Dilated Residual Spatial Attentive Generative Adversarial Network for Single Image De-raining

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Abstract. This paper propose a dilated residual spatial attentive generative adversarial network for single image de-raining. The improved spatial attentive mechanism is combined with the dilated convolution residual module to optimize the Condition Generative Adversarial Network(CGAN) structure, to solve two problems still exist in the task of removing rain from a single image: First, the rain streaks contained in the dataset we can use are limited, and in the case of real rainy days, the rain streak density is diverse, it is impossible to simulate them completely and accurately. Then, the existing rain removal models cannot remove rain streaks properly for images with different rain streak density which attend to over or under rain removal. In our methods, Firstly, the dilated convolution module is used to enhance the feature extraction of rain streaks, and then an attention map is generated by the spatial attention mechanism module to accurately locate the position of rain streaks, and the rain streaks are extracted as the foreground information by combining the two parts of the network to guide the subsequent rain removal operation; Then the rain streaks is removed through the Contextual auto-encoder, combining with PatchGAN discriminator. The experimental results on two synthetic dataset and real-world rain image show that the network model proposed in this paper has high generalization ability under different rainfall conditions. it improves the rain removal effect of the model on the most realistic public dataset, and improves the recovery ability of image details while effectively removing rain on other public datasets, which verifies the effectiveness of the model in improving the generalization ability and improving the image quality after rain removal. At the same time, the effect of rain removal is better than other methods on the real rain images, which proves that the method proposed in this paper has high practical application value.

1. Introduction
Single image rain removal is a kind of technology which can effectively remove rain and restore clear image on the premise of ensuring the image details are not lost. With the rapid development of computer vision technology, outdoor vision system has been widely used in military, traffic, safety monitoring and other fields. Many outdoor vision systems require accurate outdoor scene detection. However, in severe weather, the visibility of the scene is greatly reduced, and the pictures and video data taken are greatly affected by raindrops, it causes that various details of images cannot be recognized, and the value of image usage is debased. At present, most of the researches on rain removal are focused on the video or multi frame image, because more prior information, such as spatial-temporal correlation, can be used in the video or multi frame image to confirm the location of raindrops by analyzing the changes of the sensitivity of raindrops in the continuous frame image,
which is not available in a single image. Based on the limitation of lack of prior information in a single image, there are two major difficulties in this technology: First, although rain lines can show thin and bright lines in the image, it is difficult to accurately detect complex and changeable rain lines due to wind direction factors, similar background interference and other problems; Secondly, when removing the rain streaks, the phenomenon of excessive or insufficient rain removal often occurs, which will lead to the loss of image details and the problem of discontinuity of pixels when filling the background of the image after rain removal.

Recently, several deep learning based de-raining methods achieve advantage performance, nonetheless, there are still limitations of the existing methods. For example, there is only one kind of rain streak is simulated in a training dataset, the trained network can only deal with the situation which is similar to the training dataset. For the extreme situation of the real-world images, they often tend to under de-raining or leave unsmooth streaks in the image after rain removal. We still need to improve the generalization ability of the model to deal with this problem.

In order to address these issues, we propose a Dilated Residual Spatial Attentive Generative Adversarial Network called DRSA-GAN, which uses an dilated residual module to enhance the extraction and detection of rain streaks, and assists the spatial attentive mechanism to generate an attention map more accurately for improving the location of variable and complex rain streaks to guide the contextual auto-encoder to remove rain streaks from a single image. In addition, our method can generate a higher quality image after rain removal without losing the details of the image due to as a result of the good performance of the generative adversarial network with PatchGAN discriminator. A number of evaluation results show that our proposed network achieves an excellent performance of single image de-raining.

Hence, this paper makes the following contributions:

- We propose a new generative adversarial network to remove rain streaks from a single image, through which we can remove rain streaks while preserving image details. The generator network consists of the dilated residual module, the spatial attentive module and the contextual auto-encoder.
- By optimizing and improving the spatial attentive mechanism, the generalization ability of rain streaks location is improved. Under the condition of training a kind of rain streaks density instead of a large number of datasets to include several rain streaks, we can remove rain streaks from single image with a variety of densities.
- Thanks to the excellent performance of GAN in image generation and the training mechanism of mutual game, the quality of output image of our method is higher after de-raining especially in real-world rainy image.

2. Related Works

Originally, some traditional methods regard the problem of removing rain streaks from a single image as a separation problem. they model a rain image as a linear combination of a clean background image x and rain streaks map r to recover x by y. For instance, Kang et al.[1] extract the high-frequency layer of a rain image, and separate the rain streaks from it by sparse coding. There are still some methods that include non-local mean filter methods [2], Gaussian mixture model methods [3] and low-rank representation-based methods [4]. However, due to the lack of temporal prior and other key information in the single image de-raining task compared with the video-based de-raining task, the results of rain removal often have problems of over-smoothness that leads to loss of image details. Some traditional methods regard the problem of removing rain streaks from a single image as a separation problem[5]. However, due to the lack of temporal prior and other key information in the single image de-raining task compared with the video-based de-raining task, the results of rain removal often have problems of over-smoothness that leads to loss of image details.

In recent years, the advantages of deep learning in feature extraction make it make great progress in the problem of removing rain from a single image. Fu [6] et al. first introduce the deep learning method into the single image rain removal. They constructed an end-to-end single image de-raining network to operate the high-frequency layer by using the deep residual network. Yang [7] et al.
proposed a multi-task context dilated network and adopted the additional information of detected rain regions to solve the problem of incomplete rain removal.

With the appearance of GAN network, the game training mechanism between generator and discriminator has made a great breakthrough in the quality of image generation. Therefore, some scholars have gradually applied GAN network to the task of removing rain from a single image and achieved relatively ideal results. Zhang [8] et al. first use the conditional generative adversarial network to study the rain removal from a single image, and add the perceptual loss to improve the visual quality of the generated image. All of these methods improve the performance of rain removal to some extent, but to the real-world rainy image of complex rainfall situation will appear different degrees of unclear phenomenon. Qian [9] proposed a GAN model with attention mechanism built by LSTM to remove raindrops from a single image, and achieved ideal effect. However, raindrops are different from rain lines. Raindrops are a kind of interference attached to the lens, which can affect the overall quality of the image. However, because most of the raindrops are transparent, some background information can still be reflected through raindrops, thus providing valuable information for image restoration.

Zhang and Patel [10] proposed a 1200 synthetic dataset with three kinds of rainfall density labels, which is currently the most widely used and the closest to the real rain streak features. They train a residual-aware rain-density classifier to first classify the images with different rainfall density, so as to guide the model to carry out different degrees rain removal. This method solves the problem of excessive or insufficient rain removal in the previous model. But in the real-world rainy image, we cannot divide the rain distribution into several grades accurately, and due to the influence of wind and background, there are often different distribution of rain streaks in different parts of an image. It is necessary to improve the ability of generalization of rain streak recognition to improve the effect of rain removal of a single image.

In 2019, Chen [11] proposed an end-to-end gated context aggregation network to solve the problem of removing rain and fog from a single image, and achieved the best results in the training and testing on the data set it used. However, when the real rain image is used for testing, it is found that the network is basically unable to effectively remove rain from the image, and will lead to the change of image contrast saturation. In conclusion, although the deep learning model has made a great breakthrough in the field of single image rain removal, there are still problems such as low generalization ability of the model and poor image detail recovery. Therefore, it is still necessary to improve the generalization ability of the model for rain line recognition and enhance the recovery of image details.

Therefore, from the perspective of improving the generalization ability of the model, we propose a dilated residual spatial attentive generative adversarial network for single image de-raining. The network can better extract the rain streak features, improve the generalization ability of the network, and achieve more excellent rain removal effect.

3. Proposed Method

In this paper, we propose a Dilated Residual Spatial Attentive Generative Adversarial Network (DRSA-GAN) to effectively retain background details while removing rain streaks. Following the idea of generative adversarial networks [12], our backbone network consists of the generative and discriminative networks. In the generation network, a rain image first through two convolution relu layers to generate the feature map 1, and then enters the dilated residual module to extract the rain streak features preliminarily, providing effective rain streak features for the spatial attentive mechanism module. Then, the generated feature map 2 and the previously generated feature map 1 are input into the spatial attentive mechanism together to generate the attention map to ensure that the contextual auto-encoder will pay more attention to the location of the rain streak. Finally, the contextual auto-encoder effectively removes rain according to the guidance of attention map. Discrimination network is used to distinguish whether the input image is real data or generated data. The entire network architecture of the DRSA-GAN is shown in Figure 1.
3.1. Generative Network

The generation network model of this paper can be divided into three parts: 1) dilated residual module; 2) spatial attentive module; 3) contextual auto-encoder. Firstly, the input rain image is mapped to feature space through two `conv + relu` layers to generate `feature map1`, then `feature map1` enters into dilated residual convolution module to extract features of rain streak, then its output and `feature map1` are input into spatial attentive module to generate an `attention map` at the same time. Finally, the `attention map` and rain image are dot multiplied, the `attention map` is used to guide contextual auto-encoder performs the operation of rain removal on rainy image to generate the final image after rain removal.

3.1.1. Dilated residual module. Due to the shape and position of rain streaks is important for single image removal, how to extract rain streak information from a single rain image is one of the difficulties of single image removal. In general, a pixel on the feature map after the convolutional layer can correspond to the size of the receptive field on the original map, which determines the upper limit of the size that the network can detect, while ensuring that the receptive field is large enough depends on downsampling operation. The purpose of dilated convolution is to expand the receptive field of convolution operation without increasing the parameters and losing the resolution. However, it will lead to grid artifact because the convolution kernels are spaced. In this paper, we use the continuous dilated convolution composed of the dilated factor of not multiple to extract features. At the same time, in the training of deep learning model, with the deepening of the network model, the problem of gradient disappearance may lead to the model can not continue to optimize and it is difficult to get the optimal result, and the residual network can solve the problem of gradient vanish. In [13], the global residual network is used to extract rain streak features, which proves that this operation can extract rain streak features better. In this paper, we use dilated convolution to construct a dilated residual network to extract rain streak features. The output of the front residual block and the subsequent residual block are connected to ensure that the feature information of the shallower rain streak is not lost. Through this operation, we can effectively enhance the feature extraction of rain streaks, so as to facilitate the next step of spatial
attentive module to better generate attention map. The structure of the dilated residual module is shown in Figure 2.

3.1.2. Spatial attentive block. In recent years, the research of deep learning and visual attentive mechanism mostly focuses on using mask to form attention mechanism. For example, Qian et al. [9] proposed an attentive mechanism recurrent network structured by a convolutional LSTM unit. Wang et al. [14] confirm that the direction-aware attention mechanism constructed by IRNN also plays an important role in the single image de-raining problem.

From the perspective of the receptive field, one pixel in the feature map originally can only get its own information, through the first round of IRNN, the pixel in the same position achieves the information of its previous pixel, which achieves the information of its previous pixel, the original-centered cross context information is obtained after repeating the above operation \( n \) times in four directions. Then, repeat the whole process, each pixel in the center can feel its own cross-context information, and then generate the whole spatial context.

In this paper, we use feature map1 as input of two rounds of IRNN to generate attention map. Because some edge information in the image background will interfere with the calculation of IRNN, when we calculate the IRNN in four directions, we multiply the four feature maps with the weight learned by the up branch, which is used to selectively highlight the rain streak features. Unlike [14] and [15], we connect feature map1 and feature map2 to the branch instead of using feature map1 only as the input to learn the weights. Since the learning weight is used to judge from the feature map whether the edge information comes from the rain streaks or the background, by carrying out this operation, we can learn more valuable weights to achieve a more accurate feature fusion effect as a result of combining shallow features. The schematic illustration of the spatial attentive block is shown in Figure 3.
3.1.3. Contextual auto-encoder. We propose a contextual auto-encoder to generate the final result. In the middle of contextual auto-encoder, four successive dilated convolution layers with different dilated factors are used to increase the receptive field to varying degrees without increasing the parameters, and skip connections are added to prevent the loss of high-resolution features during the downsampling. The schematic illustration of the Contextual auto-encoder is shown in the top right of Figure 1.

3.2. Discriminative Network
In order to solve the problem that the traditional Gan discriminator ignores the extreme results of a region in the process of averaging, we use PatchGAN [16] to enhance the ability of our discriminator. Specifically, the N×N size of patch is used as input of discriminator instead of the whole image. This discriminator classifies whether each patch in an image is real, we run discriminator on the whole image and average all the results to avoid the extreme output of the discriminator.

We summarize the calculation formula of the receptive field as:

\[ S_{\text{input}} = (S_{\text{output}} - 1) \times \text{Stride} + \text{Size}_{\text{kernel}} \] (2)

Where \( S_{\text{input}} \) denotes the receptive field size of output node, \( \text{Stride} \) is step size, and \( \text{Size}_{\text{kernel}} \) is the size of convolution kernel. Through this formula, it can be calculated that the size of the input receptive field corresponding to the output of the discriminator is 70×70.

3.3. Training Details

3.3.1. Loss function. We adopt the following loss function to train our generator:

\[ L_G = L_1 + L_A + L_{GAN} \] (3)

We use the \( L_1 \) loss to measure the per-pixel reconstruction accuracy to capture low-frequency information, \( L_A \) presents the MSE distance between the attention map and the binary mask map, and the binary mask map is obtained by calculating the difference between the rain image and original clean image that used to constrain the generation of the attention map.

3.3.2. Dataset. We use the most realistic and widely used synthetic dataset which is proposed by [10] for training and testing. Its training dataset includes 12000 images of three rain streaks density levels, light, medium and heavy, and there are 4000 images per density level. Similarly, the testing dataset includes 1200 images with three rain streaks density levels. Different from the training method of using the whole training dataset to classify and de-raining with lables, we only choose 2000 images of the medium density level from the training dataset to train our network and test on the whole testing dataset to verify the generalization ability of our network and the effectiveness our method on small sample dataset.

4. Experiments
In this section, we validate our method on the synthetic testing dataset in terms of PSNR and SSIM compared with the state-of-the-art single-image de-raining methods. Lastly, the effectiveness of our method is further verified by comparing it with other methods of on real-world images.

4.1. Quantitative Evaluation on the Proposed Network
We test our network on the testing dataset containing three kinds of rain streaks density levels, this testing dataset is proposed by [10] called Test1, As shown in Figure 4, although we only choose 4000 images of the medium rain streaks density level from the training dataset to train our network, our method also achieve excellent rain removal results for images of the other two rain streaks density levels. It shows that our network can deal with the situation that images are degraded by rain streaks to varying degrees without a large number of datasets consists of different rain streaks density levels, it proves the generalization of our network.
Then, we compare the quantitative performance of our method with previous state-of-the-art single image de-raining methods on Test1. In a single image rain removal task, visual effect is the most intuitive evaluation criterion for rain removal effect, and the comparison results are shown in Figure 5. It can be seen from the figure that JODER [7] algorithm can not effectively remove rain, and this method basically does not remove rain lines. The image of DNN [6] algorithm after rain removal is relatively fuzzy, leaving a lot of traces of rain removal. Although the algorithm of DID [10] has a good effect of removing rain, there are some mottled points in the image, which affect the image quality. Through comparison, we can see that the method proposed in this paper can effectively remove the rain line, and leave no trace after rain, and well retain the image details, the image is clear, the image quality is the highest, which verifies the superiority of the method proposed in this chapter. However, the proposed DRSA-GAN can identify the rain streaks accuracy and remove them to generate a smooth clear background without losing details. For the quantitative evaluation index, we achieve a superior de-raining performance in the terms of both PSNR and SSIM, as shown in Table 1, our final results are closer to the ground truth.

**Table 1.** Quantitative results evaluated in terms of average SSIM and PSNR (dB).

| Methods        | Input          | GMM [18] (CVPR’16) | CNN [19] (TIP’17) | JODER [7] (CVPR’17) | DNN [6] (CVPR’17) | JOB [15] (ICCV’17) | DID-MDN [10] (CVPR’18) | DRSA-GAN |
|----------------|----------------|--------------------|--------------------|--------------------|--------------------|--------------------|------------------------|----------|
| PSNR (dB)      | 21.15          | 22.75              | 22.07              | 24.32              | 27.33              | 23.05              | 27.95                  | 28.66    |
| SSIM           | 0.7781         | 0.8352             | 0.8422             | 0.8622             | 0.8978             | 0.8522             | 0.9087                 | 0.9161   |

**Figure 4.** Rain-streak removal results on sample images from the synthetic datasets Test1 in three different conditions.

**Figure 5.** Rain-streak removal results on sample images from the synthetic datasets Test1 compared with other state-of-the-art single-image de-raining methods.
4.2 Ablation analysis for each component

In order to verify the effectiveness of each component added in our structure, we carry out the ablation analysis for different combinations of each component. As shown in Table 2, GAN is our baseline module. The second line indicates whether there is an attention mechanism module or not, the third line indicates there is a three-way multi-scale dilated convolution network or a single-way network without dilated convolution. The results show that each component of our network improves the final result to a certain extent. We also test these structure in Table 2 on another dataset, as shown in Figure 6, the network with spatial attention mechanism can capture the location of rain streaks more accurately and remove it.

|                           | GAN | Improved spatial attentive mechanism | multi-scale dilated | PSNR(dB) |
|---------------------------|-----|-------------------------------------|--------------------|----------|
|                           | √   | √                                   | -                  | 25.2860  |
|                           |     |                                     | √                  | 27.4345  |
|                           |     |                                     | -                  | 25.4364  |
|                           |     |                                     | √                  | 28.0216  |

**Figure 6**: Rain-streak removal results of ablation study on sample images from another synthetic datasets. G denotes GAN, M denotes multi-scale dilated block, S denotes spatial attentive block, F denotes gated fusion operation.

4.3. Qualitative Evaluation on the Proposed Network

We also evaluated the proposed DRSA-GAN on real-world images and compare with the previous state-of-the-art single image de-raining methods. The Figure 7 shows the effect of rain removal on real-world images. It can be seen from the comparison results that JODER [7] algorithm is basically unable to effectively remove rain from the image. Although DNN [6] algorithm can remove rain to some extent, the image becomes blurred after removing rain, and the effect of removing rain is not ideal. Although the algorithm of DID [10] is better than the other two algorithms in the effect of rain removal, but changes the contrast and saturation of the image. Compared with other methods, the method proposed in this chapter can get the best rain removal effect when processing the rain images taken in real rainy days, can retain the image details while removing the rain line, and will not appear the situation that the image becomes blurred after removing the rain line with large density, we can see that our method can identify the rain streaks accurately under different rainfall conditions and
generate a clearer image with less blur and variegated. In addition, it will not change the contrast and saturation of the image.

![Rain-streak removal results on sample real-world images.](image)

**Figure 7.** Rain-streak removal results on sample real-world images.

5. Conclusion

In this paper, we propose a dilated residual spatial attentive generative adversarial network for single image rain removal to effectively retain background details while removing rain streaks. In generative network, the dilated residual module aims to enhance the extraction of rain streak features to help the spatial attentive mechanism to generate the attention map, and locate the rain streaks more accurately. Then, the attention map is used to guide the contextual auto-encoder and the PatchGAN discriminator, so that the network can focus on the location of rain streak, and generate a clearer and more realistic image after rain removal without losing the details of the image. Though we only adopt the images with one rain streak density level to train our network, we achieved satisfied rain removal effect on the images with three rain streak density level and different distribution, which proves the generalization ability of our method for rain streak recognition and removal. Comparing the test results of our method with other mainstream algorithms on data sets on the evaluation index and visual effects, it verifies the advanced nature of the algorithm proposed in this paper. At the same time, ablation experiments are carried out on other datasets to verify the effectiveness of each module in this paper. Finally, we test the real rain image and compare it with other mainstream algorithms to verify that the method proposed in this paper can get the same good rain removal effect on the real rain image, and the method in this paper is superior to other algorithms in terms of the generality of different rain line removal and the quality of the image after rain removal. It is verified that the algorithm in this paper has higher practical value.

However, our network has limitations, rainy days are often accompanied by fog. For real-world rainy images, we can only remove the rain streaks, but cannot restore the clear background image without fog. Because only the rain streaks are synthesized in the synthetic images at present. In further research, we can improve the synthetic image pairs in order to train the networks to restore clear images after removing the fog while removing the rain streaks.

In this paper, through the analysis and research on the current situation of single image rain removal, we find that there are still some problems waiting for further research. It is mainly reflected in the following aspects:

- At present, the data sets used in the task of removing rain from a single image are all synthetic data, which lacks authenticity. Because the task of image restoration needs to control the constraints of variables, the real rain - no rain image pairs can not be obtained by the means of real shooting. Although the video sequence can be used to remove the rain from the real rain video to get a real image pair of rain and no rain, the existing video rain removal methods are difficult to cope with the heavy rain and the interference of rain and fog caused by the heavy rain. Therefore, how to build a real or as close as possible to the reality of a single image rain dataset has great research value.
At present, most of the single image rain removal models improve the performance of rain removal by increasing the depth of the model. The calculation of the model is large, the training and testing time is long, and it is difficult to achieve the real-time performance of rain removal. Therefore, the design of a simple and effective rain removal model to apply to intelligent driving and other fields has a high research and application value.

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