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A review of image dehazing based on deep learning

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Abstract— **The purpose of single-image dehazing technology is to recover a clean image from hazy inputs, reduce the impact of weather on image quality, improve the visual effect of the image, and are essential for subsequent advanced tasks, such as image recognition and scene understanding. Due to the rapid development of computer technology and deep learning for image processing, researchers have the ability to dehaze foggy images, especially in recent years, the innovation of image dehazing technology is used to support more accurate advanced tasks. Based on the perspectives of end-to-end learning and physical modeling, this paper collates the single-image dehazing papers of the top computer vision conference in the past three years from 2018 to 2020, and discusses the two types of articles and experimental results in depth. At the end of this paper, the problems existing in the current image dehazing technology and the direction of improvement are analyzed, and the development trend of single-image dehazing algorithm is prospected.**

Index Terms—**Deep learning, Image dehazing.**

I. INTRODUCTION

This chapter introduces the causes of fog formation in images from two aspects: the transmission medium of fog and the complex causes of imaging images, and explains the importance of studying single-image dehazing technology.

Transmission Media: Haze is an atmospheric phenomenon that affects the clarity of the sky and is mainly composed of aerosols of a dispersed system of small particles suspended in the air. There are many sources of smoke, such as combustion products, volcanic ash and leaves oozing smoke, dust and other substances suspended in the air as condensation nuclei, constituting the core substance of haze. When the relative humidity of the air is below 80 percent, these substances are suspended in the air, creating haze. When images are taken in hazy weather, the images will produce a unique blue, yellow, or gray hue, which will inevitably affect the visibility of the images and the subsequent advanced visual processing.

The origin of imaging is complex: When the weather conditions are bad, the quality of the digital pictures obtained by outdoor photography is affected by the suspended particles in the air, which is mainly because the suspended particles can scatter the light, and the light reflected by the scene is weakened, and the light that the observer can receive. When performing advanced visual tasks or obtaining high-definition visual images, it is often necessary to use deep learning and convolutional neural networks to extract image feature information processing images, but due to the reasons of transmission medium and imaging, for the image that is reduced by the foggy environment, researchers need to carry out image dehazing operations. Image dehazing is actually about implementing a defined algorithm to reduce the effect of particles suspended in the air on the resulting image, and it is best to completely remove its adverse effects. is mixed with scattered ambient light, which causes the characteristics of the picture to change after imaging, such as the contrast and color of the picture.

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II. RELATED WORK

A. *Deep learning-based dehazing*

With the development of Convolutional Neural Network (CNN), significant progress has been made in defogging methods based on deep learning. Deep learning-based defogging methods can be roughly divided into two categories: model-based dehazing methods and model-free dehazing methods. Most of the model-based defogging methods are based on the atmospheric scattering model. These methods use CNN to estimate the projection map, and then estimate atmospheric light by traditional methods or CNN. Then, the atmospheric light is estimated by the traditional method or CNN, and finally the fog-free image is obtained by the atmospheric scattering model. In recent years, most of the innovations in image dehazing have focused on two aspects: on the one hand, the innovation of estimating the transmission map or atmospheric light value, such as DCPDN [1] using a densely connected codec for multi-level pooling to estimate the projection map, and MSCNN [2] using a coarse-scale network to predict the overall transmission map based on the whole image, and then using a fine-scale network to refine it locally. On the other hand, skipping the estimation of the transmission map and atmospheric light value in the atmospheric scattering model, and outputting the fog-free image based on the end-to-end direct training network, such as AOD-Net[3], which is the first to propose an end-to-end dehazing model, introduces the reformulation of the atmospheric scattering model, directly estimates the K value through the K estimation module, and then uses the K value to estimate the deformed atmospheric scattering model to obtain the fog-free image, FFA-Net [4] The blurry image is input into three large dense blocks after a convolution learning, and the purpose of dehazing is achieved by training the dense blocks.

B. *Atmospheric scattering model*

Although the end-to-end dehazing model has become more and more popular in recent years, and it is widely loved by the demand for image processing technology because of its black box characteristics, the atmospheric scattering model is still the basis for the continuous development of image dehazing and the rational explanation of the dehazing technology.

In 1999, Srinivasa G. Narasimhan et al. [6] established a mathematical model to explain the imaging process of foggy images and the various elements included in foggy images. Figure 1 below illustrates the imaging model for foggy days:

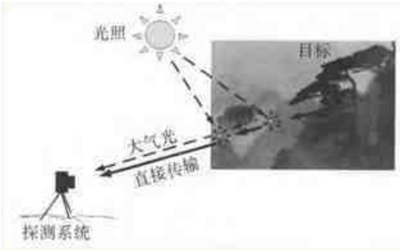

Figure 1

The figure shows that the light source received by the detection system during imaging mainly comes from two parts, one is the light reflected by the target through the particle attenuation to the detection system, and the other is the atmospheric light formed by the scattering of the particles by the light source (in this case, the light). The mathematical model of foggy imaging established by this physical model is as follows:

$$I(x,\lambda)=e^{-\beta(\lambda)d(x)}R(x,\lambda)+L_{\infty}(1-e^{-\beta(\lambda)d(x)})=D(x,\lambda)+A(x,\lambda)$$

In this Formula, $I(x,\lambda)$ is the foggy image obtained by the detection system, $R(x,\lambda)$ indicates a fog-free image that needs to be restored; parameter x represents the position of pixels in an image , λ Indicates the wavelength of light ; L_{∞} represents the value of atmospheric light at infinity; $t(x)=e^{-\beta(\lambda)d(x)}$ represents a transfer function, the physical meaning is the proportion of light that can reach the detection system through particle attenuation. Most of the teams and scholars use the above atmospheric scattering model as the theoretical model for foggy imaging when they obtain foggy images through detection systems and process them for dehazing images. The main idea is based on various prior knowledge or image processing methods, estimating the transfer function from foggy images $t(x)=e^{-\beta(\lambda)d(x)}$ or atmospheric light $A(x,\lambda)$, by substituting the solved parameters into the atmospheric scattering model, the target image can be recovered $R(x,\lambda)$. For the sake of calculation, the atmospheric transmittance is $t(x)=e^{-\beta(\lambda)d(x)}$, the target reflects light for $J(x)=\frac{L_{\infty}\rho(x)}{d^2}$, the target attenuates the reflected light as $D(x)=J(x)t$, atmospheric light is $A=L_{\infty}(1-t)$, so the mathematical expression for the final atmospheric scattering model is:

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

III. END-TO-END IMAGE DEHAZING

In this section, we will introduce the papers based on end-to-end image dehazing in the past three years from 2018 to 2020, based on the atmospheric scattering model, which we divide into two types: calculating the parameters of the scattering model and not calculating the parameters of the atmospheric scattering model.

Calculate the parameters

People often embed traditional physical models into neural networks for training, DCPDN [1], as the most indexed image dehazing paper in recent years, is also based on this method, not only that, it also takes the adversarial generative network as the basic architecture to form an end-to-end network model, as shown in Figure 2, the transmission map is estimated by using a densely connected codec with multi-level pooling, the network design can integrate multi-layer features to evaluate the transmission map, and the atmospheric light value is evaluated by the U-Net network. After the relevant parameters are obtained, the dehazing image can be obtained by combining with the atmospheric scattering model. Not only that, the network also innovates in the adversarial generation network, in which the trained transmission map and dehazing image are input into the joint discriminator to determine whether there is a match. The combination of traditional physical model and neural network is more convincing, and it is also an end-to-end network that is easy to apply to other learning.

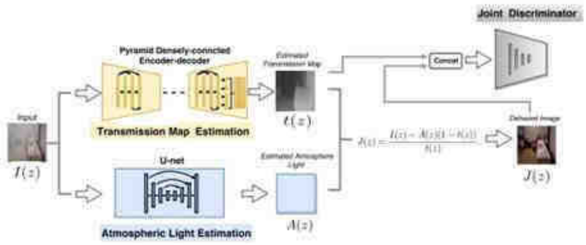

Figure 2

Parameters are not calculated

In recent years, most of the papers published in the conference hope to break away from the traditional atmospheric scattering model and try to use novel methods or network models to apply image defogging to try to produce better results. Judging from the results of the published papers, it is indeed better than before, and we will introduce several representative articles below.

The GAN structure used for dehazing has always been a classical structure that researchers cannot abandon, and CGA-Net [7], published in 2018, uses a conditional generative adversarial network to perform single-image dehazing, as shown in Figure 3, the foggy image is input into the codec to train the dehazing image, and then put it into the discriminator for identification. We find that the connection of the codec symmetry layer breaks through the information bottleneck, and introduces pixel-level loss and perceptual loss due to the artifacts generated by traditional GAN images, including color shift or noise interference. Therefore, this paper abandons the traditional physical model, innovates the GAN, and adds a new loss function to constrain the image training process to optimize the drawbacks of GAN.

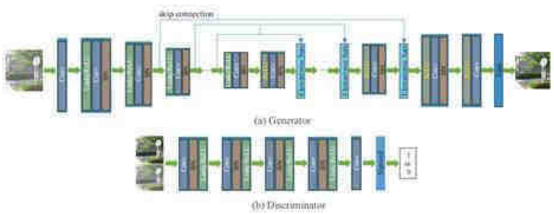

Figure 3

Published in 2020, the FD-GAN [8] network is similar to CGA-Net, as shown in Figure 4, the network structure is also based on the adversarial generation network, and the foggy image is put into the codec for training. However, the author innovates the discriminator, decomposes the trained dehazing image and the real image into high-frequency information and low-frequency information at the same time, and corresponds them to each other to identify the true and false, and the loss function follows the pixel-level loss and perceptual loss in CGAN-Net. Through qualitative and quantitative analysis, the fusion discrimination network is indeed more conducive to image dehazing.

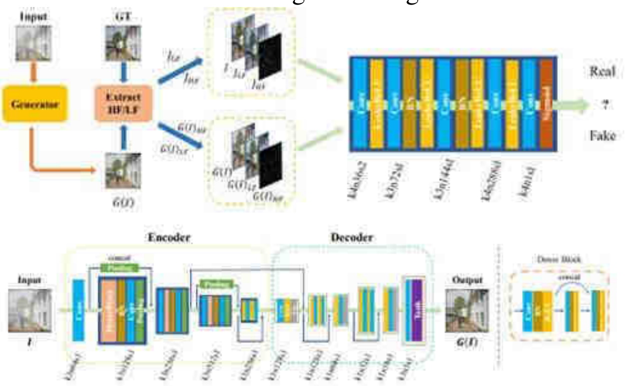

Figure 4

The above two articles introduce the improvement of the classical GAN network for image dehazing, in fact, researchers have been trying other more novel networks for image dehazing. AIPNet [9], published in the journal in 2019, introduced an atmospheric-first lighting prior to maintain the intrinsic color of the hazy scene and enhance its visual contrast, based on the fact that the atmospheric illuminance in hazy weather mainly affects the brightness channel in the YCrCb color space, but has little influence on the chromaticity channel. The multi-scale network consists of feature extraction and multi-scale restoration, the first part is used for haze-related feature extraction to identify hazy areas, and the latter part uses the multi-scale reduction method to restore the lack of texture information.

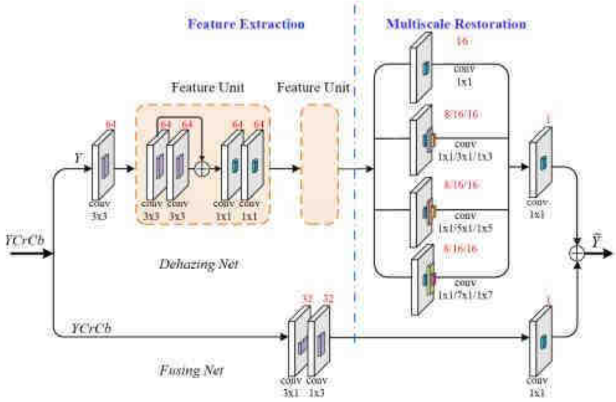

Figure 5

The article published in CVPR in 2020 applies knowledge distillation to image dehazing [10], as shown in Figure 6 of the network model. Firstly, a clean image is used to train a self coding network as a teacher, and the dehazing network is used as a student. The teacher is used to mine the hidden features and reconstruction information of clean images to guide the mapping from foggy images to clean images Obviously, this method relies too much on special datasets and cannot produce good results when processing foggy images in real scenes But this method provides a good idea that knowledge distillation can be used for image dehazing training.

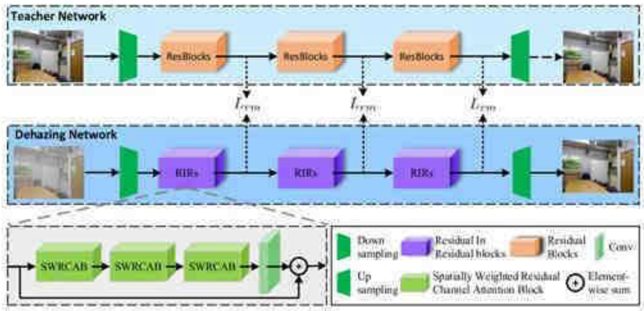

Figure 6

Using atmospheric scattering models to remove fog from images

Although end-to-end network models are more popular, innovation can still be made based on traditional atmospheric scattering models, resulting in new breakthroughs in training results.

PMS Net [11], presented at the CVPR conference in 2019, designed an adaptive and automatic patch size selection model based on atmospheric scattering models As shown in the network model in Figure 7, the foggy image is processed through a patch network to obtain a patch image. The corresponding pixel level transmission map and atmospheric light values are obtained through dark channel prior processing. Then, the corresponding parameters are output based on the atmospheric scattering model, and the restored image is finally obtained Unlike the original dark channel prior, in order to adapt to the uneven distribution of haze, the author designed a pixel level dark channel prior.

Figure 7

Bid-Net [12] applies binocular image features to image dehazing and designs a binocular image dehazing method without disparity estimation, combined with atmospheric scattering models As shown in Figure 8, the network model adopts a dataset with left and right views. The left and right views are respectively fed into the encoder and decoder to learn the features of the left and right images. Then, the STM layer converts the depth information to each other and outputs the corresponding transmission map of the left and right images. In addition, the left image is fed into a new encoder and decoder to train the atmospheric light value of the image. Then, the restored image is obtained by inputting the corresponding parameters based on the atmospheric scattering model.

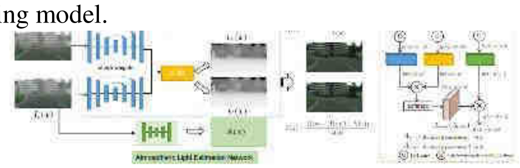

Figure 8

IV. THE PROBLEMS AND SOLUTIONS OF IMAGE DEHAZING TECHNOLOGY

The problems of image dehazing technology

After the intervention of deep learning, researchers mainly studied the problem of single image dehazing technology from two aspects: end-to-end and physical model-based directions.

The use of end-to-end dehazing methods does not seem to take into account the physical process of image quality degradation in foggy weather conditions. What is completely different is that it specifically refers to the image itself after reducing image quality, using image processing methods to improve image contrast, and then highlighting the colors and other characteristics of the image. This way, the visual effect of the image will be much better, and for computer vision systems, processing the analyzed information will become easier Early researchers basically started from this, and this type of method can be applied appropriately in various aspects based on the special conditions of image dehazing and existing mature technologies Many technologies have reached a certain level in other fields, and the processed images can also meet the clarity requirements of the system However, this type of method is difficult to adapt to different backgrounds, especially for objects with a wide depth range. What is more noteworthy is that this method is based on end-to-end and does not consider the process of fog decomposition. It can only increase the definition of the image in a limited way, cannot "eliminate" fog, and then restore the original appearance of the scene, causing the image to lose its authenticity After processing, the visual appeal of the image is poor, which naturally makes it difficult for the computer's visual system to further process the image.

So, current researchers have a general interest in physics based modeling methods From a physical perspective, explore the mechanism of fog degradation images and form corresponding physical models to obtain the visual changes caused by fog In cases where the system has a significant impact, the changes in the image caused by fog have been eliminated Firstly, this method requires the use of specific instruments or equipment, or 3D models, so its scope of use is greatly limited and cannot be used in image processing In recent years, there have been several single image processing methods based on physical models, especially those that have won the favor of CVPR So far, based on physical models, existing single images can be well processed, and this approach is usually useful for images with slight depth changes The processed and restored images are closer to the original scene, with distinct features and excellent visual results However, this method typically relies on different images for testing Relying on tests, slightly more parameters need to be manually adjusted, which cannot be automatically adjusted. There is also a slightly higher complexity in time and direction, and relatively more computational complexity, and adjustments cannot be completed in a timely manner.

Key technologies that need to be addressed

The image dehazing can be improved in the following areas:

Firstly, in order to better address such issues, people need to conduct more in-depth research on fog and haze images, especially in terms of their degradation models Through literature review, it has been found that the most crucial aspect of image restoration and dehazing methods is the use of robust physical models, including their construction and solution In addition, the most effective computer vision and image processing technologies are often widely used to study fog and haze degradation models For example, atmospheric scattering models Despite continuous research and innovation, many other methods have been found to describe fog and haze degradation models, such as Retinex model and bicolor atmospheric scattering model, etc. However, it is difficult to accurately describe the degradation phenomenon of images under weather conditions such as fog and haze In order to better address such shortcomings, it is necessary to study modern atmospheric optics The construction of a more robust physical model is highly effective, as it not only takes into account factors such as haze degradation, but also introduces multiple factors such as complex atmospheric turbulence and complex atmospheric light.

Secondly, explore the application of prior information in model solving The problem of image dehazing is a typical pathological inverse problem Although there is already some existing prior information, it cannot be applied in harsh climates such as dense fog or severe haze, as a large amount of variable relationships and hypothesis testing of objectives are still needed in the entire model optimization solution The author's goal is to accurately solve the scene albedo, so after a series of analyses, it is necessary to study prior information The main research topics include prior knowledge of fog and haze degradation, as well as prior knowledge of clear scenes Among them, research on clear scene priors can be explored based on existing statistical knowledge The study of prior knowledge on degraded images of fog and haze can also start by studying the effects of turbid and turbulent media on imaging Prior information should not be ignored, but should be fully explored and utilized. The determination of prior distribution should be based on suitability as the primary principle, and attention should be paid to obtaining prior information for various scenarios, different haze concentrations, and other backgrounds. This can scientifically improve the accuracy of estimating scene albedo.

Thirdly, design a model solving method based on human visual mechanism Research has shown that enhanced physical models can be used to solve problems Because the advantage of this method is that it can better restore the true colors of the image. Its principle is to simulate the human visual mechanism, which can be achieved through image enhancement methods. The application of human visual cognitive mechanism in model construction can help optimize and solve the model Therefore, for the process of obtaining and enhancing information in human visual perception, researchers need to continuously explore and design fast optimization methods.

V. SUMMARY AND OUTLOOK

Single image dehazing technology is a hot topic in the fields of computer vision and image processing This topic is interdisciplinary, interdisciplinary, and has many applications When applied, researchers have the following requirements for technology: robustness, universal adaptability, and immediacy So, this topic will definitely spark another trend in its future development Based on previous analysis, researchers should make corresponding improvements in the following areas during defogging:

1. To improve the algorithm's self adjustment ability Not all of these technologies can be applied appropriately in all scenarios, and it may be necessary to change the parameters yourself to achieve the goal But many computer vision systems, such as security monitoring systems, require technology to automatically process different images and do not require human modification of relevant data It can fully analyze image data according to changes in the environment, flexibly make adjustments that can adapt to the environment in different scenes and weather conditions, meet the requirements of defogging effect in different scenes, and also meet the requirements of clarity of the processed images. This technology is considered ideal.

2. The quality of dehazing algorithm processing still needs to be improved, and current image dehazing techniques still suffer from distortion, especially in the processing of dense fog images Based on the information contained in the degraded image, try to obtain the image that the actual object should have before its quality is reduced by fog In this way, not only can the image be visually appealing, but it can also display the characteristics of the actual object such as color and contrast, achieving the effects required by computer vision systems The dehazing technology that the author currently understands cannot achieve this in most images, so relevant technology personnel still need to work on dehazing technology.

3. Improve the real-time performance of image dehazing methods Image dehazing is actually quite complex and requires processing a lot of data and applying different algorithms These algorithms are time-consuming and complex to process, and can be applied to problems such as solving large-scale equations and decomposing large matrices Real time performance is crucial for dehazing, so there is an urgent need for researchers to find simple and fast methods to optimize and process existing algorithms, so as to achieve the speed that researchers want and overcome these problems Furthermore, we can imagine that if defogging can be done in the programming direction, it will inevitably be a new hotspot in this field.

4. The objective evaluation method of defogging technology still needs continuous improvement by researchers So far, the image dehazing techniques that I know of are still subjectively biased and can achieve the same results However, the objective evaluation methods learned from current research cannot accurately explain the advantages and disadvantages of fog technology, and the evaluation results obtained are difficult to convince others So in the field of image dehazing research, a standardized objective evaluation system will definitely be established.

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