ACM Multimedia 2022
Lisbon, Portugal | 10-14 October

AI&Multimedia Lab

HUAWEI

Image Enhancement: Disentanglement

Kui Jiang

Huawei Technologies, Cloud BU

2022.10

1. **Disentangle in Stage**
2. **Disentangle in Process**
3. **Disentangle in Content**

Disentangle----image deraining

Image Deraining

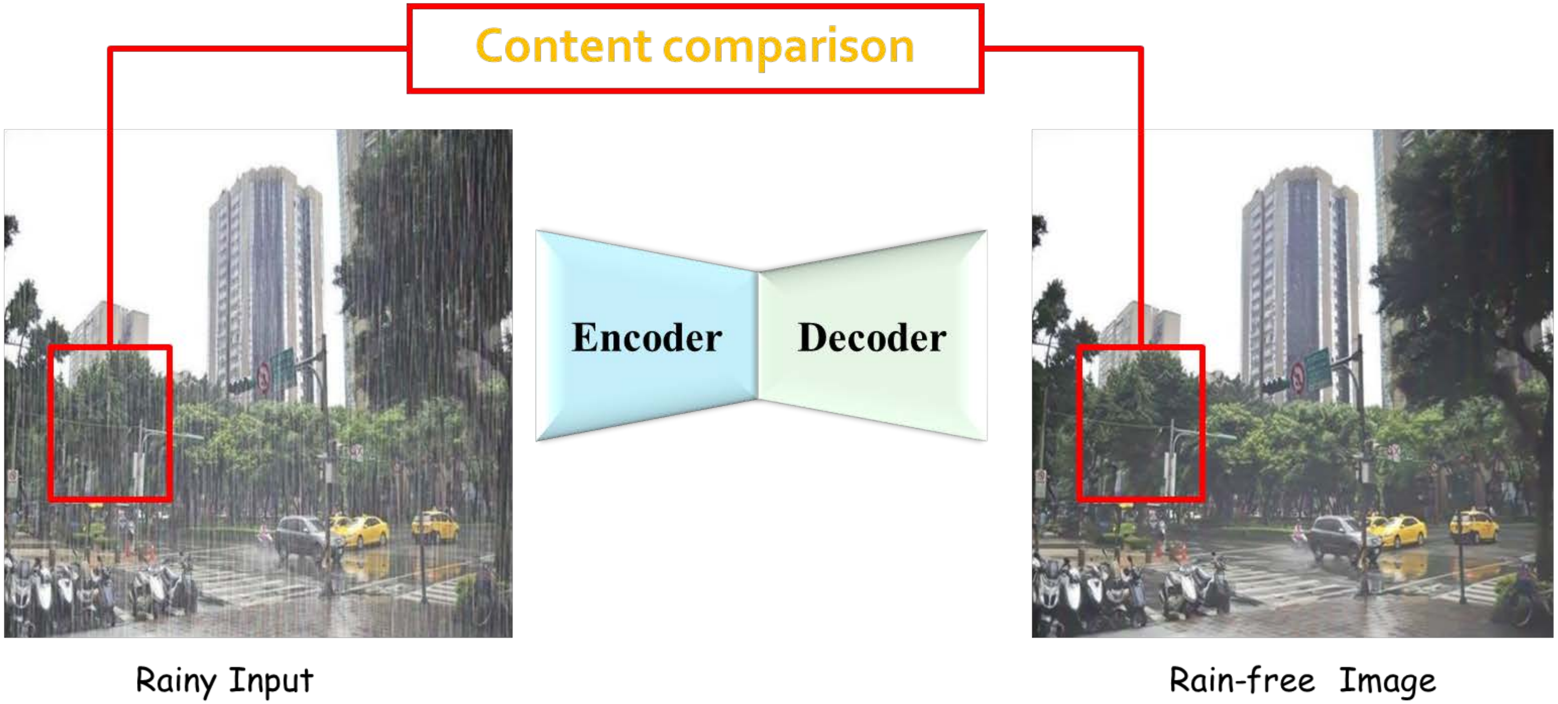
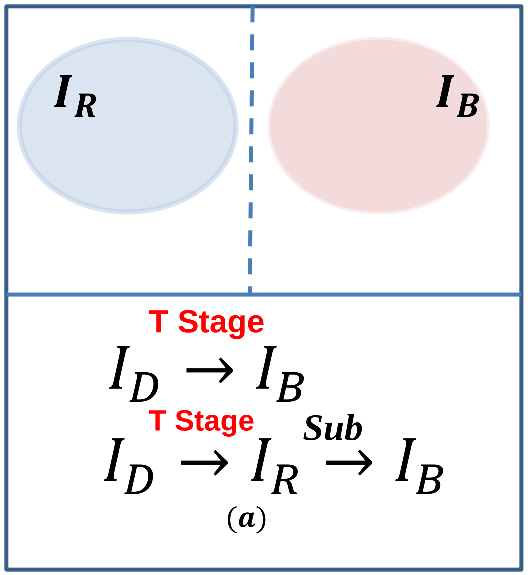


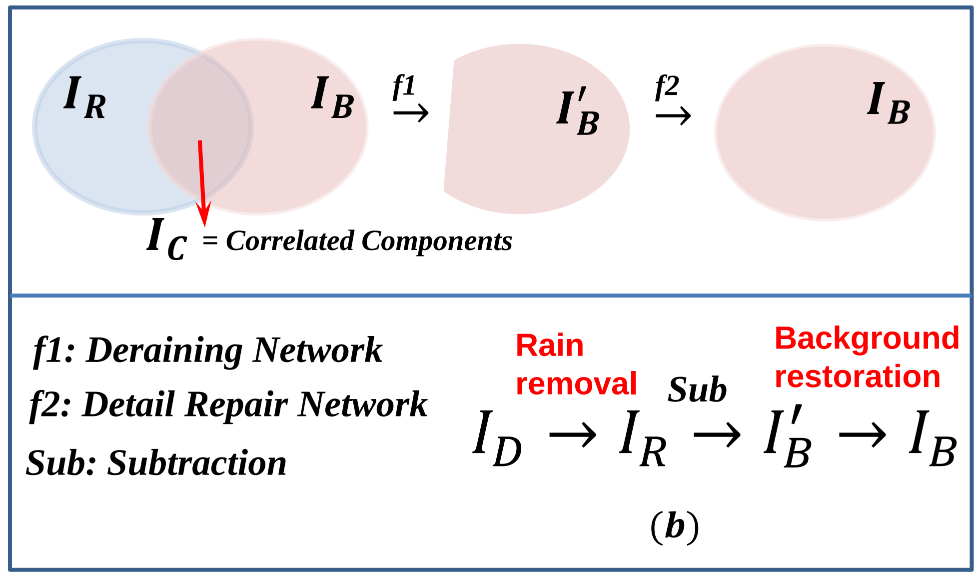
Image deraining, refers to the technique that can eliminate the rainy perturbation from rainy input while recovering credible background details.

Disentangle----image deraining

Degradation learning **or** recovery

Degradation learning **+** recovery





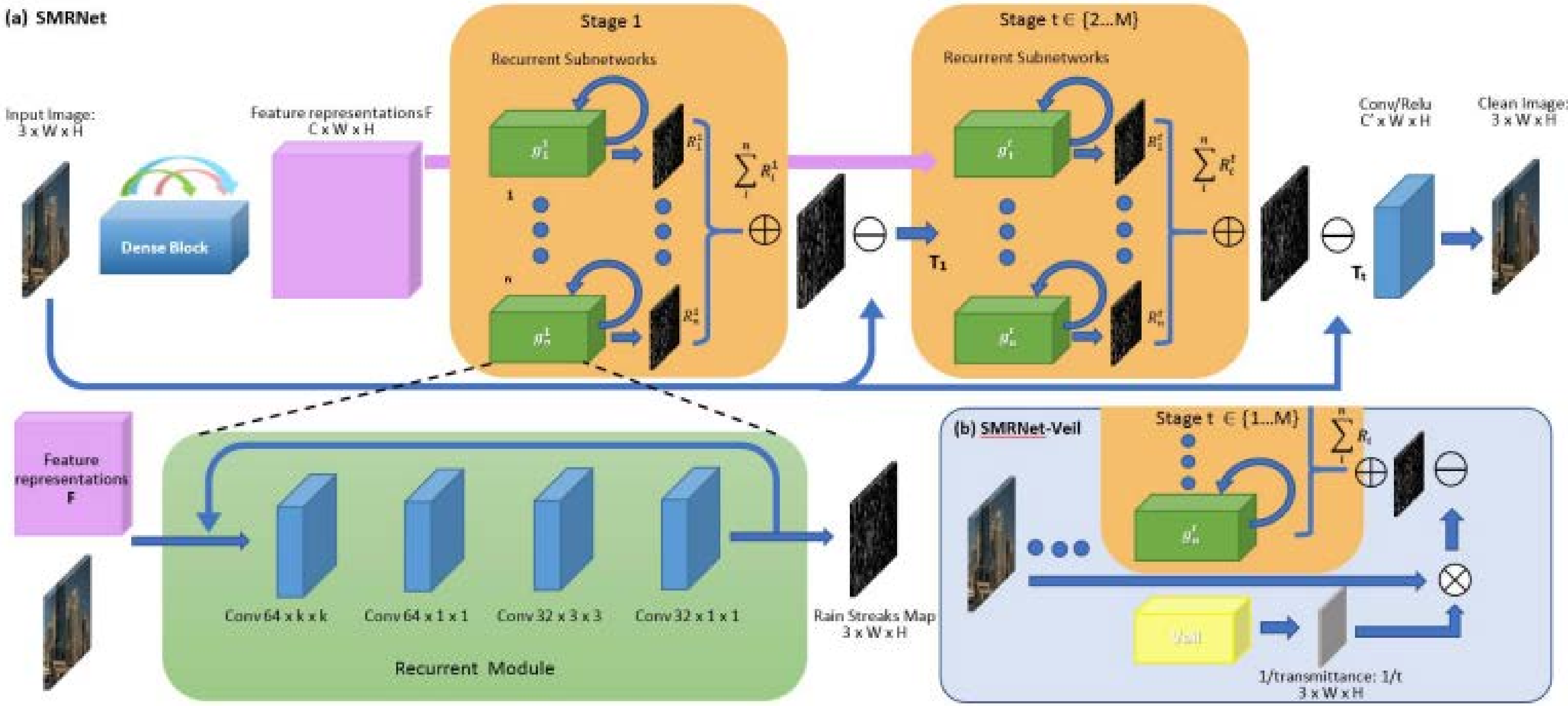
Disentangle in Stage

$$I_B = I_{Rain} - \sum_{i=1}^{n} I_{R,i}$$

Disentangle in Process

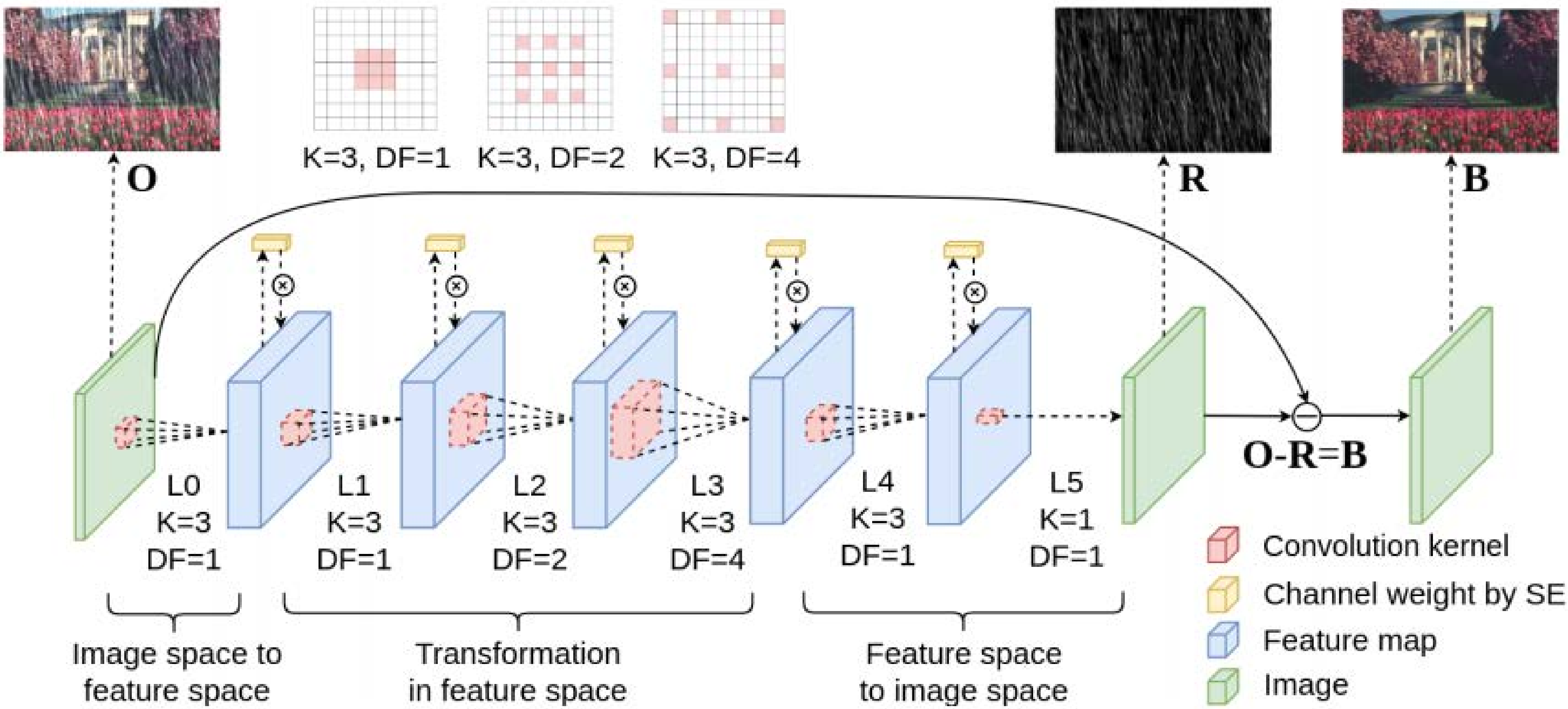
$$I_B = f_B(I_{Rain} - f_R(I_{Rain}))$$

Disentangle in Stage---image deraining



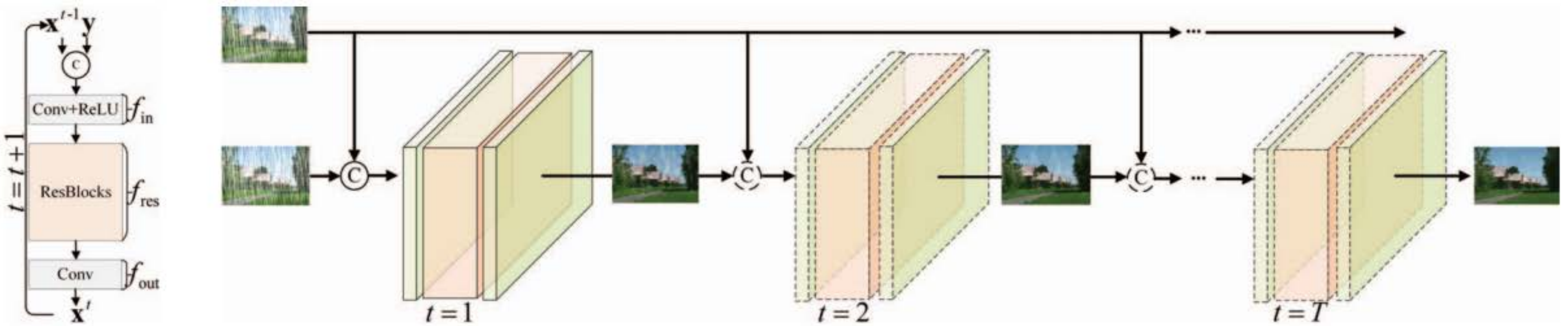
Li R, Cheong L F, Tan R T. Single image deraining using scale-aware multi-stage recurrent network[J]. arXiv preprint arXiv:1712.06830, 2017.

Disentangle in Stage---image deraining

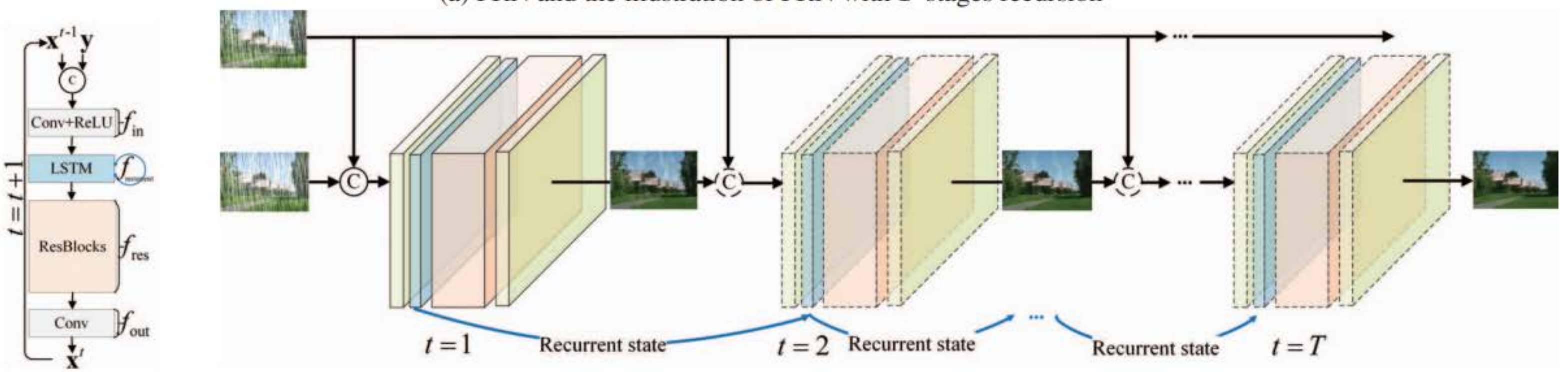


Li X, Wu J, Lin Z, et al. Recurrent squeeze-and-excitation context aggregation net for single image deraining [C]// Proceedings of the European conference on computer vision (ECCV). 2018: 254-269.

Disentangle in Stage---image deraining



(a) PRN and the illustration of PRN with T stages recursion



(b) PReNet and the illustration of PReNet with T stages recursion

Rainy image | RESCAN [20] | $t = 1$ | $t = 2$ | $t = 6$

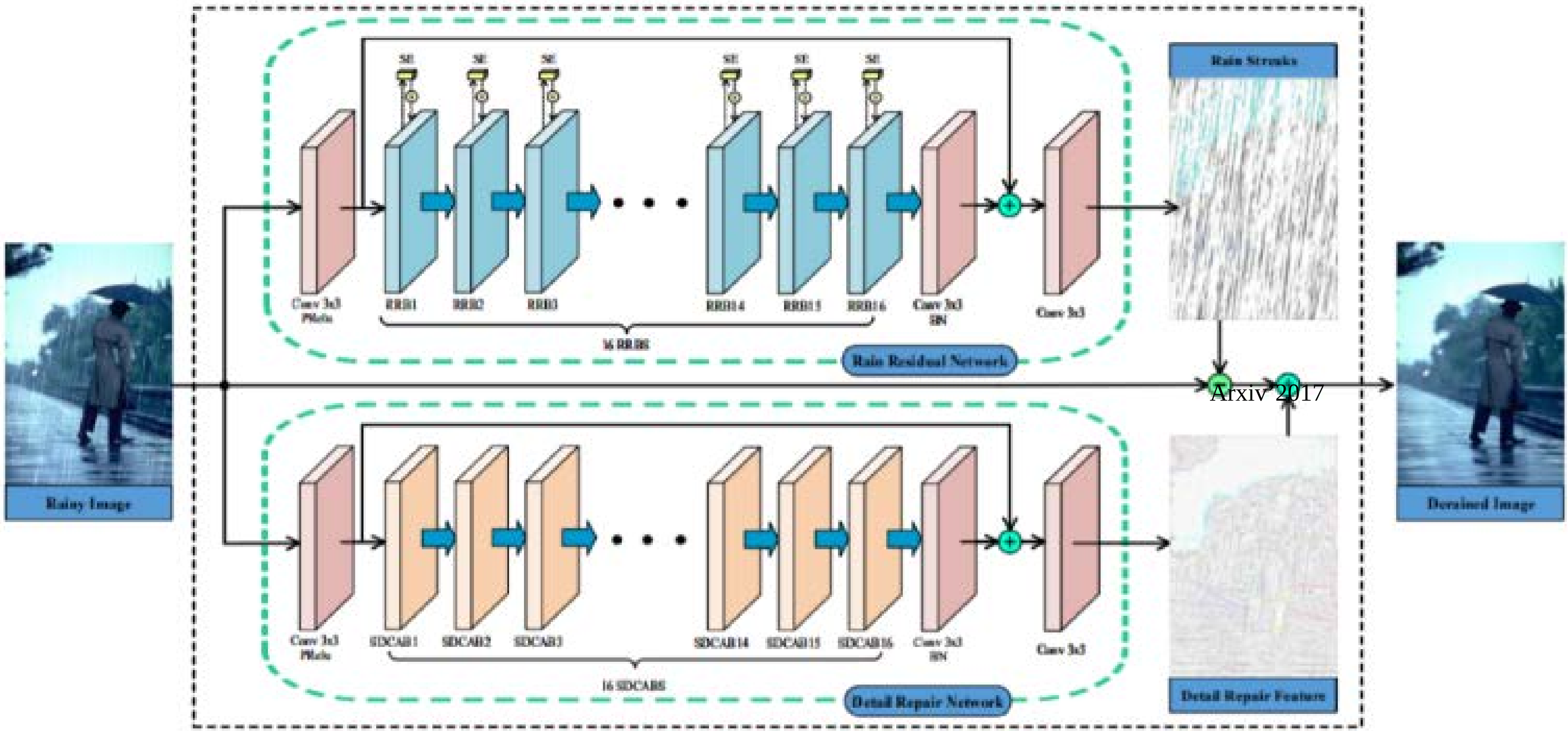
Ren D, Zuo W, Hu Q, et al. Progressive image deraining networks: A better and simpler baseline[C]// Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2019: 3937-3946.

Disentangle in Stage----image deraining

Limitations:

1) Existing methods regard the image deraining as a simple rain streaks removal problem, which ignores the additional degradation side effects for background recovery
2) The cascaded and recurrent manners cause great computational cost, which is computationally or memory expensive for many real-world applications with resource-constrained devices

Disentangle in Process----image deraining

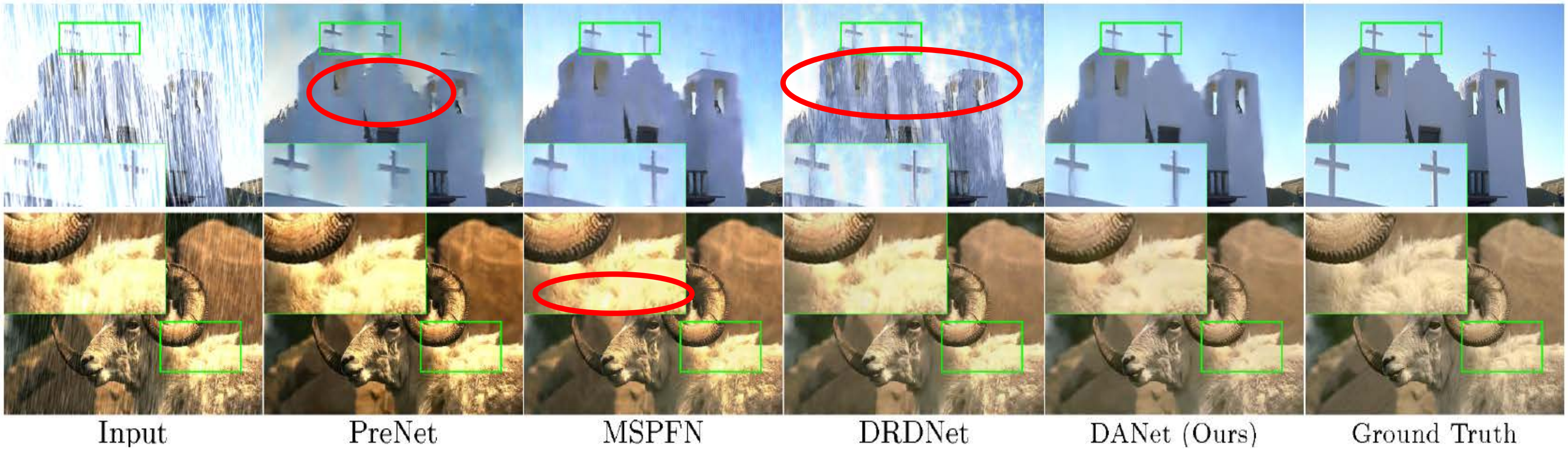


Deng S, Wei M, Wang J, et al. Detail-recovery image deraining via context aggregation networks [C]// Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2020: 14560-14569.

Disentangle in Process----image deraining

Limitations:

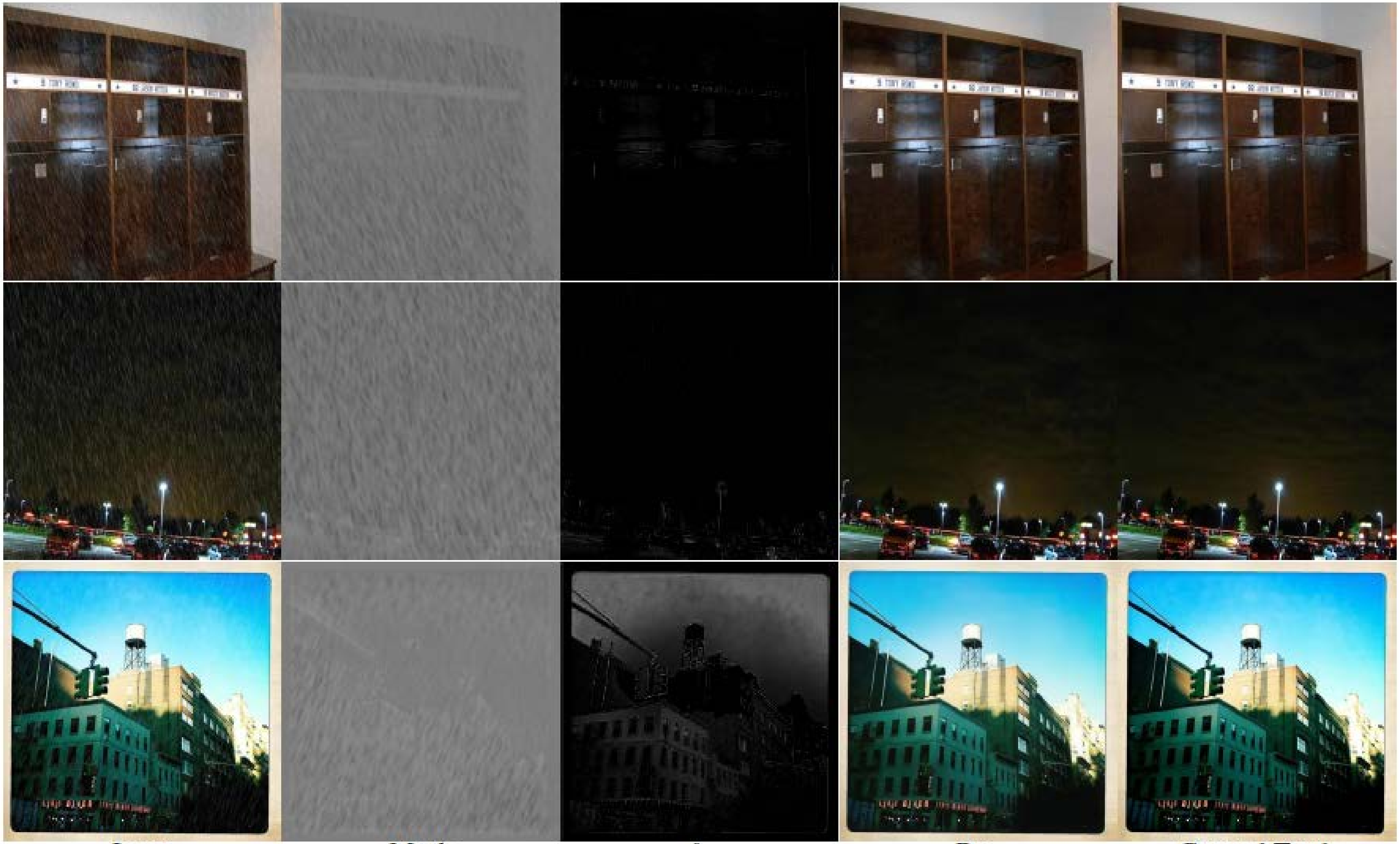
1) The rain estimation and detail recovery are isolated.
2) The network treats the whole image equally, which fail to focus on the degradation regions.



Disentangle in Process----image deraining

◆ Motivation

Degradation $\xrightarrow{\text{mask}}$ location and intensity

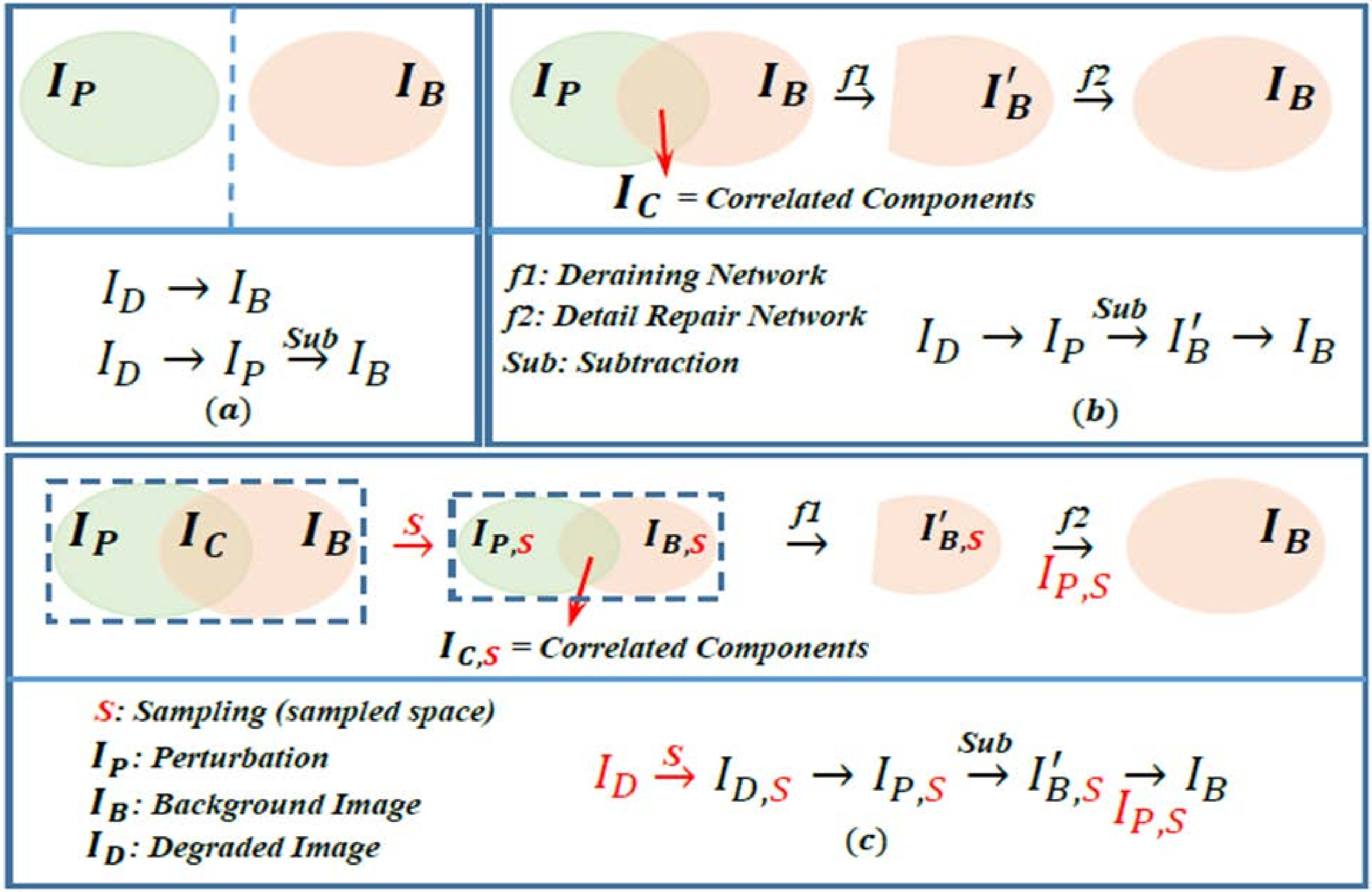


Input | Mask | f_{ti} | Pre. | Ground Truth

Disentangle in Process----image deraining

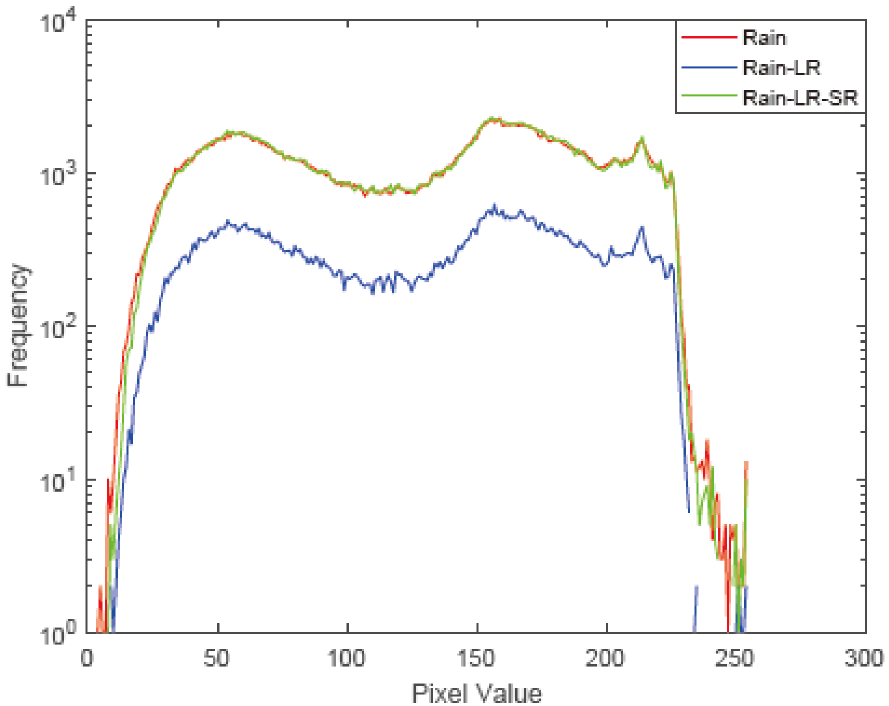
Degradation learning **or** recovery

Degradation learning **+** recovery

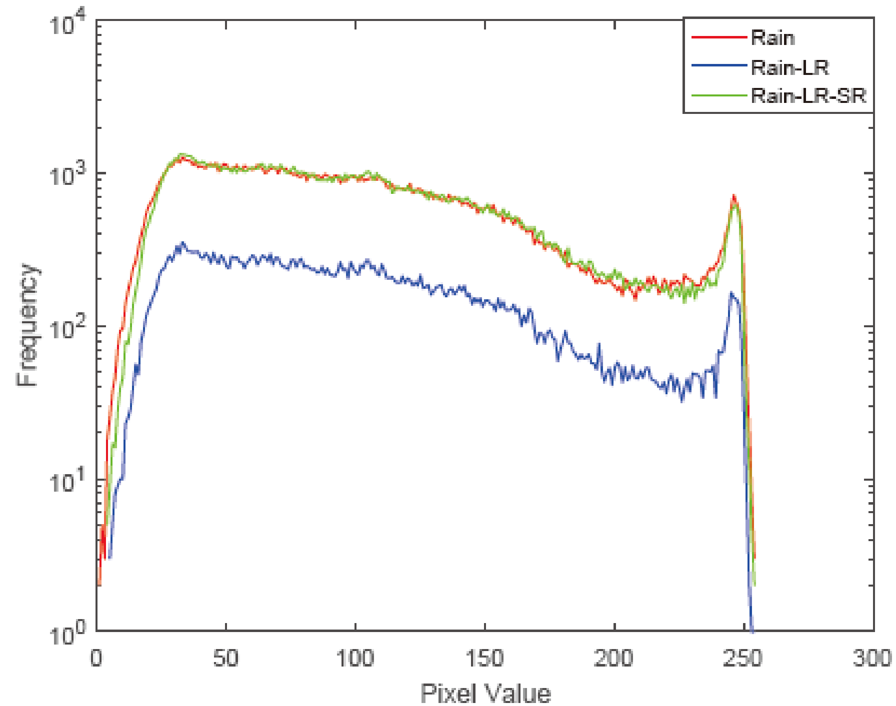


Degradation learning **+** recovery **+** association

Disentangle in Process----image deraining



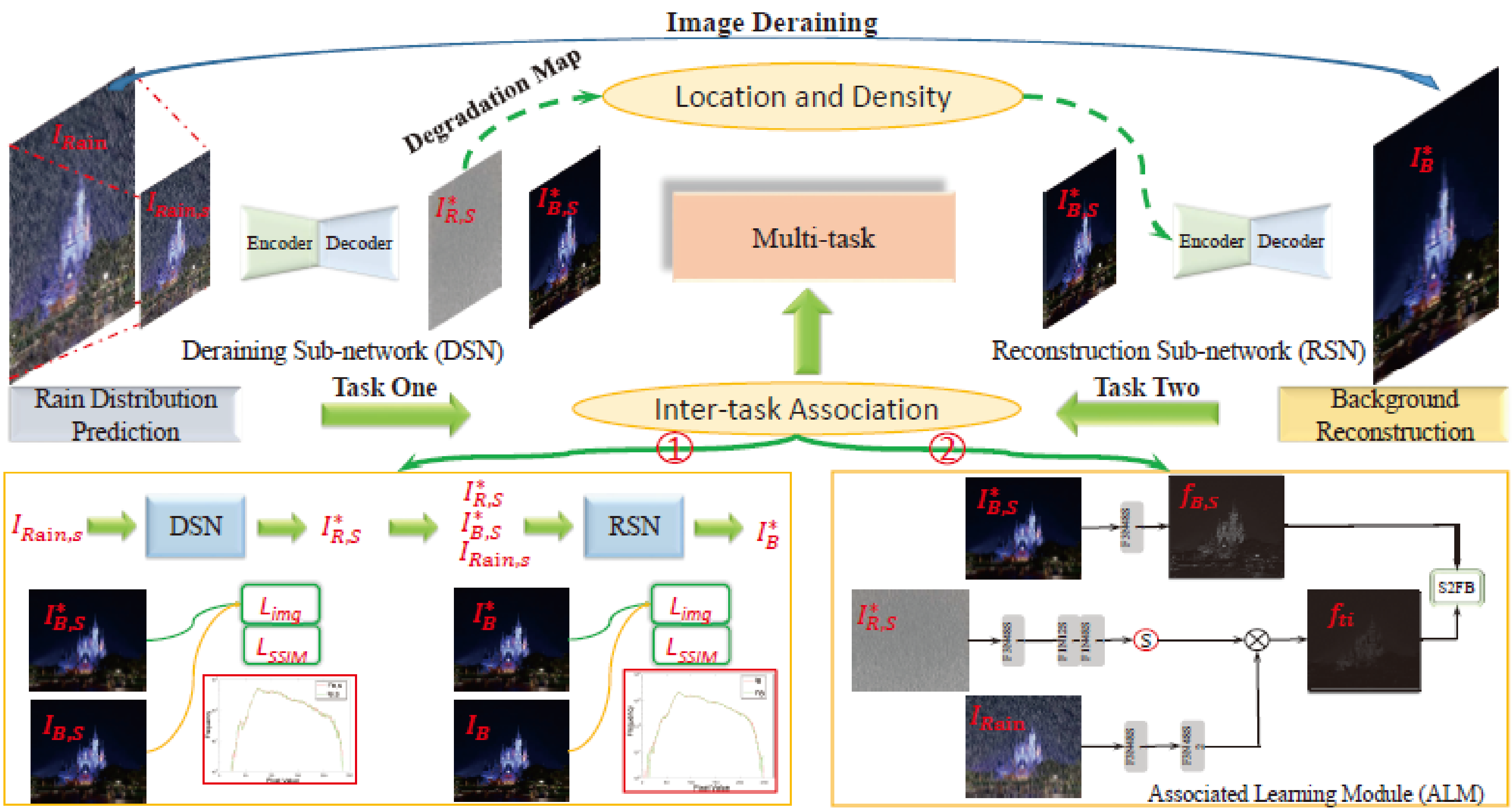
Real-world Sample



Synthetic Sample

Fitting results of “Y" channel histogram for Real and Synthetic samples. “Rain" and “Rain-LR" denote the original and corresponding low-dimension space distribution of rainy image.

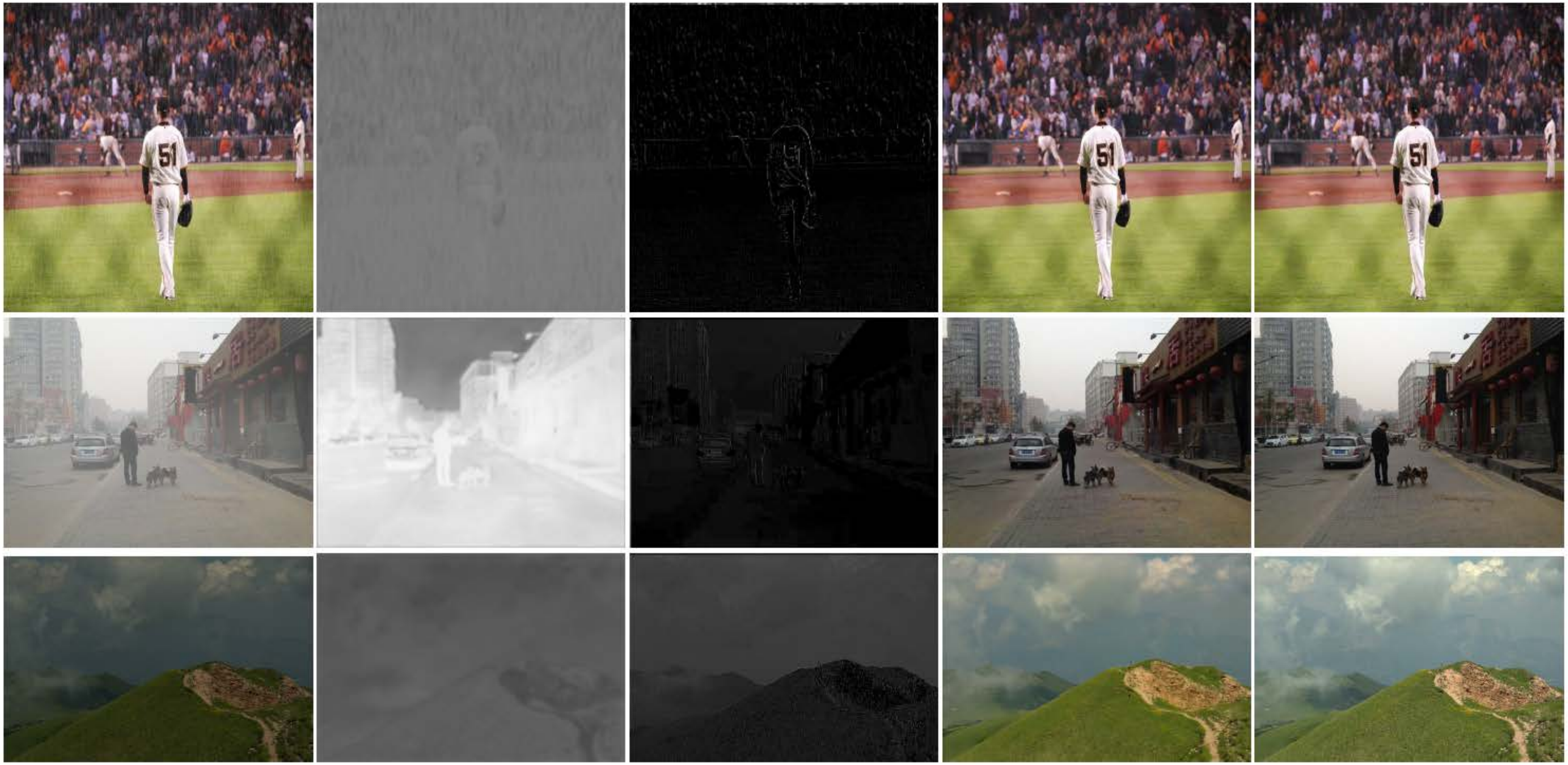
Disentangle in Process----image deraining



Jiang K, Wang Z, Wang Z, et al. et al. DANet: Image Deraining via Dynamic Association Learning[C]//IJCAI. 2022.

Disentangle in Process----image deraining

◆ visualization



(a) Input image **(b) Perturbation mask** **(c) Association feature** **(d) Enhanced results** **(f) Ground Truth**

Disentangle in Process----image deraining

◆ Ablation Studies

Model	SR	DSC	SFB	ALM	SSIM	PSNR↑	SSIM↑	Par.↓	Time↓	GFlops↓
Rain Image	–	–	–	–	–	22.16	0.732	–	–	–
w/o DSC	✓	×	✓	✓	✓	32.06	0.912	1.596	0.077	43.56
w/o SFB	✓	✓	×	✓	✓	31.98	0.904	1.520	0.056	54.66
w/o ALM	✓	✓	✓	×	✓	30.12	0.874	1.544	0.078	48.94
w/o SSIM	✓	✓	✓	✓	×	32.35	0.914	1.547	0.079	49.11
w/o all	✓	×	×	×	×	29.48	0.862	1.582	0.053	45.57
DANet*	×	✓	✓	×	✓	32.37	0.916	1.535	0.107	166.83
DANet	✓	✓	✓	✓	✓	32.57	0.917	1.547	0.079	49.11

Model	ORB	EDB	PSNR	SSIM	Par.	Time.	GFlops
w/o ORB	×	✓	31.42	0.896	1.557	0.081	27.59
w/o EDB	✓	×	32.22	0.910	1.583	0.045	101.48
DANet	✓	✓	32.57	0.917	1.547	0.079	49.11

Table.1. Ablation study on the depth-wise separable convolutions (DSC), associated learning module (ALM), selective fusion block (SFB), SSIM loss, super-resolution (SR), original resolution branch (ORB) and encoder-decoder branch (EDB) on Test1200 dataset. We obtain the model parameters (Million (M)), average inference time (Second (S)), and calculation complexity (GFlops (G)) of deraining on images with the resolution size of 512x512.

Disentangle in Process----image deraining

◆ Compared results on synthetic rainy datasets

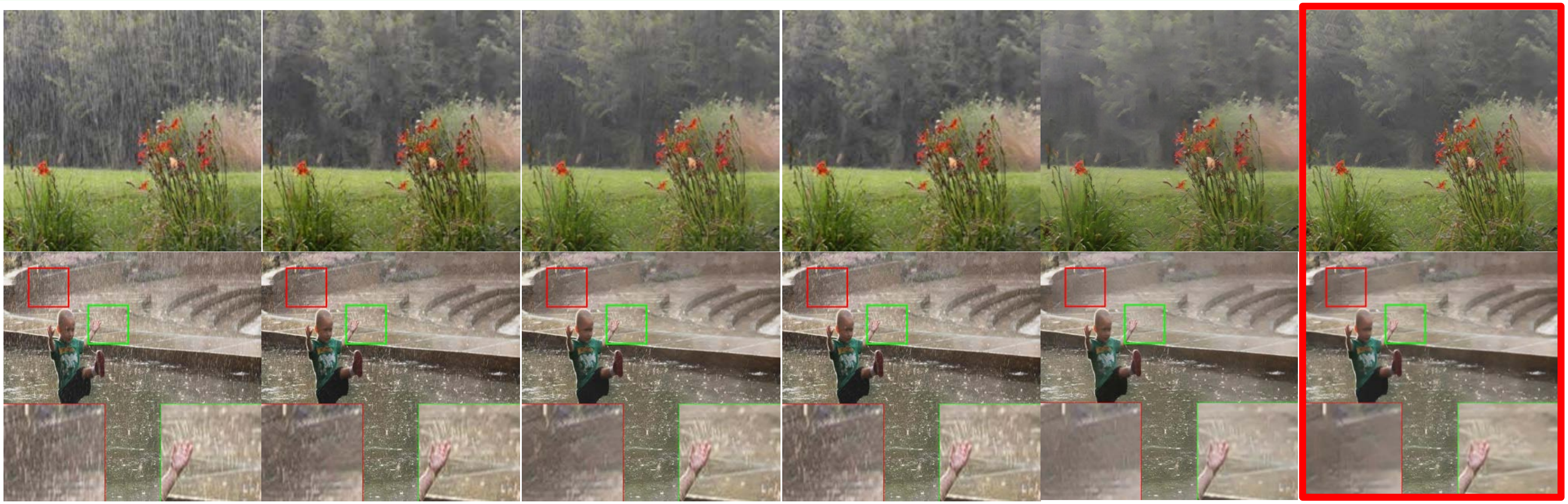
Methods	RESCAN*	DIDMDN	UMRL	PreNet*	DDC	IADN	MSPFN	DRDNet	MPRNet	SWAL	DANet (Ours)	DANet♠ (Ours)
Datasets							**Test100/Test1200**					
PSNR↑	25.00/30.51	22.56/29.65	24.41/30.55	24.81/31.36	23.47/28.65	26.71/32.29	27.50/32.39	28.06/26.73	**30.27**/32.91	28.47/30.40	29.23/32.57	29.90/**33.10**
SSIM↑	0.835/0.882	0.818/0.901	0.829/0.910	0.851/0.911	0.806/0.854	0.865/0.916	0.876/0.916	0.874/0.824	**0.897**/0.916	0.889/0.892	0.892/0.917	0.893/**0.919**
FSIM↑	0.909/0.944	0.899/0.950	0.910/0.955	0.916/0.955	0.898/0.936	0.924/0.958	0.928/0.960	0.925/0.920	**0.939**/0.959	0.936/0.950	0.935/0.961	0.938/**0.962**
Par.(M)↓	0.150	0.372	0.984	0.169	31.46	0.980	13.35	5.230	3.637	156.54	1.547	2.943
Time (S)↓	0.546	0.315	0.112	0.163	0.125	0.132	0.507	1.426	0.207	0.116	0.079	0.109
GFlops (G)↓	129.28	xx	65.74	265.76	42.49	80.99	708.39	–	565.81	614.35	49.11	130.91

◆ Compared results on real rainy datasets

Datasets	DIDMDN	RESCAN	DDC	LPNet	UMRL	PreNet	IADN	MSPFN	DRDNet	DANet (Ours)
Real127 (127)	3.929/32.42	3.852/30.09	4.022/29.33	3.989/29.62	3.984/29.48	3.835/29.61	**3.769**/29.12	3.816/29.05	4.208/30.34	3.817/**28.73**
RID (2495)	5.693/41.71	6.641/40.62	6.247/40.25	6.783/42.06	6.757/41.04	7.007/43.04	6.035/40.72	6.518/40.47	5.715/39.98	**4.565/38.20**
RIS (2348)	5.751/46.63	6.485/50.89	5.826/47.80	6.396/53.09	**5.615**/43.45	6.722/48.22	5.909/**42.95**	6.135/43.47	6.269/45.34	5.896/43.27

Disentangle in Process----image deraining

◆ Visual results on real-world rainy scenarios



(a) Rainy input **(b) PreNet** **(c) IADN** **(d) MSPFN** **(e) DRDNet** **(f) DANet**

[b] D. Ren, W. Zuo, Q. Hu, P. Zhu, and D. Meng, “Progressive image deraining networks: a better and simpler baseline,” in ***CVPR, 2019***, pp. 3937–3946.
[c] K. Jiang, Z. Wang, P. Yi, C. Chen, Z. Han, T. Lu, B. Huang, and J. Jiang, “Decomposition makes better rain removal: An improved attention-guided deraining network***,” IEEE Trans. Circuits Syst. Video Technol***., pp. 1–1, 2020.
[d] Jiang K, Wang Z, Yi P, et al. "Multi-Scale Progressive Fusion Network for Single Image Deraining***," IEEE CVPR, 2020***, pp. 8343-8352.
[e] S. Deng, M. Wei, J. Wang, Y. Feng, L. Liang, H. Xie, F. L. Wang, and M. Wang, “Detail-recovery image deraining via context aggregation networks,” ***in CVPR, 2020***, pp. 14 548–14 557.
[f] Jiang K, Wang Z, Yi P, et al. “Image Enhancement via Associated Perturbation Removal and Texture Reconstruction Learning,” 2021.

Disentangle in Process----low-light enhancement

Analyses

(a) scene one

(b)   scene one

I_L :denotes the low-light input ; I_N :is the degradation perturbation, including the noise, exposure, etc; I: refers to the normal-light image; I_R : the reflectance ; I_T : is the illumination ; $\circ$ denotes the element-wise product

$$I_L = \theta(I, I_N) \qquad (1) \begin{cases} I_L \rightarrow I \\ I_L - I_N \rightarrow I \end{cases}$$

Additive model

$$I_L = I_R \circ I_T \qquad (2) \begin{cases} I_T \rightarrow I \\ I_R, I_T \rightarrow I \end{cases}$$

Retinex model

Drawbacks:

1) heavily rely on the diversity and quality of synthetic training samples
2) simplify the imaging model when coping with the enhancement task, thus sacrificing representation precision,

Disentangle in Process----low-light enhancement

motivation

Degradation learning

$$I_L = I_D + I + f(I, I_D) \quad (3)$$

$$I_L = I_D + I + f(I, I_D) = I_D + \varphi(I, I_D) \quad (4)$$

$$\varphi(I, I_D) = I_L - I_D \quad (5)$$

$$I_D = \emptyset(I_L)$$

Image enhancement

$$I = \varphi^{-1}(I_L - \emptyset(I_L)) \quad (6)$$

Disentangle in Process----low-light enhancement

motivation

Degradation learning

$$I_L = I_D + I + f(I, I_D) \quad (3)$$

$$I_L = I_D + I + f(I, I_D) = I_D + \varphi(I, I_D) \quad (4)$$

$$\varphi(I, I_D) = I_L - I_D \quad (5)$$

$$I_D = \emptyset(I_L)$$

Image enhancement

$$I^*_{L,ref} = I_D + I^*_{ref} + f\left(I^*_{ref}, I_D\right) \quad (7)$$

$$I^*_{L,ref} = I_D + \varphi\left(I^*_{ref}, I_D\right) \quad (8)$$

$$I_{\mathrm{ref}} = \varphi\left(I^*_{ref}, I_D\right)$$

$$I^*_{L,ref} = I_D + I_{\mathrm{ref}} \quad (9)$$

Disentangle in Process----low-light enhancement

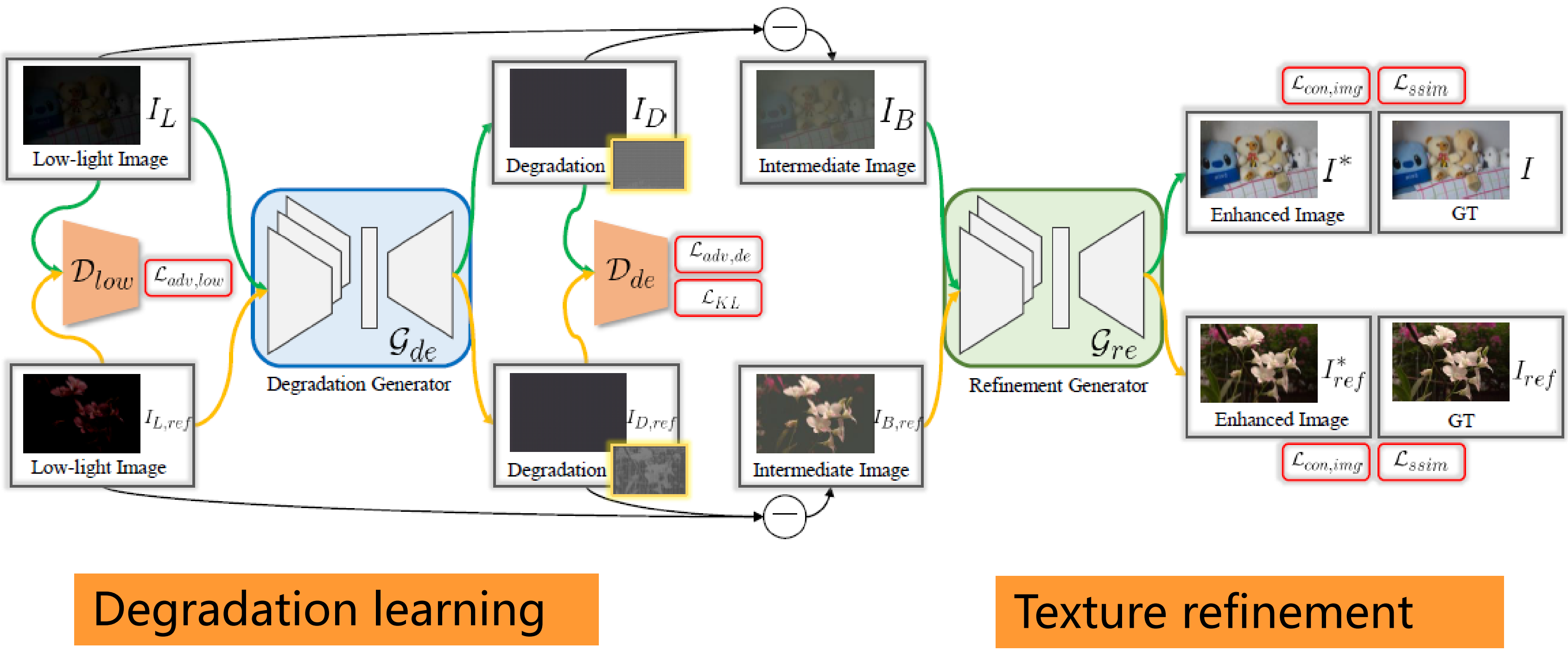
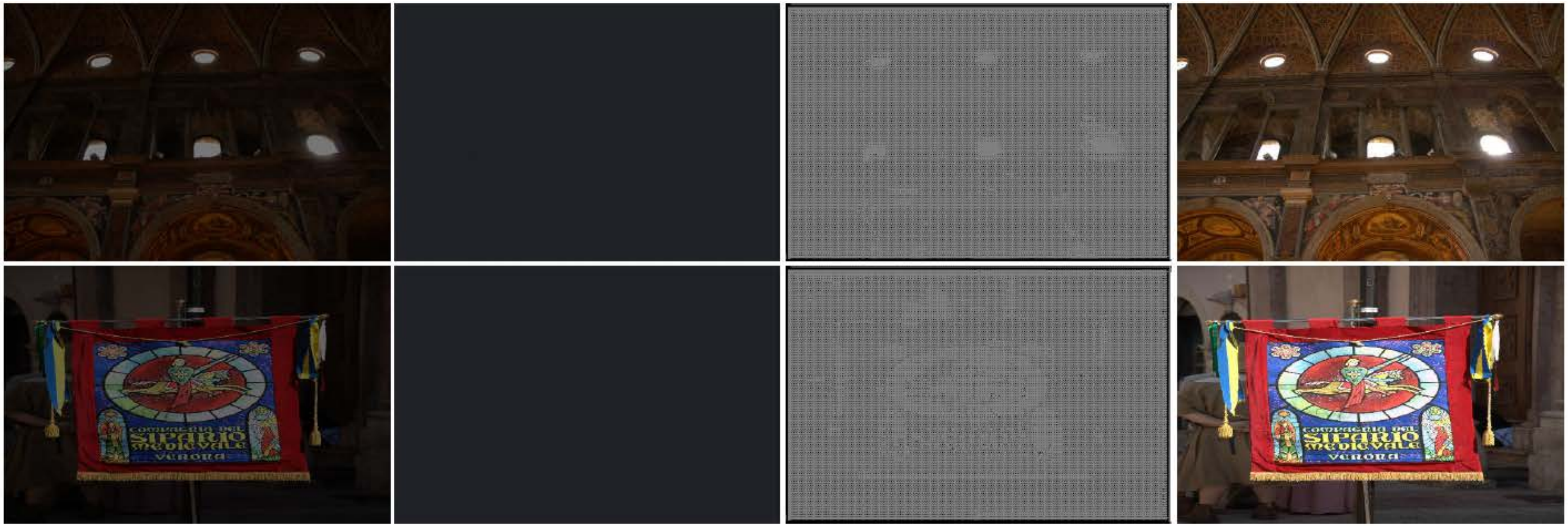


Figure 2: Architecture of Degradation-to-Refinement Generation Network (DRGN). It consists of two subnetworks to tackle degradation estimation and content refinement, respectively. A degradation generator (DeG) learns degradation I_D from the low-light input I_L in the first stage, and produces the base enhanced result I_B by removing I_D. Then, a refinement generator (ReG) takes I_B as input and produces the refined prediction (I^*) of the normal-light image (I). We also apply DeG to generate the synthetic paired samples $[I_{L,ref}, I_{ref}]$ to augment the sample space to help train these two generators.

Jiang K, Wang Z, Wang Z, et al. Degrade is upgrade: Learning degradation for low-light image enhancement[C]//Proceedings of the AAAI Conference on Artificial Intelligence. 2022, 36(1): 1078-1086.

Disentangle in Process----low-light enhancement

◆ Visualization of the degradation learning

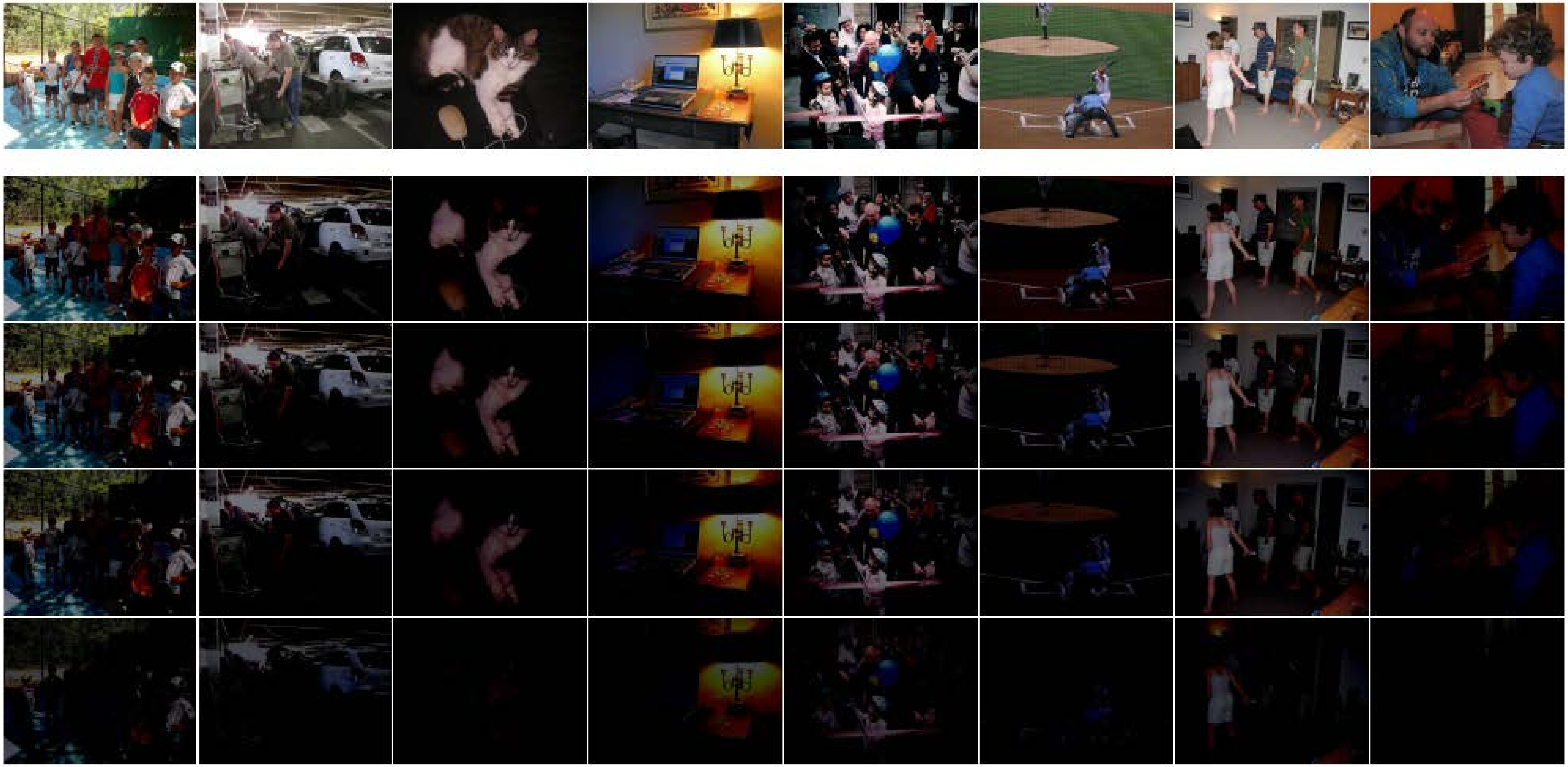


(a) Low-light input (b) Degrdation factors (b) Visualiozation (f) Normal-light image

Visualization of the degradation learning

Disentangle in Process----low-light enhancement

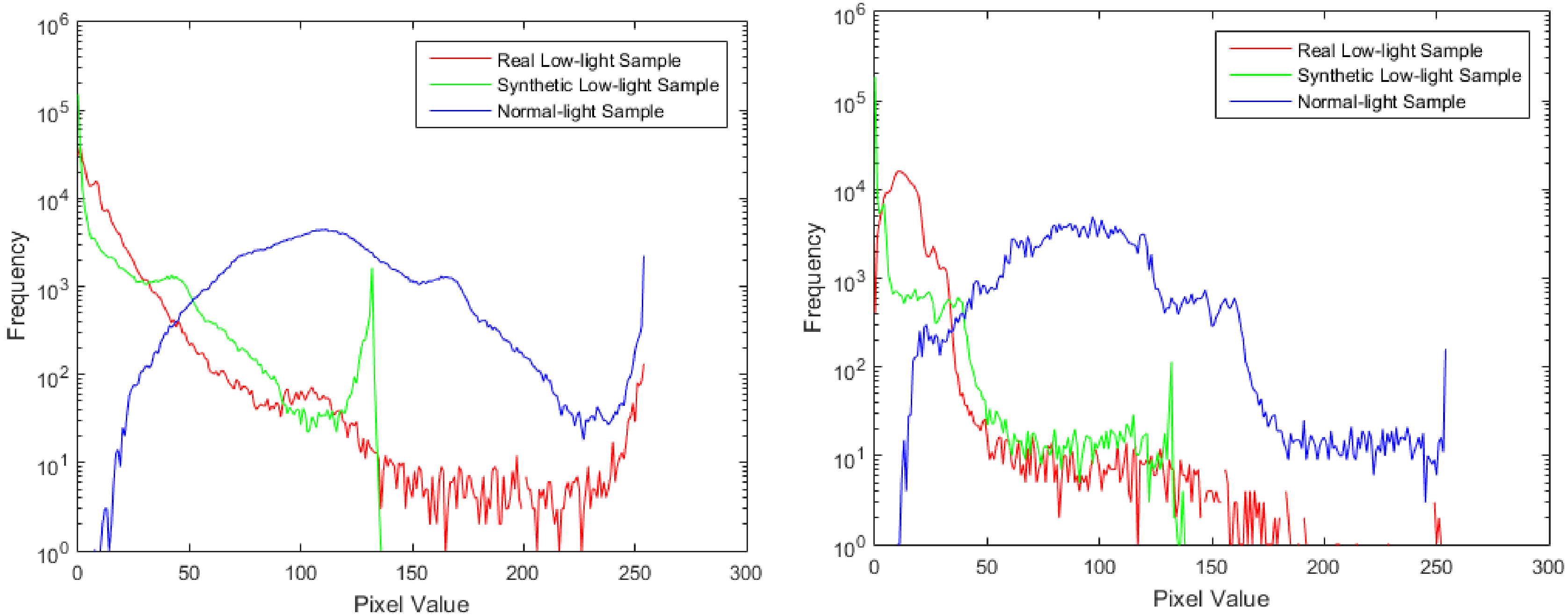
◆ Sample generation



Visualization of the synthetic low-light images by the degradation generator (DeG)

Disentangle in Process----low-light enhancement

◆ Sample generation evaluation



Fitting results of Y channel histogram

Disentangle in Process----low-light enhancement

◆ Comparison results on real-world scenarios

(a) Low-light input (b) RetinenNet (c) Kind (d) MIRNet (e) CSRNet (f) EnlightenGAN (g) Ours

[b] C. Wei, W. Wang, W. Yang, and J. Liu, “Deep retinex decomposition for low-light enhancement,” ***in BMVC, 2018***, p. 155.
[c] Y. Zhang, J. Zhang, and X. Guo, “Kindling the darkness: A practical low-light image enhancer,” ***ACM MM., 2019***.
[d] S. W. Zamir, A. Arora, S. H. Khan, M. Hayat, F. S. Khan, M. Yang, and L. Shao, “Learning enriched features for real image restoration and enhancement,” ***in ECCV,*** vol. 12370, ***2020***, pp. 492–511.
[e] J. He, Y. Liu, Y. Qiao, and C. Dong, “Conditional sequential modulation for efficient global image retouching,” ***in ECCV***, vol. 12358, ***2020***,
pp. 679–695.
[f] Y. Jiang, X. Gong, D. Liu, Y. Cheng, C. Fang, X. Shen, J. Yang, P. Zhou, and Z. Wang, “Enlightengan: Deep light enhancement without paired supervision,” ***IEEE Trans. Image Process.,*** vol. 30, pp. 2340–2349, ***2021***.
[g] Jiang K, Wang Z, Yi P, et al. “Degrade is Upgrade: Learning Degradation for Low-light Image Enhancement,” AAAI, 2022.

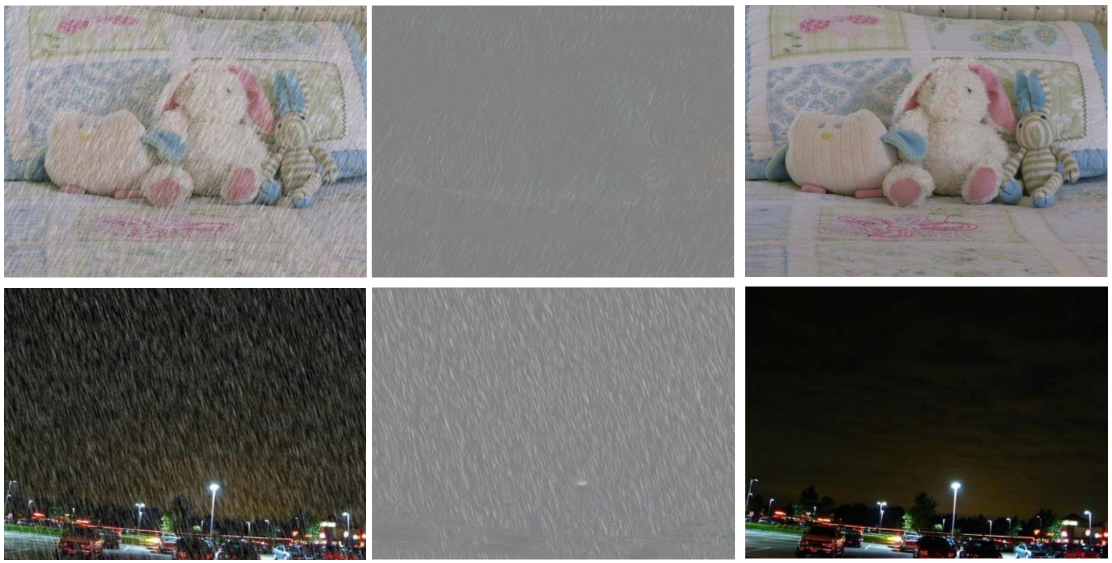
Disentangle in Process----low-light enhancement

◆ Low-light enhancement + detection

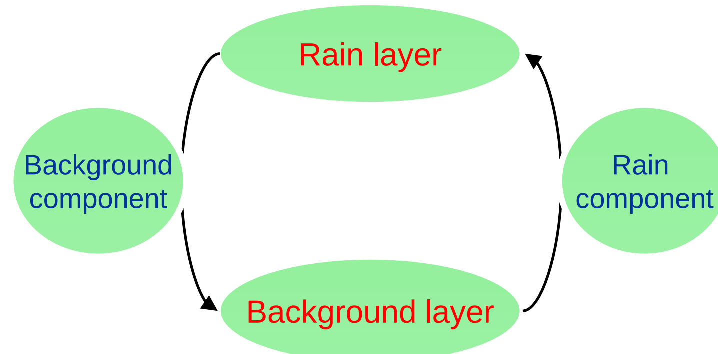
(a) low-light input (b) LIME (c) RetinenNet (d) Deep-UPE (e) Zero-DCE (f) Kind (g) Ours

[b] X. Guo, Y. Li, and H. Ling. Lime: Low-light image enhancement via illumination map estimation. ***IEEE Trans. Image Process***., 26(2):982–993, ***2017***.
[c] C. Wei, W. Wang, W. Yang, and J. Liu, "Deep retinex decomposition for low-light enhancement," ***in BMVC, 2018***, p. 155.
[d] Ruixing Wang, Qing Zhang, Chi-Wing Fu, Xiaoyong Shen, Wei-Shi Zheng, and Jiaya Jia. Underexposed photo enhancement using deep illumination estimation***. In CVPR***, pages 6849–6857, ***2019***.
[e] C. Guo, C. Li, J. Guo, C. C. Loy, J. Hou, S. Kwong, and R. Cong. Zero-reference deep curve estimation for low-light image enhancement. In ***CVPR***, pages 1777–1786, ***2020***.
[f] Y. Zhang, J. Zhang, and X. Guo, "Kindling the darkness: A practical low-light image enhancer," ***ACM MM., 2019***.
[g] Jiang K, Wang Z, Yi P, et al. "Degrade is Upgrade: Learning Degradation for Low-light Image Enhancement," AAAI, 2022.

Disentangle in Content----image deraining



Rainy input   Rain layer   Background layer



$$
\begin{aligned}
I_{Rain} &= I_R + I_B + f(I_R + I_B) \\
&= \sum_{i=1}^{n} (I_{i,R} + I_{i,B} + f(I_{i,R} + I_{i,B})),
\end{aligned}
$$

Processes –based method

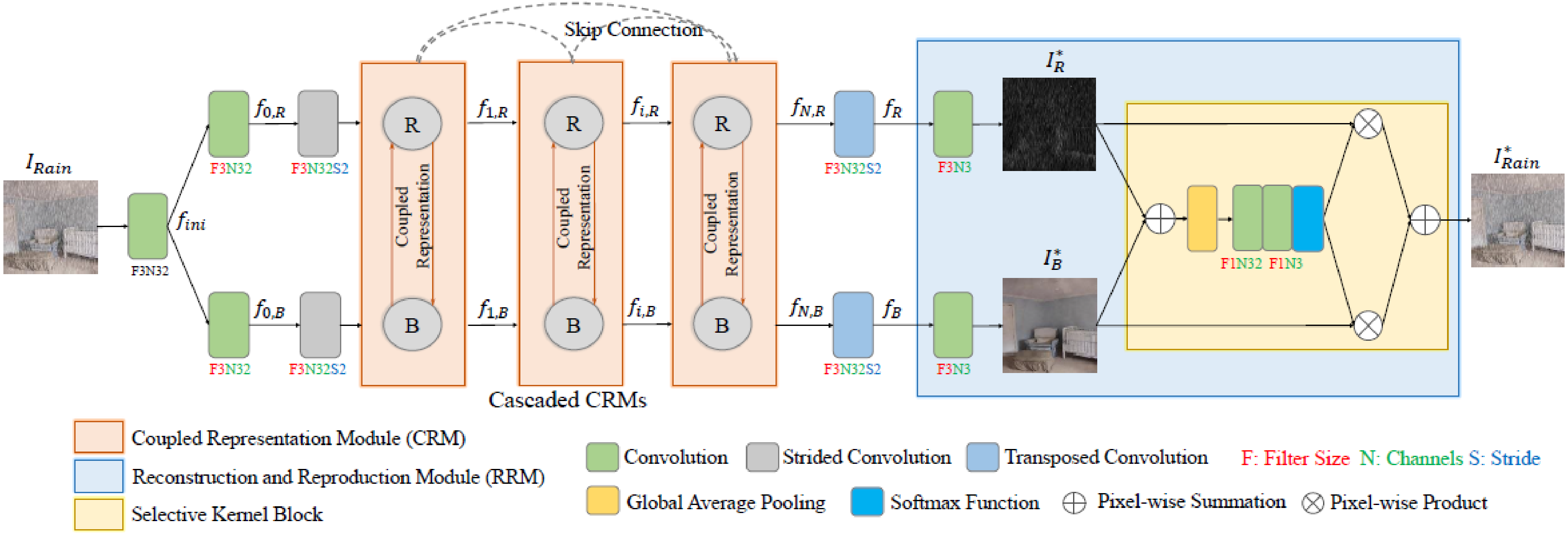
Content –based method

stage –based

process –based

Disentangle in Content----image deraining

◆ Framework

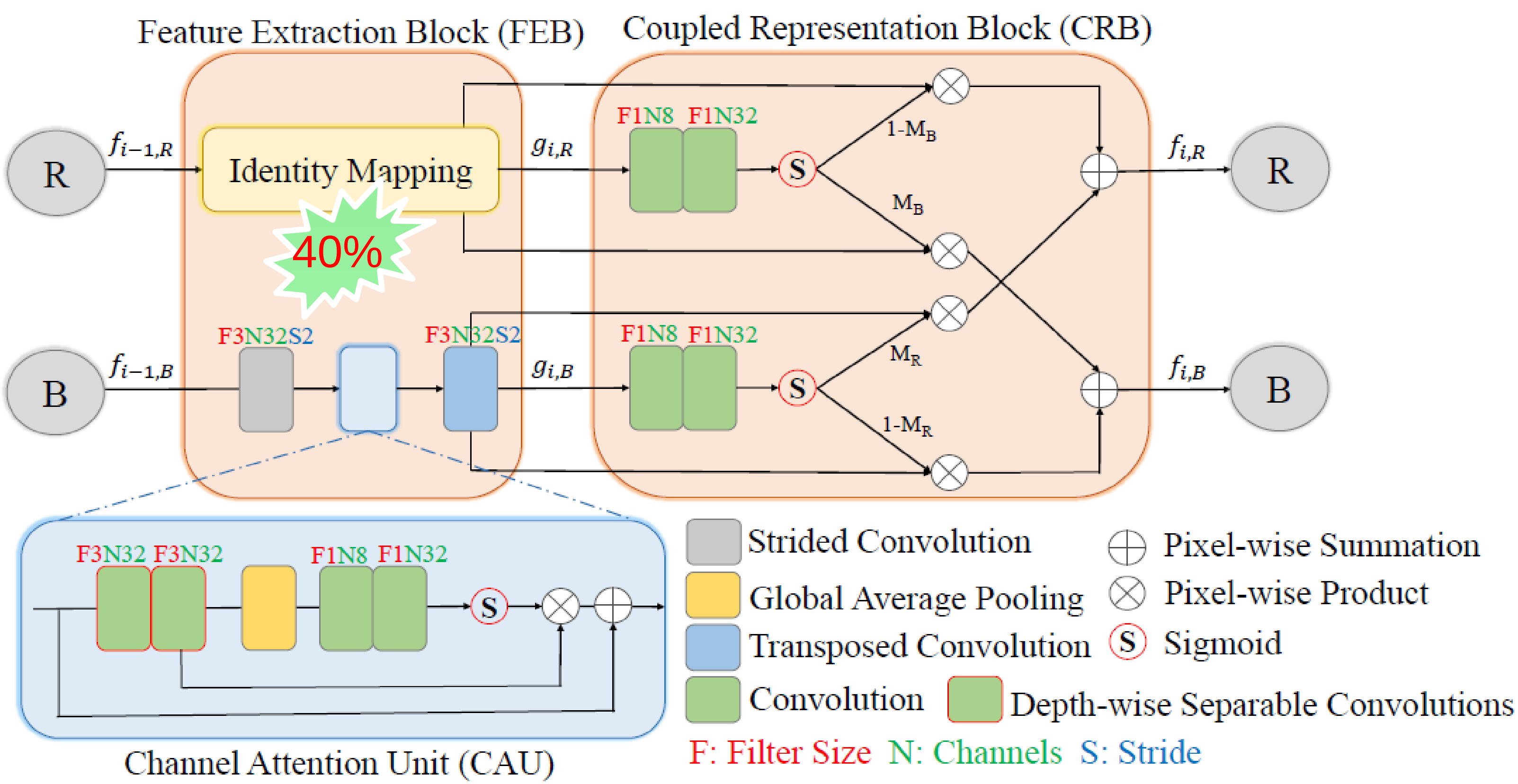


Framework of the proposed progressive coupled network (PCNet)

[1] Jiang K, Wang Z, Yi P, et al. "Rain-free and Residue Hand-in-Hand: A Progressive Coupled Network for Real-Time Image Deraining," IEEE T-IP, 2021.

Disentangle in Content----image deraining

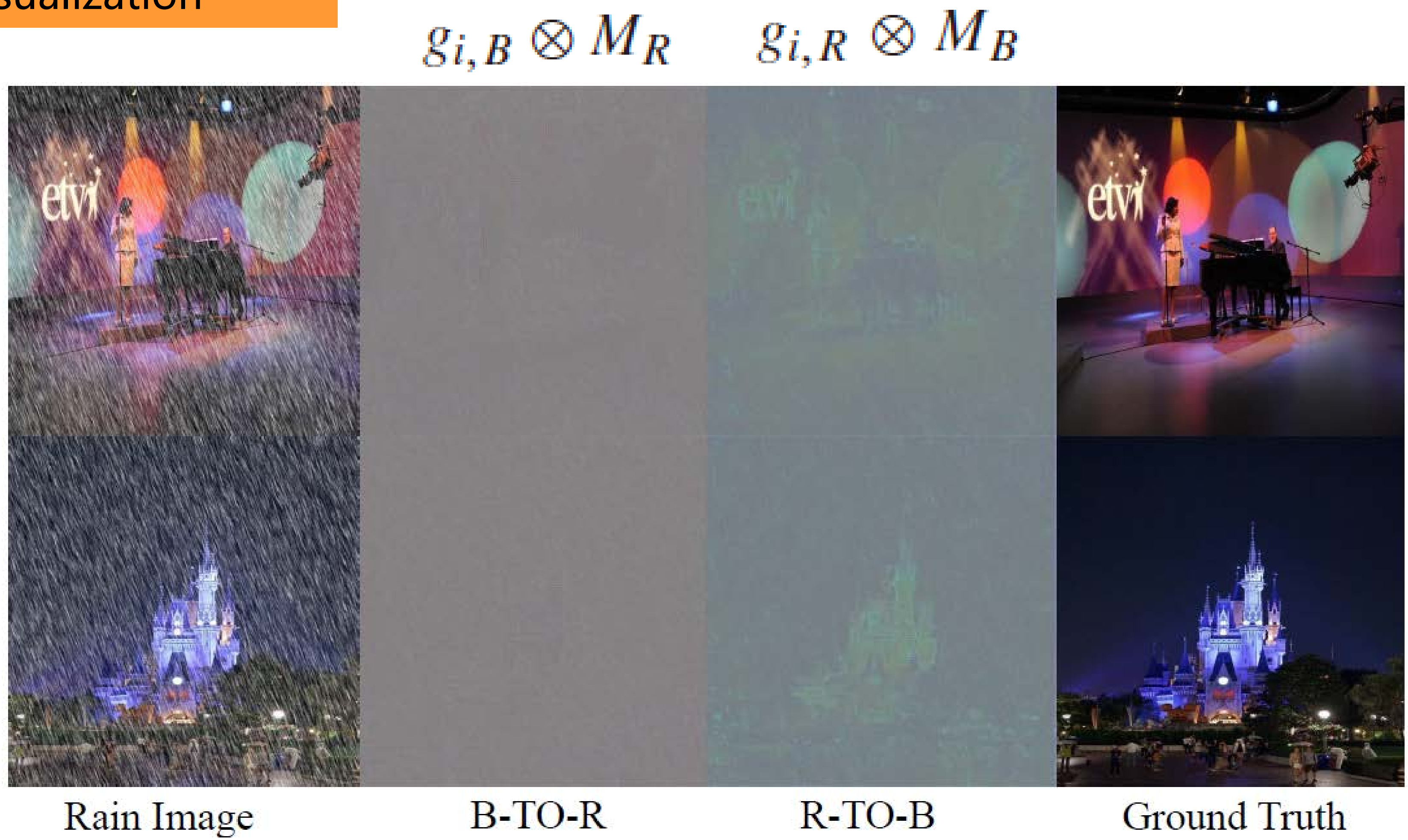
◆ Coupled representation module



Architecture of our proposed coupled representation module (CRM)

Disentangle in Content----image deraining

◆ Visualization



Visualization of the effects of our coupled representation.

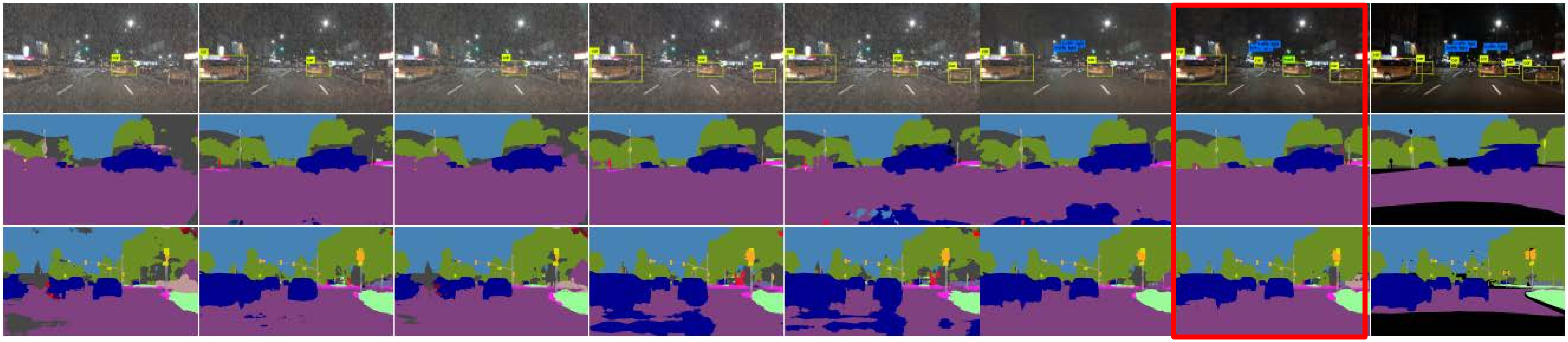
Disentangle in Content----image deraining

◆ Compared results on synthetic rainy datasets

Methods	Rain100H PSNR/SSIM/FSIM	Rain100L PSNR/SSIM/FSIM	Average PSNR/SSIM/FSIM	Time Second (S)	Parameter Million (M)	FLOPs GFLOPs (G)
DerainNet [55]	14.92/0.592/0.755	27.03/0.884/0.904	20.97/0.738/0.829	0.074	0.763	197.56
RESCAN [36]	26.36/0.786/0.864	29.80/0.881/0.919	28.08/0.833/0.891	0.546	0.150	129.28
DIDMDN [34]	17.35/0.524/0.726	25.23/0.741/0.861	21.29/0.632/0.793	0.315	0.372	44.23
DDC [76]	15.53/0.450/0.664	27.60/0.877/0.902	21.56/0.663/0.783	0.125	3146	42.49
LPNet [54]	16.00/0.517/0.699	25.57/0.728/0.832	20.79/0.625/0.766	0.027	0.007	1.49
UMRL [129]	26.01/0.832/0.876	29.18/0.923/0.940	27.60/0.878/0.908	0.112	0.984	65.74
SEMI [63]	16.56/0.486/0.692	25.03/0.842/0.893	20.80/0.664/0.793	0.546	0.150	129.28
PreNet [20]	26.77/0.858/0.890	32.44/0.950/0.956	29.61/0.904/0.923	0.163	0.169	265.76
IADN [59]	27.86/0.835/0.875	32.53/0.934/0.942	30.20/0.885/0.909	0.132	0.980	80.99
MSPFN [58]	28.66/0.860/0.890	32.40/0.933/0.943	30.53/0.897/0.917	0.546	13.35	708.39
SWAL [187]	**29.30/0.887/0.908**	**34.60/0.958/0.963**	**31.95/0.923/0.935**	0.116	156.54	614.35
PCNet (Ours)	28.45/0.871/0.897	34.42/0.952/0.959	31.44/0.912/0.928	0.062	0.655	28.21

Disentangle in Content----image deraining

◆ Image deraining+ segmentation



(a) Rainy input **(b) RESCAN** **(c) LPNet** **(d) DDC** **(e) PreNet** **(f) MSPFN** **(g) Ours** **(h) Ground Truth**

[b] X. Li, J. Wu, Z. Lin, H. Liu, and H. Zha, “Recurrent squeeze-and excitation context aggregation net for single image deraining,” in ***ECCV, 2018,*** pp. 254–269.

[c] [d] X. Fu, B. Liang, Y. Huang, X. Ding, and J. Paisley, “Lightweight pyramid networks for image deraining,” ***IEEE Transactions on Neural Networks and Learning Systems***, vol. 31, no. 6, pp. 1794–1807, ***2020***.

[d] S. Li, W. Ren, J. Zhang, J. Yu, and X. Guo, “Single image rain removal via a deep decomposition–composition network,” ***Computer Vision and Image Understanding, 2019.***

[e] D. Ren, W. Zuo, Q. Hu, P. Zhu, and D. Meng, “Progressive image deraining networks: a better and simpler baseline,” in ***CVPR, 2019***, pp. 3937–3946.

[f] Jiang K, Wang Z, Yi P, et al. "Multi-Scale Progressive Fusion Network for Single Image Deraining***," IEEE CVPR, 2020***, pp. 8343-8352.

[g] Jiang K, Wang Z, Yi P, et al. “Rain-free and Residue Hand-in-Hand: A Progressive Coupled Network for Real-Time Image Deraining,” IEEE T-IP, 2021.

Disentangle in image enhancement

Low-light + rainy input

Deraining + low-light enhancement

If you have any questions or concerns, please do not hesitate to email:

kuijiang@whu.edu.cn