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Image Dehazing Networks Based on Residual Blocks and Feature Fusion

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Nowadays, the quality of haze images has been greatly improved after defogging, but there are still some problems such as incomplete defogging and color bias. To solve these problems, an image-defogging network based on residual parameter block and feature fusion is proposed in this paper. The network includes the feature module of the extracted image, the color feature and content feature fusion module of the image, and the restored image module. In order to extract image color features and content features effectively, residual blocks and mixed attention are used in the color feature and content feature extraction module, which can remove fog and better maintain the color and content of the original image. Finally, in the image restoration module, the fused image feature map is non-linear mapped to obtain the image after removing haze. Compared with the existing methods, the proposed method has achieved good image visual effects in both computer-generated scene images and actual scene images.

Keywords: Image dehazing; Feature extraction; Residual block; Feature fusion; Convolutional neural network.

1. INTRODUCTION

Although the development of industrialization has brought about many positive social and economic changes, it has also led to the production of a great deal of particulate matter suspended in the air. These particles cause light scattering, thereby attenuating the light reflected by objects. When framing images in hazy weather, the reflected light and the light received during shooting are mixed, resulting in changes in the contrast and clarity of the captured image. Therefore, image dehazing technology has important research value. Today, there are many image-dehazing algorithms, and these techniques can be categorized into three types.

(1) Dehazing algorithm for image enhanced image. This type of algorithm is based on image-enhancement technology, which improves the brightness of the image, and makes the image look sharper. Examples of this algorithm are: Retinex, wavelet transform, partial differential equation, and histogram equalization, to name a few. According to the imaging principle, the Retinex algorithm eliminates the influence of the reflection component and achieves the effect of image enhancement and dehazing; the wavelet transform algorithm decomposes the image and enlarges the useful part; the partial differential equation algorithm treats the image as a partial differential equation, and improves contrast by calculating the gradient field; the histogram equalization algorithm makes the pixel distribution of the image more uniform so that the details of the image can be highlighted. In regard to this kind of algorithm, there are many improved algorithms based on the principle of image enhancement [1, 4]. However, these algorithms do not consider the main cause of image degradation produce a certain degree of distortion to some image information, and does not address the root cause of the haze in the image.

(2) Dehazing algorithm for image restoration. This type of algorithm performs inverse operations according to the formation process of foggy images, thereby restoring

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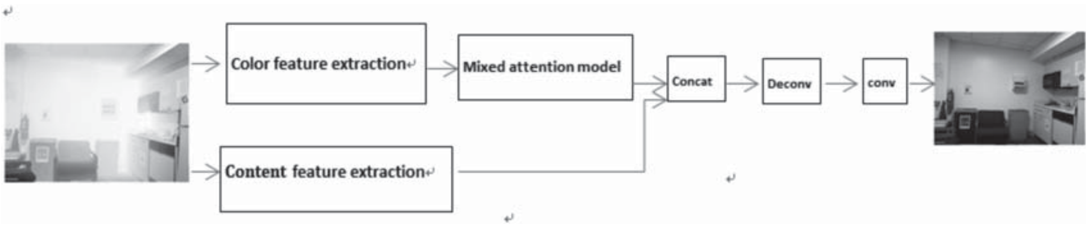

Figure 1 Architecture of the network.

clear images. Examples of this algorithm are: the DCP (dark channel prior) algorithm proposed by Kaiming He et al. [5] has low complexity and good dehazing effect, and was the basis for further improved algorithms proposed by Meng [6] and [7, 11]. However, these algorithms produce excessive dehazing, resulting in image color cast and the halo phenomenon.

(3) Dehazing algorithm based on convolutional neural network (CNN). There are two approaches to this algorithm: in one, CNN is used to generate the T and the A of the atmospheric scattering model, and then restore the fog-free image according to the atmospheric scattering model. [12] used the random forest model to learn the scene features in a large number of foggy images to obtain the optimal propagation map. The CNN-based DehazeNet network proposed by Cai et al [13] estimates the transmission map, which is then constructed from prior information in traditional dehazing methods. The CNN-based MSCNN was proposed by Ren et al. [14]. Zhang et al. [15] proposed the CNN-based Densely Connected Pyramid Dehazing Network (DCPDN) which was combined with the Generative Adversarial Networks (GAN) training to obtain the final haze-free image. [16] reconstructed the atmospheric scattering model and integrated the transmission map and atmospheric light value into a parameter K, and designed AOD-Net based on CNN to estimate this parameter. Another method uses a convolutional neural network to generate clear images without haze directly from blurred images. An example of this approach is the Enhanced Pix2pix Dehazing Network (EPDN) proposed by Qu et al. [17], which directly learns the difference between foggy and fog-free images, and the restored haze-free images are clearer and more natural. The FFA-Net proposed by Qin et al. [18] can effectively extract image features, but the network is dehazed by learning the difference between foggy and sharp images, ignoring the color and content features of the image. The dehazing effect is not ideal for actual images. The Y-Net was proposed by Yang et al. [19], but continuous down-sampling in the network may lead to the loss of image features, so that the details and color of the restored haze-free image are insufficiently preserved. These algorithms improve the image quality to a certain extent, but overfitting often occurs in the learning process, ignoring the original color features and content features of the image, resulting in incomplete or excessive dehazing in some areas, restoring the color of the image.

To address the aforementioned problems, in this paper, a dehazing network is proposed that combines residual blocks in order to extract image features and fuse features. Using the cascaded residual block and the cascaded residual dense block as the main frame [20, 21], a color extraction module and a content extraction module are designed to extract image features. Convolution and nonlinear transformation are performed on the extracted color feature map and the content feature map to obtain a haze-free image. The network image has much better dehazing, high image definition, and no color distortion or halo phenomenon.

2. THE PROPOSED ALGORITHM

The algorithm proposed in this paper is a dehazing network that combines residual blocks and image feature fusion. The network can achieve end-to-end dehazing of hazy images to produce non-haze images. This network includes three sub-networks: image feature extraction, feature fusion and image restoration. The feature extraction network consists of two sub-networks, one is to obtain the color feature of the image, and the other is to obtain the content feature of the image. Using two sub-networks to extract the color features and content features of the image respectively can better maintain the original color of the image while dehazing, and overcome the problems of incomplete image dehazing and color distortion obtained with existing methods. In addition, in order to fully capture the color features and content features of the image, the feature extraction module combines the residual block idea and the mixed attention mechanism, and uses the cascaded skip-layer residual blocks combined with the mixed attention mechanism to extract the color features of the image. The cascaded residual dense blocks extract the content features of the image. Then, the color features are fused with the content features. Finally, the fused feature maps are nonlinearly transformed to obtain a clear image. The dehazing network proposed in this paper is shown in Figure 1.

2.1 Feature Extraction Network

Each image has features such as spatial relationship, color, shape, texture, etc., which can be extracted from the image after detection.

2.1.1 Color Feature Extraction Module

In order to achieve image dehazing and ensure that the image is not color cast or distorted, it is necessary to accurately

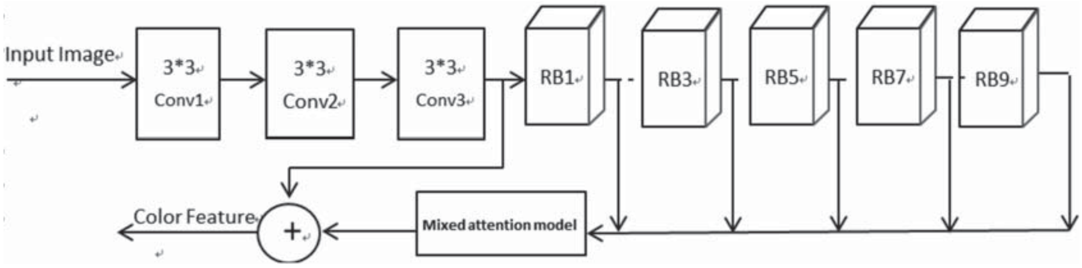

Figure 2 Color feature extraction.

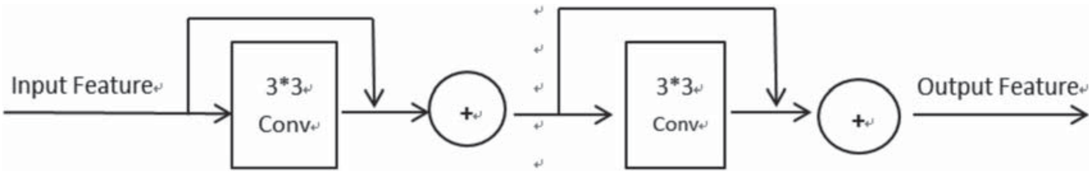

Figure 3 The residual block.

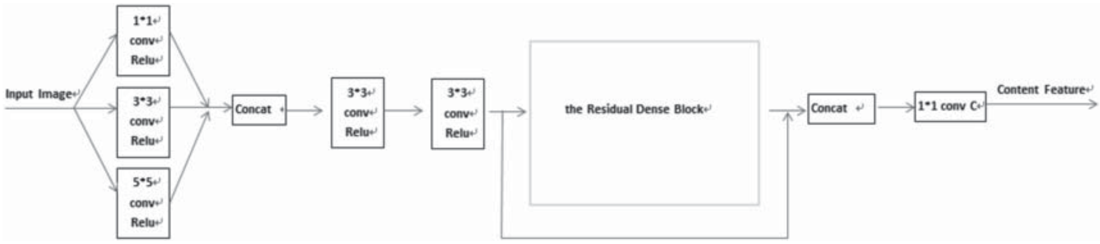

Figure 4 Content feature extraction.

and effectively obtained the color features of the image. In order to do so, this paper introduces the residual idea to design a color feature extraction module. This module extracts image features from two levels respectively. The first three convolutional layers (Conv1∼Conv3) extract the shallow features of the image and, in the last nine, the residual module composed of cascaded skip-layer connection residual blocks (RB1∼RB9) combines the hybrid attention mechanism to extract the deep features of the image. Then, the shallow features and the deep features have a large residual. The convolution kernels of the first three convolutional layers are all $3 * 3$, the number of output channels are all 64, and the strides are $\{1,\ 1,\ 2\}$. Since the color feature has little relationship with the direction, size and other changes in the image, it belongs to the global feature of the image, and the 3×3 convolution kernel is relative to the larger convolution kernels can effectively extract image features while reducing the number of parameters and calculations, so the first three layers of convolution kernels use $3 * 3$ convolutions. The step size of the first two layers is 1, which can extract image features more comprehensively, and the step size of the third layer is 2, which can reduce the size of the feature map and reduce the number of calculations. The shallow features obtained by the convolution of the first three layers are then sent to the residual module to extract the deep features of the image. The structure of each residual block in the residual parameter module is the same, including two convolution layers, the size of the convolution kernel is 3×3, the stride is 1, and the number of output channels is 64. After convolution, the activation function adopts the PReLU function. The cascaded residual block adopts a skip-layer connection method to convolve the features output by the residual blocks RB1, RB5, RB7 and RB9 and transfer them to the deeper hybrid attention module of the network. This connection method is equivalent to performing an identity transformation. It will not increase the computational complexity, and can effectively solve the problem of gradient disappearance in the deep network, which improves the network learning ability. Figure 2 is the color feature extraction module, and Figure 3 is a residual block.

2.1.2 Content Feature Extraction Module

In order to effectively obtain the content features of images, a content feature extraction module is designed in this paper, which includes three convolutional layers (Conv1∼Conv3) and 9 cascaded incremental residual dense blocks (ERB1∼ERB9). The convolution kernels of the first three convolutional layers are all $3 * 3$, the number of output channels are all 64, and the strides are $\{1,\ 1,\ 2\}$. Conv1 is the convolution of three parallel convolution kernels of $3 * 3$, $5 * 5$, and $7 * 7$. The convolution kernels of different scales extract different feature information from the original foggy image, and deepen the network so that it can learn the features of the image more comprehensively.

Studies have shown that using a larger number of feature maps before the activation function layer (PReLu) helps the model to better learn the image features. In order to extract the content features of the image more effectively, the residual block of this network is relative to the color feature. The residual block in the extraction module is modified, and the

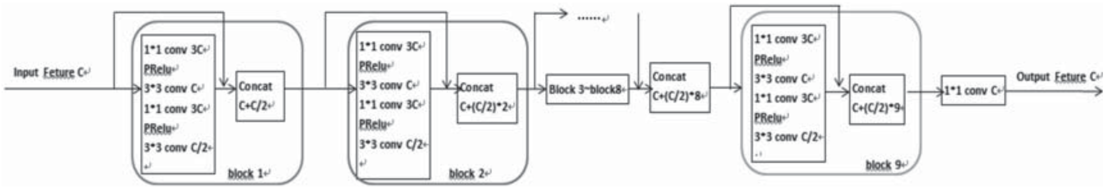

Figure 5 The residual dense block.

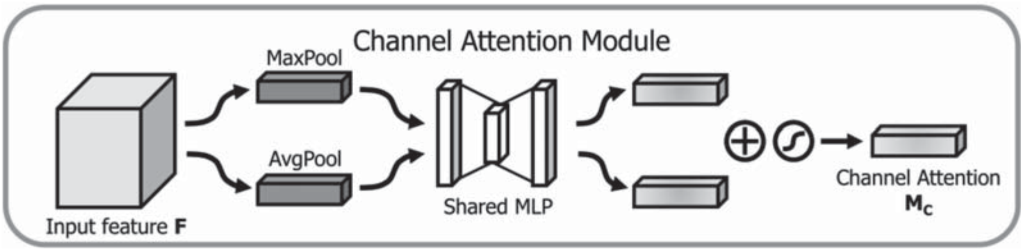

Figure 6 CAM.

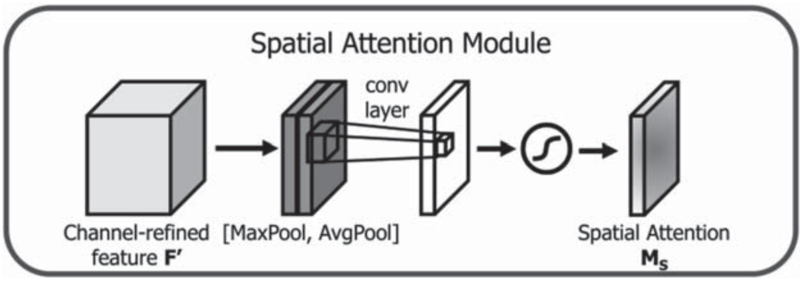

Figure 7 SAM.

two $3*3$ convolution kernels are adjusted into two sets of $1*1$ and $3*3$ convolution kernels, namely the enhanced residual dense module (ERDB). The $1*1$ convolution kernel expands the number of feature maps, and after the activation function layer is cropped, the $3*3$ convolution kernel is used to extract image feature information. The structure is shown in Figure 5. Each residual dense module contains 9 dense residual layers and one convolutional sorting layer. Suppose the input dense residual module has C channels of feature maps. Input it into the first dense residual layer, expand the feature to $3*C$ channels through a $1*1$ convolution kernel, and then input the activation function layer to crop, and then go through a $3*3$ convolution kernel and use the channel addition (Concat) method to retain c/2 channel feature maps that are added to the total input. For every dense residual layer, the total number of feature maps increases by c/2 channels. Finally, the obtained feature map is input into the convolution sorting layer to complete the residual operation. This modular structure allows the shallow learning information to be retained and used multiple times, and to share part of the data between the input and output.

2.2 Hybrid Attention Module

Each different region contributes something different to the feature extraction. The attention mechanism finds the most important feature parts in the network for processing, and we integrate it into the image feature extraction network to improve the performance of the model. The attention mechanism can be designed in terms of two dimensions: image space and channel space. In this paper, two modules are serialized. The channel attention module(CAM)is shown in Figure 6. After the channel attention module, the spatial attention module (SAM) is used to focus on features that are meaningful. The spatial attention module is shown in Figure 7.

2.3 Feature Fusion

The feature fusion module fuses color features and content features, including: (a) Channel weighting in the color feature extraction module; the output of the residual blocks RB1, RB3, RB5, RB7 and RB9 is obtained by stacking the channel weighting. The weighted color feature map is denoted as Cr_F. (b) Fusion: the output of the content feature module is recorded as the content feature map Ct_F; the weighted color feature map Cr_F and the content feature map Ct_F are stacked, and the fused feature map IF is obtained through deconvolution layer and convolution layer operations. The deconvolution layer plays an important role in this network structure in order to increase the size of the image, and this layer is equivalent to upsampling. In order to reduce the number of parameters and computations, a convolution with a stride of 2 is performed on the feature map during image feature extraction to achieve the purpose of scaling the image feature size. Therefore, the image restoration module needs to upsample the image features so as to restore the original size of the image.

2.4 Image Restoration

For the fused feature map, a convolution is done with a kernel size of 1*1 and a step size of 1, and the output is a haze-free image.

2.5 Loss Function

The activation function is connected to each convolutional layer. In this paper, the network uses PRelu as the activation function. This function can effectively avoid the disappearance of the gradient, realize the sparseness of the network, and increase the convergence speed of the algorithm.

3. EXPERIMENT AND RESULT ANALYSIS

The details of the experimental environment of this algorithm are as follows:

Hardware equipment: CPU: Intel Core i7 Acceleration frequency: 4.7GHz quad-core; Memory: 16GB.

Software configuration: Operating system: 64-bit Win10; Python 3.7.

3.1 Dataset

The dataset used for this experiment comprises blurred images that are computer-generated, the dataset is divided into indoor data set and outdoor dataset. The indoor dataset uses the public dataset NYU2, which contains 1449 clear images and 1449 blurred images of 464 different indoor scenes. The outdoor dataset adopts the public dataset RESIDE. The RESIDE training set contains 1399 clear images, 1 clear image is synthesized with 10 blurred images, and there are a total of 13,990 synthesized blurred images. In addition, in order to enrich the test set and verify the robustness of the method proposed in this paper, the foggy image dataset, Middlebury Stereo Datasets (MSD) is used, which is synthesized by the atmospheric scattering model, and selects the foggy image with richer colors as the test image to verify the color fidelity obtained by the dehazing network.

3.2 Evaluation Criteria

The objective evaluation criteria are: the recognized Structural Similarity (SSIM), Peak Signal to Noise Ratio (PSNR), Information Entropy (IE) and Average Gradient (AG) is used as an objective evaluation index. SSIM is a measure of image structure similarity. PSNR is a measure of the completeness of image structure information. IE is a measure of the size of the amount of information of an image contains. AG is a measure of image sharpness. The PSNR calculation is shown in Equation 1, and the SSIM calculation is shown in Equation 2.

$$MSE = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} (X(i,j) - Y(i,j))^2$$

$$PSNR = 10 \log_{10} \left(\frac{(2^n - 1)^2}{MSE} \right) \tag{1}$$

MSE: Mean Square Error, $X(i,j)$:the pixel at the (i,j) position of X, $Y(i,j)$: the pixel at the (i,j) position of Y, H: the height of the image, W: the width of the image; n 8.

$$SSIM(x,y) = [l(x,y)]^{\alpha} [c(x,y)]^{\beta} [s(x,y)]^{\gamma} \tag{2}$$

$l(x,y)$: the brightness of x and y, $c(x,y)$: the contrast of x and y, $s(x,y)$: the structure of x and y.

3.3 Experimental Steps

The experimental steps taken are: 1) network model training; 2) network model testing; 3) dehazing results and analysis based on image library; 4) dehazing results and analysis of foggy images in real scenes; 5) subjective experimental evaluation. The network input crops the foggy image into a 320pixel*240pixel foggy image, and the cropping operation is only to reduce the training time of the model. The training labels are clear and fog-free images, the training learning rate of the network model is 0.0001, and the batch size is 16.

3.4 Experiments on Synthetic Datasets

The training process selects 70% of the data in the dataset as the training set, and 30% of the data as the test set. In this paper, the dehazing effect of three indoor images and three outdoor images is selected to be the same for DCP[5], DehazeNet[13], MSCNN[14], AOD-Net[16], DCPDN[15], EPDN[17], FFA-Net[18] and Y-Net[19]. The algorithms are compared. The comparison diagram is shown in Figure 8, and the parameter evaluation is shown in Table 1.

In Figure 8, the color of the image restored by the DCP method is darker and the overall image brightness is low, and there are color distortion problems in the floor of the indoor image and the sky and wall areas of the outdoor image. The DehazeNet method does not dehaze thoroughly in the wall and table and chair areas of the indoor images. The MSCNN and AOD-Net methods are not completely dehazed, and the restored image seems to have a layer of haze on the clear image, and the color fidelity of the image is insufficiently restored. The DCPDN method is more thorough in dehazing, but the color distortion of the sky area image is serious, and the desktop details of the image are insufficiently restored. The EPDN method has excessive dehazing phenomenon in the misty area, and insufficient dehazing in the dense fog area. With the Y-Net method, the haze removal is not thorough

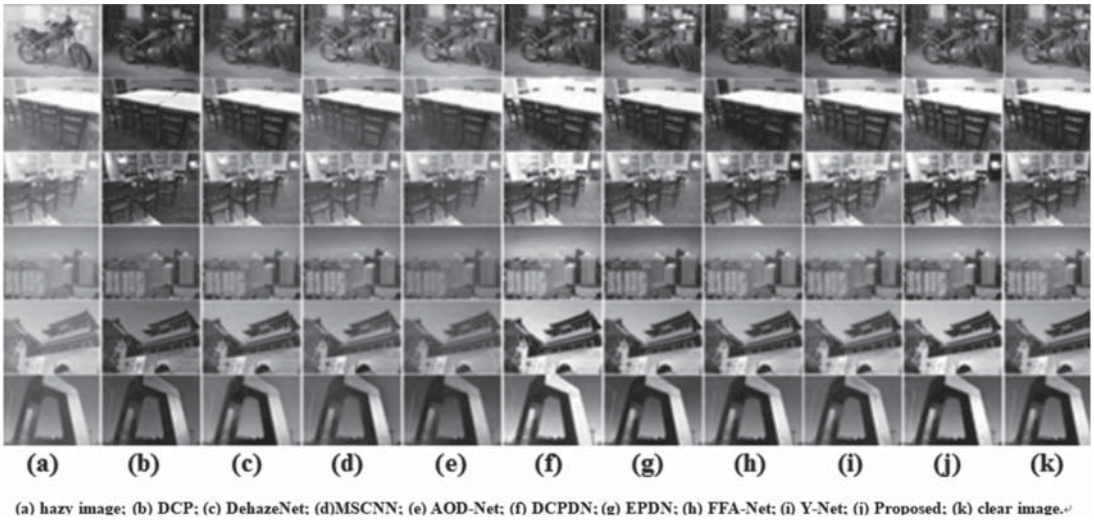

Figure 8 Experimental results of the synthetic hazy images.

Table 1 Comparison of PSNR and SSIM tested on synthetic hazy images.

Method	Indoor		Outdoor	
	PSNR/db	SSIM	PSNR/db	SSIM
DCP(5)	16.62	0.8179	19.13	0.8148
DehazeNet	21.14	0.8472	22.46	0.8154
MSCNN	17.57	0.8102	22.06	0.9078
AOD-Net	19.06	0.8504	22.29	0.8765
DCPDN	15.85	0.8175	19.93	0.8449
EPDN	25.06	0.9232	22.57	0.9840
FFA-Net	36.39	0.9886	33.57	0.8741
Y-Net	19.04	0.8465	24.07	0.9012
Proposed	31.83	0.9872	31.52	0.9884

enough, and the sky color is too dark. Table 1 shows that the dehazing image PSNR and SSIM metrics obtained by our method are better than those of most dehazing methods.

3.5 Experiments in Real Scene Images

In order to verify the effectiveness of the model proposed in this paper for restoring actual foggy images, three real outdoor foggy images were selected for dehazing experiments. The comparison of experimental results of Tang[12], DehazeNet[13], and MSCNN[14] algorithms is shown in Figure 9. It can be seen from Figure 9 that the DCP algorithm has a good dehazing effect when there is no or a small amount of sky area in the foggy image, but the overall brightness of the image after dehazing is low. When the foggy image contains a large area of sky, the sky part of the image has different degrees of color distortion after dehazing. Compared to the results obtained by DCP, Meng's algorithm improves the brightness, but color distortion occurs when foggy images contain large areas of sky. The dehazing effect of the Tang algorithm is better, but the color of the sky area after dehazing is seriously distorted.

DehazeNet and MSCNN do not produce sky distortion effects, but there is incomplete dehazing in areas with greater depth of field. The method proposed in this paper effectively removes the fog in the image; there is no distortion in the sky area; the overall brightness of the image is moderate; and a good visual effect is maintained. In order to further verify the effectiveness of our model in recovering outdoor foggy images, IE and AG are selected for data comparison and analysis of the experimental results. The parameters are shown in Table 2. Analysis of the data in Table 2 shows that the performance of IE and AG of the algorithm in this paper is better than other algorithms. The values of IE and AG prove that the dehazing image of the algorithm proposed in this paper is clearer and the dehazing effect is better.

4. CONCLUSIONS

In this paper, an image-dehazing network based on residual block and fusion image features is proposed to address the problems associated with poor dehazing, such as sky color distortion and low image contrast. An end-to-end convolutional dehazing network is designed, which consists of three parts: extraction of image feature modules, fusing image features, and image restoration. The feature extraction module is divided into two parallel branches: one branch extracts the color feature of the image, and the other branch extracts the content feature of the image. The common point of the two branches is the extraction of the shallow features of the

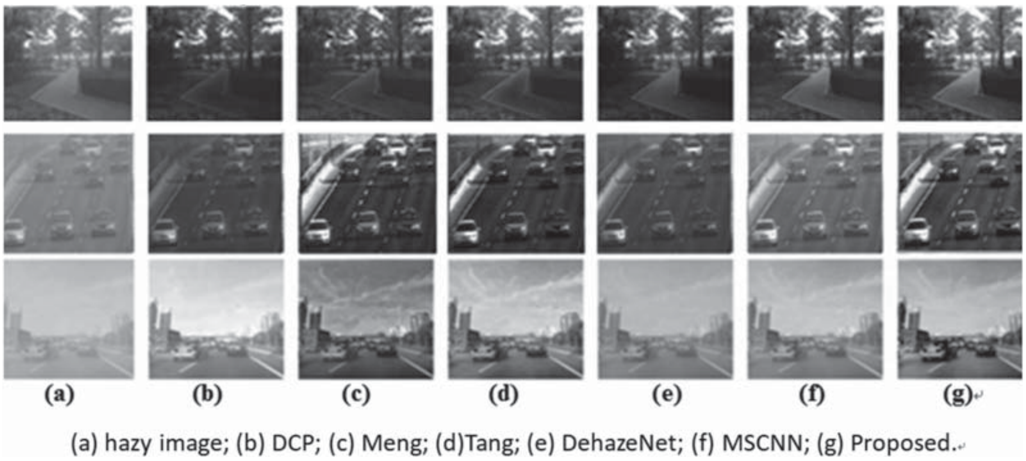

Figure 9 Experimental results of the real outdoor hazy images.

Table 2 Analysis of experimental data of outdoor hazy images.

Method	Image1		Image2		Image3	
	IE	AG	IE	AG	IE	AG
DCP	7.0555	14.64	7.2625	10.94	6.2721	5.88
Meng	7.0652	18.34	7.1136	12.96	7.1459	7.32
Tang	7.3984	18.52	7.68344	13.71	7.3561	7.55
DehazeNet	7.2445	17.22	7.3200	8.67	6.8363	5.97
MSCNN	7.4048	20.25	7.5189	9.59	6.9818	6.39
Proposed	7.5879	22.12	7.8204	13.98	7.5203	7062

foggy image through the convolution layer operation, and then the extraction of the detailed features of the deep layer of the foggy image through the residual block, followed by a fusion of the shallow features and deep features. The difference is that the color feature extraction module uses a cascaded skip layer residual block, and the feature maps of RB1, RB3, RB5, RB7 and RB9 are improved by the hybrid attention module. The content feature extraction module first uses three convolution kernels of different scales to perform the first layer of convolution to extract the shallow features of the image, and the residual module uses the cascaded residual dense blocks to extract the detailed features of the image. The two output color features and content features of the feature extraction module are fused; finally, the non-haze image is restored by nonlinear regression. The model is trained using the fog image dataset, and the trained model is used to conduct various tests on foggy images in different indoor and real scenes, and obtain clear fog-free images. The method proposed in this paper can effectively extract the color features and content features of fog images, improve the clarity and quality of images, and provide a good foundation for subsequent image processing. The next work to be done involves the optimization of the dehazing model so as to obtain a better dehazing result.

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