A Model-driven Deep Neural Network for Single Image Rain Removal

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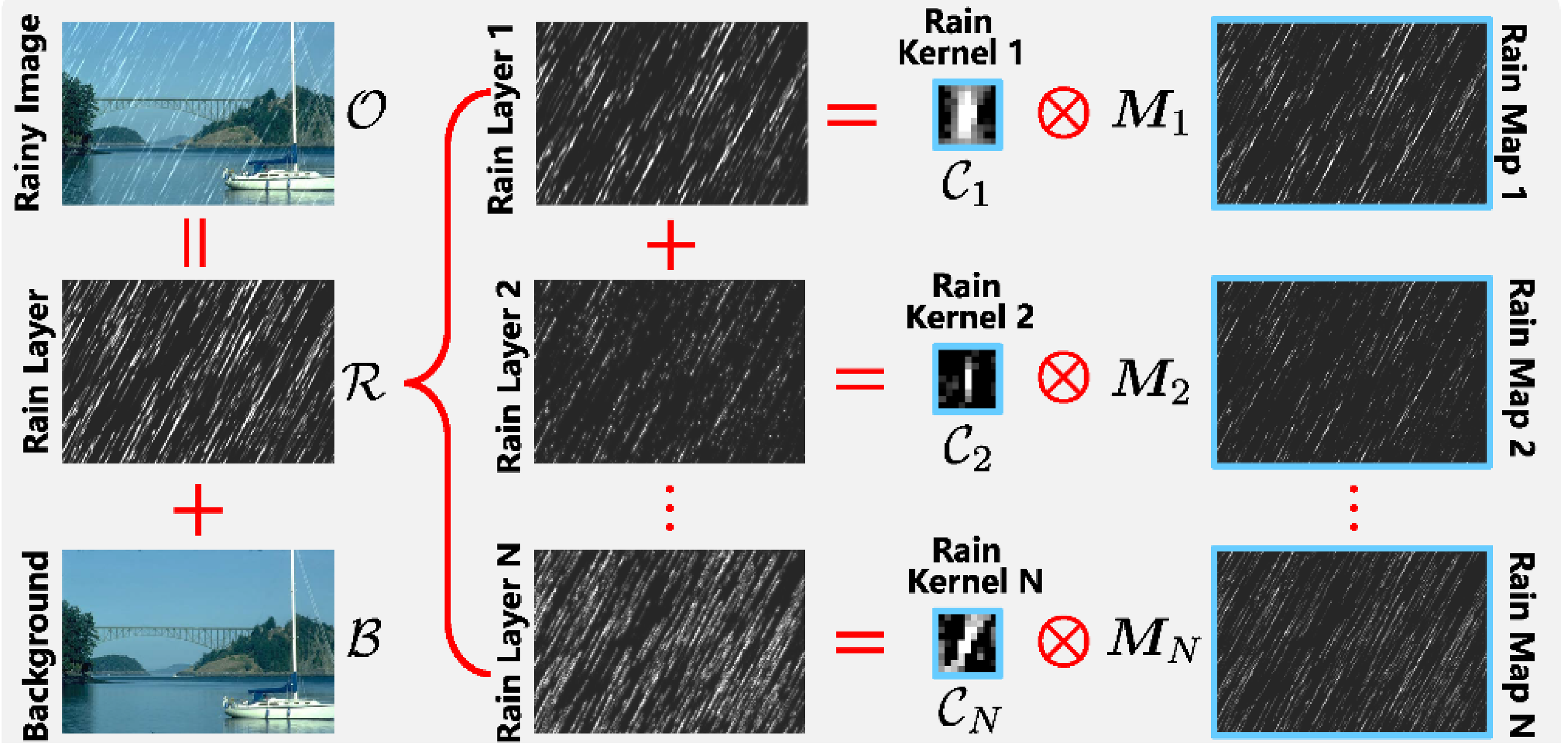
Introduction

Single Image Rain Removal:

Given $\mathcal{O}$

Estimate $\mathcal{B}$ and $\mathcal{R}$

Rain Convolutional Dictionary for Rain Layer:



$\mathcal{C}_n$ Rain pattern

M_n Rain location

Traditional Methods:
- Rely on subjective prior assumptions
- Performance drawback
- Speed drawback

Current DL-based Methods:
- Weak interpretability
- Neglect the intrinsic priors of rain
- Easily trapped into the overfitting issue

Rain Convolutional Dictionary Model

Model Formulation:

$$\mathcal{O}=\mathcal{B}+\sum_{n=1}^{N}\mathcal{C}_n\otimes M_n$$

$$\min_{\mathcal{M},\mathcal{B}}\left\|\mathcal{O}-\mathcal{B}-\sum_{n=1}^{N}\mathcal{C}_n\otimes M_n\right\|_F^2+\alpha g_1(\mathcal{M})+\beta g_2(\mathcal{B}) \quad (1)$$

$\mathcal{C}_n$ is common knowledge learned by end-to-end training, $g_1(\cdot)$ and $g_2(\cdot)$ are regularizers to deliver the priors of M_n and $\mathcal{B}$, respectively.

Optimization Algorithm:

Step 1: At the s-th iteration, adopting quadratic approximation of Eq. **(1)**

Updating $\mathcal{M}$: $\min_{\mathcal{M}}\frac{1}{2}\left\|\mathcal{M}-\left(\mathcal{M}^{(s-1)}-\eta_1\nabla f\left(\mathcal{M}^{(s-1)}\right)\right)\right\|_F^2+\alpha\eta_1 g_1(\mathcal{M})$

Updating $\mathcal{B}$: $\min_{\mathcal{B}}\frac{1}{2}\left\|\mathcal{B}-\left(\mathcal{B}^{(s-1)}-\eta_2\nabla h\left(\mathcal{B}^{(s-1)}\right)\right)\right\|_F^2+\beta\eta_2 g_2(\mathcal{B})$

Step 2: Using proximal gradient algorithm with iteration

$$\left.\begin{aligned}\mathcal{M}^{(s)}&=\operatorname{prox}_{\alpha\eta_1}\left(\mathcal{M}^{(s-1)}-\eta_1\mathcal{C}\otimes^T\left(\sum_{n=1}^{N}\mathcal{C}_n\otimes M_n^{(s-1)}+\mathcal{B}^{(s-1)}-\mathcal{O}\right)\right)\\ \mathcal{B}^{(s)}&=\operatorname{prox}_{\beta\eta_2}\left((1-\eta_2)\,\mathcal{B}^{(s-1)}+\eta_2\left(\mathcal{O}-\sum_{n=1}^{N}\mathcal{C}_n\otimes M_n^{(s)}\right)\right)\end{aligned}\right\}\ \textbf{updating rule}$$

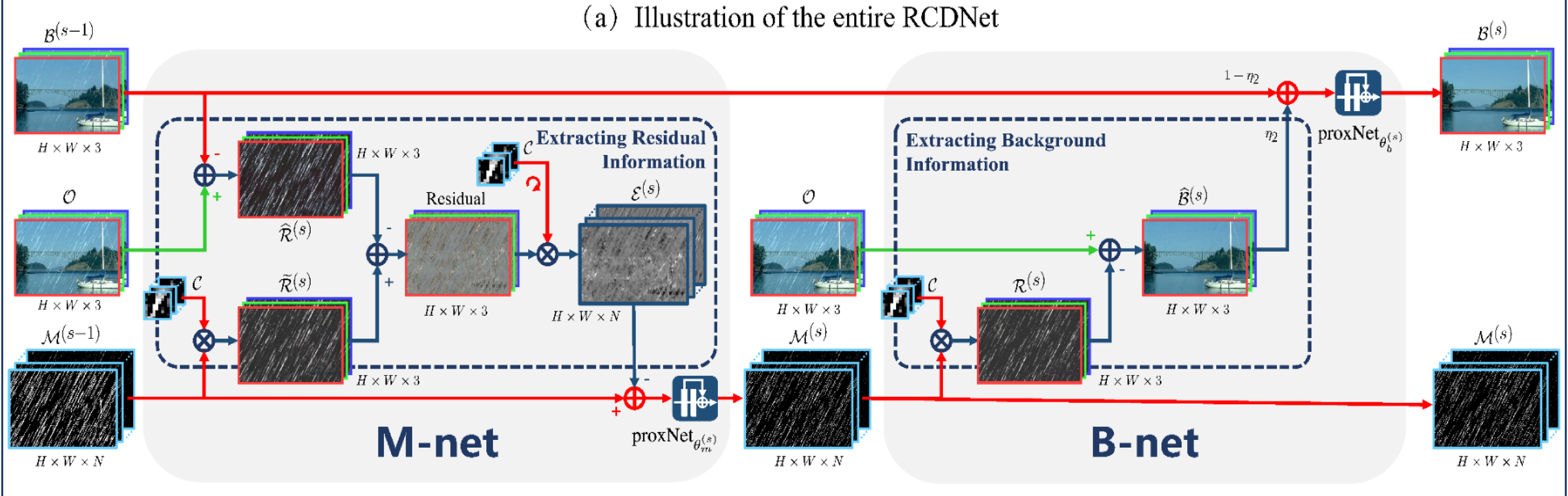
Rain Convolutional Dictionary Network

Step 3: Decomposing the updating rules into sub-steps and unfolding them into network modules

M-net :
$$\begin{cases}\widehat{\mathcal{R}}^{(s)}=\mathcal{O}-\mathcal{B}^{(s-1)},\\ \widetilde{\mathcal{R}}^{(s)}=\sum_{n=1}^{N}\mathcal{C}_n\otimes M_n^{(s-1)},\\ \mathcal{E}^{(s)}=\eta_1\mathcal{C}\otimes^T\left(\widetilde{\mathcal{R}}^{(s)}-\widehat{\mathcal{R}}^{(s)}\right),\\ \mathcal{M}^{(s)}=\operatorname{proxNet}_{\theta_m^{(s)}}\left(\mathcal{M}^{(s-1)}-\mathcal{E}^{(s)}\right)\end{cases}$$

B-net :
$$\begin{cases}\mathcal{R}^{(s)}=\sum_{n=1}^{N}\mathcal{C}_n\otimes M_n^{(s)},\\ \widehat{\mathcal{B}}^{(s)}=\mathcal{O}-\mathcal{R}^{(s)},\\ \mathcal{B}^{(s)}=\operatorname{proxNet}_{\theta_b^{(s)}}\left((1-\eta_2)\mathcal{B}^{(s-1)}+\eta_2\widehat{\mathcal{B}}^{(s)}\right)\end{cases}$$

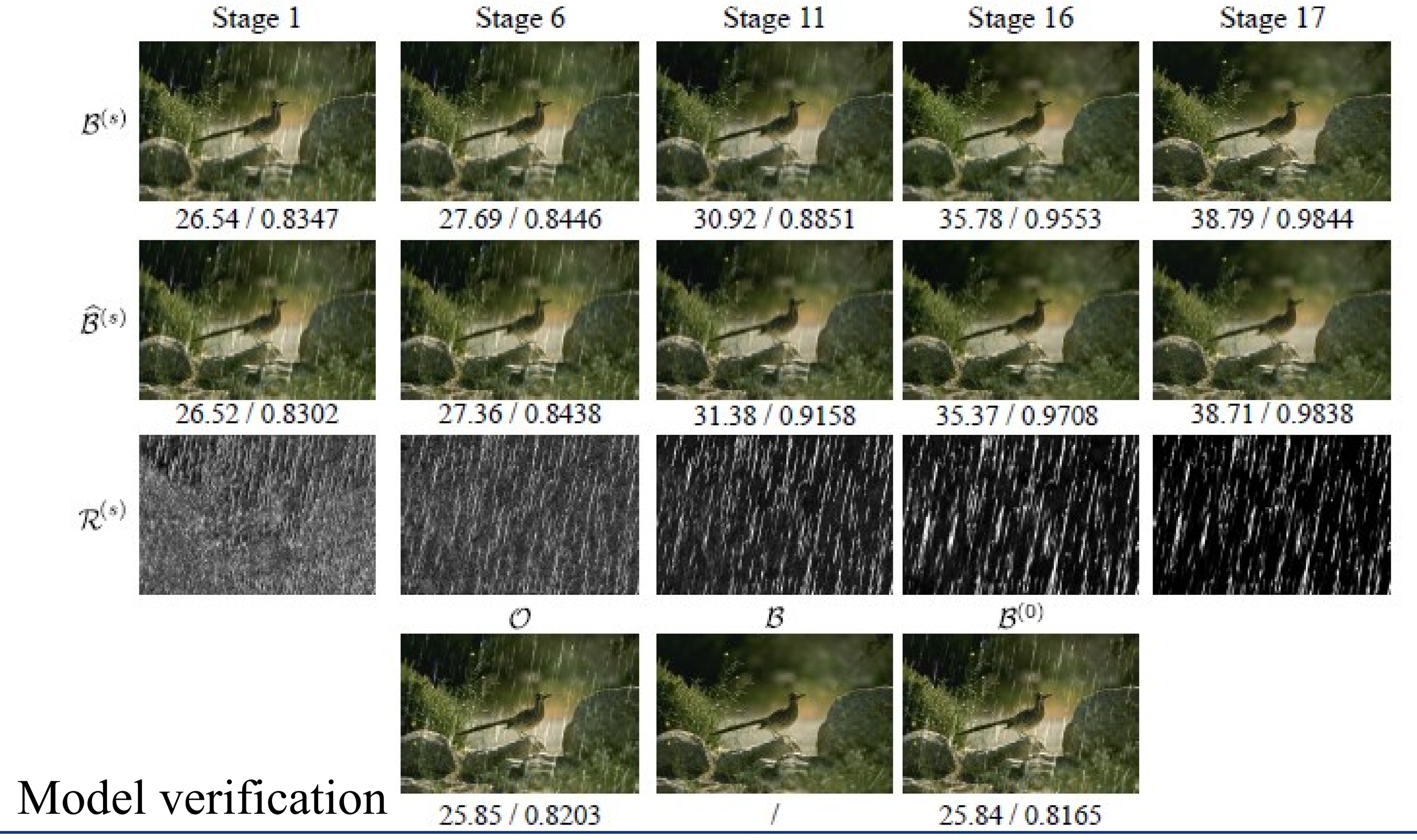
(a) Illustration of the entire RCDNet



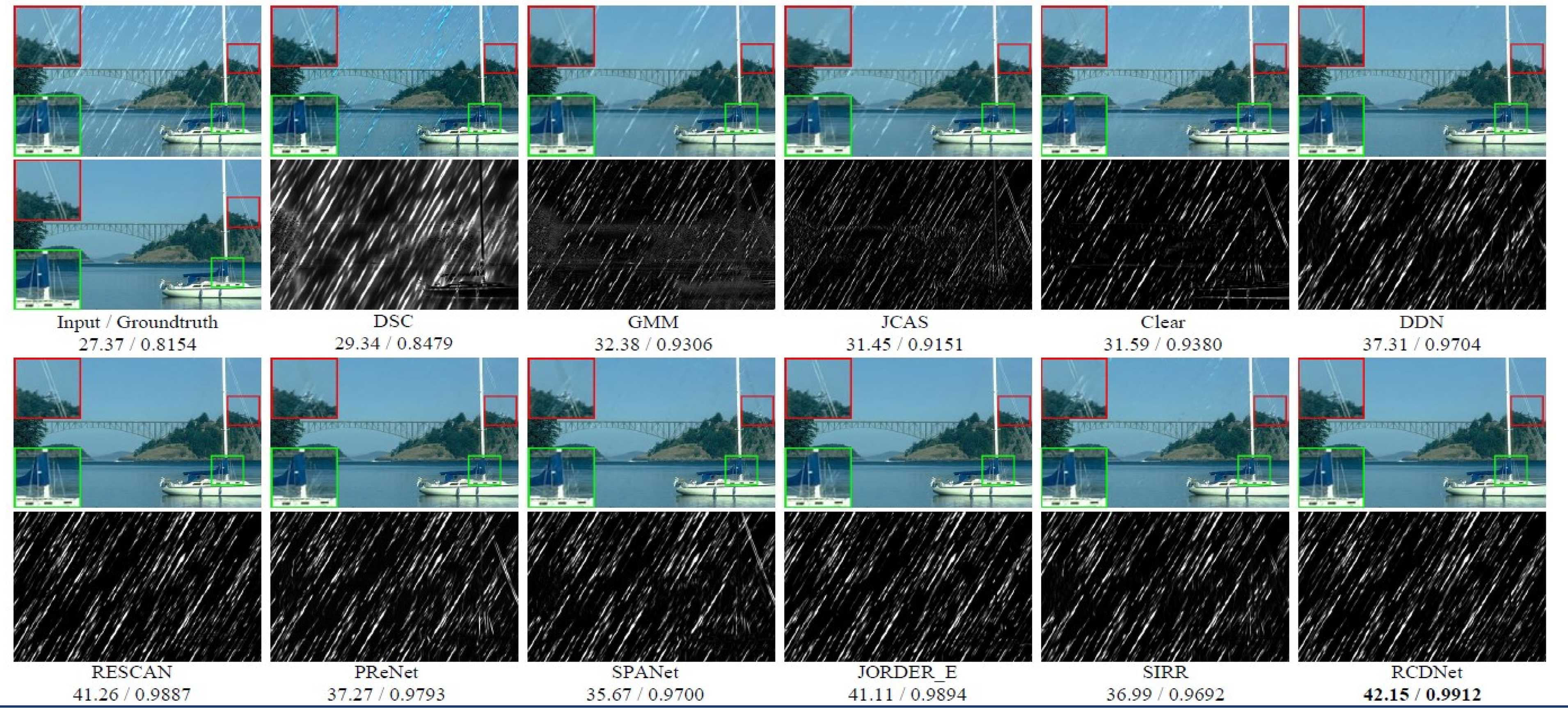
(b) The design of a single stage

RCDNet is with a structure of S stages, corresponding to S iterations in the algorithm. Every module is one-to-one corresponding to each sub-step of the algorithm and has its own specific physical meanings.

Experimental Results



Model verification



Datasets	Rain100L		Rain100H		Rain1400		Rain12	
Metrics	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Input	26.90	0.8384	13.56	0.3709	25.24	0.8097	30.14	0.8555
DSC[51]	27.34	0.8494	13.77	0.3199	27.88	0.8394	30.07	0.8664
GMM[28]	29.05	0.8717	15.23	0.4498	27.78	0.8585	32.14	0.9145
JCAS[13]	28.54	0.8524	14.62	0.4510	26.20	0.8471	33.10	0.9305
Clear[8]	30.24	0.9344	15.33	0.7421	26.21	0.8951	31.24	0.9353
DDN[9]	32.38	0.9258	22.85	0.7250	28.45	0.8888	34.04	0.9330
RESCAN[27]	38.52	0.9812	29.62	0.8720	32.03	0.9314	36.43	0.9519
PReNet[35]	37.45	0.9790	30.11	***0.9053***	***32.55***	***0.9459***	36.66	0.9610
SPANet[41]	35.33	0.9694	25.11	0.8332	29.85	0.9148	35.85	0.9572
JORDER_E[49]	***38.59***	***0.9834***	***30.50***	0.8967	32.00	0.9347	***36.69***	***0.9621***
SIRR[44]	32.37	0.9258	22.47	0.7164	28.44	0.8893	34.02	0.9347
RCDNet	**40.00**	**0.9860**	**31.28**	**0.9093**	**33.04**	**0.9472**	**37.71**	**0.9649**

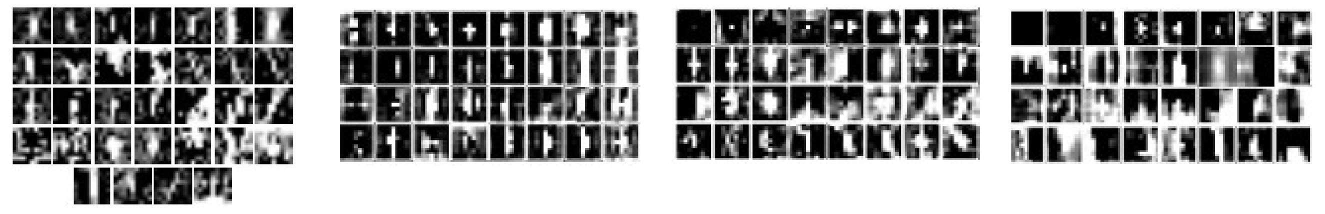
Average quantitative results on 4 benchmark synthetic datasets

Average quantitative results on real SPA-Data

Methods	Input	DSC	GMM	JCAS	Clear	DDN
PSNR	34.15	34.95	34.30	34.95	34.39	36.16
SSIM	0.9269	0.9416	0.9428	0.9453	0.9509	0.9463
Methods	RESCAN	PReNet	SPANet	JORDER_E	SIRR	RCDNet
PSNR	38.11	40.16	40.24	***40.78***	35.31	**41.47**
SSIM	0.9707	***0.9816***	0.9811	0.9811	0.9411	**0.9834**

More verifications and generalization results

Code Downloading: https://github.com/hongwang01/RCDNet



Learned rain kernels for different datasets