and there will inevitably be errors when estimating the parameters in the model, And the limitation and singleness of prior knowledge make this method not universal. The dehazing based on deep learning has made great progress on the basis of traditional algorithms. It does not need the support of prior knowledge, but directly estimates the transmittance using physical models through different network structures or defogs directly. Compared with traditional algorithms, the increase of the accuracy of transmittance by deep learning algorithms increases the contrast and saturation of images, However, there is still a certain gap between the original image and the original image in terms of contrast, color saturation and detail features, and the dependence of the deep learning method on the physical model leads to the existence of errors, the diversity of training data sets and the complexity of network model still need to be further studied. The commonly used dehazing evaluation indexes SSIM and PSNR are commonly used image evaluation indexes, and there are no scientific and convincing indexes for dehazing for everyone to use. Therefore, we need to further study the problem of dehazing indexes.

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