



香港中文大學  
The Chinese University of Hong Kong

# Structure-Preserving Deraining with Residue Channel Prior Guidance

Juncheng Li

[cvjunchengli@gmail.com](mailto:cvjunchengli@gmail.com)

**Join work with Qiaosi Yi, ..., and Tieyong Zeng**

# Outline

- Background
- Motivation
- Related Work
- Method
- Experiment
- Ablation Study
- Conclusion



# Outline

- Background
- Motivation
- Related Work
- Method
- Experiment
- Ablation Study
- Conclusion



# Background

## Single Image Deraining (单图像去雨) :

Single image deraining (SID) aims to reconstruct a visually pleasing image from its corresponding rain-streaks degraded image. 单图像去雨旨在从其相应的雨条纹退化图像上重建视觉上令人愉悦的图像。



$$\mathbf{O} = \mathbf{B} + \mathbf{R}.$$

$$\mathbf{O} = \mathbf{B} + \sum_{i=1}^n \mathbf{R}^i$$

$$\mathbf{O} = \left(1 - \sum_{i=0}^n \alpha_i\right) \mathbf{B} + \alpha_0 \mathbf{A} + \sum_{i=1}^n \alpha_i \mathbf{R}^i, \text{ s.t. } \alpha_i \geq 0, \sum_{i=0}^n \alpha_i \leq 1.$$



# Background

## Single Image Deraining (单图像去雨) :

Single image deraining is **important** for many **high-level computer vision tasks** since the rain streaks can severely degrade the visibility of images, thereby affecting the recognition and analysis of the image.

1. The quality of the image will affect the analysis of the image.
2. Affect the accuracy of object detection and image segmentation.
3. Affect the accuracy of security monitoring equipment.
4. **Affect autonomous driving. (Extreme weather)**



# Background

## How to reconstruct high-quality rain-free images?



Rainy Image

Traditional methods



Rain-free Image

DL-based methods



# Background

## How to reconstruct high-quality rain-free images?

### Traditional Methods:

- focused on exploring the physical properties of the rain and background layers (专注于探索雨和背景层的物理特性)
- various priors have been proposed to regularize and separate them (各种先验被提出用于规范和分离它们)
  - ✓ layer priors with Gaussian mixture model (GMM)
  - ✓ discriminative sparse coding (DSC)
  - ✓ sparse representation

The physical model is very complex and has poor versatility.

Require complex iterative optimization to find the best solution.

The result is not satisfactory.



# Background

## How to reconstruct high-quality rain-free images?

DL-based Methods:



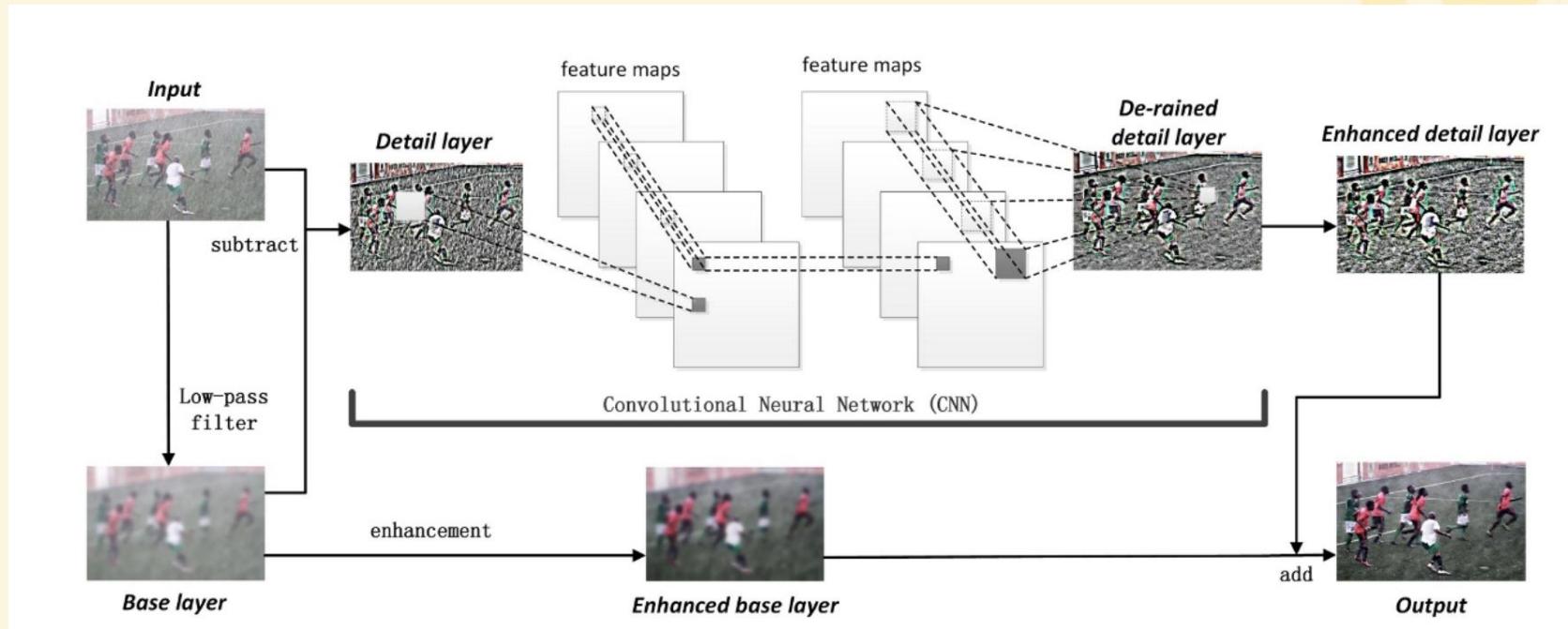
Training datasets



# Background

## DL-based Methods:

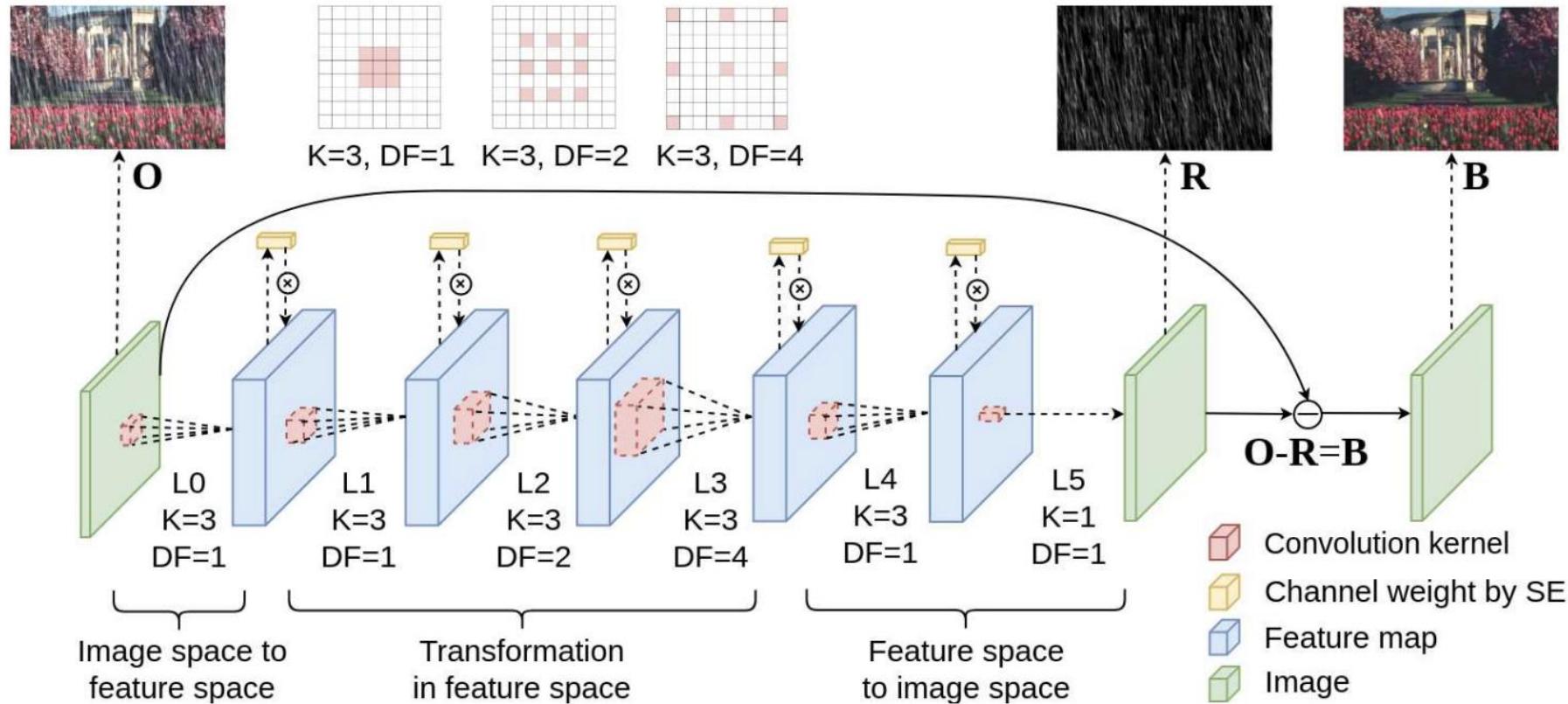
DerainNet, first CNN-based model for image deraining.



# Background

DL-based Methods:

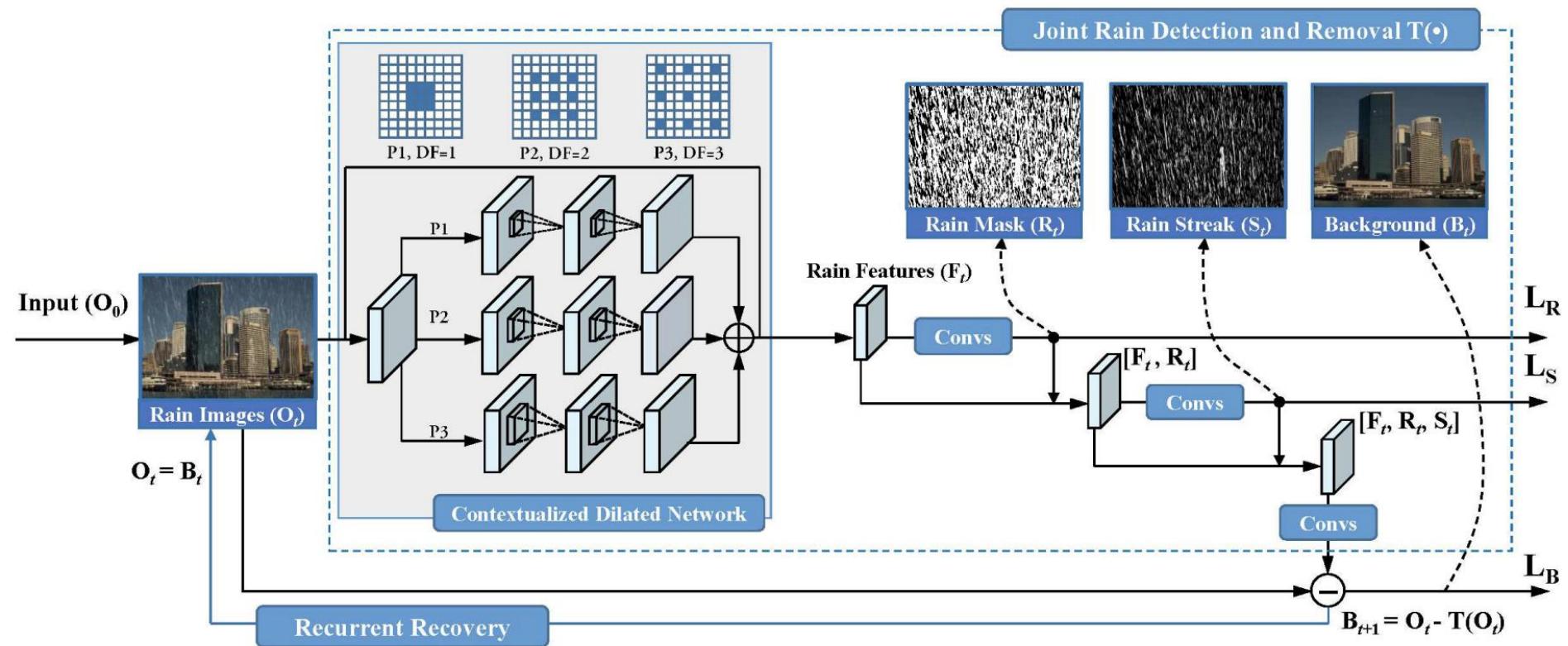
Recurrent Squeeze-and-Excitation Context Aggregation Net (SCAN)



# Background

DL-based Methods:

Joint Rain Detection and Removal from a Single Image.



More DL-based models: <https://www.jiqizhixin.com/articles/2020-06-29-7>



# Background

## DL-based Methods:

- End-to-end model, simple and efficient.
- Good results.

However...

- Most methods **predict rain streaks** via the built CNN model and then **subtract rain streaks** from rainy images to get the final output. But the density of rain streaks varies leads to **excessive or insufficient removal** of rain streaks, resulting in **incomplete structural information** of the reconstructed images.
- They pay less attention to learning the structure of objects and ignore the importance of image prior.



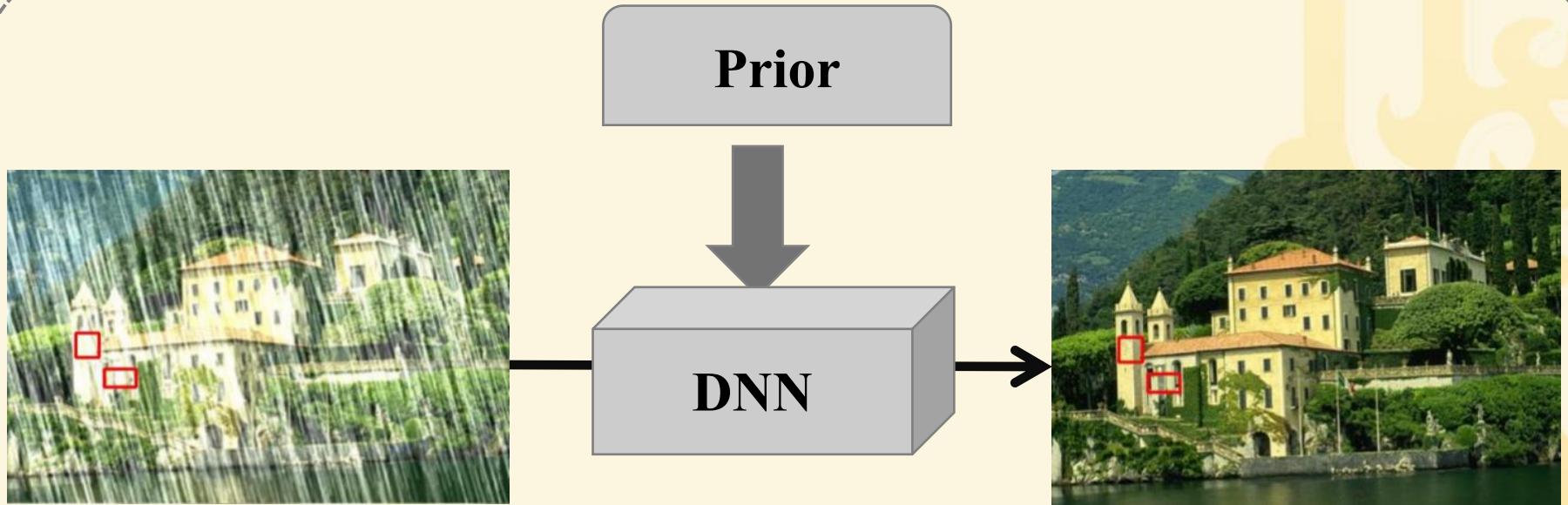
# Outline

- Background
- Motivation
- Related Work
- Method
- Experiment
- Ablation Study
- Conclusion



# Motivation

## Prior-guided image deraining:



SPDNet directly generates high-quality rain-free images **with clear and accurate structures** under the **guidance of RCP** but does **not rely on any rain-generating assumptions**.



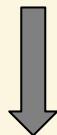
# Outline

- Background
- Motivation
- Related Work
- Method
- Experiment
- Ablation Study
- Conclusion



# Related Work

- Total Variation (TV) prior will smooth texture details in the restored images.
- Sparse prior is usually difficult to model because it requires other domain knowledge.
- Edge prior is difficult to obtain from the rainy image since the off-the-shelf edge detectors are sensitive to the rain streaks.



## Residue Channel Prior (RCP, 通道残差先验)

- Residue channel prior (RCP) show clear structures even extracted from the rainy image.
- Compared with other priors, RCP is the residual result of the maximum channel value and minimum channel value of the rainy image, calculated without any additional parameters.



# Related Work

## Residue Channel Prior (RCP, 通道残差先验)

RCP is the residual result of the maximum channel value and minimum channel value of the image.

$$\mathcal{P}(x) = \max_{c \in r,g,b} \mathcal{O}^c(x) - \min_{d \in r,g,b} \mathcal{O}^d(x)$$



A. Rainy Image



B. RCP of A

Figure 2: B is the residue channel prior (RCP) extracted from the rainy image. Obviously, even the RCP is extracted from the rainy image, it still contains clear structures.



# Related Work

## Residue Channel Prior (RCP, 通道残差先验)



This ECCV 2018 paper, provided here by the Computer Vision Foundation, is the author-created version.

The content of this paper is identical to the content of the officially published ECCV 2018 LNCS version of the paper as available on SpringerLink: <https://link.springer.com/conference/eccv>

### Robust Optical Flow in Rainy Scenes<sup>★</sup>

Ruoteng Li<sup>1</sup>, Robby T. Tan<sup>1,2</sup>, and Loong-Fah Cheong<sup>1</sup>

<sup>1</sup> National University of Singapore

<sup>2</sup> Yale-NUS College



# Related Work

## Residue Channel Prior (RCP, 通道残差先验)

The colored-image intensity of a rain streak image can be expressed as (雨条纹图像的彩色强度可以表示为):

$$\tilde{\mathcal{O}}(x) = \frac{t\beta_{rs}(x)\mathcal{B}\alpha}{\text{雨条纹项}} + \frac{(T-t)\mathcal{R}\pi}{\text{背景项}}$$

$\tilde{\mathcal{O}}(x)$  表示颜色强度的颜色向量

$\beta_{rs}$  由雨滴的折射、镜面反射和内反射系数组成

$\mathcal{B} = B_r + B_g + B_b$      $\mathbf{B} = (B_r, B_g, B_b)^T$  代表光亮度

$\mathcal{R} = R_r + R_g + R_b$ .     $\mathbf{R} = (R_r, R_g, R_b)^T$  代表背景反射

$\alpha = \mathbf{B}/\mathcal{B}$      $\pi = \mathbf{R}/\mathcal{R}$      $T$  为曝光时间代表

$t$  为雨滴通过像素  $x$  的时间



# Related Work

## Residue Channel Prior (RCP, 通道残差先验)

When employing any an existing color constancy algorithm to estimate  $\alpha$   
(当使用任何现有的颜色恒常算法来估计  $\alpha$  时):

$$\mathcal{O}(x) = \frac{\tilde{\mathcal{O}}(x)}{\alpha} = O_{rs}(x)\mathbf{i} + O_{bg}(x)$$

$$O_{rs} = t\beta_{rs}\mathcal{B} \quad \mathbf{i} = (1, 1, 1)^T \quad O_{bg} = (T - t)\mathcal{R}/\alpha$$

When we normalize the image, the light chromaticity will be cancelled and the color effect of the spectral sensitivities will also be cancelled (当我们对图像进行归一化时，光色度会被抵消，光谱灵敏度的颜色效应也会被抵消)

$$\mathcal{P}(x) = \max_{c \in r, g, b} \mathcal{O}^c(x) - \min_{d \in r, g, b} \mathcal{O}^d(x)$$



# Related Work

## Residue Channel Prior (RCP, 通道残差先验)

Due to the rain streak term is achromatic(消失/无色/透明), whose values are canceled when employing color constancy, residue channel prior can be free from rain streaks.

Since the dominant gray atmospheric light is generated by a cloudy sky, the appearance of rain streaks is already achromatic in most cases. Based on this observation, RCP can extract a more complete and accurate object structure.

由于主要的灰色大气光是由多云的天空产生的，因此在大多数情况下，雨条纹的外观已经是无色的。基于这种观察，RCP 可以提取出更加完整和准确的对象结构。



# Outline

- Background
- Motivation
- Related Work
- Method
- Experiment
- Ablation Study
- Conclusion



# Method

- We explore the importance of residue channel prior (RCP) for rain removal and propose a Structure Preserving Deraining Network (SPDNet) with RCP guidance. Extensive experimental results show that SPDNet achieves new state-of-the-art results.
- We design a Wavelet-based Multi-Level Module (WMLM) as the backbone of SPDNet to learn the background of the area covered by the rain streak.
- We propose an RCP extraction module and an Interactive Fusion Module (IFM) for RCP extraction and guidance, respectively. Meanwhile, an iterative guidance strategy is designed for progressive image reconstruction.



# Method-SPDNet

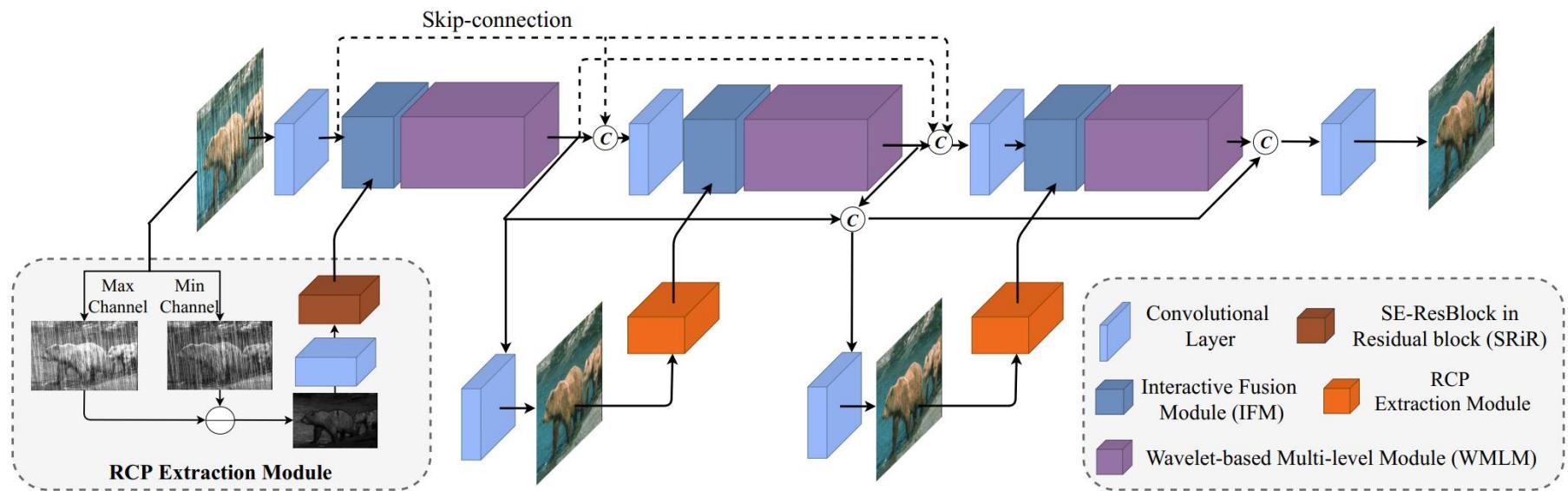


Figure 3: The overall architecture of the proposed Structure-Preserving Deraining Network (SPDNet).

SPDNet uses the **wavelet-based feature extraction backbone** as the main structure and introduces a **residue channel prior (RCP)** guided mechanism for structure-preserving deraining.



# Method-SPDNet

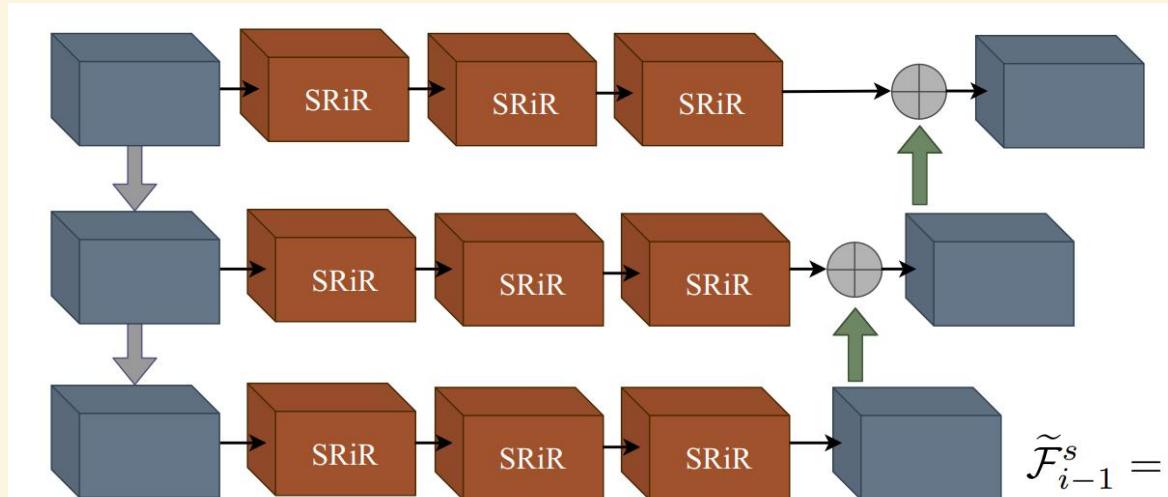
- **Wavelet-based Feature Extraction Backbone**  
(基于小波变化的特征提取主干)
- **RCP Guided Structure-Preserving Deraining**  
(RCP 指导的结构保护去雨)
  - **Residue Channel Prior** (RCP, 通道残差先验)
  - **RCP Extraction Module** (RCP提取模块)
  - **Interactive Fusion Module** (交互式融合模块)
  - **Iterative Guidance Strategy** (迭代指导策略)
- **Loss Function**



# Method-SPDNet

## Wavelet-based Feature Extraction Backbone:

基于小波变化的多层次模块 (WMLM)



$$\begin{cases} \tilde{\mathcal{F}}_i = \tilde{\mathcal{F}}, & \text{if } i = 0, \\ \tilde{\mathcal{F}}_i = \text{Conv}(DWT(\tilde{\mathcal{F}}_{i-1})), & \text{if } i > 0, \end{cases}$$

$$\tilde{\mathcal{F}}_i^s = SRiR(\tilde{\mathcal{F}}_i), \quad i = 0, 1, 2.$$
$$\tilde{\mathcal{F}}_{i-1}^s = IWT(\text{Conv}(\tilde{\mathcal{F}}_i^s)) + \tilde{\mathcal{F}}_{i-1}^s, \quad i = 2, 1,$$

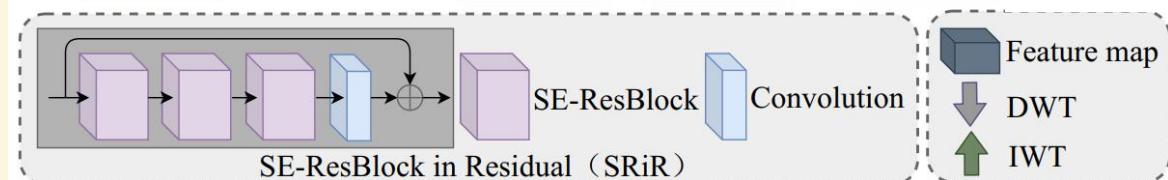


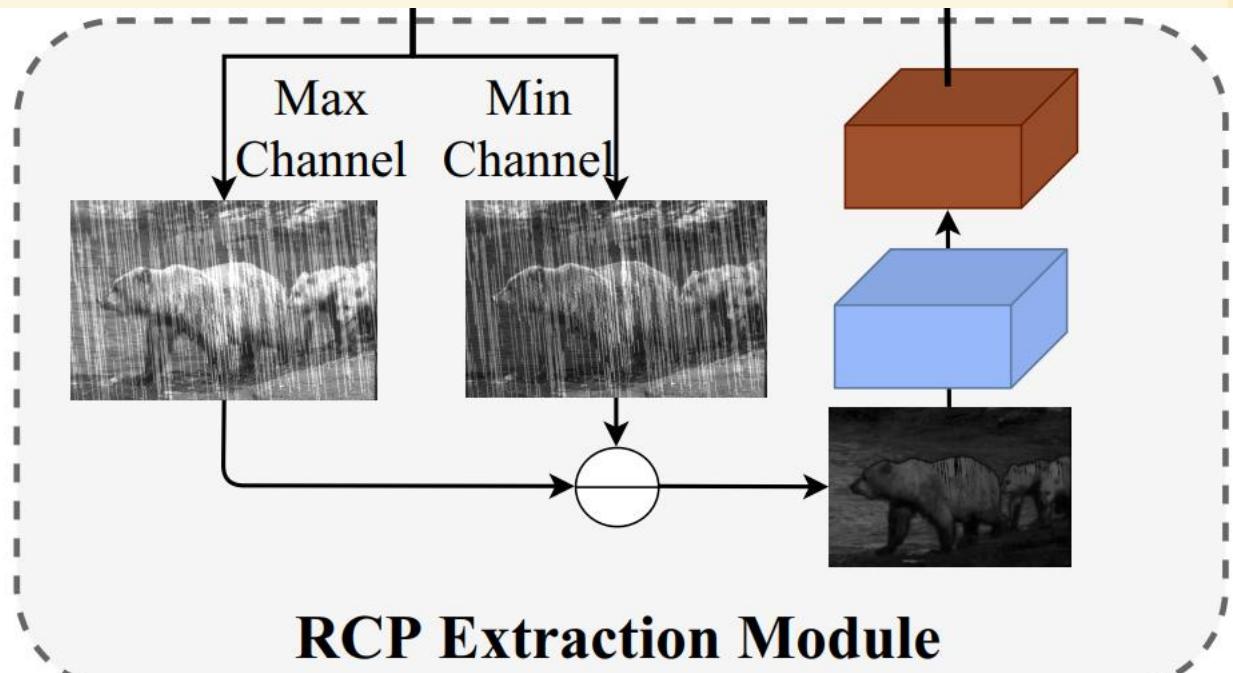
Figure 4: The architecture of the proposed Wavelet-based Multi-Level Module (WMLM).



# Method-SPDNet

## RCP Guided Structure-Preserving Deraining:

Residue Channel Prior (RCP, 通道残差注意力)



$$\mathcal{P}(x) = \max_{c \in r,g,b} \mathcal{O}^c(x) - \min_{d \in r,g,b} \mathcal{O}^d(x).$$

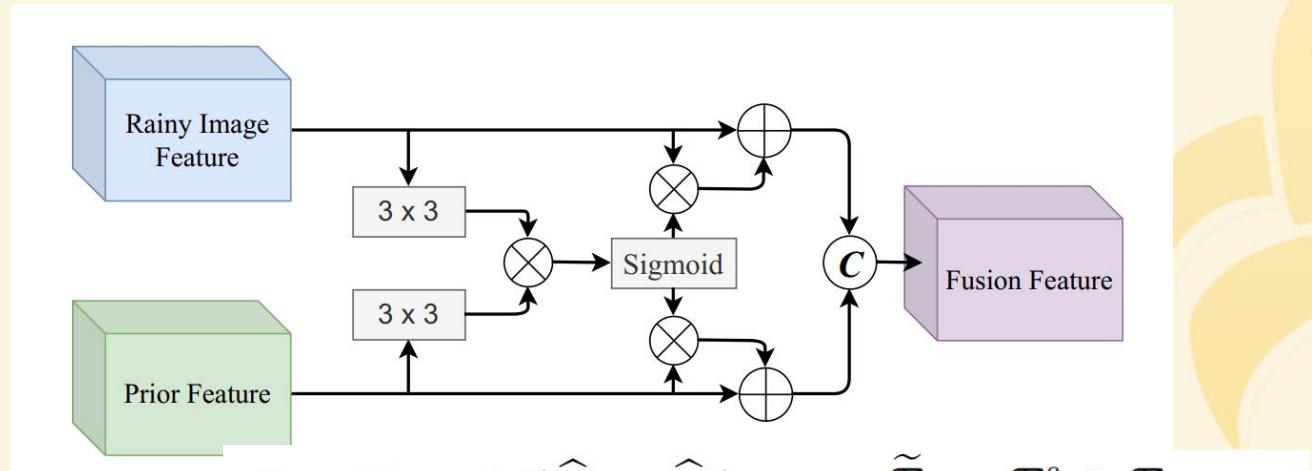


# Method-SPDNet

## RCP Guided Structure-Preserving Deraining:

Interactive Fusion Module (IFM, 交互式融合模块)

The background of RCP is similar to the rainy image, the similarity map S can also highlight the feature information in the prior features, thereby further strengthening the similar structure of the prior feature. RCP的背景类似于雨图，相似度图S也可以突出先验特征中的特征信息，从而进一步加强先验特征的相似结构。



$$\hat{\mathcal{F}}_o = Conv(\mathcal{F}_o),$$

$$\hat{\mathcal{F}}_p = Conv(\mathcal{F}_p),$$

$$\mathcal{S} = Sigmoid(\hat{\mathcal{F}}_o \otimes \hat{\mathcal{F}}_p),$$

$$\mathcal{F}_o^s = \mathcal{S} \otimes \mathcal{F}_o,$$

$$\mathcal{F}_p^s = \mathcal{S} \otimes \mathcal{F}_p,$$

$$\tilde{\mathcal{F}}_o = \mathcal{F}_o^s + \mathcal{F}_o,$$

$$\tilde{\mathcal{F}}_p = \mathcal{F}_p^s + \mathcal{F}_p,$$

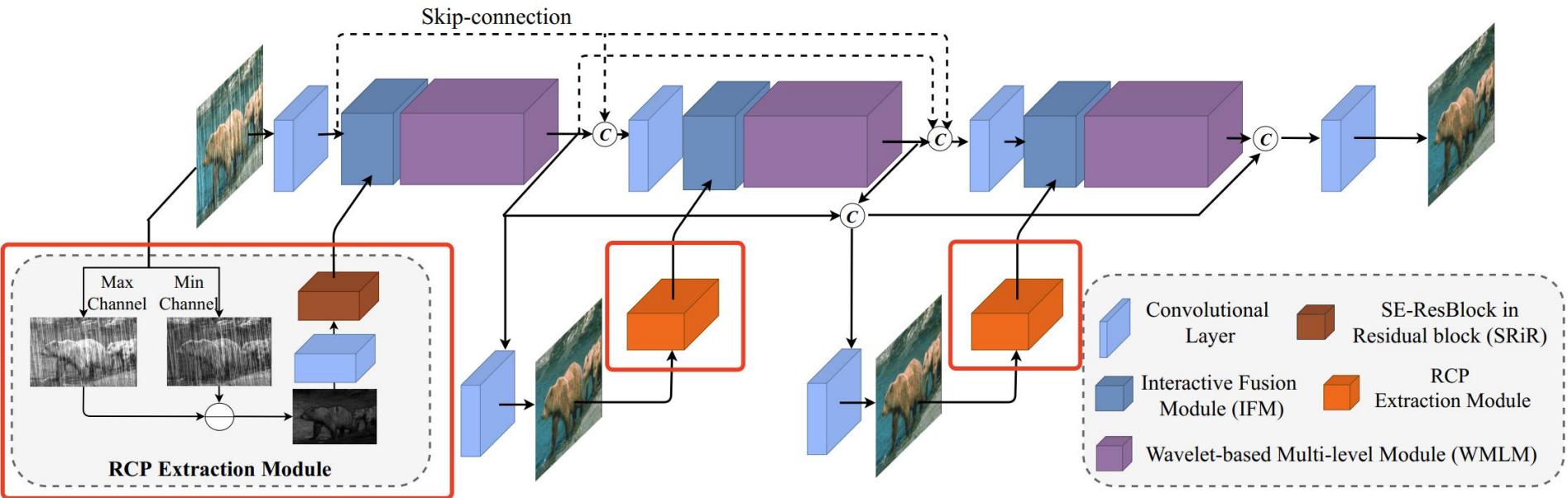
$$\tilde{\mathcal{F}} = Concat(\tilde{\mathcal{F}}_o, \tilde{\mathcal{F}}_p),$$



# Method-SPDNet

## RCP Guided Structure-Preserving Deraining:

Iterative Guidance Strategy (迭代指导策略)



$$\begin{cases} \mathcal{F}_n = WMLM_n(\hat{\mathcal{F}}_n, \mathcal{P}_n; \theta_n), \\ \mathcal{B}_n = Conv(\mathcal{F}_n), \\ \mathcal{P}_{n+1} = PEB(\mathcal{B}_n), \quad if \ n = 1, 2, \end{cases}$$



# Method-SPDNet

## Loss Function:

$$\mathcal{L} = \sum_i \left\| \mathcal{B}_i - \hat{\mathcal{B}} \right\|^2, \quad i = 1, 2, 3.$$

Where,  $\hat{\mathcal{B}}$  denotes the rain-free image(GT) and  $\mathcal{B}_i$  denotes output results in different stage.



# Outline

- Background
- Motivation
- Related Work
- Method
- Experiment
- Ablation Study
- Conclusion



# Experiment

Methods	Param	Time 128 × 128	Rain200L		Rain200H		Rain800		Rain1200		SPA-Data	
			PSNR	SSIM								
GMM[24]	—	27.961s	28.66	0.8652	14.50	0.4164	25.71	0.8020	25.81	0.8344	34.30	0.9428
DSC[27]	—	7.947s	27.16	0.8663	14.73	0.3815	22.61	0.7530	24.24	0.8279	34.95	0.9416
DDN[8]	0.06M	0.278s	34.68	0.9671	26.05	0.8056	25.87	0.8018	30.97	0.9116	36.16	0.9463
RESCAN[23]	0.15M	0.016s	36.09	0.9697	26.75	0.8353	26.58	0.8726	33.38	0.9417	38.11	0.9707
PReNet[31]	0.17M	0.012s	37.70	0.9842	29.04	0.8991	27.06	0.9026	33.17	0.9481	40.16	0.9816
DCSFN[34]	6.45M	0.253s	39.37	0.9854	29.25	0.9075	28.38	0.9072	34.31	0.9545	—	—
DRDNet[6]	2.72M	0.069s	39.05	0.9862	29.15	0.8921	28.21	0.9012	34.02	0.9515	40.89	0.9784
RCDNet[37]	3.17M	0.068s	39.87	0.9875	30.24	0.9098	28.59	0.9137	34.08	0.9532	41.47	0.9834
SPDNet(Ours)	3.04M	0.055s	<b>40.59</b>	<b>0.9880</b>	<b>31.30</b>	<b>0.9217</b>	<b>30.21</b>	<b>0.9152</b>	<b>34.57</b>	<b>0.9561</b>	<b>43.55</b>	<b>0.9875</b>

Table 1: Quantitative experiments evaluated on four recognized synthetic datasets. The best and the second best results have been boldfaced and underlined.

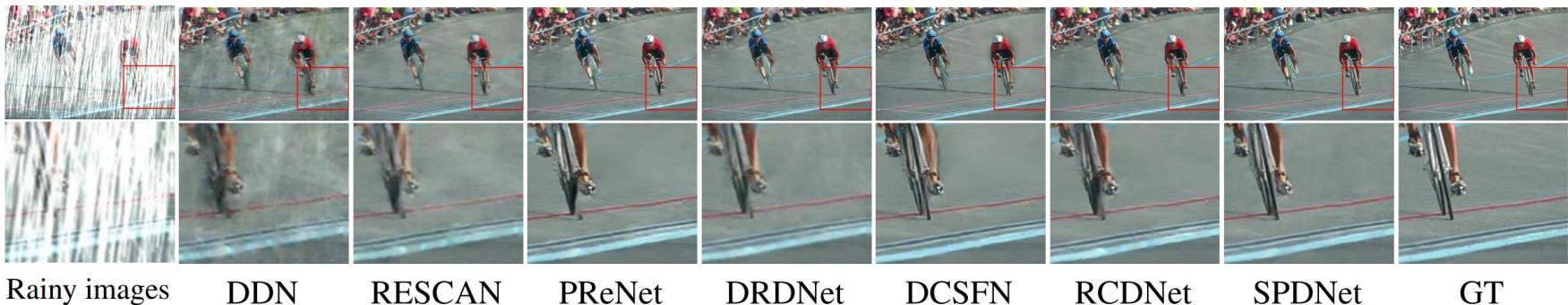
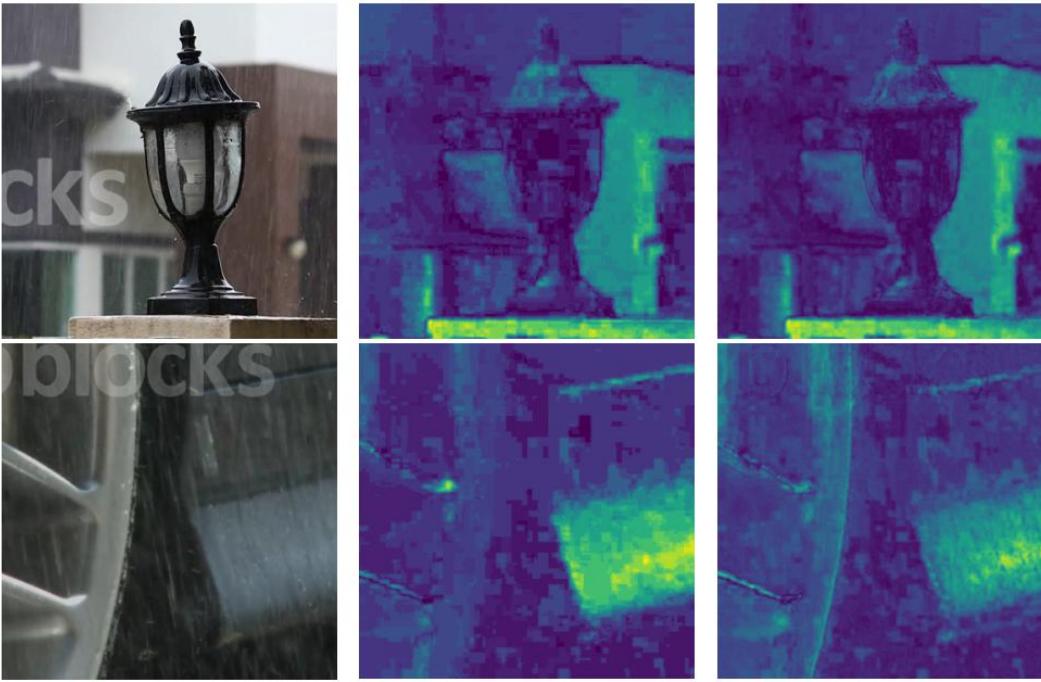


Figure 7: Image deraining results tested in the synthetic datasets. The first row is rainy image, the output of different methods, and GT. The second row is the zoom results of the red window. It is obvious that SPDNet can reconstruct rain-free image with clearer structure.



# Experiment



(a)

(b)

(c)

Figure 6: Comparison between the RCP of rainy images and the RCP of output results. (a) is rainy images, (b) is the RCP of rainy images, and (c) is the RCP of output results. It is obvious observed that the structure of RCP of output results is more obvious than rainy images.



# Experiment

	RESCAN	PReNet	DRDNet	DCSFN	RCDNet	SPDNet
NIQE↓	3.7774	3.5891	3.8719	3.5326	3.5567	3.4603
PI↓	2.8069	2.7045	2.8980	2.6427	2.6946	2.6254

Table 2: Performance comparison on real-world dataset.

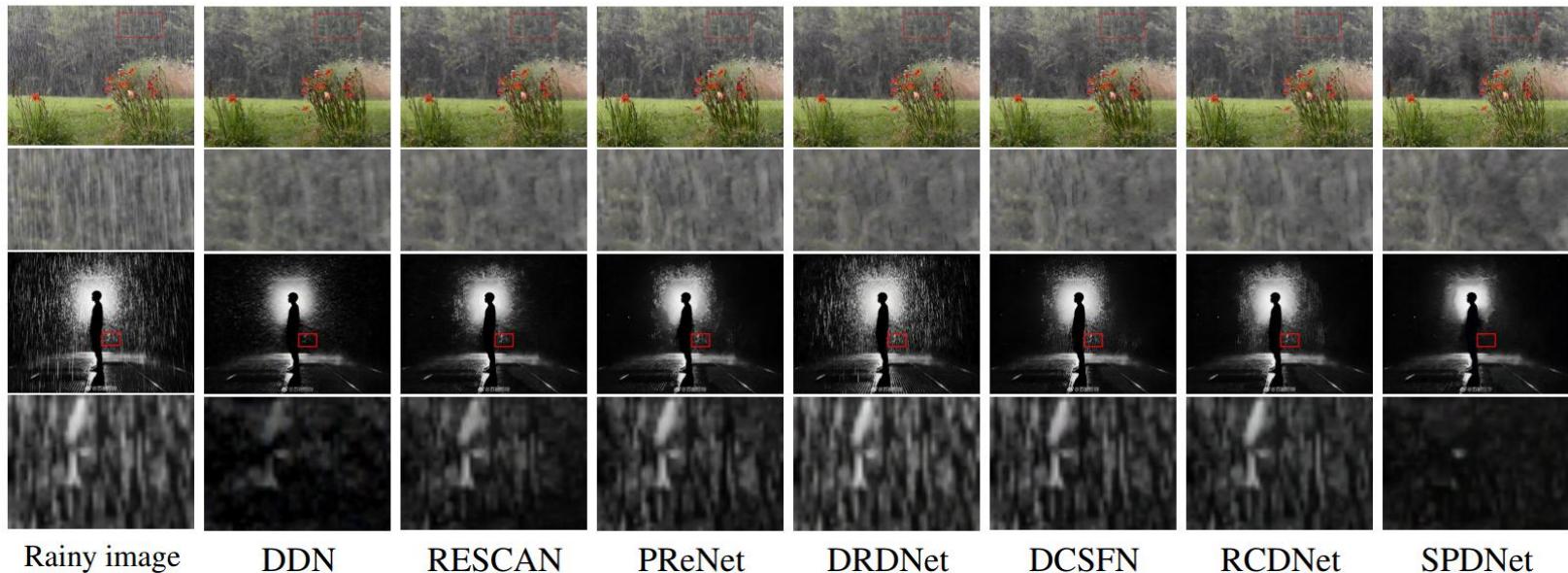


Figure 8: Image deraining results tested in the real-world dataset. The first row is rainy image and the output of different methods. The second row is the zoom results of the red window.



# Experiment

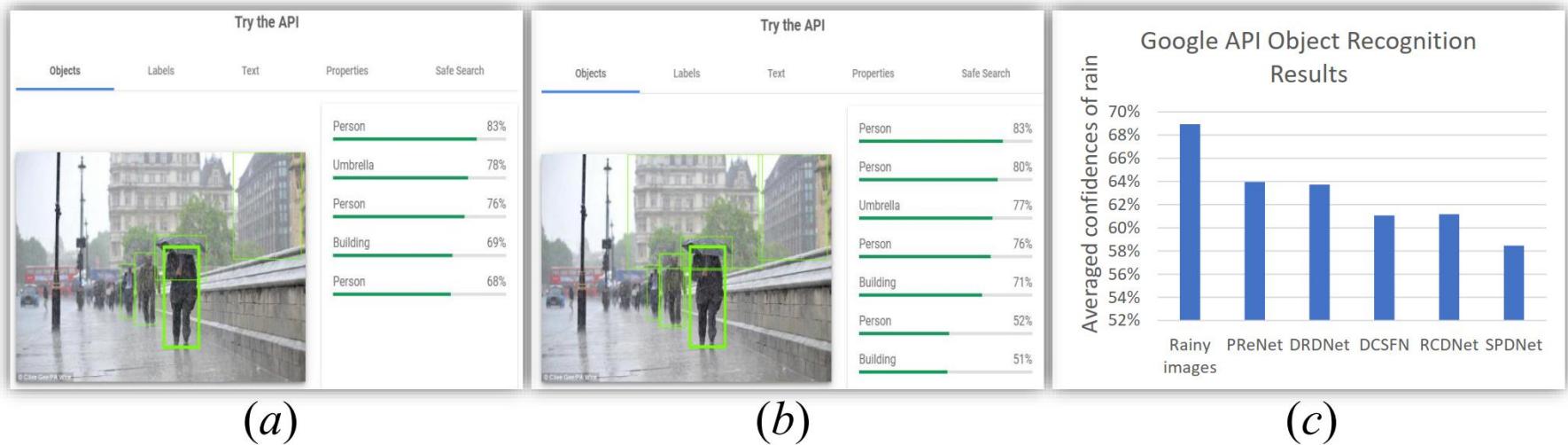


Figure 9: The deraining results are tested on the Google Vision API. *a*: object recognition result in the real-world rainy image, *b*: object recognition result after deraining by our proposed model, and *c*: the averaged confidences in recognizing rain from 30 sets of the real-world rainy images and output results of different methods. The lower averaged confidences, the better performance of deraining.



# Outline

- Background
- Motivation
- Related Work
- Method
- Experiment
- Ablation Study
- Conclusion



# Ablation Study

Method	Fusion method		Ensemble	Rain200H	
	IFM	Concat		PSNR	SSIM
w/o IFM		✓	✓	31.05	0.9167
w/o Ensemble	✓			30.98	0.9142
SPDNet	✓		✓	31.30	0.9217

Table 3: Ablation study on different settings of SPDNet on Rain200H.



# Ablation Study

Iteration	RCP Update	PSNR	SSIM
0		30.56	0.9144
1		30.82	0.9161
2	✓	31.04	0.9197
3	✓	31.30	0.9217
3		31.12	0.9191

Table 5: Explore the influence of RCP on Rain200H. RCP Update means whether to use the iterative guidance strategy to update RCP and Iteration means the number of RCP guidance.

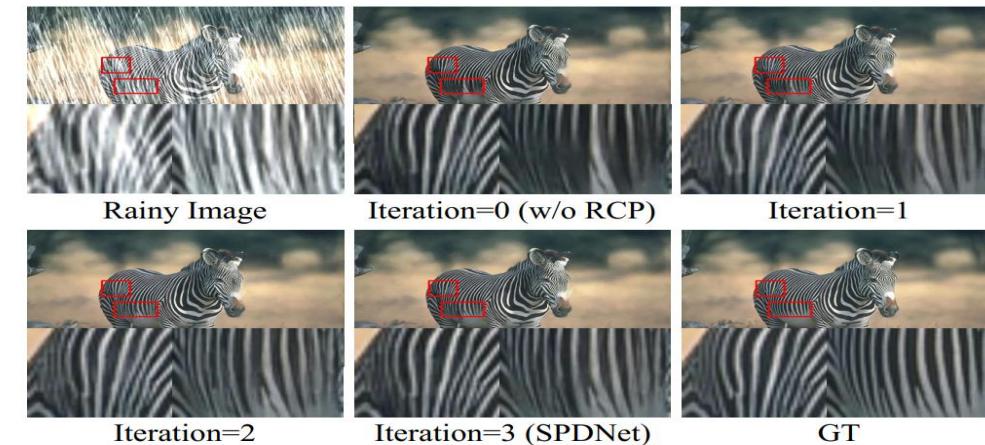


Figure 10: Comparison results on different numbers of RCP guidance. Obviously, compared with the method without RCP, the methods using RCR guidance can reconstruct the high-quality image with a clear and accurate structure.



# Outline

- Background
- Motivation
- Related Work
- Method
- Experiment
- Ablation Study
- Conclusion



# Conclusion

- We proposed a Structure-Preserving Deraining Network (**SPDNet**) with residue channel prior (**RCP**) guidance.
- An effective WMLM is proposed as the backbone to fully learn the background information.
- The RCP is introduced as reference information to guide the learning of WMLM, and **IFM** is designed to make full use of the RCP information.
- An **iterative guidance strategy** are proposed for structure preserving deraining.

Code : <https://github.com/Joyies/SPDNet>

Homepage: [https://junchenglee.com/projects/ICCV2021\\_SPDNet](https://junchenglee.com/projects/ICCV2021_SPDNet)



# Thank You

