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RESEARCH ON DEHAZING OF SURVEILLANCE IMAGES BASED ON DEEP LEARNING

Abstract.With the widespread application of surveillance systems in security, transportation, and other fields, image dehazing has become a key technology to improve the quality of surveillance images. This paper conducts research on surveillance image dehazing using the All-in-One Dehazing Network (AOD-Net) technology. The dataset consists of nearly 4,000 images, including the OTS subset from the RESIDE dataset and foggy images captured in real campus scenarios, which are divided into a training set and a test set at a ratio of 9:1. In terms of qualitative evaluation, the dehazed images conform to human visual perception, with details and colors close to the original images. For quantitative assessment, the mean Peak Signal-to-Noise Ratio (PSNR) reaches 15.25 dB, and the mean Structural Similarity Index (SSIM) is 0.839. Experimental results demonstrate that the AOD-Net technology achieves excellent dehazing performance for surveillance images.

Keywords: Deep Learning; Dehazing Model; Surveillance Images.

1. INTRODUCTION

Under natural weather conditions such as rain, fog, and haze, images are prone to degradation. Compared with visual perception in sunny environments, degraded images usually exhibit reduced contrast and blurred target details. These issues significantly affect the accuracy of algorithms like face recognition and license plate recognition, and may even lead to misjudgments by surveillance systems. Image dehazing technology can effectively enhance image details and improve the precision of target recognition, thereby addressing the aforementioned problems. With the continuous development of deep learning technology, image dehazing technology has also undergone constant innovation. Deep learning-based image dehazing has become a focus of research in the field of computer vision [1-4]. However, practical application scenarios of image dehazing technology are complex and diverse, and existing algorithms have limitations to varying degrees. This paper studies deep learning-based image dehazing algorithms, aiming to provide theoretical support and practical basis for algorithm performance optimization and practical problem-solving.

Cai et al. [5] pioneered the introduction of deep learning algorithms into the field of image dehazing and proposed the DehazeNet algorithm. This algorithm integrates convolutional neural networks (CNNs) with prior knowledge, trains the model using massive datasets, automatically calculates image transmittance through learning, and then restores clear images based on the atmospheric scattering model. Ren et al. [6] constructed a multi-scale convolution theoretical model based on a deep learning framework to solve the transmittance estimation problem and designed an algorithm architecture consisting of two processing stages. In the first stage, the research team used a multi-scale CNN to achieve initial transmittance estimation; in the second stage, a generative adversarial network (GAN) mechanism was introduced to refine the preliminary results. However, this algorithm has insufficient adaptability in practical applications. When processing images with different fog concentration characteristics, manual parameter adjustment is often required to obtain ideal dehazing effects. Li et al. [7] proposed the All-in-One Dehazing Network (AOD-Net) model. To address the problem that separately solving two unknown variables in the atmospheric scattering model tends to amplify errors, this model first transforms the atmospheric scattering model, integrates the two unknown parameters into a single joint parameter, estimates the joint parameter using a CNN, and then substitutes the estimated result into the transformed model to obtain clear dehazed images. The Multi-Scale Boosted Dehazing Network (MSBDN) proposed by Dong et al. [8] innovatively constructs a dense feature fusion mechanism, which effectively alleviates the spatial information loss commonly found in traditional dehazing networks. This algorithm optimizes the decoder structure and adopts a progressive processing strategy to achieve high-quality haze-free image reconstruction.

Hou Ming et al. [9] improved AOD-Net in three aspects—adding an attention mechanism, adjusting the network structure, and modifying the loss function—to address issues related to dehazing algorithm efficiency and detail restoration, thereby enhancing its feature extraction and restoration capabilities for clear dehazed images. Dong Tian et al. [10] improved and optimized the AOD-Net algorithm based on the Zynq platform, designing and implementing an image dehazing system. While improving dehazing effects, it effectively reduces algorithm computational complexity and resource consumption, enhances system real-time performance and practicality, and is applicable to various image dehazing scenarios. Xu Yue et al. [11] addressed the problems existing in traditional image dehazing algorithms and AOD-Net by adding a spatial pyramid attention mechanism, adjusting the network structure to a Laplacian pyramid type, and modifying the loss function to restore clear images.

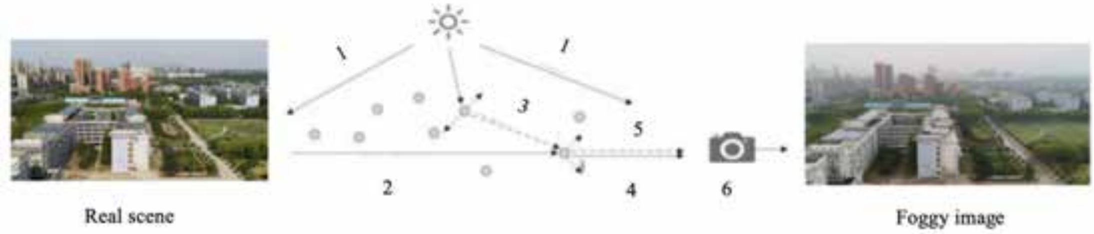
Image dehazing technology can be divided into three categories [12-14]: (1) Enhancing visual features such as contrast and brightness of foggy images to achieve dehazing. However, due to the lack of in-depth analysis of image degradation mechanisms, detail information is often lost during enhancement, affecting the final dehazing quality. (2) Estimating atmospheric scattering model parameters using prior knowledge to reconstruct clear images through the model. Nevertheless, these prior knowledge may fail in complex scenarios, leading to parameter estimation deviations and limiting the algorithm's scope of application. (3) Two deep learning-based image dehazing methods: one predicts the transmittance map using CNNs and then reconstructs images combined with the atmospheric scattering model, but the process is overly cumbersome; the other adopts an end-to-end network architecture to directly restore haze-free images, avoiding the parameter estimation process and thus achieving better dehazing results. Therefore, this paper adopts the end-to-end network architecture to restore haze-free images.

2. Theoretical Basis

This chapter first introduces the characteristics and formation principles of foggy images, then outlines theories related to image dehazing, focusing on the basic structure and principles of neural networks.

2.1 Foggy Images

Foggy images typically exhibit reduced contrast, decreased color saturation, and blurred details. Their generation is mainly affected by two factors [15], as shown in Figure 1. (Atmospheric Light Imaging Model). Firstly, scene reflected light interacts with suspended particles in the air during transmission. According to the Mie scattering theory, the scattering intensity difference between different wavelength lights is weak, and particles absorb incident light, resulting in a significant attenuation of the energy of scene reflected light reaching the optical imaging equipment. Secondly, background light in the atmospheric environment (including atmospheric light and ambient light generated by scattering) is affected by secondary scattering of suspended particles, and part of the stray light enters the imaging system to form noise. These two effects together constitute the mechanism by which suspended particles affect optical imaging quality, hindering light propagation, causing problems such as reduced intensity and color homogenization, and ultimately leading to reduced contrast, decreased color saturation, and blurred details in captured images.



1:Lighting; 2:Scene reflected light; 3:Haze particle reflection; 4:Attenuated reflected light; 5:Atmospheric light; 6:Optical imaging equipment

Fig. 1. Atmospheric Light Imaging Model

2.2 All-in-One Dehazing Network.

Proposed at the 2017 IEEE International Conference on Computer Vision (ICCV), AOD-Net is a lightweight deep learning dehazing model designed based on classic convolutional neural networks. It adopts an end-to-end neural network architecture, enabling image dehazing in a single forward pass and simplifying traditional multi-step dehazing algorithms. The model reduces computational complexity through a lightweight network structure and incorporates Position-wise Normalization (PONO) to enhance dehazing performance.

(1) AOD-Net Algorithm

The atmospheric scattering model is a classic description of foggy image generation:

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

Where $J(x)$ represents the clean image to be restored, $I(x)$ is the foggy image captured by the camera, $t(x)$ is the transmittance, A is the atmospheric light value, and x denotes the pixel position in the image.

The core idea of AOD-Net is to unify the transmittance $t(x)$ and atmospheric light value A in the atmospheric scattering model into a single expression represented by $K(x)$. It extracts and integrates image features using a multi-scale feature fusion network to obtain the required $K(x)$ parameters [11], and then substitutes the estimated results into the transformed model to achieve haze-free image restoration.

The expression for the image to be restored is as follows:

$$J(x) = K(x)I(x) - K(x) + b \tag{2}$$

Where b is a constant bias, defaulting to 1. The unknown value obtained by combining transmittance $t(x)$ and atmospheric light value A is expressed as:

$$K(x) = [(I(x) - A) / t(x) + (A - b)] / (I(x) - 1) \tag{3}$$

(2) AOD-Net Network Structure

The AOD-Net network structure consists of two parts: a *K*-value module and an image generation module [16], as shown in Figure 2. The *K*-value module extracts features from images through convolution operations (Conv), with each convolution followed by a ReLU activation function to achieve non-linear mapping. The feature fusion stage adopts the Concat method to enrich the extracted image feature information by concatenating features from different levels. After Conv5, the module obtains the $K(x)$ parameter. The image generation module inputs the obtained *K*-value into the expression of the image to be restored to generate the final dehazed image.

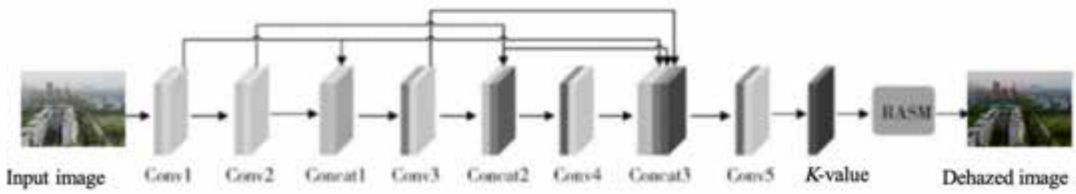


Fig. 2. AOD-Net Network Structure Diagram

With its end-to-end design, concise structure, and strong generalization ability, AOD-Net has demonstrated excellent dehazing performance in various scenarios. It is also easy to embed into other deep models for joint optimization, improving the efficiency and accuracy of image dehazing tasks.

3.Results and Analysis

3.1 Experimental Preparation

(1) Experimental Environment

The hardware configuration of the experimental computer includes an AMD Ryzen 7 5800H processor, 16G memory, and the Windows 10 operating system. The programming language version is Python 3.8, the algorithm implementation platform is PyCharm, and the deep learning framework used is PyTorch 1.8.2+cu111.

(2) Algorithm Parameter Configuration

This experiment uses the AOD-Net model for image dehazing training. During training, the batch size is set to 8, and the batch size for validation is also 8 to ensure consistency in sample processing during training and validation. To improve data loading efficiency, the number of worker processes (num_workers) is set to 2, enabling two sub-processes for data preprocessing. The total number of training epochs (num_epochs) is 10, suitable for initial training of small and medium-sized datasets. To prevent model overfitting, a weight decay mechanism is introduced with a parameter regularization coefficient (weight_decay) of 0.0001. Additionally, to avoid gradient explosion during training, a gradient clipping (grad_clip_norm) mechanism is used with a threshold of 0.1. These parameter configurations aim to enhance training stability and model generalization ability.

(3) Dataset Selection

The dataset selected in this paper consists of two groups: the first group is the OTS subset from the RESIDE dataset; the second group is composed of foggy images captured in real campus scenarios. The dataset includes various scenes under real environments to enhance the model's adaptability to complex environments.

The RESIDE [17] dataset was created by research teams from Microsoft Research and the University of Illinois at Urbana-Champaign in 2017 and first proposed in 2018. It is divided into five subsets, including the Indoor Training Set (ITS) and Outdoor Training Set (OTS). The OTS subset contains 2,061 real outdoor images from real-time weather in Beijing, which were synthesized into over 70,000 foggy images under different parameters. This paper selects more than 2,000 pairs of different images from the OST subset of the RESIDE dataset and divides them into training and test sets at a ratio of 9:1.

The dataset composed of foggy images from real campus scenarios includes images of Nanshan of the university captured from the west view of the 7th floor of the Science and Technology Building of Bengbu University, as well as images of teaching buildings, playgrounds, dormitories, and canteens taken from fixed perspectives under foggy weather, totaling more than 2,000 pairs of different images, which are also divided into training and test sets at a ratio of 9:1. Some images are shown in Figure 3 (one haze-free image corresponds to one foggy image; only part of them is displayed here).

(4) Dataset Processing

During dataset processing, original images are first paired with their corresponding images, and the image sizes are unified to ensure consistency. Next, the pixel values of the images are normalized to the range of 0 to 1 to facilitate subsequent numerical calculations. The processed image data is converted into a standard tensor format, and the dimension order is adjusted to meet the model's input requirements. The entire process maintains the corresponding relationship between images, ensuring that each pair of images can participate in calculations together to form standard input-output samples. This processing method improves data consistency and usability, laying a solid foundation for subsequent training and testing.

(a) Foggy and haze-free images from the OST dataset   (b)Foggy and haze-free images from the real campus scene dataset

Fig. 3. Display of Partial Dataset

3.2 Experimental Results and Analysis

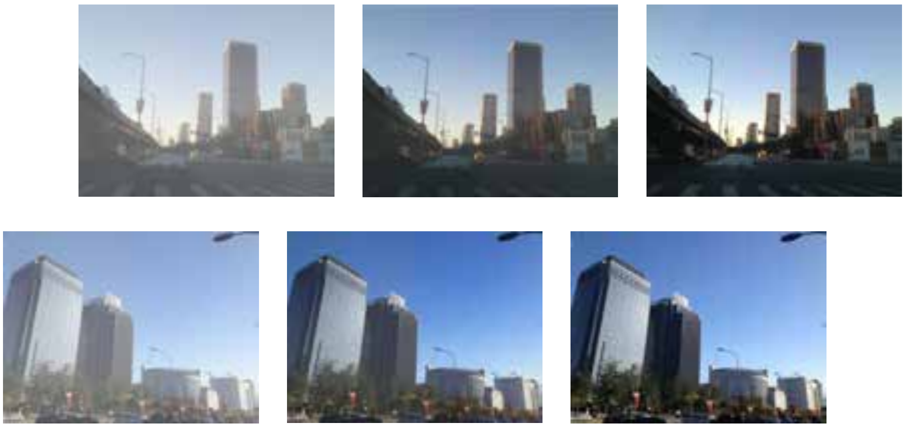
(1)Experimental Results

Figures 4 and 5 show the dehazing effects of partial scenes from the OST dataset and the real campus scene dataset in the test set, respectively. It can be observed that:

1. The restored images have good visual consistency, closely matching the perceptual effect of images under real clear scenes.

2. During the dehazing process of the network, image detail information is well preserved, resulting in dehazed images with rich details.

3. The colors of the dehazed images are close to those of real scenes.



(a) Foggy image   (b)Dehazed image   (c)Haze-free image

Fig. 4. Dehazing Effects of the OST Dataset

(a) Foggy image (b)Dehazed image (c)Haze-free image

Fig. 5. Dehazing Effects of the Real Campus Scene Dataset

Comparing the restoration effects of the two datasets, it is found that the restoration effect of the OST dataset is slightly better than that of the real campus foggy dataset. The dark areas in the restored images of the real campus scene dataset are darker, with less detailed restoration and incomplete fog removal. The OST subset mainly consists of synthetic images with uniformly distributed fog and moderate fog concentration; most haze-free images have brightness in a "daily normal exposure" state. The fog in the real campus scene dataset may be morning fog or polluted haze with higher local density; the haze-free images are captured under "strong sunny lighting" conditions, featuring high brightness and strong contrast. During training, "synthetic fog + non-uniform natural fog" was used, and the AOD-Net model training was overly conservative, leading to incomplete dehazing. Meanwhile, as a shallow convolutional network, the AOD-Net model processes the entire image evenly without regional perception and distance recognition, causing the trained model to misclassify dark foreground areas as "light fog areas" with underestimated transmittance, resulting in over-dehazing and reduced brightness.

(2) Analysis of Experimental Results

To quantitatively reflect the image dehazing effect of the deep neural network, this paper uses two evaluation methods: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM).

1. Mean Squared Error (MSE): A commonly used loss function to measure the difference between predicted values and true values. The expression is as follows:

$$MSE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[x(i,j)-y(i,j)\right]^2}{N_x \times N_y} \tag{6}$$

Where $x(i,j)$ and $y(i,j)$ represent the pixel values of the original image x and the processed image y at the corresponding positions, respectively, and $N_x \times N_y$ is the size of the image.

2. Peak Signal-to-Noise Ratio (PSNR): Detects image distortion pixel by pixel. A higher evaluation value indicates better image restoration effect, making it the most widely used evaluation standard in signal processing. Its unit is decibels (dB), and the expression is as follows:

$$PSNR = 20 \cdot \log_{10}\left(\frac{255}{\sqrt{MSE}}\right) \tag{7}$$

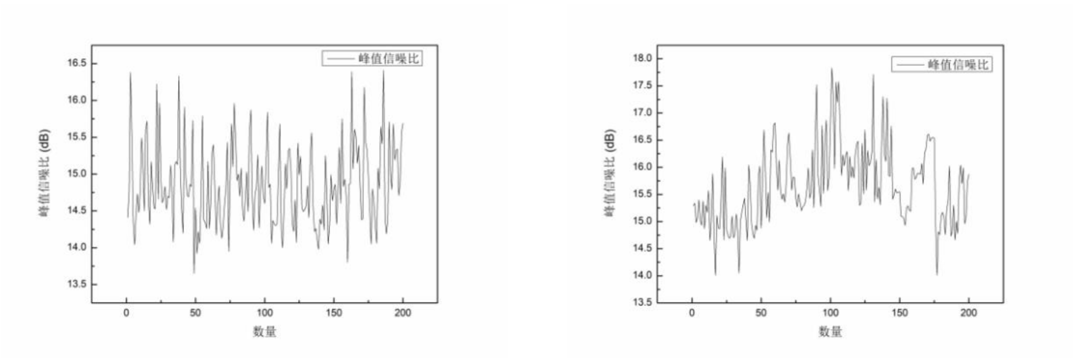
3. Structural Similarity Index (SSIM): An image quality evaluation index closer to human subjective perception. Since pixels in an image form a specific structure with

surrounding pixels, SSIM compares the similarity between two images based on changes in image information structure. The expression is as follows:

$$SSIM(x,y)=\frac{\left(2\mu_x\mu_y+c_1\right)\left(2\sigma_{xy}+c_2\right)}{\left(\mu_x^2+\mu_y^2+c_1\right)\left(\sigma_x^2+\sigma_y^2+c_2\right)} \tag{8}$$

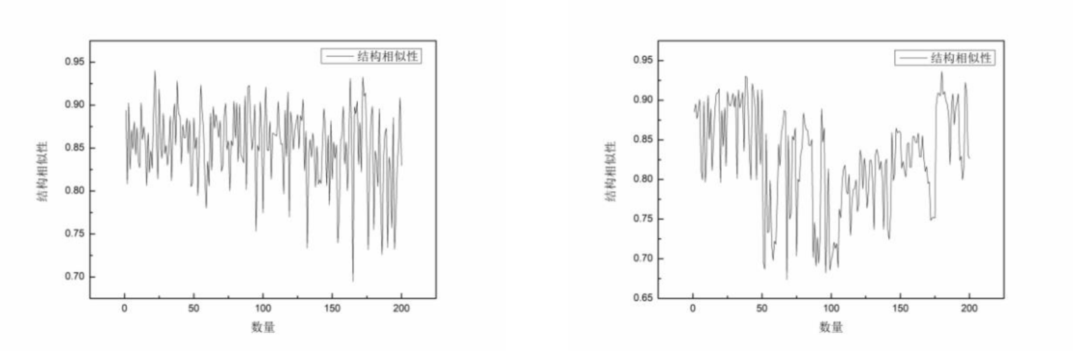
Where c_1 and c_2 are constants, x and y are the original image and the processed image, respectively, μ is the mean value of the image, σ^2 is the variance of the image, and σ_{xy} is the covariance between the two images.

The distributions of PSNR and SSIM test results for the OTS dataset and the real campus scene dataset are shown in Figures 6 and 7. The mean values of PSNR and SSIM for the two groups of test results are listed in Table 1.



(a)PSNR distribution of the OTS dataset (b)PSNR distribution of the real campus scene dataset

Fig. 6. PSNR Test Results



(a)SSIM distribution of the OTS dataset (b)SSIM distribution of the real campus scene dataset

Fig. 7. SSIM Test Results

Table 1

Mean Values of PSNR and SSIM

	PSNR	SSIM
Mean value of the OTS dataset	14.84dB	0.853
Mean value of the real campus scene dataset	15.665dB	0.825
Overall mean value	15.25dB	0.839

Quantitative evaluation results show that the PSNR and SSIM of the OTS dataset are relatively concentrated, with mean values of 14.84 dB and 0.853, respectively. The PSNR and SSIM of the real campus scene dataset fluctuate more significantly compared to the OTS dataset, with mean values of 15.665 dB and 0.825, respectively. The overall mean PSNR of the two groups is 15.25 dB, and the overall mean SSIM is 0.839. The OTS dataset consists of artificially synthesized foggy images, while the real campus scene dataset is captured in real environments with greater randomness. Therefore, the PSNR and SSIM of the OTS dataset are more concentrated, with higher SSIM values and more stable structure restoration effects. The possible reason for the higher PSNR in the real campus scene dataset than in the OTS dataset is that the dehazed images of the real scene are generally darker with poor visual effects, but the errors can be evenly distributed across the entire image, resulting in a not necessarily large MSE but possibly a more stable one. In contrast, the OST dataset consists of synthetic images, and slight inadequate restoration can lead to large local errors, increasing the MSE and thus reducing the PSNR. Both subjective and objective evaluations indicate that the model achieves good dehazing effects. However, there are still issues such as incomplete dehazing and insufficient detail restoration. In the future, the training dataset size can be increased and the network structure can be optimized to achieve better restoration effects.

CONCLUSIONS AND PROSPECTS FOR FURTHER RESEARCH

This paper constructs a dataset of nearly 4,000 images, including the OTS subset from the RESIDE dataset and real campus foggy images, split into training and test sets at a 9:1 ratio. Foggy images, restored images, and evaluation metrics are intuitively presented via a visualization interface. Qualitatively, the model performs well for both synthetic (OTS) and real campus foggy images—with slightly better color restoration and detail clarity for the former. Quantitatively, the OTS dataset shows concentrated PSNR (14.84 dB) and SSIM (0.853), while the real campus dataset has more fluctuating values (15.665 dB PSNR, 0.825 SSIM). The OTS dataset's synthetic nature ensures stable structural restoration, while real-scene dehazed images are darker but with evenly distributed errors (stable MSE). In contrast, synthetic images' local errors inflate MSE and lower PSNR, leading to higher PSNR in the real campus dataset. Overall, the model's restored images align with human visual perception (details and colors close to original), achieving a mean PSNR of 15.25 dB and SSIM of 0.839, demonstrating AOD-Net's excellent dehazing performance for surveillance images.

The model proposed in this paper performs well in eliminating fog from input foggy images. However, there are phenomena such as significant brightness differences between foggy and haze-free images in the real dataset, generally dark restored dehazed images, and incomplete dehazing. In the future, position attention or multi-scale mechanisms can be introduced to enhance the model's ability to distinguish foreground and background regions. Brightness normalization can be applied to images to avoid the model mistakenly learning the relationship between brightness and fog. Additionally, generative adversarial networks can be used to improve the model's generation ability, and the dataset including different lighting conditions and scenes can be expanded to enhance the model's generalization ability and improve the overall restoration effect of AOD-Net.

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