

Motivation

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- Rainy image decomposition problem is ill-posed. However, most learning based deraining methods remove rain streaks in one stage directly.

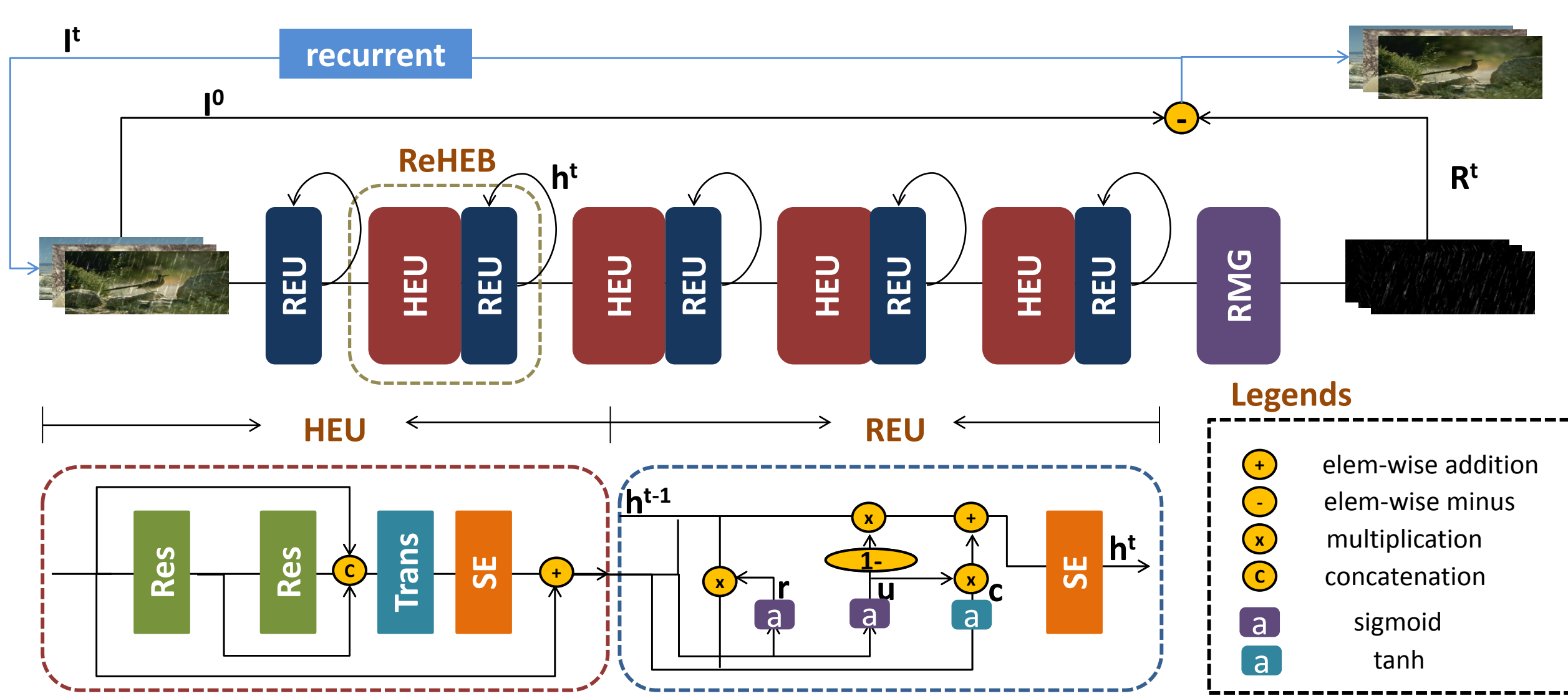
$$I = B + R \quad (1)$$

- Existing stage-by-stage methods neglect the correlations between neighboring stages. Though **RESCAN** applies recurrent unit to preserve useful information in current stage and benefit the later stages, the direct flow of rain details from previous recurrent block to current recurrent block leads to the redundant background details.



Recurrent Hierarchy and Enhancement Network (ReHEN)

Recurrent Hierarchy and Enhancement Network



- The formulation of the proposed method is defined as follows:

$$\begin{aligned} R^t &= f_{ReHEN}(I^{t-1}) \\ I^t &= I^0 - R^t \\ 1 &\leq t \leq K \end{aligned} \quad (2)$$

- Recurrent hierarchy enhancement block (ReHEB) is formulated as follow:

$$\begin{aligned} F_{HEU,i}^t &= f_{HEU,i}(F_{ReHEB,i-1}^t) \\ F_{REU,i}^t &= f_{REU,i}(F_{HEU,i}^t, h_{ReHEB,i}^{t-1}) \\ F_{ReHEB,i}^t &= h_{ReHEB,i}^t = F_{REU,i}^t \end{aligned} \quad (3)$$

Contributions

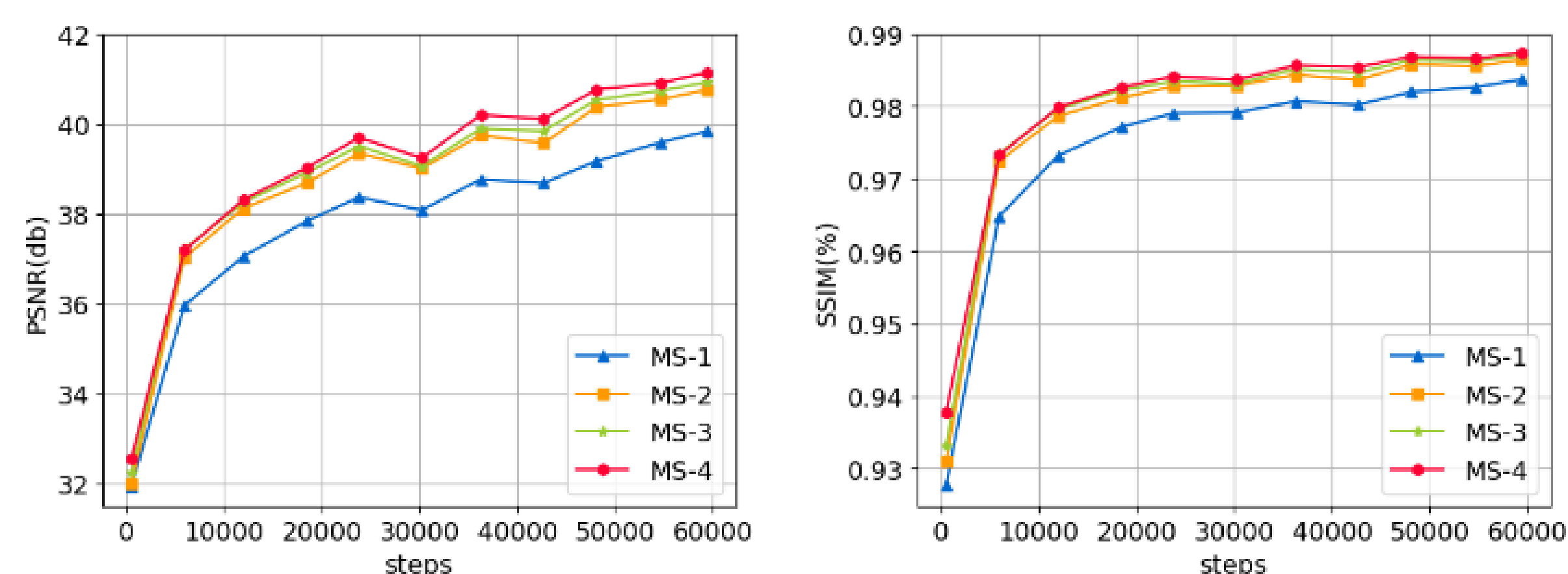
- We propose a novel method named recurrent hierarchy enhancement network (ReHEN) for single image deraining
- In ReHEN, we construct a recurrent hierarchy enhancement block (ReHEB). In ReHEB, hierarchy enhancement unit (HEU) is applied for effective feature extraction. And by incorporating recurrent enhancement unit (REU), information from previous stage has access to the later stages and guide them to remove rain streaks.
- The proposed method outperforms the state-of-the-art methods on five synthetic datasets and a real-world rainy image set.

- Furthermore, recurrent enhancement unit (REU) is formulated as follow:

$$\begin{aligned} u_i^t &= \sigma(W_{u,i} \otimes F_{HEU,i}^t + U_{u,i} \otimes h_{ReHEB,i}^{t-1} + b_{u,i}) \\ r_i^t &= \sigma(W_{r,i} \otimes F_{HEU,i}^t + U_{r,i} \otimes h_{ReHEB,i}^{t-1} + b_{r,i}) \\ c_i^t &= \sigma_h(W_{c,i} \otimes F_{HEU,i}^t + U_{c,i} \otimes (r_i^t \odot h_{ReHEB,i}^{t-1}) + b_{c,i}) \\ h_{ReHEB,i}^t &= (1 - u_i^t) \odot h_{ReHEB,i}^{t-1} + u_i^t \odot c_i^t \\ s_{REU,i}^t &= f_{SE,i}(h_{ReHEB,i}^t) \\ F_{REU,i}^t &= g_{scale,i}(s_{REU,i}^t, h_{ReHEB,i}^t) \end{aligned} \quad (4)$$

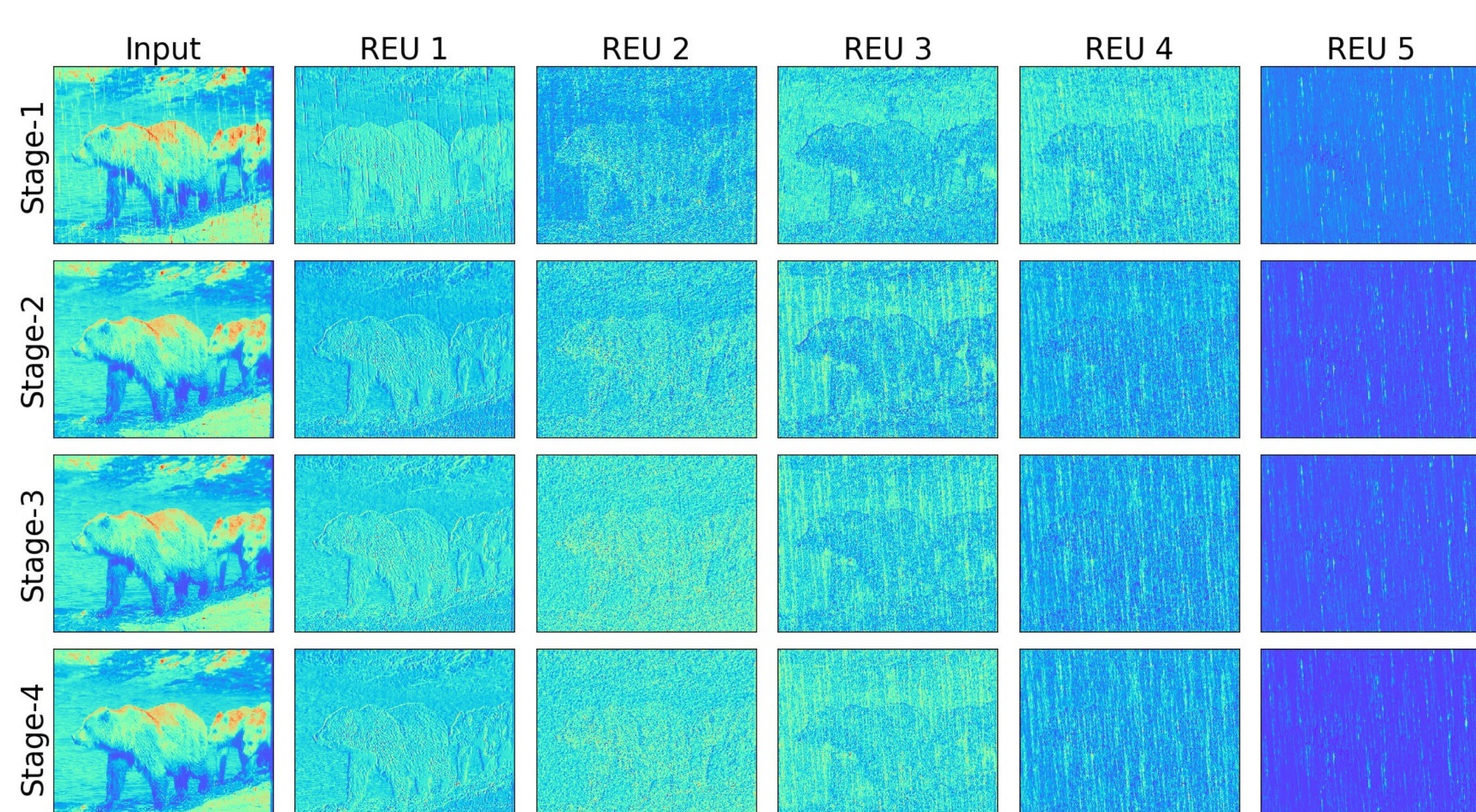
Experimental Results

Ablation Study on Rain Removal Stage



- Training convergence analysis on PSNR/SSIM of ReHEN with different recurrent rain removal stages is shown above. The gap between one stage and two stages is large which demonstrates that recurrent enhancement unit (REU) can preserve rain details from previous stage and guide the later stages to remove rain streaks efficiently.

Visualization of Hidden States



Quantitative and Qualitative Results on Synthetic Datasets and Real-world Datasets

		Time (s)	Rain100L		Rain100H		Rain800		Rain1200		Rain1400	
Methods	Params	512×512	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Rainy	-	-	25.52	0.825	12.13	0.349	21.16	0.652	21.15	0.778	23.69	0.757
DSC (ICCV'15)	-	-	24.16	0.870	15.66	0.544	18.56	0.599	21.44	0.789	22.03	0.799
LP (CVPR'16)	-	-	29.11	0.880	14.26	0.423	22.27	0.741	22.75	0.835	25.64	0.836
JCAS (ICCV'17)	-	-	28.40	0.881	13.65	0.459	22.19	0.766	27.91	0.778	28.77	0.819
DDN (CVPR'17)	57,369	0.547	32.04	0.938	24.95	0.781	21.16	0.732	27.33	0.898	27.61	0.901
ID_CGAN ('17)	817,824	0.286	25.88	0.891	14.16	0.607	22.73	0.817	23.32	0.803	21.93	0.784
JORDER (CVPR'17)	369,792	0.268	36.11	0.970	22.15	0.674	22.24	0.776	24.32	0.862	27.55	0.853
DID-MDN (CVPR'18)	372,839	0.532	25.70	0.858	17.39	0.612	21.89	0.795	27.95	0.908	27.99	0.869
DualCNN (CVPR'18)	687,008	20.19	26.87	0.860	14.23	0.468	24.11	0.821	23.38	0.787	24.98	0.838
RESCAN (ECCV'18)	134,424	0.750	36.64	0.975	26.45	0.846	24.09	0.841	29.95	0.884	28.57	0.891
Ours	298,263	0.531	37.41	0.980	27.97	0.864	26.96	0.854	32.64	0.914	31.33	0.918

