Supplementary Material:
UPS: Unified Projection Sharing for Lightweight Single-Image Super-resolution and Beyond

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1 Quantitative Comparison with More Methods.

In Table 1 and Table 2, we present additional lightweight SISR models for comparison. It is evident that UPS demonstrates state-of-the-art performance across various public benchmarks and settings. Furthermore, UPS-S, which is even more lightweight, achieves comparable results compared to other methods. Particularly noteworthy is the substantial performance improvement of UPS-S over our baseline model (SwinIR-S [1]), thereby validating the efficacy of our proposed unified projection-sharing strategy.

Table 1: Quantitative results of SOTA lightweight SISR methods ($\times 2$).

Method ($\times 2$)	Venue	Set5 PSNR/SSIM	Set14 PSNR/SSIM	BSD100 PSNR/SSIM	Urban100 PSNR/SSIM	Manga109 PSNR/SSIM
SRCNN [2]	ECCV14	36.66/0.9542	32.42/0.9063	31.36/0.8878	29.50/0.8946	35.74/0.9661
VDSR [3]	CVPR16	36.53/0.9587	33.03/0.9124	31.90/0.8960	30.76/0.9140	37.22/0.9750
MemNet [4]	ICCV17	37.78/0.9597	33.28/0.9142	32.08/0.8978	31.31/0.9195	37.72/0.9740
SRMDNF [5]	CVPR18	37.79/0.960	33.32/0.915	32.05/0.8985	31.33/0.9204	38.07/0.9761
CARN [6]	ECCV18	37.76/0.9590	33.52/0.9166	32.09/0.8978	31.92/0.9256	38.36/0.9765
SRFBN-S [7]	CVPR19	37.78/0.9597	33.35/0.9156	32.00/0.8970	31.41/0.9207	38.06/0.9757
IMDN [8]	MM19	38.00/0.9605	33.63/0.9177	32.19/0.8996	32.17/0.9283	38.88/0.9774
RFDN-L [9]	ECCV20	38.08/0.9606	33.67/0.9190	32.18/0.8996	32.24/0.9290	38.95/0.9773
MAFFSRN [10]	ECCV20	37.97/0.9603	33.49/0.9170	32.14/0.8994	31.96/0.9268	-/-
LatticeNet [11]	ECCV20	38.15/0.9610	33.78/0.9193	32.25/0.9005	32.43/0.9302	-/-
LAPAR-A [12]	NeurIPS20	38.01/0.9605	33.62/0.9183	32.19/0.8999	32.10/0.9283	38.67/0.9772
RLFN [13]	CVPRW22	38.07/0.9607	33.72/0.9187	32.22/0.9000	32.33/0.9299	-/-
SwinIR-light [14]	ICCVW21	38.14/0.9611	33.86/0.9206	32.31/0.9012	32.76/0.9340	39.12/0.9783
NGswin [15]	CVPR23	38.05/0.9610	33.79/0.9199	32.27/0.9008	32.53/0.9324	38.97/0.9777
SwinIR-NG [15]	CVPR23	38.17/0.9612	33.94/0.9205	32.31/0.9013	32.78/0.9340	39.20/0.9781
DLGSA-l [16]	ICCV23	38.20/0.9612	33.89/0.9203	32.30/0.9012	32.94/0.9355	39.29/0.9780
UPS (Ours)	—	38.26/0.9642	34.16/0.9232	32.42/0.9031	33.08/0.9373	39.62/0.9800
SwinIR-S [14]	ICCVW21	38.06/0.9603	33.80/0.9186	32.23/0.9006	32.24/0.9301	38.76/0.9778
UPS-S (Ours)	—	38.16/0.9638	34.00/0.9220	32.36/0.9023	32.79/0.9346	39.26/0.9790

2 More Qualitative Results

We provide additional visual examples in Fig. 1 and Fig. 2 for several widely used benchmarks, including Set14 [19], BSD100 [20], DIV2K [21], Manga109 [22]. Compared with SOTA SISR methods, i.e., LAPAR-A [12], SwinIR-light [1], NGSwin [15], UPS reconstructs clearer image textures and fewer artifacts, demonstrating its effectiveness of similarity modeling.

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Table 2: Quantitative results of SOTA lightweight SISR methods (×3, ×4).

Method (×3)	Venue	Set5 PSNR/SSIM	Set14 PSNR/SSIM	BSD100 PSNR/SSIM	Urban100 PSNR/SSIM	Manga109 PSNR/SSIM
SRCNN [2]	ECCV14	32.75/0.9090	29.28/0.8209	28.41/0.7863	26.24/0.7989	30.59/0.9107
VDSR [3]	CVPR16	33.66/0.9213	29.77/0.8314	28.82/0.7976	27.14/0.8279	32.01/0.9340
MemNet [4]	ICCV17	34.09/0.9248	30.00/0.8350	28.96/0.8001	27.56/0.8376	32.51/0.9369
EDSR [17]	CVPRW17	34.37/0.9270	30.28/0.8417	29.09/0.8052	28.15/0.8527	33.45/0.9439
SRMDNF [5]	CVPR18	34.12/0.9254	30.04/0.8382	28.97/0.8025	27.57/0.8398	33.00/0.9403
CARN [6]	ECCV18	34.29/0.9255	30.29/0.8407	29.06/0.8034	28.06/0.8493	33.50/0.9440
IMDN [8]	MM19	34.36/0.9270	30.32/0.8417	29.09/0.8046	28.17/0.8519	33.61/0.9445
SRFBN-S [7]	CVPR19	34.20/0.9255	30.10/0.8372	28.96/0.8010	27.66/0.8415	33.02/0.9404
RFDN-L [9]	ECCV20	34.47/0.9280	30.35/0.8421	29.11/0.8053	28.32/0.8547	33.78/0.9458
MAFFSRN [10]	ECCV20	34.45/0.9277	30.40/0.8432	29.13/0.8061	28.26/0.8552	-/-
LatticeNet [11]	ECCV20	34.53/0.9281	30.39/0.8424	29.15/0.8059	28.33/0.8538	-/-
LAPAR-A [12]	NeurIPS20	34.36/0.9267	30.34/0.8421	29.11/0.8054	28.15/0.8523	33.51/0.9441
ESRT [14]	CVPRW22	34.42/0.9268	30.43/0.8433	29.15/0.8063	28.46/0.8574	33.95/0.9455
SwinIR-light [14]	ICCVW21	34.62/0.9289	30.54/0.8463	29.20/0.8082	28.66/0.8624	33.98/0.9478
NGswin [15]	CVPR23	34.52/0.9282	30.53/0.8456	29.19/0.8078	28.52/0.8603	33.89/0.9470
SwinIR-NG [15]	CVPR23	34.64/0.9293	30.58/0.8471	29.24/0.8090	28.75/0.8639	34.22/0.9488
DLGSA-l [16]	ICCV23	34.70/0.9295	30.58/0.8465	29.24/0.8089	28.83/0.8653	34.16/0.9483
UPS (Ours)	–	34.66/0.9322	30.72/0.8489	29.31/0.8114	28.98/0.8685	34.53/0.9505
SwinIR-S [14]	ICCVW21	34.38/0.9281	30.46/0.8448	29.15/0.8073	28.37/0.8572	33.77/0.9464
UPS-S (Ours)	–	34.53/0.9312	30.55/0.8463	29.24/0.8093	28.60/0.8614	34.12/0.9484

Method (×4)	Venue	Set5 PSNR/SSIM	Set14 PSNR/SSIM	BSD100 PSNR/SSIM	Urban100 PSNR/SSIM	Manga109 PSNR/SSIM
SRCNN [2]	ECCV14	30.48/0.8628	27.49/0.7503	26.90/0.7101	24.52/0.7221	27.66/0.8505
VDSR [3]	CVPR16	31.35/0.8838	28.01/0.7674	27.29/0.7251	25.18/0.7524	28.83/0.8870
LapSNR [18]	CVPR17	31.54/0.8850	28.19/0.7720	27.32/0.7280	25.21/0.7560	29.09/0.8845
MemNet [4]	ICCV17	31.74/0.8893	28.26/0.7723	27.40/0.7281	25.50/0.7630	29.42/0.8942
EDSR [17]	CVPRW17	32.09/0.8938	28.58/0.7813	27.57/0.7357	26.04/0.7849	30.35/0.9067
SRMDNF [5]	CVPR18	31.96/0.8925	28.35/0.7787	27.49/0.7337	25.68/0.7731	30.09/0.9024
CARN [6]	ECCV18	32.13/0.8937	28.60/0.7806	27.58/0.7349	26.07/0.7837	30.47/0.9084
IMDN [8]	MM19	32.21/0.8948	28.58/0.7811	27.56/0.7353	26.04/0.7838	30.45/0.9075
SRFBN-S [7]	CVPR19	31.98/0.8923	28.45/0.7779	27.44/0.7313	25.71/0.7719	29.91/0.9008
RFDN-L [9]	ECCV20	32.28/0.8957	28.61/0.7818	27.58/0.7363	26.20/0.7883	30.61/0.9096
MAFFSRN [10]	ECCV20	32.20/0.8953	26.62/0.7822	27.59/0.7370	26.16/0.7887	-/-
LatticeNet [11]	ECCV20	32.30/0.8962	28.68/0.7830	27.62/0.7367	26.25/0.7873	-/-
LAPAR-A [12]	NeurIPS20	32.15/0.8944	28.61/0.7818	27.61/0.7366	26.14/0.7871	30.42/0.9074
RLFN [13]	CVPRW22	32.24/0.8952	28.62/0.7813	27.60/0.7364	26.17/0.7877	-/-
ESRT [14]	CVPRW22	32.19/0.8947	28.69/0.7833	27.69/0.7379	26.39/0.7962	30.75/0.9100
SwinIR-light [14]	ICCVW21	32.44/0.8976	28.77/0.7858	27.69/0.7406	26.47/0.7980	30.92/0.9151
NGswin [15]	CVPR23	32.33/0.8963	28.78/0.7859	27.66/0.7396	26.45/0.7963	30.80/0.9128
SwinIR-NG [15]	CVPR23	32.44/0.8980	28.83/0.7870	27.73/0.7418	26.61/0.8010	31.09/0.9161
DLGSA-l [16]	ICCV23	32.54/0.8993	28.84/0.7871	27.73/0.7415	26.66/0.8033	31.13/0.9161
UPS (Ours)	–	32.50/0.9024	28.90/0.7892	27.79/0.7435	26.83/0.8073	31.39/0.9194
SwinIR-S [14]	ICCVW21	32.14/0.8955	28.67/0.7832	27.63/0.7382	26.22/0.7906	30.68/0.9111
UPS-S (Ours)	–	32.41/0.9008	28.80/0.7863	27.73/0.7414	26.58/0.7995	31.13/0.9163

2
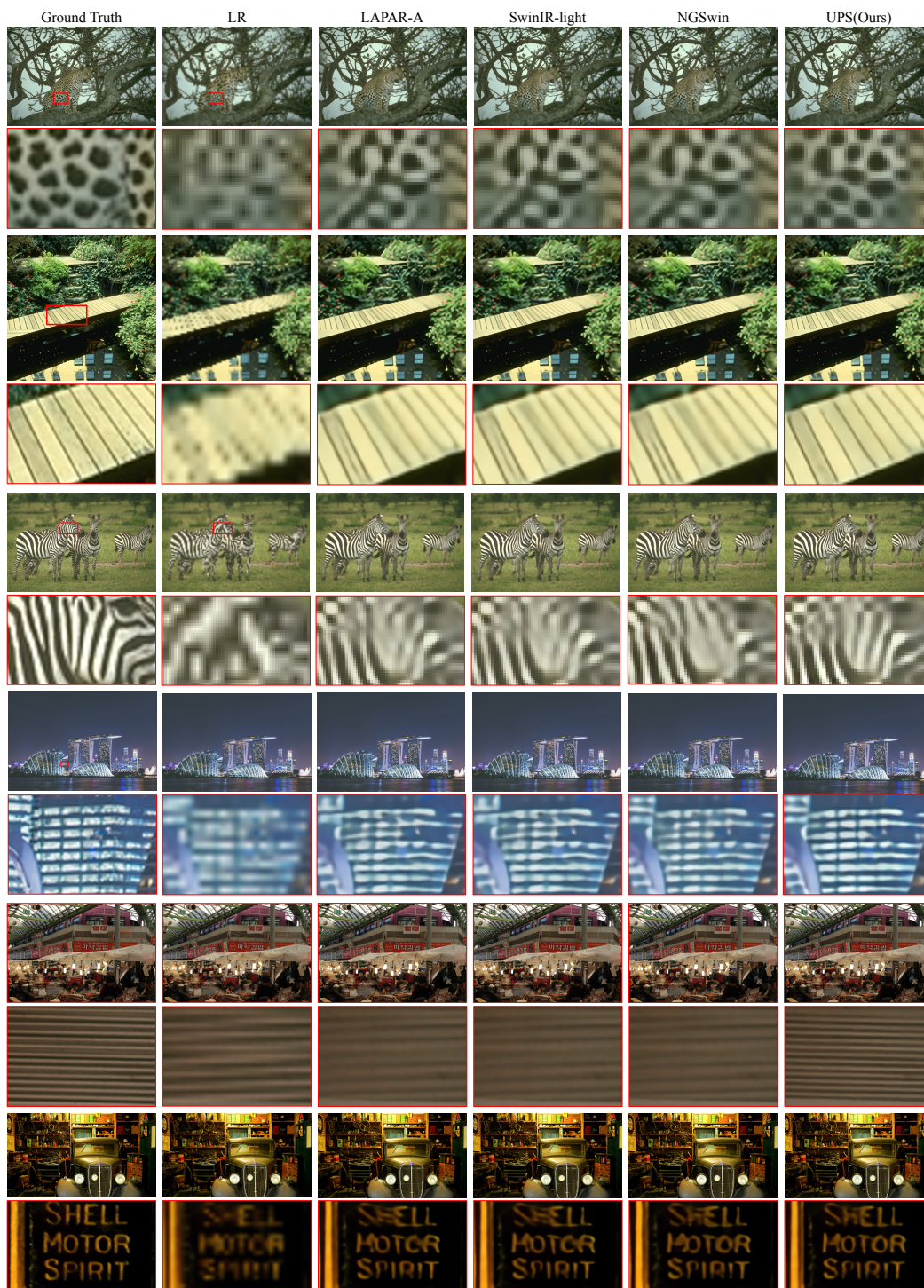
Figure 1: Qualitative evaluation on BSD100 [20] and DIV2K [21] dataset.

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Figure 2: Qualitative evaluation on Manga109 [22] and Set14 [19] datasets.

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