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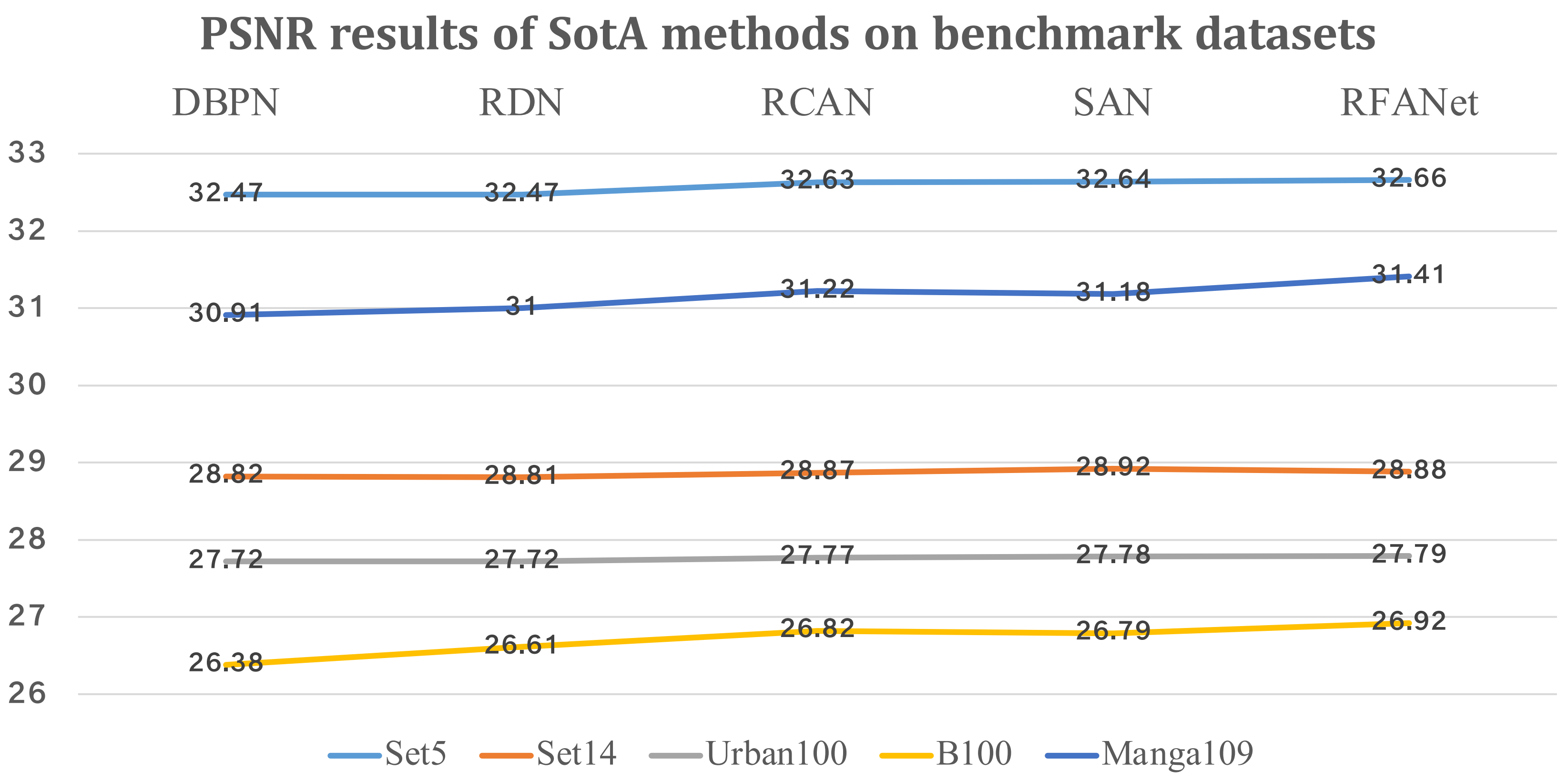
Efficient Super Resolution by Recursive Aggregation

Zhengxiong Luo[1,2,3] , Yan Huang[1,2] , Shang Li[2,3] , Liang Wang[1,4,5] , and Tieniu Tan[1,4]

[1]Center for Research on Intelligent Perception and Computing (CRIPAC)
National Laboratory of Pattern Recognition (NLPR)
[2]Institute of Automation, Chinese Academy of Sciences (CASIA)
[3]School of Artificial Intelligence, University of Chinese Academy of Sciences (UCAS)
[4]Center for Excellence in Brain Science and Intelligence Technology (CEBSIT)
[5]Chinese Academy of Sciences, Artificial Intelligence Research (CAS-AIR)

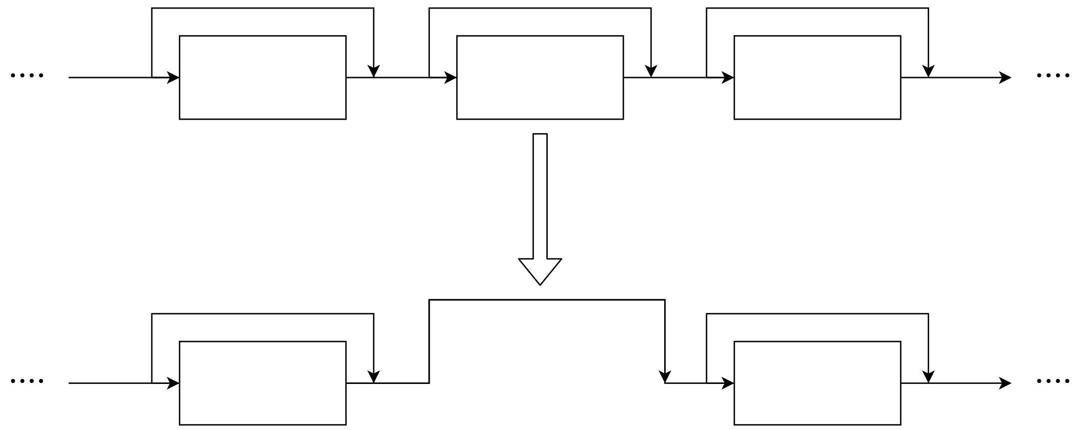
Background:

- Nowadays super-resolutions are becoming dramatically deep and large. While their performances on benchmark datasets are beginning to saturate.

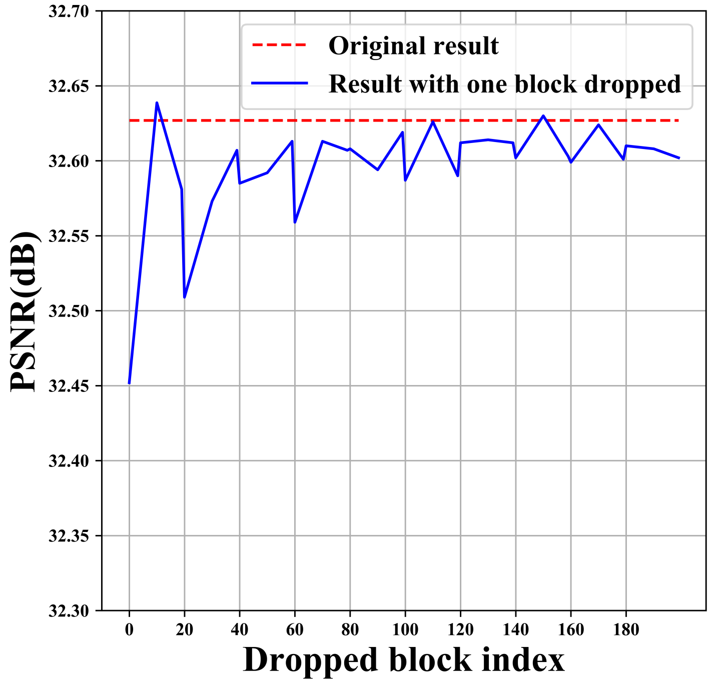


Background:

- Gradients cannot flow to all layers when the model is too deep. Therefore, there might be a large proportion of sub-optimized layers or blocks in these models



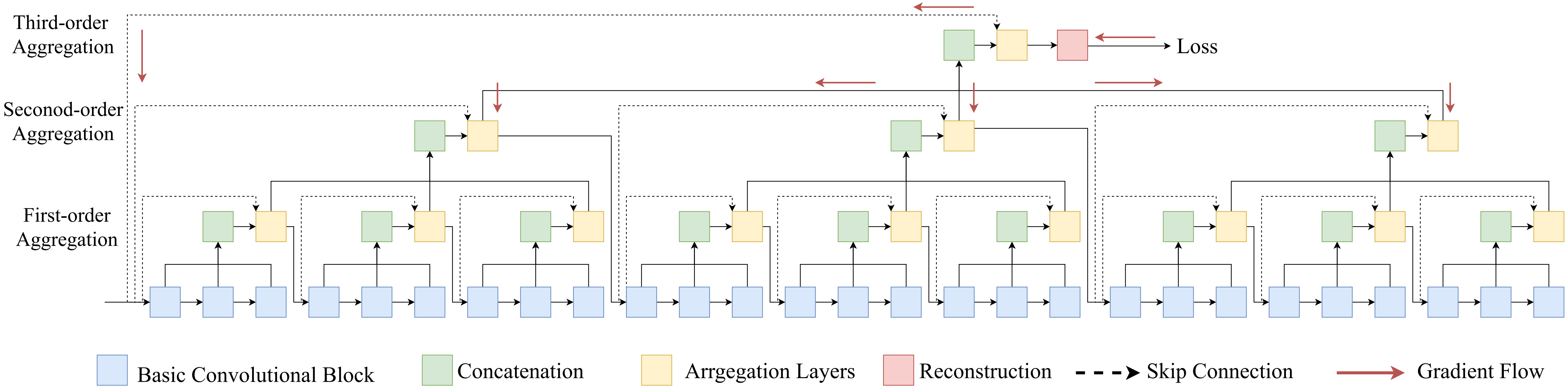
(a) Drop one Residual Block in a trained model



(b) Averagre PSNR on Set5 [7]

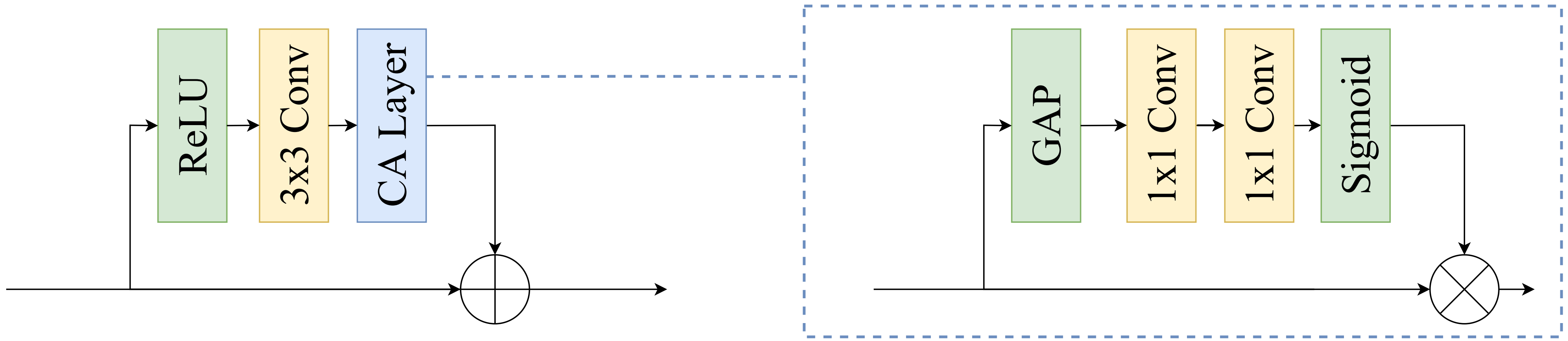
We in turn drop each residual block in a trained RCAN and report the average PSNR on Set5.

Proposed Method:



- Restrict the number of sequentially stacked blocks.
- Intensive shortcuts in the network could help gradients better conducted to all inner layers and make the networks more sufficiently optimized.

Proposed Method:



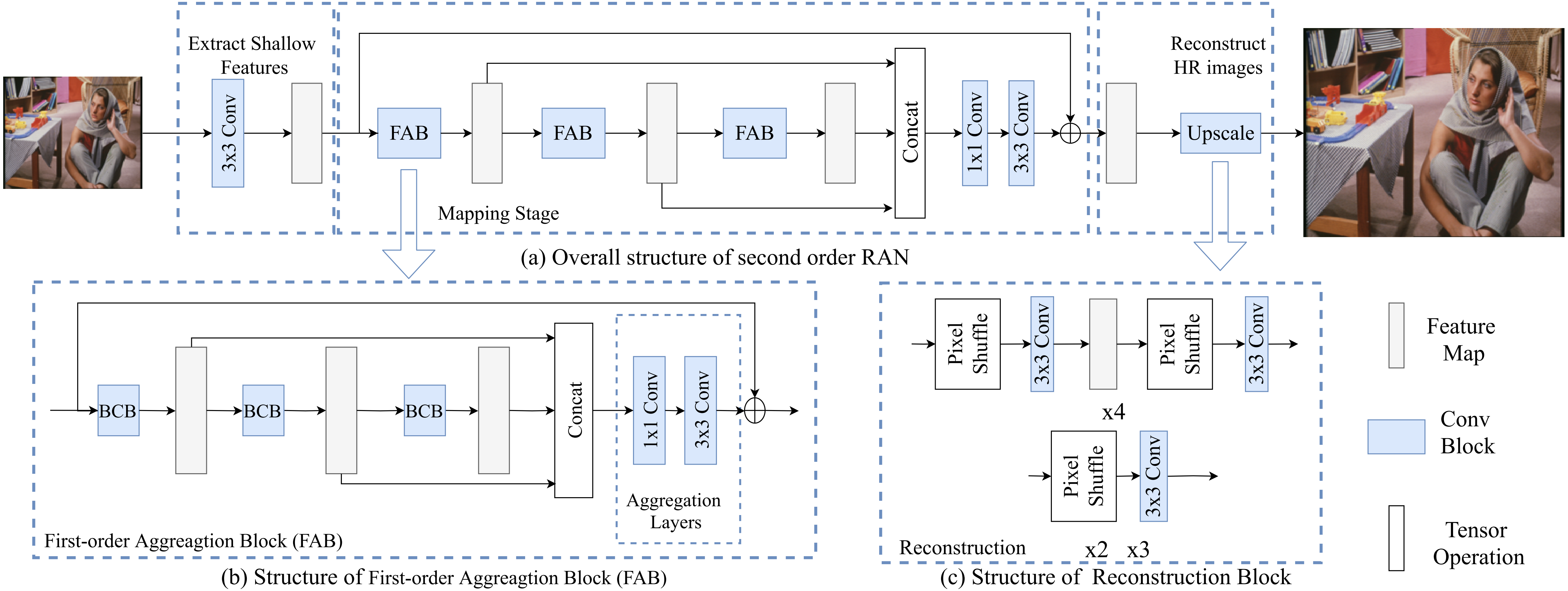
(a) Basic Convolutional Block (BCB)

(b) Channel Attention Layer (CALayer)

- BCB allows more skip connections with the same number of layers.

- The multiple skip connections introduced by BCB will lead to better gradient flow in RAN.

Proposed Method:



Details about a second-order RAN. (a) shows the overall structure of our second order RAN. (b) shows the structure of first-order aggregation block, which is constructed by basic convolutional blocks (BCBs). (c) shows the structure of our reconstruction module. Two PixelShuffle layers are used for ×4 and one is used for ×2 and ×3.

Experiments:

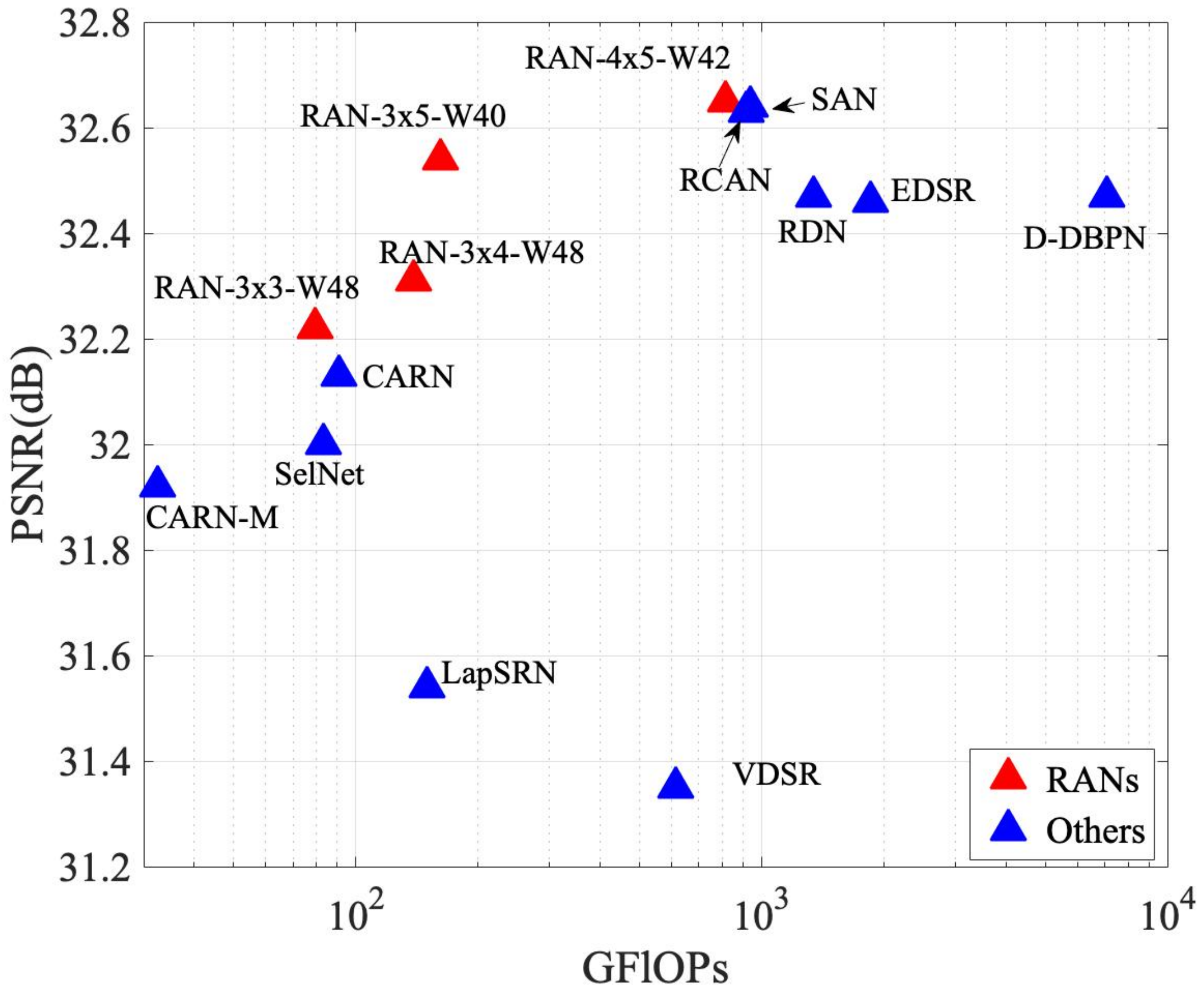
Benchmark results for relative small models. average PSNR/SSIM for ×2, ×3, ×4 models.

	Scale	Bicubic	FSRCNN[45]	LapSRN[46]	SelNet [47]	CARN [38]	CARN-M [38]	RAN-3x3-W48	RAN-3x4-W48	RAN-3x5-W40
Params(K)	—	—	12	813	1427	1592	412	1146.88	2222.08	2723.84
GFlops	—	—	4.6	149.4	83.1	90.9	32.5	79.30	139.02	162.15
Set5	×2	33.66/0.9299	37.00/0.9558	37.52/0.9590	37.89/0.9598	37.76/0.9590	37.53/0.9583	38.09/0.9608	38.18/0.9611	38.25/0.9133
	×3	30.39/0.8682	33.16/0.9140	−/−	34.27/0.9257	34.29/0.9255	33.99/0.9236	34.39/0.9270	34.56/0.9286	34.68/0.9311
	×4	28.42/0.8104	30.71/0.8657	31.54/0.8850	32.00/0.8931	32.13/0.8937	31.92/0.8903	32.22/0.8955	32.31/0.8969	32.54/0.8995
Set14	×2	30.24/0.8688	32.63/0.9088	33.08/0.9130	33.61/0.9160	33.52/0.9166	33.26/0.9141	33.58/0.9175	33.82/0.9200	33.96/0.9236
	×3	27.55/0.7742	29.43/0.8242	−/−	30.30/0.8399	30.29/0.8407	30.08/0.8367	30.31/0.8410	30.42/0.8441	30.50/0.8465
	×4	26.00/0.7027	27.59/0.7535	28.19/0.7720	28.49/0.7783	28.60/0.7806	28.42/0.7762	28.61/0.7822	28.67/0.7839	28.77/0.7864
B100	×2	29.56/0.8431	31.53/0.8920	31.80/0.8950	32.08/0.8984	32.09/0.8978	31.92/0.8960	32.16/0.8995	32.50/0.9010	32.31/0.9022
	×3	27.21/0.7385	28.53/0.7910	−/−	28.97/0.8025	29.06/0.8034	28.91/0.8000	29.08/0.8041	29.17/0.8677	29.23/0.8098
	×4	25.96/0.6675	26.98/0.7150	27.32/0.7280	27.44/0.7325	27.58/0.7349	27.44/0.7304	27.58/0.7365	27.64/0.7383	27.71/0.7412
Urban100	×2	26.88/0.8403	29.88/0.9020	30.41/0.9100/	−/−	31.51/0.9312	30.83/0.9233	32.10/0.9277	32.48/0.9312	32.77/0.9350
	×3	24.46/0.7349	26.43/0.8080	−/−	−/−	27.38/0.8404	26.86/0.8385	28.11/0.8505	28.44/0.8590	28.66/0.8635
	×4	23.14/0.6577	24.62/0.7280	25.21/0.7560	−/−	26.07/0.7837	25.63/0.7688	26.16/0.7878	26.35/0.7948	26.62/0.8020

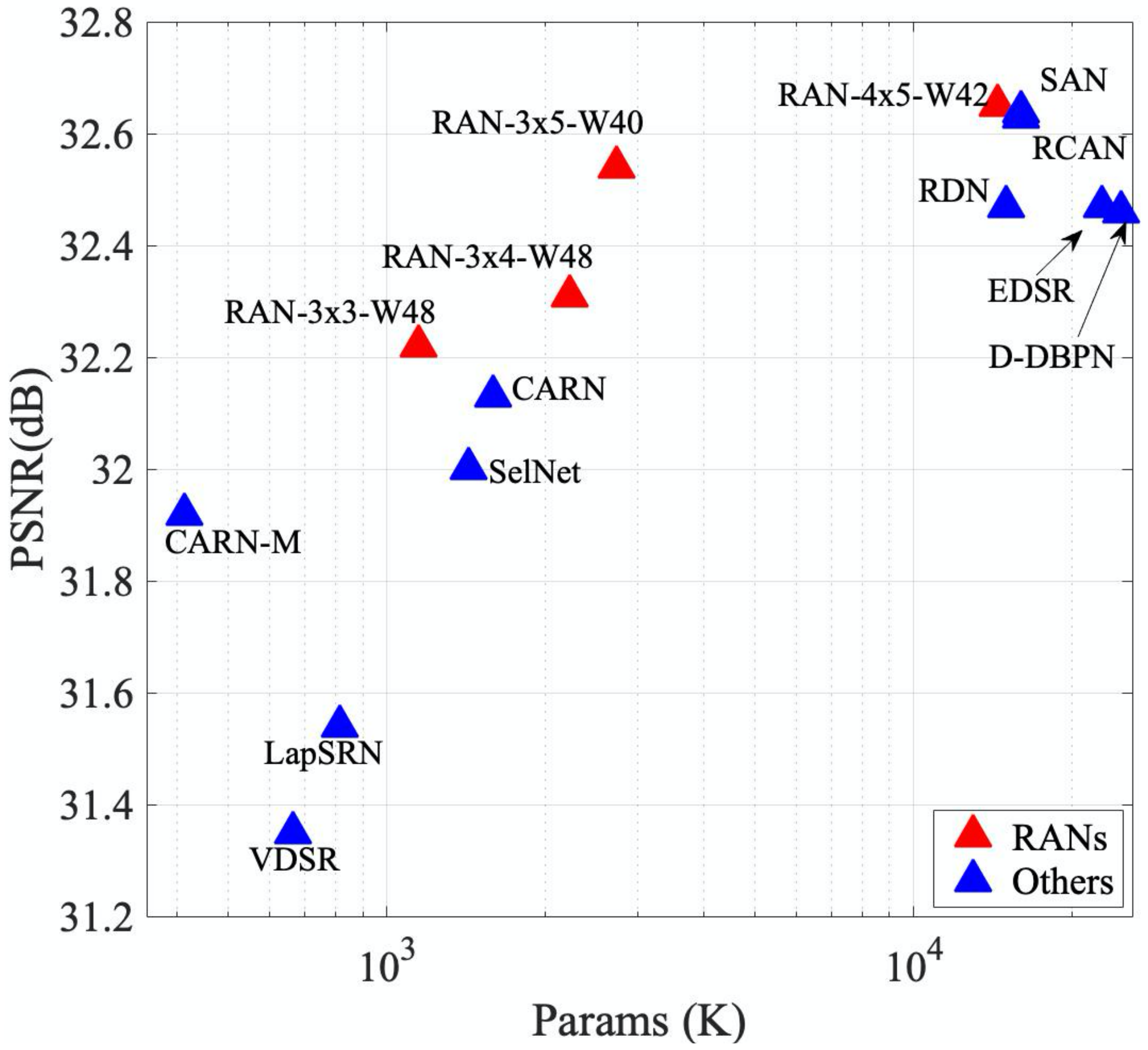
Benchmark results for relative large models. average PSNR/SSIM for ×2, ×3, ×4 models.

	Scale	EDSR [30]	D-DBPN[28]	VDSR [25]	RDN [7]	RCAN [4]	SAN [5]	RAN-4x5-W42	RAN-4x5-W42+
Params(K)	—	24780.80	14988.58	664.70	22804.48	15964.16	16020.13	14428.16	14428.16
GFlops	—	1850.78	7099.19	612.59	1340.42	916.86	936.21	813.76	813.76
Set5	×2	38.11/0.9602	38.09/0.9600	37.53/0.9587	38.24/0.9614	38.27/0.9614	38.31/0.9620	38.32/0.9617	38.36/0.9619
	×3	34.65/0.9280	−/−	33.66/0.9213	34.71/0.9296	34.74/0.9299	34.75/0.9300	34.79/0.9301	34.85/0.9307
	×4	32.46/0.8968	32.47/0.8980	31.35/0.8388	32.47/0.8990	32.63/0.9002	32.64/0.9003	32.65/0.9005	32.75/0.9016
Set14	×2	33.92/0.9195	33.85/0.9190	33.03/0.9142	34.01/0.9212	34.12/0.9216	34.07/0.9213	34.14/0.9217	34.20/0.9224
	×3	30.52/0.8462	−/−	29.77/0.8314	30.57/0.8468	30.65/0.8482	30.59/0.8476	30.64/0.8483	30.70/0.8487
	×4	28.80/0.7876	28.82/0.7860	28.01/0.7674	28.81/0.7871	28.87/0.7889	28.92/0.7888	28.87/0.7888	28.97/0.7943
B100	×2	32.32/0.9013	32.27/0.9000	31.90/0.8960	32.34/0.9017	32.41/0.9027	32.42/0.9028	32.36/0.9022	32.42/0.9028
	×3	29.25/0.8093	−/−	28.82/0.7976	29.26/0.8093	29.32/0.8111	29.33/0.8112	29.32/0.8012	29.34/0.8110
	×4	27.71/0.7420	27.72/0.7400	27.29/0.7251	27.72/0.7419	27.77/0.7436	27.78/0.7436	27.75/0.7436	27.83/0.7441
Urban100	×2	32.93/0.9351	32.55/0.9324/	30.76/0.9140	32.89/0.9353	33.34/0.9384	33.10/0.9370	33.10/0.9370	33.33/0.9385
	×3	28.80/0.8653	−/−	27.29/0.7251	28.80/0.8653	29.09/0.8702	28.93/0.8671	29.09/0.8705	29.14/0.8705
	×4	26.64/0.8033	26.38/0.7946	25.18/0.7524	26.61/0.8028	26.82/0.8087	26.79/0.8068	26.83/0.8089	27.02/0.8116

Experiments:



a) PSNR with respect to flops



b) PSNR with respect to Params

Experiments:

- Study of Basic Convolutional Block (BCB).

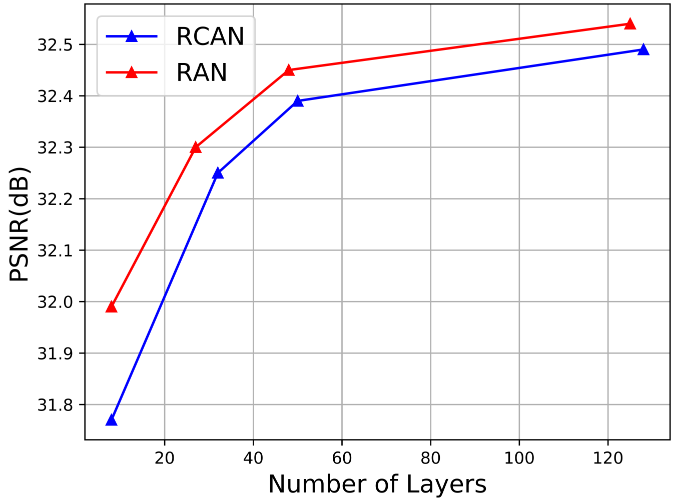
Datasets	RANv2-244-W48	RAN-444-W48
Set5	32.27/0.8963	32.31/0.8970
Se14	28.70/0.7845	28.67/0.7838
B100	27.63/0.7385	27.64/0.7383
Urban100	26.31/0.7935	26.35/0.7046

- Study of Aggregation Period.

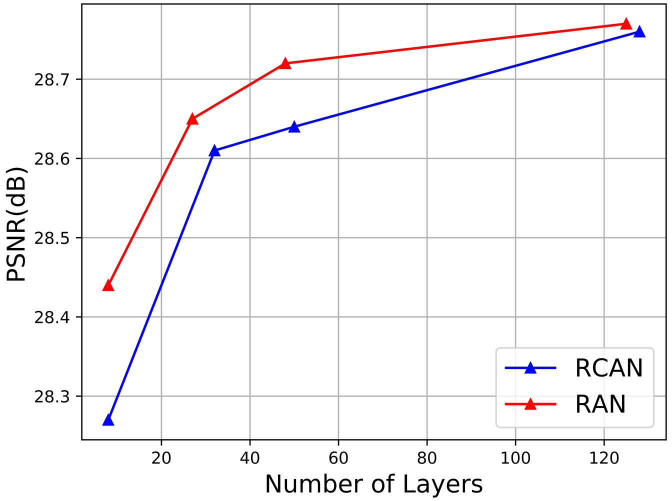
Datasets	RAN-4422-W40	RAN-88-W48	RAN-444-W48
Set5	32.26/0.8962	32.31/0.8966	32.31/0.8970
Se14	28.65/0.7835	28.65/0.7835	28.67/0.7838
B100	27.63/0.7381	27.63/0.7380	27.64/0.7383
Urban100	26.32/0.7933	26.30/0.7932	26.35/0.7046

Experiments:

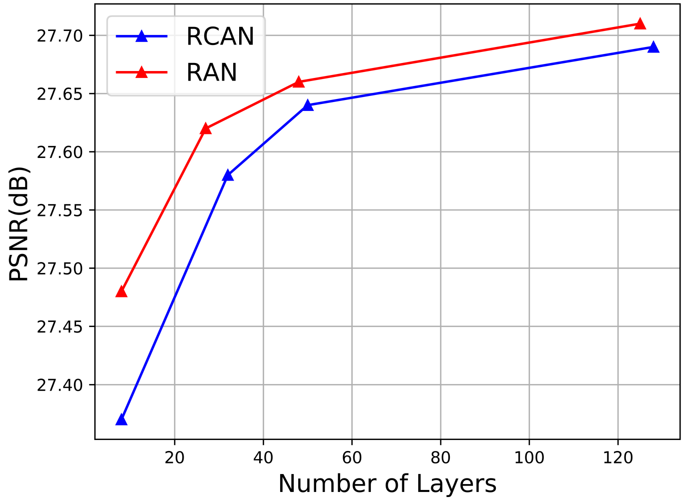
- Better Results with Less Layers



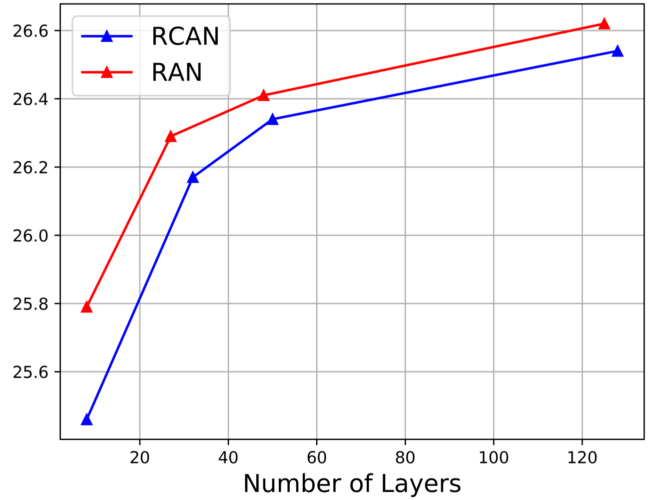
(a) Results on Set5



(b) Results on Set14



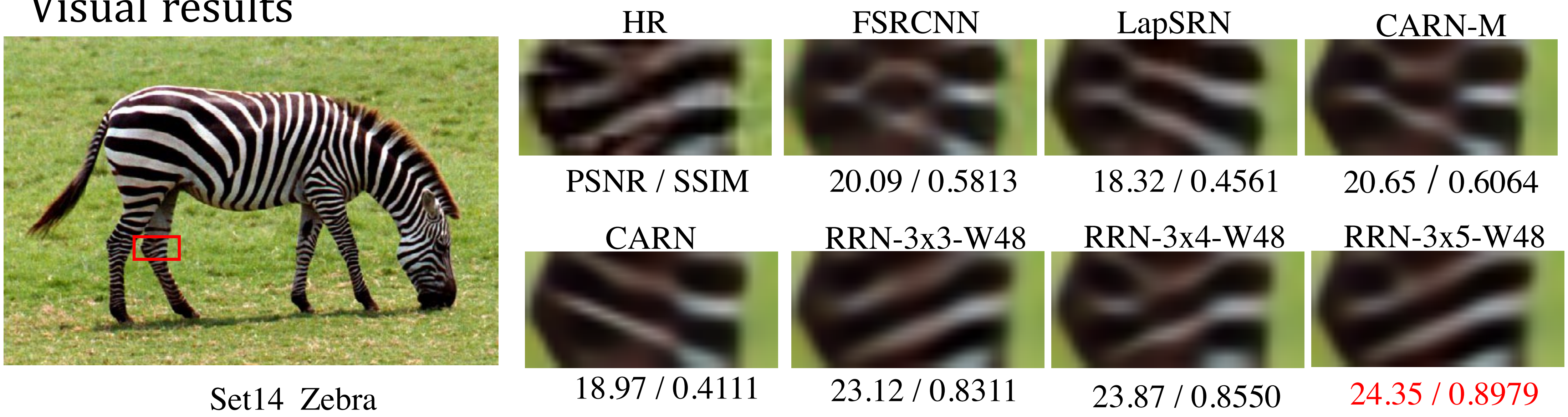
(c) Results on B100



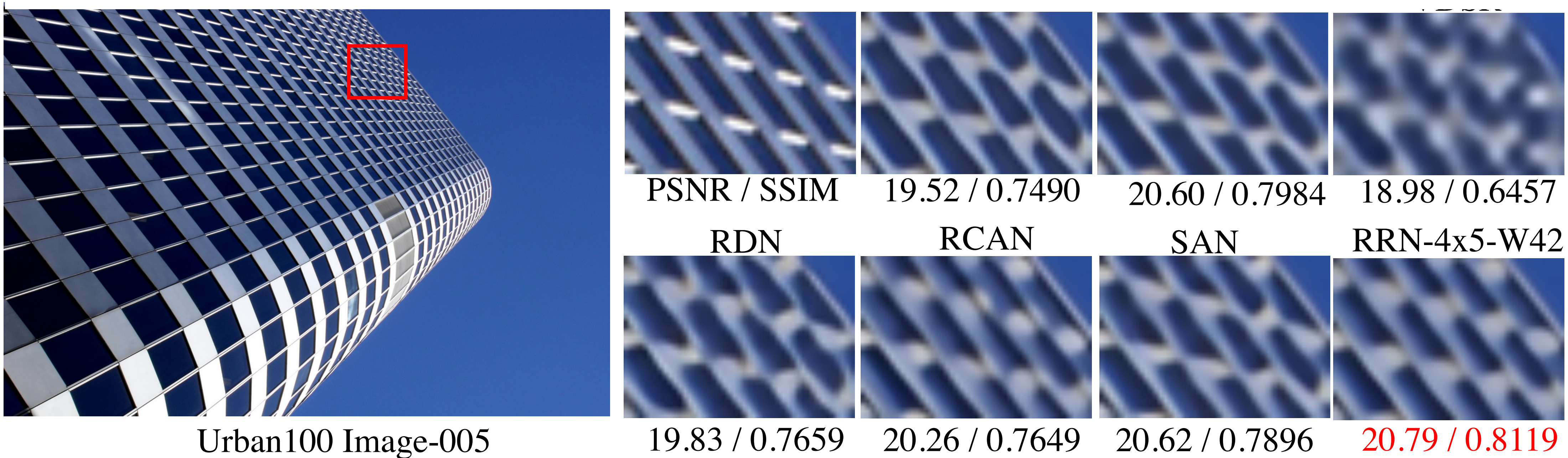
(d) Results on Urban100

Experiments:

- Visual results



Set14 Zebra



Urban100 Image-005

Thanks！

Zhengxiong Luo Ph.D.

Center for Research on Intelligent
Perception and Computing

E-mail: zhengxiong.luo@cirpac.ia.ac.cn