
Image Super-Resolution Using Very Deep Residual Channel Attention Networks

This repository is for RCAN introduced in the following paper

Yulun Zhang, Kunpeng Li, Kai Li, Lichen Wang, Bineng Zhong, and Yun Fu, “Image Super-Resolution Using Very Deep Residual Channel Attention Networks”, ECCV 2018, [arXiv]

The code is built on EDSR (PyTorch) and tested on Ubuntu 14.04/16.04 environment (Python3.6, PyTorch_0.4.0, CUDA8.0, cuDNN5.1) with Titan X/1080Ti/Xp GPUs. RCAN model has also been merged into EDSR (PyTorch).

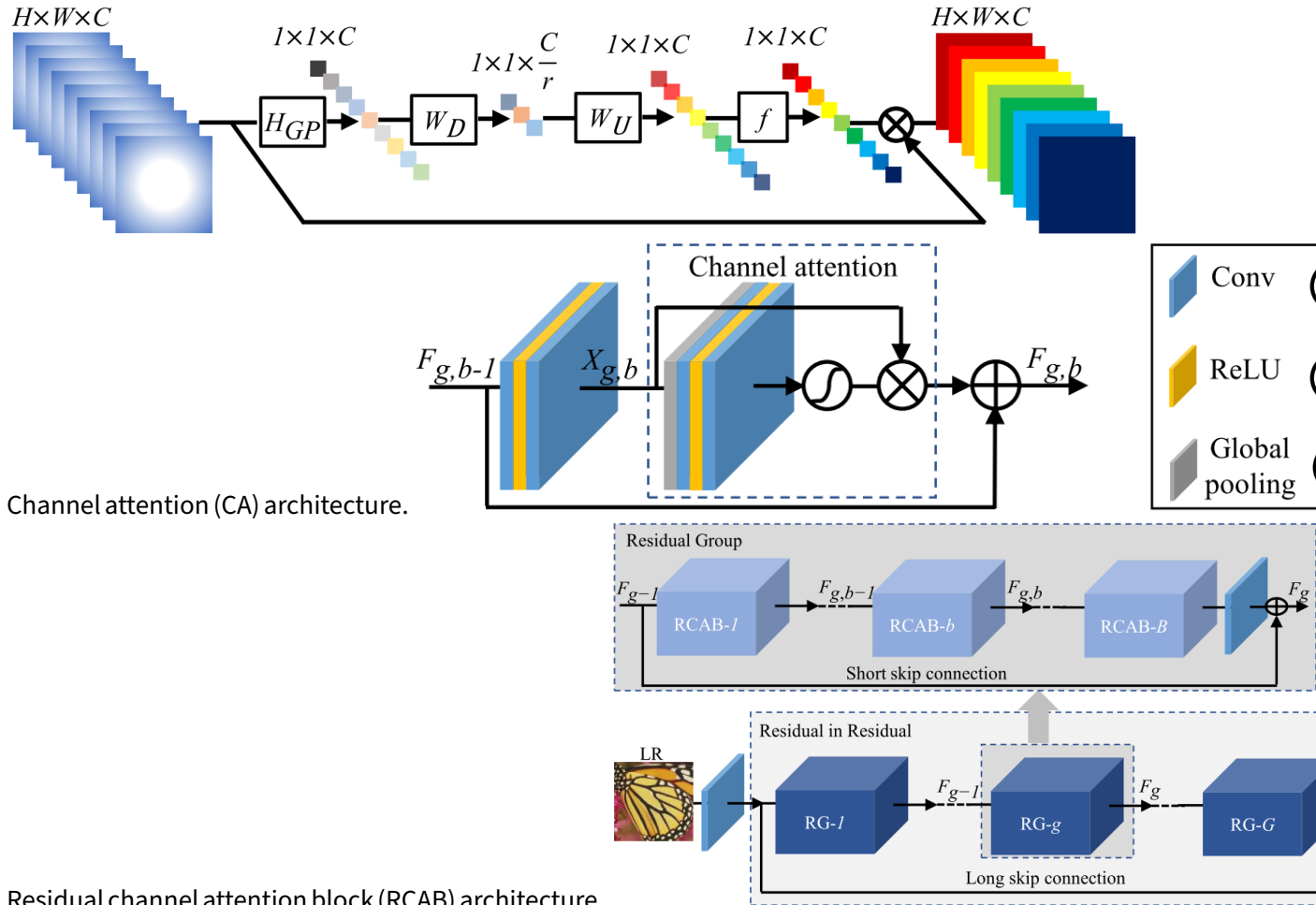
Visual results reproducing the PSNR/SSIM values in the paper are available at GoogleDrive. For BI degradation model, scales=2,3,4,8: Results_ECCV2018RCAN_BIX2X3X4X8

Contents

1. Introduction
2. Train
3. Test
4. Results
5. Citation
6. Acknowledgements

Introduction

Convolutional neural network (CNN) depth is of crucial importance for image super-resolution (SR). However, we observe that deeper networks for image SR are more difficult to train. The low-resolution inputs and features contain abundant low-frequency information, which is treated equally across channels, hence hindering the representational ability of CNNs. To solve these problems, we propose the very deep residual channel attention networks (RCAN). Specifically, we propose a residual in residual (RIR) structure to form very deep network, which consists of several residual groups with long skip connections. Each residual group contains some residual blocks with short skip connections. Meanwhile, RIR allows abundant low-frequency information to be bypassed through multiple skip connections, making the main network focus on learning high-frequency information. Furthermore, we propose a channel attention mechanism to adaptively rescale channel-wise features by considering interdependencies among channels. Extensive experiments show that our RCAN achieves better accuracy and visual improvements against state-of-the-art methods.



Residual channel attention block (RCAB) architecture.

The architecture of our proposed residual channel attention network (RCAN).

Train

Prepare training data

1. Download DIV2K training data (800 training + 100 validation images) from DIV2K dataset or SNU_CVLab.
2. Specify '-dir_data' based on the HR and LR images path. In option.py, '-ext' is set as 'sep_reset', which first convert .png to .npy. If all the training images (.png) are converted to .npy files, then set '-ext sep' to skip converting files.

For more information, please refer to EDSR(PyTorch).

Begin to train

1. (optional) Download models for our paper and place them in '/RCAN_TrainCode/experiment/model'.

All the models (BIX2/3/4/8, BDX3) can be downloaded from Dropbox, BaiduYun, or GoogleDrive.

2. Cd to 'RCAN_TrainCode/code', run the following scripts to train models.

You can use scripts in file 'TrainRCAN_scripts' to train models for our paper.

```
1 # BI, scale 2, 3, 4, 8
2 # RCAN_BIX2_G10R20P48, input=48x48, output=96x96
3 python main.py --model RCAN --save RCAN_BIX2_G10R20P48 --scale 2
  --n_resgroups 10 --n_resblocks 20 --n_feats 64 --reset --chop
  --save_results --print_model --patch_size 96
4
5 # RCAN_BIX3_G10R20P48, input=48x48, output=144x144
6 python main.py --model RCAN --save RCAN_BIX3_G10R20P48 --scale 3
  --n_resgroups 10 --n_resblocks 20 --n_feats 64 --reset --chop
  --save_results --print_model --patch_size 144 --pre_train ../
  experiment/model/RCAN_BIX2.pt
7
8 # RCAN_BIX4_G10R20P48, input=48x48, output=192x192
9 python main.py --model RCAN --save RCAN_BIX4_G10R20P48 --scale 4
  --n_resgroups 10 --n_resblocks 20 --n_feats 64 --reset --chop
  --save_results --print_model --patch_size 192 --pre_train ../
  experiment/model/RCAN_BIX2.pt
10
11 # RCAN_BIX8_G10R20P48, input=48x48, output=384x384
12 python main.py --model RCAN --save RCAN_BIX8_G10R20P48 --scale 8
  --n_resgroups 10 --n_resblocks 20 --n_feats 64 --reset --chop
  --save_results --print_model --patch_size 384 --pre_train ../
  experiment/model/RCAN_BIX2.pt
13
14 # RCAN_BDX3_G10R20P48, input=48x48, output=144x144
15 # specify '--dir_data' to the path of BD training data
16 python main.py --model RCAN --save RCAN_BIX3_G10R20P48 --scale 3
  --n_resgroups 10 --n_resblocks 20 --n_feats 64 --reset --chop
  --save_results --print_model --patch_size 144 --pre_train ../
  experiment/model/RCAN_BIX2.pt
```

Test

Quick start

1. Download models for our paper and place them in '/RCAN_TestCode/model'.

All the models (BIX2/3/4/8, BDX3) can be downloaded from Dropbox, BaiduYun, or GoogleDrive.

2. Cd to '/RCAN_TestCode/code', run the following scripts.

You can use scripts in file 'TestRCAN_scripts' to produce results for our paper.

```
1 # No self-ensemble: RCAN
2 # BI degradation model, X2, X3, X4, X8
3 # RCAN_BIX2
4 python main.py --data_test MyImage --scale 2 --model RCAN --
  n_resgroups 10 --n_resblocks 20 --n_feats 64 --pre_train ../
  model/RCAN_BIX2.pt --test_only --save_results --chop --save '
  RCAN' --testpath ../LR/LRBI --testset Set5
5 # RCAN_BIX3
6 python main.py --data_test MyImage --scale 3 --model RCAN --
  n_resgroups 10 --n_resblocks 20 --n_feats 64 --pre_train ../
  model/RCAN_BIX3.pt --test_only --save_results --chop --save '
  RCAN' --testpath ../LR/LRBI --testset Set5
7 # RCAN_BIX4
8 python main.py --data_test MyImage --scale 4 --model RCAN --
  n_resgroups 10 --n_resblocks 20 --n_feats 64 --pre_train ../
  model/RCAN_BIX4.pt --test_only --save_results --chop --save '
  RCAN' --testpath ../LR/LRBI --testset Set5
9 # RCAN_BIX8
10 python main.py --data_test MyImage --scale 8 --model RCAN --
  n_resgroups 10 --n_resblocks 20 --n_feats 64 --pre_train ../
  model/RCAN_BIX8.pt --test_only --save_results --chop --save '
  RCAN' --testpath ../LR/LRBI --testset Set5
11 # BD degradation model, X3
12 # RCAN_BDX3
13 python main.py --data_test MyImage --scale 3 --model RCAN --
  n_resgroups 10 --n_resblocks 20 --n_feats 64 --pre_train ../
  model/RCAN_BDX3.pt --test_only --save_results --chop --save '
  RCAN' --testpath ../LR/LRBD --degradation BD --testset Set5
14 # With self-ensemble: RCAN+
15 # RCANplus_BIX2
16 python main.py --data_test MyImage --scale 2 --model RCAN --
  n_resgroups 10 --n_resblocks 20 --n_feats 64 --pre_train ../
  model/RCAN_BIX2.pt --test_only --save_results --chop --
  self_ensemble --save 'RCANplus' --testpath ../LR/LRBI --testset
  Set5
17 # RCANplus_BIX3
18 python main.py --data_test MyImage --scale 3 --model RCAN --
  n_resgroups 10 --n_resblocks 20 --n_feats 64 --pre_train ../
  model/RCAN_BIX3.pt --test_only --save_results --chop --
  self_ensemble --save 'RCANplus' --testpath ../LR/LRBI --testset
  Set5
19 # RCANplus_BIX4
20 python main.py --data_test MyImage --scale 4 --model RCAN --
  n_resgroups 10 --n_resblocks 20 --n_feats 64 --pre_train ../
  model/RCAN_BIX4.pt --test_only --save_results --chop --
  self_ensemble --save 'RCANplus' --testpath ../LR/LRBI --testset
  Set5
```

```
21 # RCANplus_BIX8
22 python main.py --data_test MyImage --scale 8 --model RCAN --
    n_resgroups 10 --n_resblocks 20 --n_feats 64 --pre_train ../
    model/RCAN_BIX8.pt --test_only --save_results --chop --
    self_ensemble --save 'RCANplus' --testpath ../LR/LRBI --testset
    Set5
23 # BD degradation model, X3
24 # RCANplus_BDX3
25 python main.py --data_test MyImage --scale 3 --model RCAN --
    n_resgroups 10 --n_resblocks 20 --n_feats 64 --pre_train ../
    model/RCAN_BDX3.pt --test_only --save_results --chop --
    self_ensemble --save 'RCANplus' --testpath ../LR/LRBD --
    degradation BD --testset Set5
```

The whole test pipeline

1. Prepare test data.

Place the original test sets (e.g., Set5, other test sets are available from GoogleDrive or Baidu) in 'OriginalTestData'.

Run 'Prepare_TestData_HR_LR.m' in Matlab to generate HR/LR images with different degradation models.

2. Conduct image SR.

See **Quick start**

3. Evaluate the results.

Run 'Evaluate_PSNR_SSIM.m' to obtain PSNR/SSIM values for paper.

Results

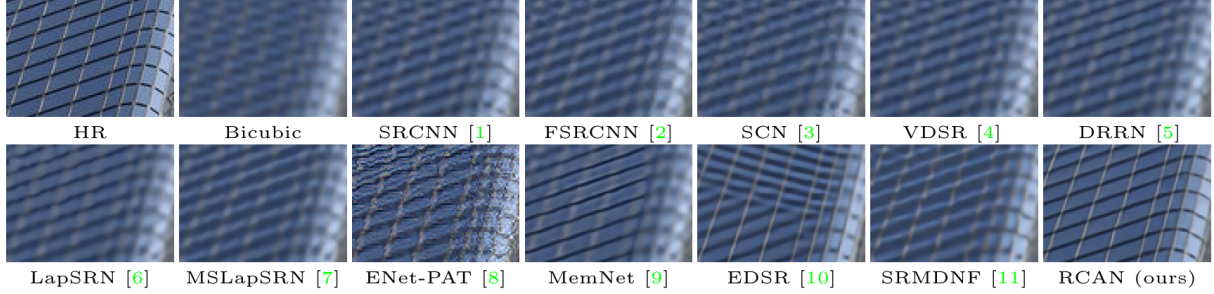
Quantitative Results

Method	Scale	Set5		Set14		B100		Urban100		Manga109	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Bicubic	×2	33.66	0.9299	30.24	0.8688	29.56	0.8431	26.88	0.8403	30.80	0.9339
SRCNN [1]	×2	36.66	0.9542	32.45	0.9067	31.36	0.8879	29.50	0.8946	35.60	0.9663
FSRCNN [2]	×2	37.05	0.9560	32.66	0.9090	31.53	0.8920	29.88	0.9020	36.67	0.9710
VDSR [4]	×2	37.53	0.9590	33.05	0.9130	31.90	0.8960	30.77	0.9140	37.22	0.9750
LapSRN [6]	×2	37.52	0.9591	33.08	0.9130	31.08	0.8950	30.41	0.9101	37.27	0.9740
MemNet [9]	×2	37.78	0.9597	33.28	0.9142	32.08	0.8978	31.31	0.9195	37.72	0.9740
EDSR [10]	×2	38.11	0.9602	33.92	0.9195	32.32	0.9013	32.93	0.9351	39.10	0.9773
SRMDNF [11]	×2	37.79	0.9601	33.32	0.9159	32.05	0.8985	31.33	0.9204	38.07	0.9761
D-DBPN [16]	×2	38.09	0.9600	33.85	0.9190	32.27	0.9000	32.55	0.9324	38.89	0.9775
RDN [17]	×2	38.24	0.9614	34.01	0.9212	32.34	0.9017	32.89	0.9353	39.18	0.9780
RCAN (ours)	×2	38.27	0.9614	34.12	0.9216	32.41	0.9027	33.34	0.9384	39.44	0.9786
RCAN+ (ours)	×2	38.33	0.9617	34.23	0.9225	32.46	0.9031	33.54	0.9399	39.61	0.9788
Bicubic	×3	30.39	0.8682	27.55	0.7742	27.21	0.7385	24.46	0.7349	26.95	0.8556
SRCNN [1]	×3	32.75	0.9090	29.30	0.8215	28.41	0.7863	26.24	0.7989	30.48	0.9117
FSRCNN [2]	×3	33.18	0.9140	29.37	0.8240	28.53	0.7910	26.43	0.8080	31.10	0.9210
VDSR [4]	×3	33.67	0.9210	29.78	0.8320	28.83	0.7990	27.14	0.8290	32.01	0.9340
LapSRN [6]	×3	33.82	0.9227	29.87	0.8320	28.82	0.7980	27.07	0.8280	32.21	0.9350
MemNet [9]	×3	34.09	0.9248	30.00	0.8350	28.96	0.8001	27.56	0.8376	32.51	0.9369
EDSR [10]	×3	34.65	0.9280	30.52	0.8462	29.25	0.8093	28.80	0.8653	34.17	0.9476
SRMDNF [11]	×3	34.12	0.9254	30.04	0.8382	28.97	0.8025	27.57	0.8398	33.00	0.9403
RDN [17]	×3	34.71	0.9296	30.57	0.8468	29.26	0.8093	28.80	0.8653	34.13	0.9484
RCAN (ours)	×3	34.74	0.9299	30.65	0.8482	29.32	0.8111	29.09	0.8702	34.44	0.9499
RCAN+ (ours)	×3	34.85	0.9305	30.76	0.8494	29.39	0.8122	29.31	0.8736	34.76	0.9513
Bicubic	×4	28.42	0.8104	26.00	0.7027	25.96	0.6675	23.14	0.6577	24.89	0.7866
SRCNN [1]	×4	30.48	0.8628	27.50	0.7513	26.90	0.7101	24.52	0.7221	27.58	0.8555
FSRCNN [2]	×4	30.72	0.8660	27.61	0.7550	26.98	0.7150	24.62	0.7280	27.90	0.8610
VDSR [4]	×4	31.35	0.8830	28.02	0.7680	27.29	0.0726	25.18	0.7540	28.83	0.8870
LapSRN [6]	×4	31.54	0.8850	28.19	0.7720	27.32	0.7270	25.21	0.7560	29.09	0.8900
MemNet [9]	×4	31.74	0.8893	28.26	0.7723	27.40	0.7281	25.50	0.7630	29.42	0.8942
EDSR [10]	×4	32.46	0.8968	28.80	0.7876	27.71	0.7420	26.64	0.8033	31.02	0.9148
SRMDNF [11]	×4	31.96	0.8925	28.35	0.7787	27.49	0.7337	25.68	0.7731	30.09	0.9024
D-DBPN [16]	×4	32.47	0.8980	28.82	0.7860	27.72	0.7400	26.38	0.7946	30.91	0.9137
RDN [17]	×4	32.47	0.8990	28.81	0.7871	27.72	0.7419	26.61	0.8028	31.00	0.9151
RCAN (ours)	×4	32.63	0.9002	28.87	0.7889	27.77	0.7436	26.82	0.8087	31.22	0.9173
RCAN+ (ours)	×4	32.73	0.9013	28.98	0.7910	27.85	0.7455	27.10	0.8142	31.65	0.9208
Bicubic	×8	24.40	0.6580	23.10	0.5660	23.67	0.5480	20.74	0.5160	21.47	0.6500
SRCNN [1]	×8	25.33	0.6900	23.76	0.5910	24.13	0.5660	21.29	0.5440	22.46	0.6950
FSRCNN [2]	×8	20.13	0.5520	19.75	0.4820	24.21	0.5680	21.32	0.5380	22.39	0.6730
SCN [3]	×8	25.59	0.7071	24.02	0.6028	24.30	0.5698	21.52	0.5571	22.68	0.6963
VDSR [4]	×8	25.93	0.7240	24.26	0.6140	24.49	0.5830	21.70	0.5710	23.16	0.7250
LapSRN [6]	×8	26.15	0.7380	24.35	0.6200	24.54	0.5860	21.81	0.5810	23.39	0.7350
MemNet [9]	×8	26.16	0.7414	24.38	0.6199	24.58	0.5842	21.89	0.5825	23.56	0.7387
MSLapSRN [7]	×8	26.34	0.7558	24.57	0.6273	24.65	0.5895	22.06	0.5963	23.90	0.7564
EDSR [10]	×8	26.96	0.7762	24.91	0.6420	24.81	0.5985	22.51	0.6221	24.69	0.7841
D-DBPN [16]	×8	27.21	0.7840	25.13	0.6480	24.88	0.6010	22.73	0.6312	25.14	0.7987
RCAN (ours)	×8	27.31	0.7878	25.23	0.6511	24.98	0.6058	23.00	0.6452	25.24	0.8029
RCAN+ (ours)	×8	27.47	0.7913	25.40	0.6553	25.05	0.6077	23.22	0.6524	25.58	0.8092

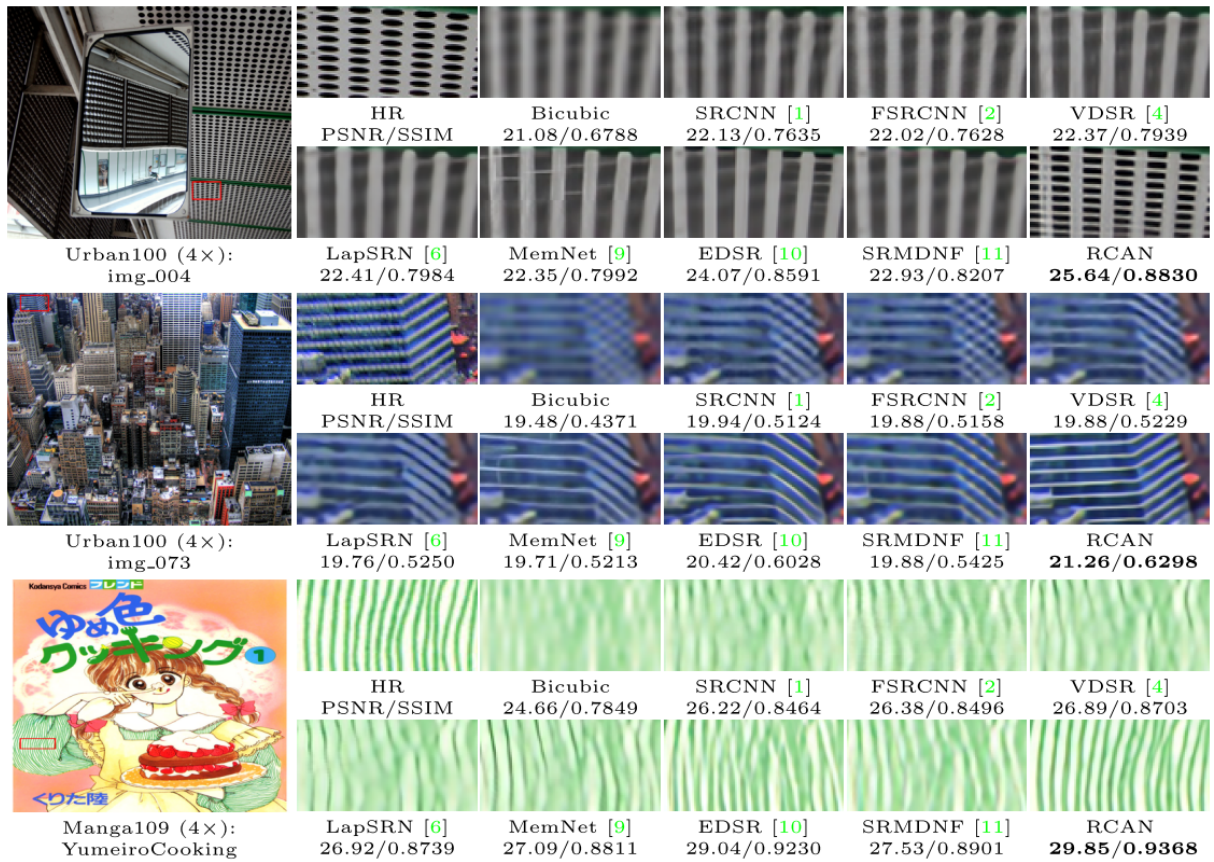
Quantitative results with BI degradation model. Best and second best results are highlighted and


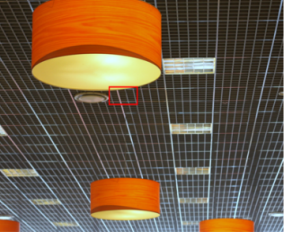


underlined

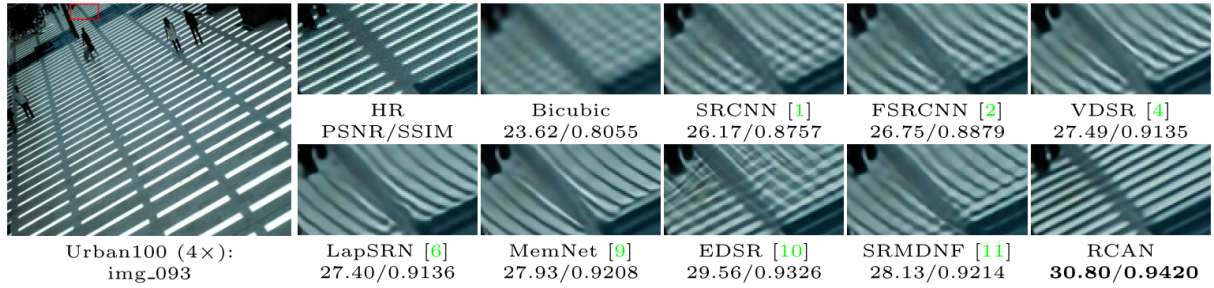
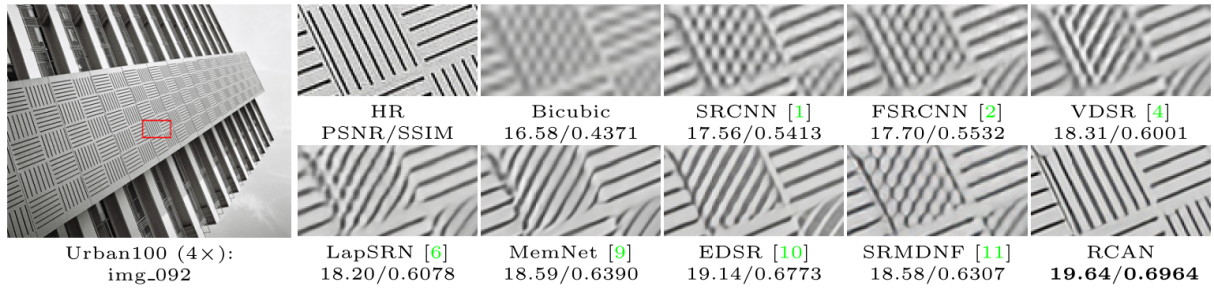
For more results, please refer to our main paper and supplementary file. ### Visual Results



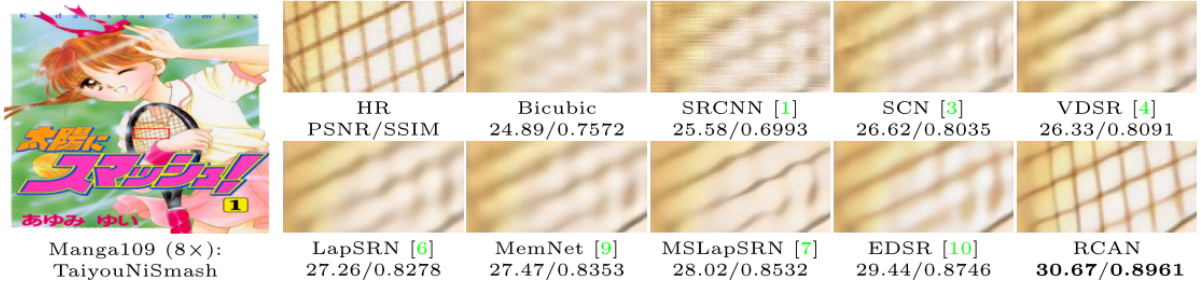
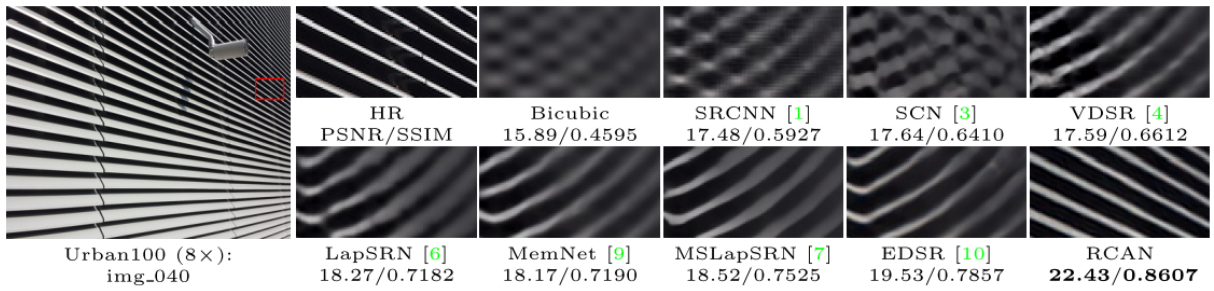
Visual results with Bicubic (BI) degradation (4×) on “img 074” from Urban100







 <p>Urban100 (4×): img_012</p>	HR	Bicubic	SRCNN [1]	FSRCNN [2]	VDSR [4]
	PSNR/SSIM	22.53/0.6128	23.21/0.6719	23.28/0.6778	23.44/0.6958
	LapSRN [6]	MemNet [9]	EDSR [10]	SRMDNF [11]	RCAN
	23.47/0.6977	23.59/0.7086	24.20/0.7572	23.64/0.7191	24.33/0.7657
 <p>Urban100 (4×): img_044</p>	HR	Bicubic	SRCNN [1]	FSRCNN [2]	VDSR [4]
	PSNR/SSIM	26.91/0.7246	29.68/0.8093	30.16/0.8242	29.66/0.8297
	LapSRN [6]	MemNet [9]	EDSR [10]	SRMDNF [11]	RCAN
	30.30/0.8393	29.20/0.8337	33.16/0.8961	31.29/0.8597	33.27/0.9055
 <p>Urban100 (4×): img_067</p>	HR	Bicubic	SRCNN [1]	FSRCNN [2]	VDSR [4]
	PSNR/SSIM	16.96/0.7019	18.31/0.7947	18.16/0.7946	18.52/0.8241
	LapSRN [6]	MemNet [9]	EDSR [10]	SRMDNF [11]	RCAN
	18.60/0.8367	18.95/0.8480	21.11/0.9021	18.99/0.8574	21.30/0.9127
 <p>Urban100 (4×): img_076</p>	HR	Bicubic	SRCNN [1]	FSRCNN [2]	VDSR [4]
	PSNR/SSIM	21.57/0.6281	22.03/0.6777	22.01/0.6772	22.14/0.6910
	LapSRN [6]	MemNet [9]	EDSR [10]	SRMDNF [11]	RCAN
	22.01/0.6917	22.11/0.6921	23.94/0.7740	22.46/0.7108	24.31/0.7896






Visual comparison for 4× SR with BI model

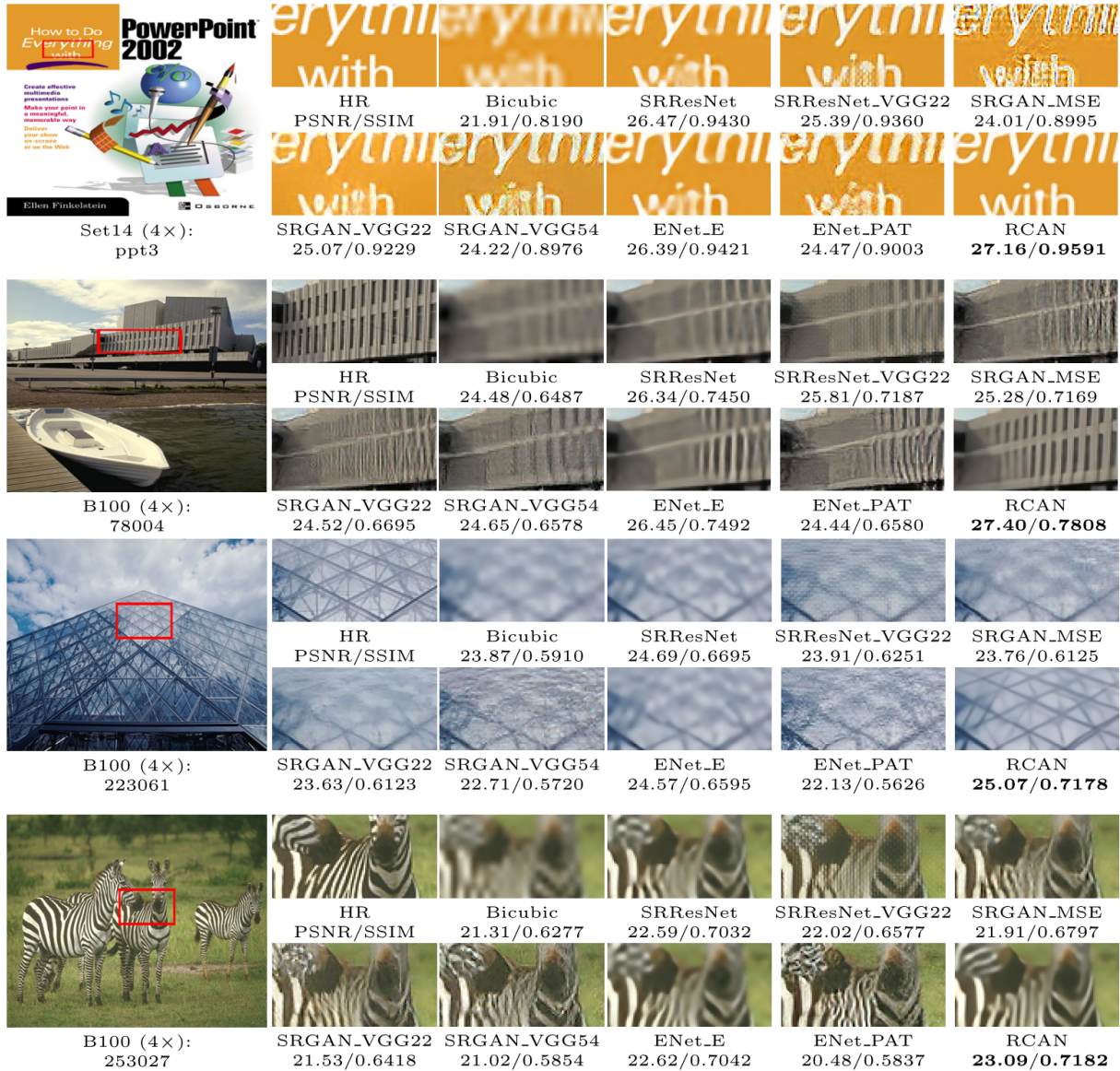


Visual comparison for 8× SR with BI model

 <p>Urban100 (3×): img_062</p>	HR	Bicubic	SPMSR [44]	SRCNN [1]	FSRCNN [2]
	PSNR/SSIM	20.20/0.6737	21.72/0.7923	21.74/0.7882	19.30/0.6960
 <p>Urban100 (3×): img_078</p>	VDSR [4]	IRCNN [39]	SRMDNF [11]	RDN [16]	RCAN
	22.36/0.8351	22.32/0.8292	23.11/0.8662	24.42/0.9052	25.73/0.9238
 <p>Urban100 (3×): img_078</p>	HR	Bicubic	SPMSR [44]	SRCNN [1]	FSRCNN [2]
	PSNR/SSIM	26.10/0.7032	28.06/0.7950	27.91/0.7874	24.34/0.6711
 <p>Urban100 (3×): img_078</p>	VDSR [4]	IRCNN [39]	SRMDNF [11]	RDN [16]	RCAN
	28.34/0.8166	28.57/0.8184	29.08/0.8342	29.94/0.8513	30.65/0.8624

Visual comparison for 3× SR with BD model

 <p>Set14 (4×): barbara</p>	HR	Bicubic	SRResNet	SRResNet_VGG22	SRGAN_MSE
	PSNR/SSIM	25.15/0.6870	25.89/0.7470	25.55/0.7287	23.74/0.6930
 <p>Set14 (4×): barbara</p>	SRGAN_VGG22	SRGAN_VGG54	ENet_E	ENet_PAT	RCAN
	24.97/0.7062	24.91/0.6857	26.00/0.7472	24.69/0.6831	26.25/0.7629
 <p>Set14 (4×): comic</p>	HR	Bicubic	SRResNet	SRResNet_VGG22	SRGAN_MSE
	PSNR/SSIM	21.69/0.5836	23.53/0.7269	22.30/0.6721	21.07/0.6284
 <p>Set14 (4×): comic</p>	SRGAN_VGG22	SRGAN_VGG54	ENet_E	ENet_PAT	RCAN
	21.35/0.6429	20.44/0.5937	23.51/0.7225	20.65/0.5870	23.85/0.7516



Visual comparison for 4x SR with BI model on Set14 and B100 datasets. The best results are highlighted. SRResNet, SRResNet VGG22, SRGAN MSE, SRGAN VGG22, and SRGAN VGG54 are proposed in [CVPR2017SRGAN], ENet E and ENet PAT are proposed in [ICCV2017EnhanceNet]. These comparisons mainly show the effectiveness of our proposed RCAN against GAN based methods

Citation

If you find the code helpful in your resarch or work, please cite the following papers.

- 1 @InProceedings{Lim_2017_CVPR_Workshops,
- 2 author = {Lim, Bee and Son, Sanghyun and Kim, Heewon and Nah, Seungjun and Lee, Kyoung Mu},

```
3   title = {Enhanced Deep Residual Networks for Single Image Super-
4           Resolution},
5   booktitle = {The IEEE Conference on Computer Vision and Pattern
6               Recognition (CVPR) Workshops},
7   month = {July},
8   year = {2017}
9 }
10 @inproceedings{zhang2018rcan,
11     title={Image Super-Resolution Using Very Deep Residual Channel
12           Attention Networks},
13     author={Zhang, Yulun and Li, Kunpeng and Li, Kai and Wang, Lichen
14            and Zhong, Bineng and Fu, Yun},
15     booktitle={ECCV},
16     year={2018}
```

Acknowledgements

This code is built on EDSR (PyTorch). We thank the authors for sharing their codes of EDSR Torch version and PyTorch version.