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BSR: A BALANCED FRAMEWORK FOR SINGLE IMAGE SUPER RESOLUTION

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Session 7 – AI, machine learning and digital transformation

Paper S7.3

Pay our sincerely respect to medical workers for their brave actions to fight against the new coronavirus!

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Related Work

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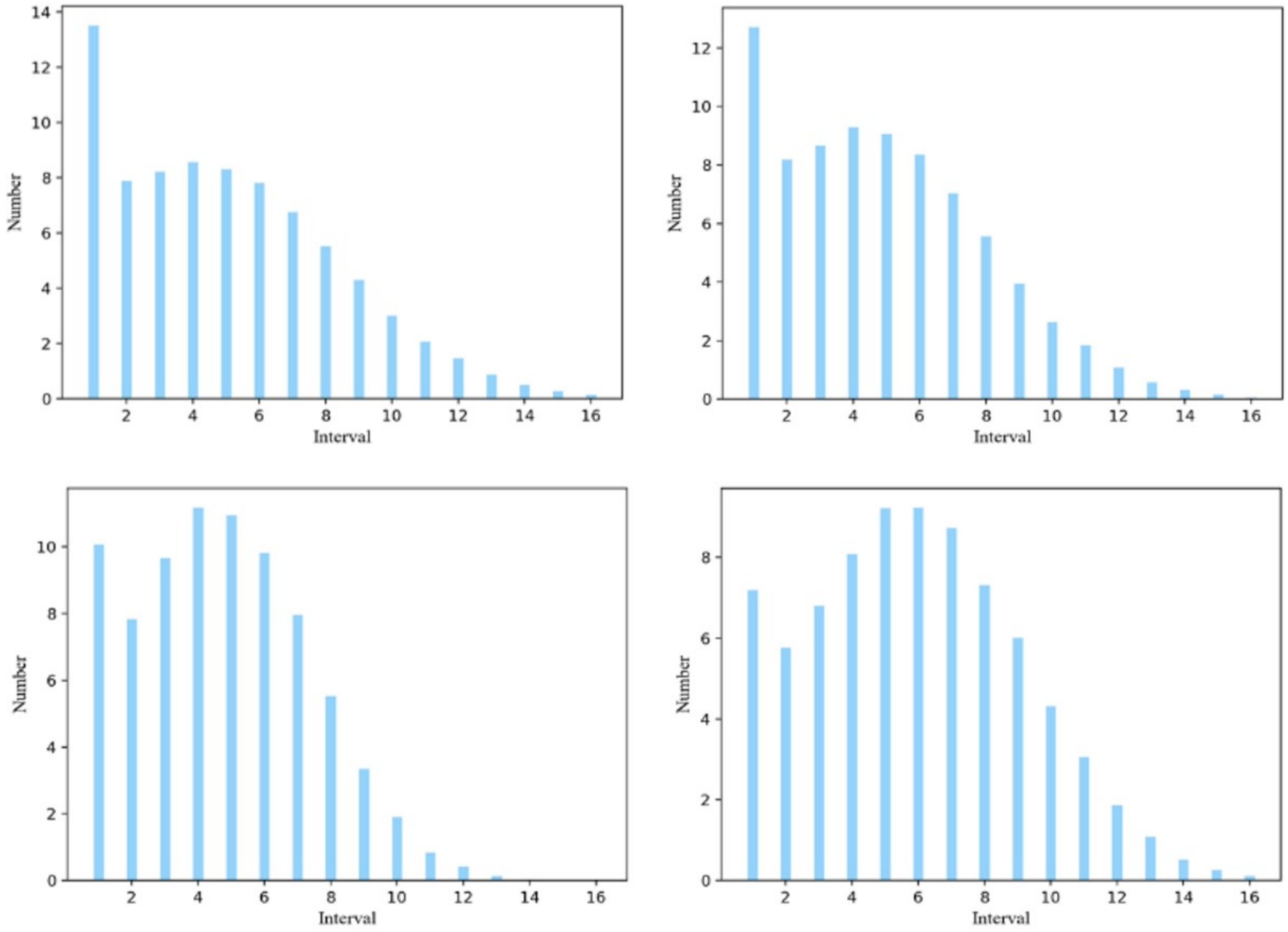
Unbalance in SISR

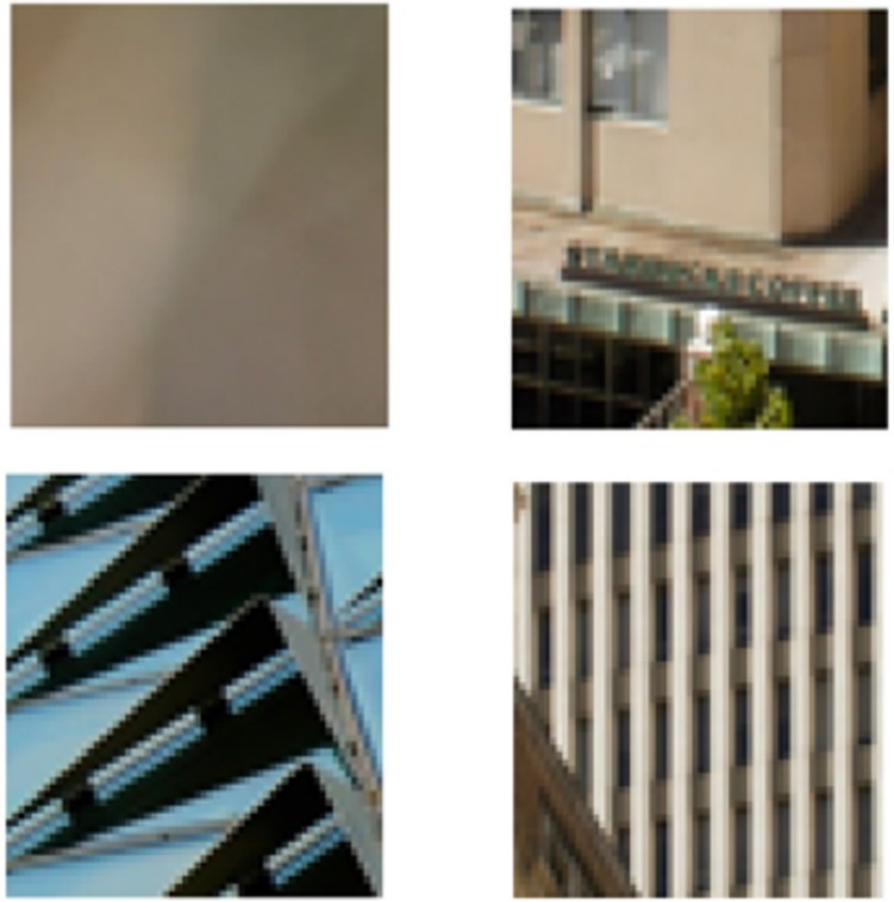
Gradient not evenly distributed and the patches featuring smaller gradients account for the majority



Gradient distribution from random samples of a DIV2K

Unbalance in SISR

Examples for different Picture Information Content(PIC).

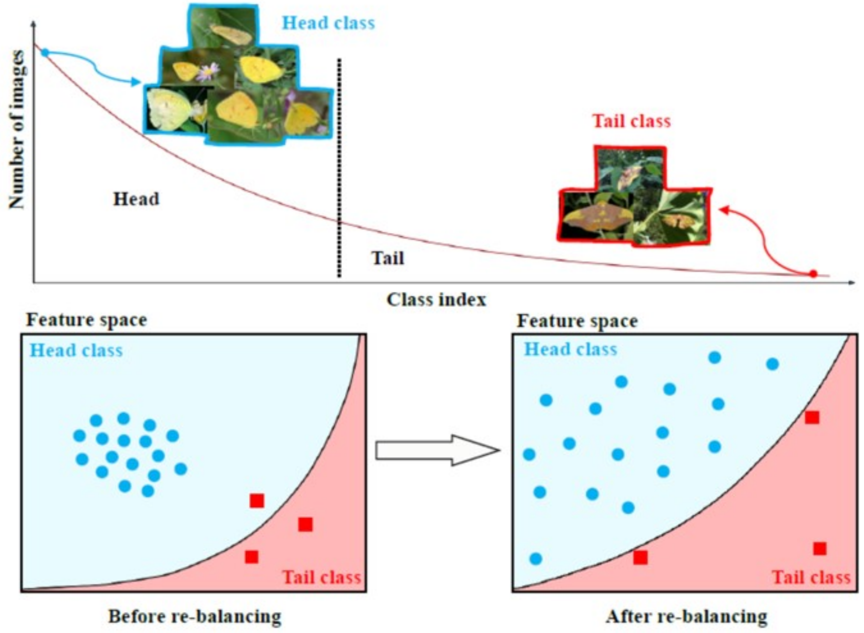


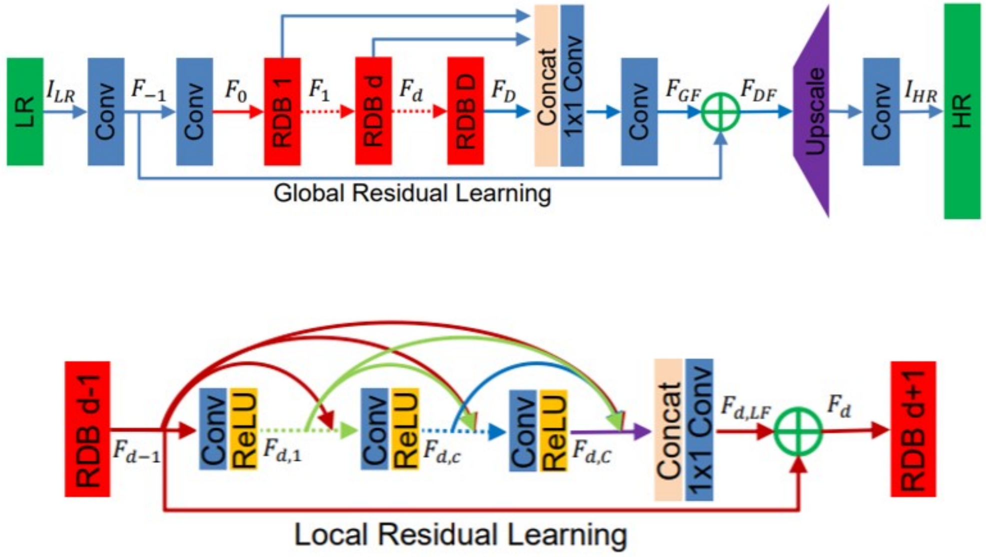
Typical patches with different gradients interval values

Contents

Related Work

- BBN[1](Left)
- RDN[2](Right)





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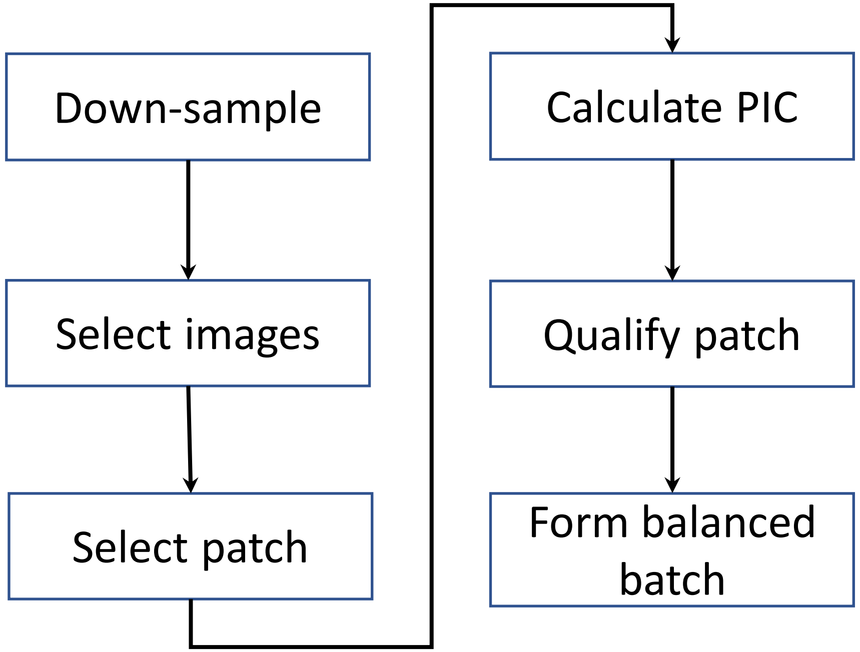
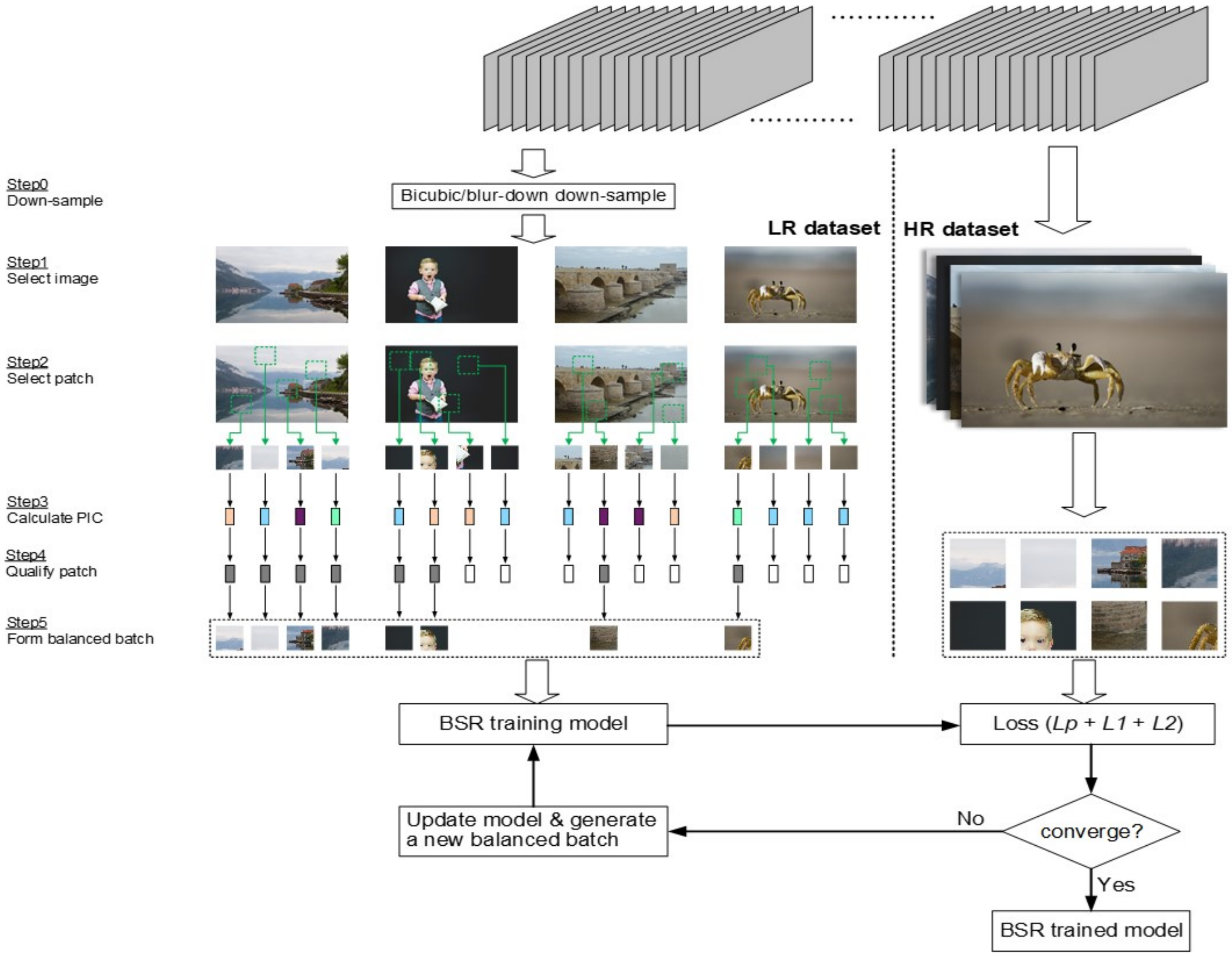
Main Framework

- Model Generation





Main Framework

- Random Filter Sampling (RFS)

$$PIC = \sum_{ch=0}^{2} \sum_{y=0}^{h-1} \sum_{x=0}^{w-1} G_{sobel}[P_{in}(x, y, w, h)]$$

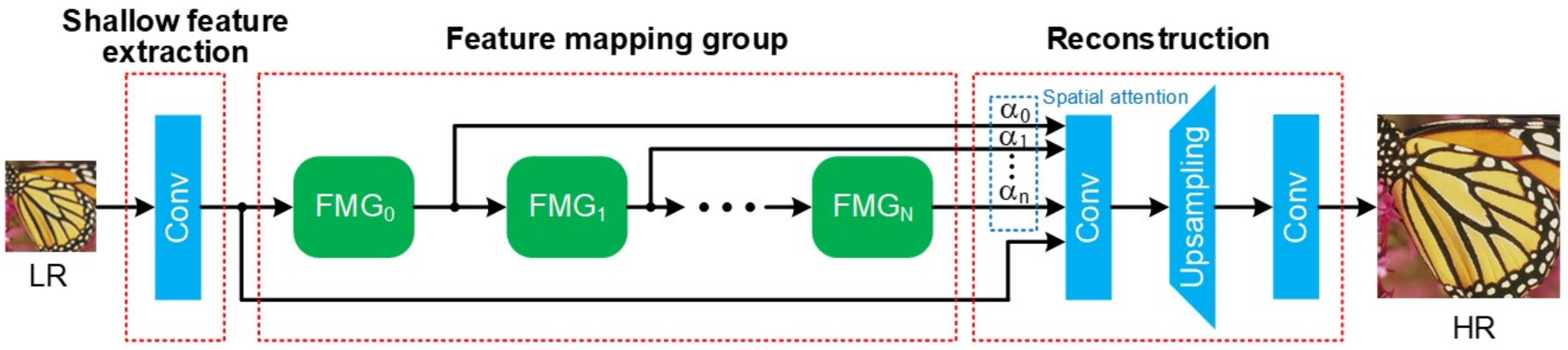
Input: M – number of randomly selected LR candidate images
N – number of patches for each batch
K – set of PIC distribution interval
T – training data set

1. Initialize sampled vector V = $[NULL \dots NULL]_{1\times k}$. Randomly select M low resolution images from training data set T.
2. While V ≠ K:
2.1) Randomly crop each input image to generate one patch p_0, p_1 … p_{m-1}
2.2) Compute PIC for each patch as equation (1), and output PIC vector [PIC_0, PIC_1 … PIC_m]
2.3) For i = 0: k-1:
If PICi ∈ interval N_i and $V_i < K_i$:
Put current patch into batch

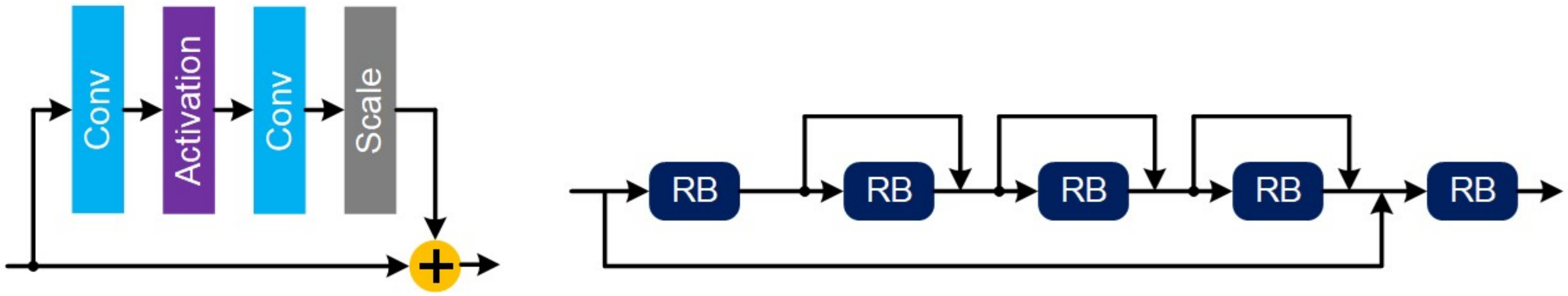
Output: Batch

Main Framework

- Network Architecture



(a) Main architecture of BSR

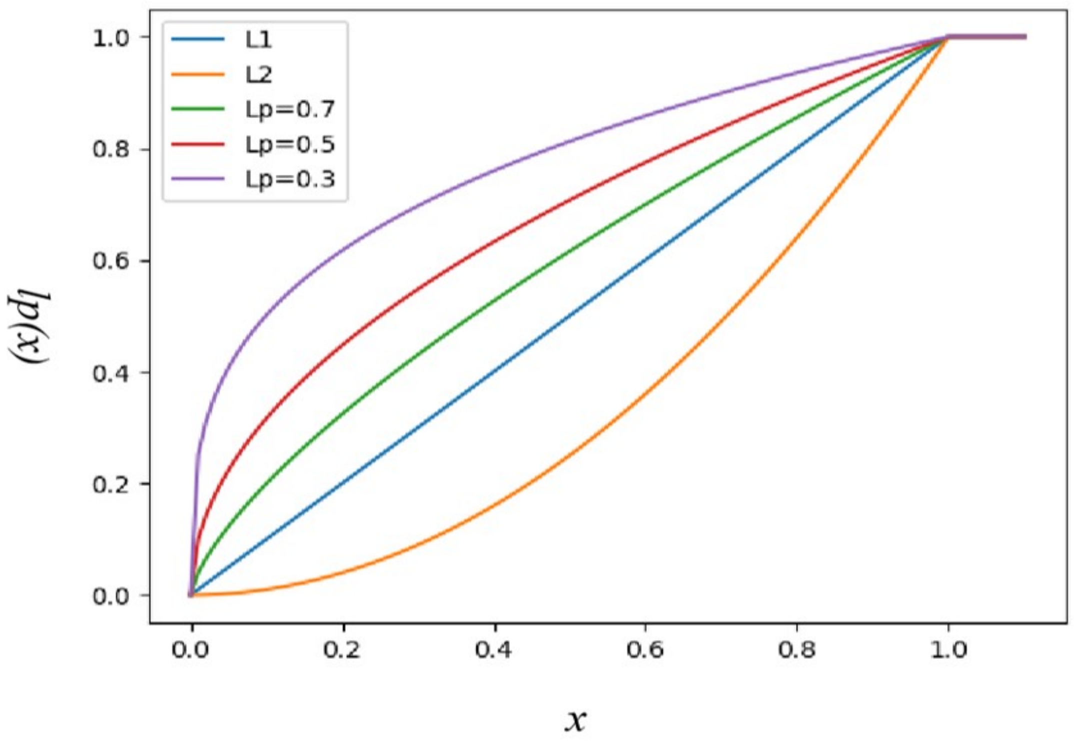


(b) Core module of BSR: Residual Block and FMG

Main Framework

- Loss Function

$$f = L_2 + \alpha \times L_1 + \beta \times L_p$$



Output comparison from different norms

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Experiments

Settings

- Training Set: DIV2K.
- Testing Set: Set5, Set14, BSD100, Urban100 and Magna 109.
- Objective Index: PSNR/SSIM.
- Platform: Nvidia GeForce RTX2080 + i9-9900k.
- Learning rate: set the initial learning rate as 2e-4 and decrease it by 0.1 after every 100 epochs.
- Data augment: rotated by 90°/180°/270° randomly.

Experiments

Bi-cubic degradation

Method	Scale	Set5		Set14		BSD100		Urban100		Manga109	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Bi-cubic	×2	33.66	0.9299	30.24	0.8688	29.56	0.8431	26.88	0.8403	30.80	0.9339
	×3	30.39	0.8682	27.55	0.7742	27.21	0.7385	24.46	0.7349	26.95	0.8556
	×4	28.42	0.8104	26.00	0.7027	25.96	0.6675	23.14	0.6577	24.89	0.7866
SRCNN	×2	36.66	0.9542	32.45	0.9067	31.36	0.8879	29.50	0.8946	35.60	0.9663
	×3	32.75	0.9090	29.30	0.8215	28.41	0.7863	26.24	0.7989	30.48	0.9117
	×4	30.48	0.8628	27.50	0.7513	26.90	0.7101	24.52	0.7221	27.58	0.8555
FSRCNN	×2	37.05	0.9560	32.66	0.9090	31.53	0.8920	29.88	0.9020	36.67	0.9710
	×3	33.18	0.9140	29.37	0.8240	28.53	0.7910	26.43	0.8080	31.10	0.9210
	×4	30.72	0.8660	27.61	0.7550	26.98	0.7150	24.62	0.7280	27.90	0.8610
VDSR	×2	37.53	0.9590	33.05	0.9130	31.90	0.8960	30.77	0.9140	37.22	0.9750
	×3	33.67	0.9210	29.78	0.8320	28.83	0.7990	27.14	0.8290	32.01	0.9340
	×4	31.35	0.8830	28.02	0.7680	27.29	0.0726	25.18	0.7540	28.83	0.8870
LapSRN	×2	37.52	0.9591	33.08	0.9130	31.08	0.8950	30.41	0.9101	37.27	0.9740
	×3	33.82	0.9227	29.87	0.8320	28.82	0.7980	27.07	0.8280	32.21	0.9350
	×4	31.54	0.8850	28.19	0.7720	27.32	0.7270	25.21	0.7560	29.09	0.8900
MemNet	×2	37.78	0.9597	33.28	0.9142	32.08	0.8978	31.31	0.9195	37.72	0.9740
	×3	34.09	0.9248	30.00	0.8350	28.96	0.8001	27.56	0.8376	32.51	0.9369
	×4	31.74	0.8893	28.26	0.7723	27.40	0.7281	25.50	0.7630	29.42	0.8942
EDSR	×2	38.11	0.9602	33.92	0.9195	32.32	0.9013	32.93	0.9351	39.10	0.9773
	×3	34.65	0.9280	30.52	0.8462	29.25	0.8093	28.80	0.8653	34.17	0.9476
	×4	32.46	0.8968	28.80	0.7876	27.71	0.7420	26.64	0.8033	31.02	0.9148
SRMDNF	×2	37.79	0.9601	33.32	0.9159	32.05	0.8985	31.33	0.9204	38.07	0.9761
	×3	34.12	0.9254	30.04	0.8382	28.97	0.8025	27.57	0.8398	33.00	0.9403
	×4	31.96	0.8925	28.35	0.7787	27.49	0.7337	25.68	0.7731	30.09	0.9024
RDN	×2	38.24	0.9614	34.01	0.9212	32.34	0.9017	32.89	0.9353	39.18	0.9780
	×3	34.71	0.9296	30.57	0.8468	29.26	0.8093	28.80	0.8653	34.13	0.9484
	×4	32.47	0.8990	28.81	0.7871	27.72	0.7419	26.61	0.8028	31.00	0.9151
RCAN	×2	38.27	0.9614	34.12	0.9216	32.41	0.9027	33.34	0.9384	39.44	0.9786
	×3	34.74	0.9299	30.65	0.8482	29.32	0.8111	29.09	0.8702	**34.44**	0.9499
	×4	32.63	0.9002	28.87	0.7889	27.77	0.7436	26.82	0.8087	31.22	0.9173
SAN	×2	**38.31**	**0.9620**	34.07	0.9213	32.42	**0.9028**	33.10	0.9370	39.32	0.9792
	×3	**34.75**	0.9300	30.59	0.8476	**29.33**	0.8112	28.93	0.8671	34.30	0.9494
	×4	**32.64**	**0.9003**	**28.92**	0.7888	27.78	0.7436	26.79	0.8068	31.18	0.9169
BSR	×2	38.30	0.9616	**34.15**	**0.9220**	**32.42**	0.9027	**33.64**	**0.9404**	**39.54**	0.9790
	×3	34.74	**0.9301**	**30.66**	**0.8501**	29.31	**0.8113**	**29.19**	**0.8710**	34.43	**0.9550**
	×4	32.64	0.9002	28.90	**0.7890**	**27.79**	**0.7436**	**26.79**	**0.8088**	**31.23**	**0.9174**

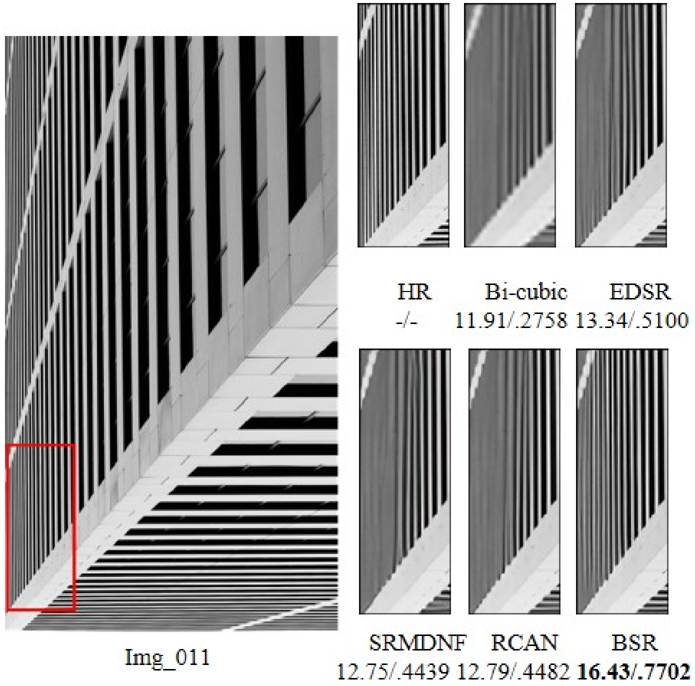
Experiments

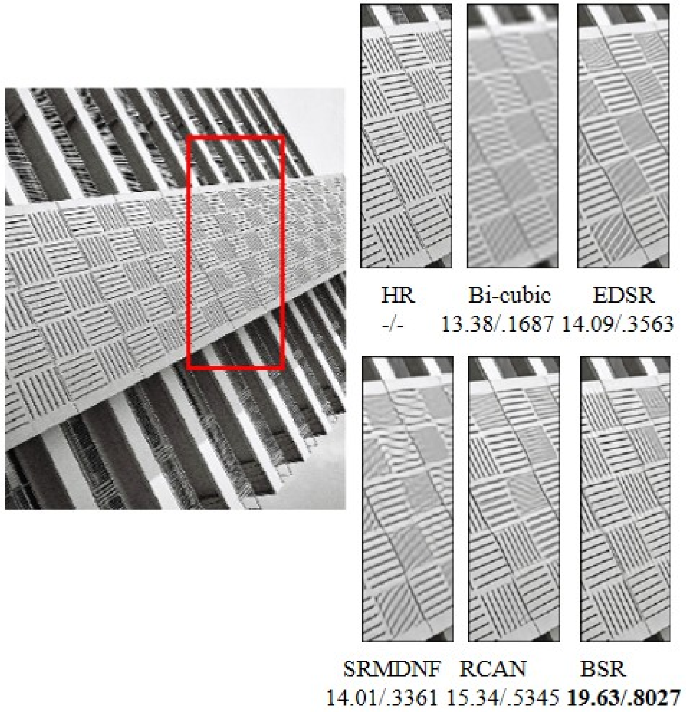
Blur degradation

Method	Scale	Set5		Set14		BSD100		Urban100		Manga109	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Bi-cubic	×3	28.78	0.8308	26.38	0.7271	26.33	0.6918	23.52	0.6862	25.46	0.8149
SPMSR	×3	32.21	0.9001	28.89	0.8105	28.13	0.7740	25.84	0.7856	29.64	0.9003
SRCNN	×3	32.05	0.8944	28.80	0.8074	28.13	0.7736	25.70	0.7770	29.47	0.8924
FSRCNN	×3	26.23	0.8124	24.44	0.7106	24.86	0.6832	22.04	0.6745	23.04	0.7927
VDSR	×3	33.25	0.9150	29.46	0.8244	28.57	0.7893	26.61	0.8136	31.06	0.9234
IRCNN	×3	33.38	0.9182	29.63	0.8281	28.65	0.7922	26.77	0.8154	31.15	0.9245
SRMDNF	×3	34.01	0.9242	30.11	0.8364	28.98	0.8009	27.50	0.8370	32.97	0.9391
RDN	×3	34.58	0.9280	30.53	0.8447	29.23	0.8079	28.46	0.8582	33.97	0.9465
RCAN	×3	34.70	0.9288	30.63	0.8462	29.32	0.8093	28.81	0.8647	34.38	0.9483
SAN	×3	34.75	0.9290	**30.68**	**0.8466**	29.33	**0.8101**	28.83	0.8646	34.46	0.9487
BSR	×3	**34.76**	**0.9292**	30.64	0.8464	**29.34**	0.8100	**28.83**	**0.8648**	**34.46**	**0.9488**

Experiments

Subjective comparison





Experiments

Ablation Study

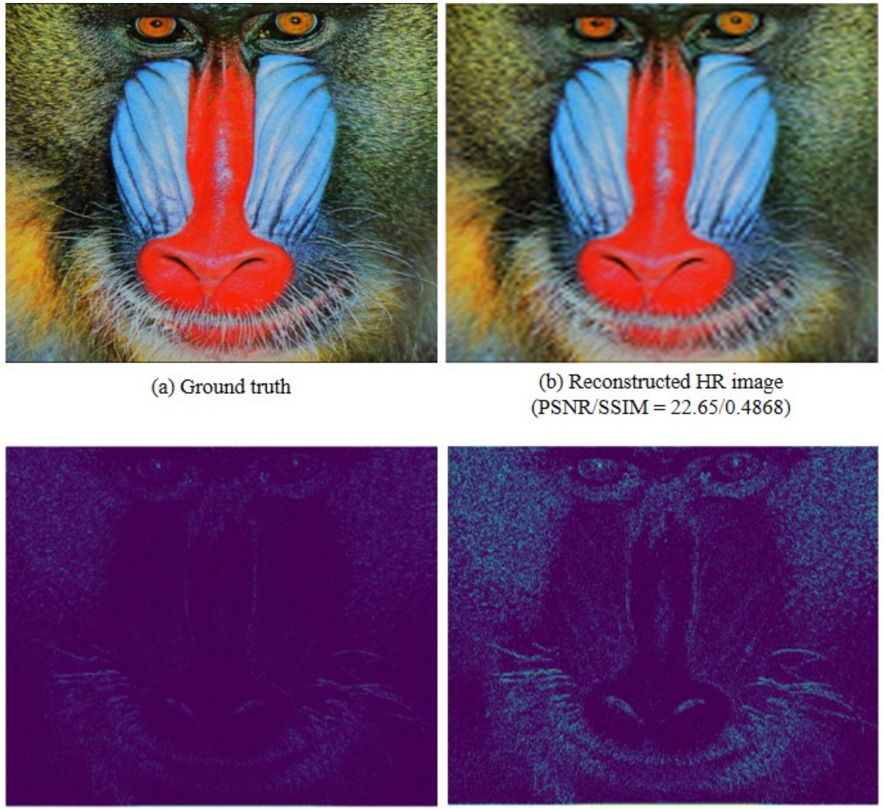
	Baseline	w/o RFS	w/o SC	L2	L2 + L1
PNSR	32.20	32.15	32.10	32.17	32.19

Experiments

Subjective comparison

Left: $L1 + L2$ norm
(PSNR/SSIM = 22.73/0.4988)

Right: $L1 + Lp$ norm
(PSNR/SSIM = 22.74/0.5015)



(a) Ground truth

(b) Reconstructed HR image
(PSNR/SSIM = 22.65/0.4868)

(c) Difference by $L2$ norm

(d) Difference by Lp norm

Experiments

- The proposed method utilizes less than 200 convolution layers which is less than half of RACN and SAN.
- The subjective and objective output show the proposed BSR realizes a better mapping between LR and SR.

- Ablation Study shows the effectiveness of core modules, i.e. RFS, FMG and object function.
- Via visualization comparison between different Lp norm, more attention should be paied to the combination optimization.

Conclusions

- The imbalance phenomenon of SR task and the difference between SR and other CV task are analyzed.
- A BSR framework based on RFS, Architecture and object function improvement is proposed .
- Experiments on testing set show that this method is superior to the SOTA methods.

Reference

1. Zhou B, Cui Q, Wei X S, et al. BBN: Bilateral-Branch Network with Cumulative Learning for Long-Tailed Visual Recognition[C] CVPR2020: 9719-9728.
2. Zhang Y, Tian Y, Kong Y, et al. Residual dense network for image super-resolution[C] CVPR2018: 2472-2481.

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Thank you!