Deep Back-Projection Networks For Super-Resolution

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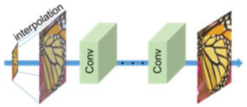
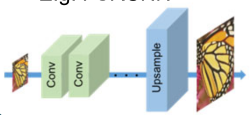
Existing Deep SR Networks

(a) Predefined Upsampling
E.g. SRCNN, VDSR

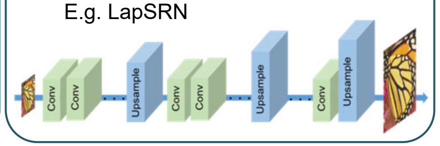


Problems:
(1) One-way mapping
(2) Limited features
(3) No explicit constraint

(b) Single Upsampling
E.g. FSRCNN



(c) Progressive Upsampling
E.g. LapSRN



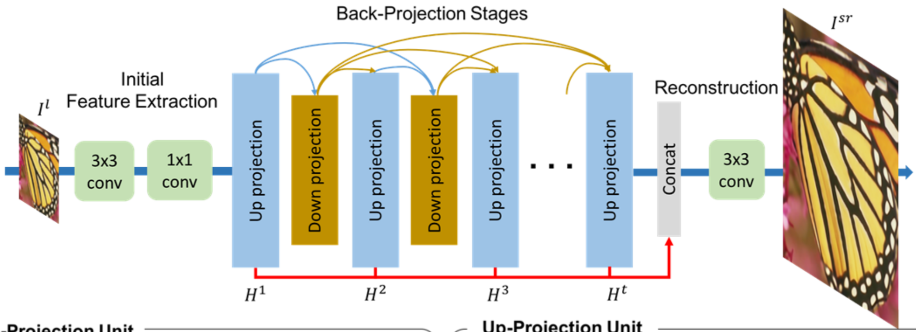
Our Contributions

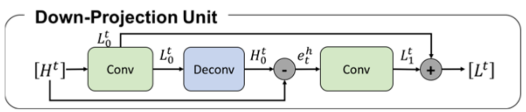
(1) Mutual-connected stages
Explicit model dependancy of LR and HR features
[Alternating between up- (blue box) and down-projection (gold box)]

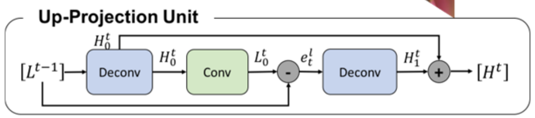
(2) Error Feedback
Guiding the network for better reconstruction
[Up- and down-projection unit]

(3) Deep Concatenation
Directly utilizes various variants of HR features
[Concatenation on each up-projection to reconstruction layer]

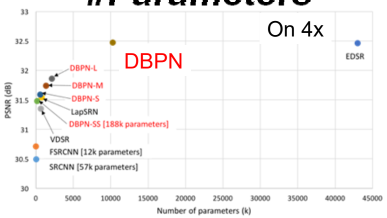
Our Proposed Networks

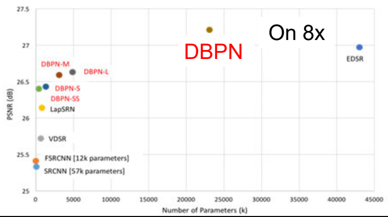






#Parameters





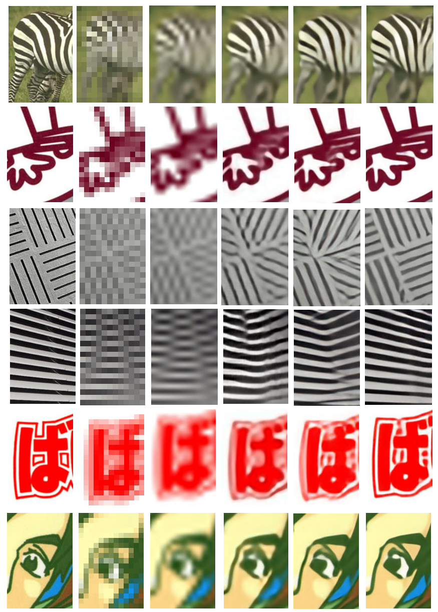
Results

Algorithm	Scale	Set5 PSNR	Set5 SSIM	Set14 PSNR	Set14 SSIM	BSDS100 PSNR	BSDS100 SSIM	Urban100 PSNR	Urban100 SSIM	Manga109 PSNR	Manga109 SSIM
Bicubic	2	33.65	0.930	30.34	0.870	29.56	0.844	26.88 (27.39*)	0.841	30.84 (31.05*)	0.935
A+ [44]	2	36.54	0.954	32.40	0.906	31.22	0.887	29.23	0.894	35.33	0.967
SRCNN [6]	2	36.65	0.954	32.29	0.903	31.36	0.888	29.52	0.895	35.72	0.968
FSRCNN [7]	2	36.99	0.955	32.73	0.909	31.51	0.891	29.87	0.901	36.62	0.971
VDSR [21]	2	37.53	0.958	32.97	0.913	31.90	0.896	30.77	0.914	37.16	0.974
DRCN [22]	2	37.63	0.959	32.98	0.913	31.85	0.894	30.76	0.913	37.57	0.973
DRRN [42]	2	37.74	0.959	33.23	0.913	32.05	0.897	31.23	0.919	37.92	0.976
LapSRN [24]	2	37.52	0.959	33.08	0.913	31.80	0.895	30.41 (31.05*)	0.910	37.27 (37.53*)	0.974
EDSR [30]	2	38.11	0.960	33.92	0.919	32.32	0.901	32.93 (33.56*)	0.935	39.10 (39.33*)	0.977
D-DBPN	2	38.09	0.960	33.85	0.919	32.27	0.900	– (33.02*)	0.931	– (39.32*)	0.978
Bicubic	4	28.42	0.810	26.10	0.704	25.96	0.669	23.15 (23.64*)	0.659	24.92 (25.15*)	0.789
A+ [44]	4	30.30	0.859	27.43	0.752	26.82	0.710	24.34	0.720	27.02	0.850
SRCNN [6]	4	30.49	0.862	27.61	0.754	26.91	0.712	24.53	0.724	27.66	0.858
FSRCNN [7]	4	30.71	0.865	27.70	0.756	26.97	0.714	24.61	0.727	27.89	0.859
VDSR [21]	4	31.35	0.882	28.03	0.770	27.29	0.726	25.18	0.753	28.82	0.886
DRCN [22]	4	31.53	0.884	28.04	0.770	27.24	0.724	25.14	0.752	28.97	0.886
DRRN [42]	4	31.68	0.888	28.21	0.772	27.38	0.728	25.44	0.764	29.46	0.896
LapSRN [24]	4	31.54	0.885	28.19	0.772	27.32	0.728	25.21 (25.87*)	0.756	29.09 (29.44*)	0.890
EDSR [30]	4	32.46	0.897	28.80	0.788	27.71	0.742	26.64 (27.30*)	0.803	31.02 (31.41*)	0.915
D-DBPN	4	32.47	0.898	28.82	0.786	27.72	0.740	– (27.08*)	0.795	– (31.50*)	0.914
Bicubic	8	24.39	0.657	23.19	0.568	23.67	0.547	20.74 (21.24*)	0.516	21.47 (21.68*)	0.647
A+ [44]	8	25.52	0.692	23.98	0.597	24.20	0.568	21.37	0.545	22.39	0.680
SRCNN [6]	8	25.33	0.689	23.85	0.593	24.13	0.565	21.29	0.543	22.37	0.682
FSRCNN [7]	8	25.41	0.682	23.93	0.592	24.21	0.567	21.32	0.537	22.39	0.672
VDSR [21]	8	25.72	0.711	24.21	0.609	24.37	0.576	21.54	0.560	22.83	0.707
LapSRN [24]	8	26.14	0.738	24.44	0.623	24.54	0.586	21.81 (22.42*)	0.582	23.39 (23.67*)	0.735
EDSR [30]	8	26.97	0.775	24.94	0.640	24.80	0.596	22.47 (23.12*)	0.620	24.58 (24.89*)	0.778
D-DBPN	8	27.21	0.784	25.13	0.648	24.88	0.601	– (23.25*)	0.622	– (25.50*)	0.799

*indicates that the input is divided into four parts and calculated separately due to computation limitation of Caffe)

Visual on 8x

HR LR Bicubic LapSRN EDSR Ours



References

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Source Code