

UPS: Uni**fi**ed Projection Sharing for Lightweight Single-Image Super-resolution and Beyond

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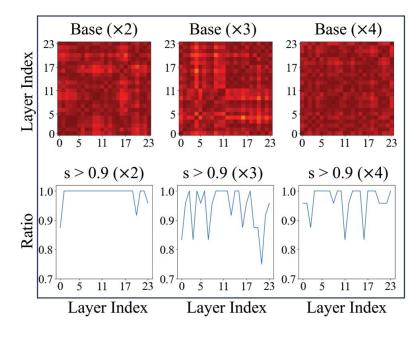








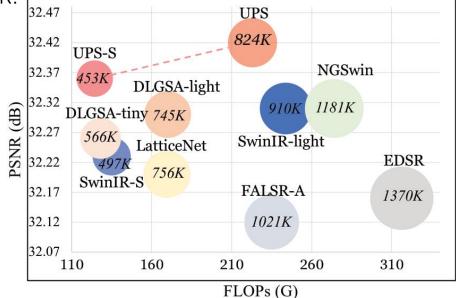
- Under practical lightweight scenarios, the complex interaction of deep image feature extraction and similarity modeling limits the performance of these methods, since they require simultaneous layer-specific optimization of both two tasks.
- We observe that the SwinIR-light (termed as Base) models exhibit significant similarities (CKA) in projection layers.



Contribution



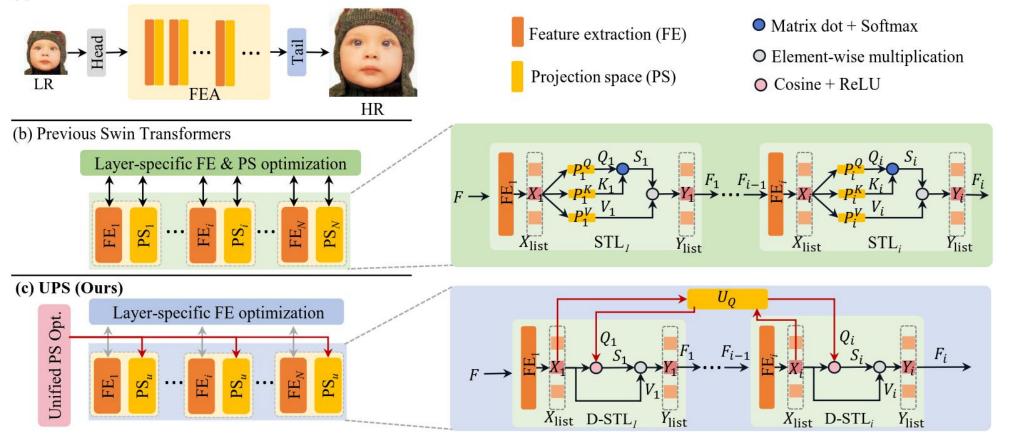
- We propose UPS, an effective decoupled SISR optimization framework, to address the challenge of simultaneous layer-specific feature extraction and similarity modeling for lightweight SISR.
- UPS simplifies the similarity optimization process by learning a layer-invariant projection space. It leads to effective aggregation and improved performance, even with reduced model capacity and less training samples
- UPS demonstrates the good generalization ability for unseen data, such as noisy image and depth map SR.



Method



(a) General transformer-based architecture for SISR



Previous Swin Transformers perform layer-specific feature extraction and projection space optimization .

Instead, UPS adopt a global and unified projection space optimization while keeping the layer-specific FE optimization.

Method



Algorithm Illustration

Algorithm 1 Pseudo Code of the <i>i</i> -th STL	Algorithm 2 Pseudo Code of the <i>i</i> -th Decoupled STL
1: Require: Input F_{i-1} , window size M 2: Feature extraction: $\hat{F}_i = \text{Conv}(F_{i-1})$ 3: Partitioning: $X_i^{\text{list}} = \text{Partitioning}(\hat{F}_i, M)$ 4: Define aggregated patch list: Y_i^{list} 5: for X_i in X_i^{list} do	1: Require: F_{i-1}, M , unified projection matrix U^Q 2: Feature extraction: $\hat{F}_i = \text{Conv}(F_{i-1})$ 3: Partitioning: $X_i^{\text{list}} = \text{Partitioning}(\hat{F}_i, M)$ 4: Define aggregated patch list: Y_i^{list}
6: Projection: $Q_i, K_i, V_i = X_i P_i^Q, X_i P_i^K, X_i P_i^V$	5: for X_i in X_i^{list} do 6: Projection: $Q_i, V_i = X_i U^Q, X_i$
7: Similarity cal.: $S_i = \text{SoftMax}\left(\frac{Q_i K_i^T}{\sqrt{d}} + B_i\right)$	7: Similarity cal.: $S_i = \text{ReLU}(\text{Cosine}(Q_i, Q_i^D) + B_i)$
8: Aggregation: $Y_i = S_i V_i$ 9: $Y_i^{\text{list}}.append(Y_i)$ 10: end for 11: return $\text{Reshape}(Y_i^{\text{list}})$	8: Aggregation: $Y_i = S_i V_i$ 9: $Y_i^{\text{list}}.append(Y_i)$ 10: end for 11: return Reshape (Y_i^{list})

• We highlighted the key difference of existing Swin-transformers and our proposed UPS.

Experiments

Quantitative Comparison

		r	No					•
Method	Scale	Parameters (K)	FLOPs (G)	Set5	Set14	BSD100	Urban100	Manga109
wiethou				PSNR / SSIM				
IMDN		694	158.8	38.00 / 0.9605	33.63 / 0.9177	32.19 / 0.8996	32.17 / 0.9283	38.88 / 0.9774
RFDN-L		626	145.8	38.08 / 0.9606	33.67 / 0.9190	32.18 / 0.8996	32.24 / 0.9290	38.95/0.9773
SwinIR-light		910	244.4	38.14 / 0.9611	33.86 / 0.9206	32.31 / 0.9012	32.76 / 0.9340	39.12/0.9783
DLGSA-light	$\times 2$	745	170.0	38.20 / 0.9612	33.89 / 0.9203	32.30 / 0.9012	32.94 / 0.9355	39.29 / 0.9780
Omni-SR	1.200-020	772	194.5	38.22 / 0.9613	33.98/0.9210	32.36 / 0.9020	33.05 / 0.9363	39.28 / 0.9784
UPS		824	162.5	38.26 / 0.9642	34.16 / 0.9232	32.42 / 0.9031	33.08 / 0.9373	39.62 / 0.9800
SwinIR-S	$\times 2$	497	107.3	38.06 / 0.9603	33.80/0.9186	32.23 / 0.9006	32.24 / 0.9301	38.76/0.9778
UPS-S	×2	453	90.6	38.16 / 0.9638	34.00 / 0.9220	32.36 / 0.9023	32.79 / 0.9346	39.26 / 0.9790
Omni-SR+	×2	772	194.5	38.29/0.9617	34.27 / 0.9238	32.41/0.9026	33.30 / 0.9386	39.53 / 0.9792
UPS+	$\times 2$	824	162.5	38.31/0.9643	34.37 / 0.9247	32.43 /0.9032	33.34 / 0.9388	39.80 / 0.9802
IMDN	1	703	71.5	34.36 / 0.9270	30.32/0.8417	29.09 / 0.8046	28.17/0.8519	33.61 / 0.9445
RFDN-L		633	65.6	34.47 / 0.9280	30.35 / 0.8421	29.11/0.8053	28.32/0.8547	33.78 / 0.9458
SwinIR-light		918	110.8	34.62/0.9289	30.54 / 0.8463	29.20 / 0.8082	28.66 / 0.8624	33.98/0.9478
DLGSA-light	×3	752	75.4	34.70 / 0.9295	30.58 / 0.8465	29.24 / 0.8089	28.83 / 0.8653	34.16/0.9483
Omni-SR		780	88.4	34.70 / 0.9294	30.57 / 0.8469	29.28 / 0.8094	28.84 / 0.8656	34.22 / 0.9487
UPS		832	72.4	34.66 / 0.9322	30.72 / 0.8489	29.31 / 0.8114	28.98 / 0.8685	34.53 / 0.9505
SwinIR-S	×3	503	47.9	34.38/0.9281	30.46 / 0.8448	29.15 / 0.8073	28.37 / 0.8572	33.77 / 0.9464
UPS-S	×3	459	40.4	34.53 / 0.9312	30.55 / 0.8463	29.24 / 0.8093	28.60 / 0.8614	34.12/0.9484
Omni-SR+	×3	780	88.4	34.77 / 0.9304	30.70 / 0.8489	29.33/0.8111	29.12/0.8712	34.64 / 0.9507
UPS+	$\times 3$	832	72.4	34.78 / 0.9325	30.78 / 0.8492	29.36 / 0.8122	29.28 / 0.8728	34.84 / 0.9517
IMDN	1	715	40.9	32.21 / 0.8948	28.58/0.7811	27.56/0.7353	26.04 / 0.7838	30.45 / 0.9075
RFDN-L		643	37.4	32.28 / 0.8957	28.61/0.7818	27.58 / 0.7363	26.20 / 0.7883	30.61 / 0.9096
SwinIR-light		930	63.6	32.44 / 0.8976	28.77 / 0.7858	27.69 / 0.7406	26.47 / 0.7980	30.92/0.9151
DLGSA-light	×4	761	42.5	32.54 / 0.8993	28.84 / 0.7871	27.73 / 0.7415	26.66 / 0.8033	31.13/0.9161
Omni-SR		792	50.9	32.49 / 0.8988	28.78/0.7859	27.71 / 0.7415	26.64 / 0.8018	31.02/0.9151
UPS		843	41.3	32.50 / 0.9024	28.90 / 0.7892	27.79 / 0.7435	26.83 / 0.8073	31.39 / 0.9194
SwinIR-S	$\times 4$	512	27.3	32.14 / 0.8955	28.67 / 0.7832	27.63 / 0.7382	26.22 / 0.7906	30.68 / 0.9111
UPS-S	×4	468	23.0	32.41 / 0.9008	28.80 / 0.7863	27.73 / 0.7414	26.58 / 0.7995	31.13/0.9163
Omni-SR+	×4	792	50.9	32.57 / 0.8993	28.95 / 0.7898	27.81/0.7439	26.95 / 0.8105	31.50/0.9192
UPS+	×4	843	41.3	32.60 / 0.9029	28.97 / 0.7896	27.83 / 0.7446	27.10/0.8136	31.79/0.9223

NEURAL INFORMATION PROCESSING SYSTEMS

Experiments



Qualitative Comparison

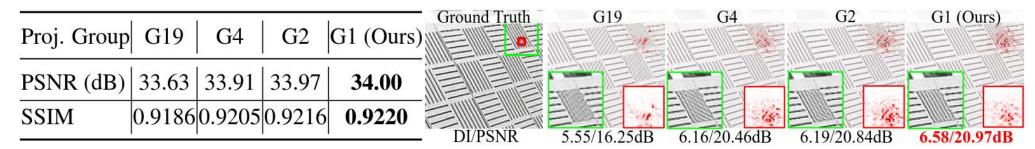
BSD100_091	LR	LAPAR-A	NGSwin	Manga109_003	LR MRUI-HAM	LAPAR-A	NGSwin
	Ground Truth	SwinIR-light	UPS		Ground Truth	SwinIR-light	UPS AKU-HAM
Urban100_003	LR	LAPAR-A	NGSwin	DIV2K_0820	LR	LAPAR-A	NGSwin
	Ground Truth	SwinIR-light	UPS		Ground Truth	SwinIR-light	UPS





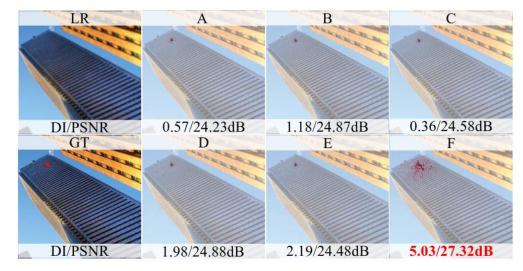
Ablation Studies

Analysis of several UPS-S models with different projection groups



• Impact of different similarity calculation methods

M	atrix do	t Cosine	SoftMax	ReLI	JPSNR/SSIM
A	1				33.60/0.9192
B	1		1		33.84/0.9202
C	\checkmark			1	33.41/0.9169
D		1			33.61/0.9208
E		1	1		33.73/0.9194
F		1		1	34.00/0.9220



Extension

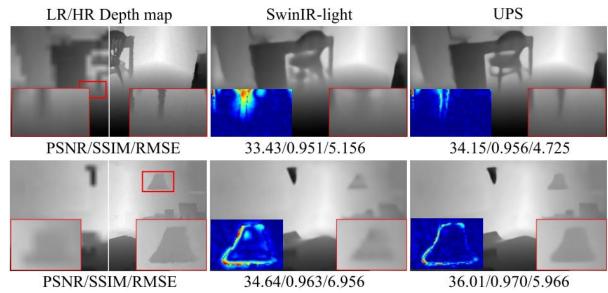


• Extension on other image restoration problems (Denoising)

Tasks	Metrics	SwinIR	SwinIR-C	UPS	Ground Truth	SwinIR	SwinIR-C	UPS
Deblocking $q = 40$	PSNR Param.	29.86 11.50M	29.63 3.89M	29.98 3.49M				
Denoising	PSNR	28.56	28.20	28.37	A REAL A	A A A A A		
$\sigma = 50$	Param.	11.50M	0.959M	0.873M				

• Generalization comparison between baseline model and UPS (Depth Map SR)

Settings	Metrics	SwinIR-light	UPS
	PSNR	47.25	47.79
$\times 4$	SSIM	0.994	0.995
	RMSE	2.339	2.198
$\times 16$	PSNR	37.25	37.98
	SSIM	0.969	0.972
	RMSE	7.832	7.236





Thank You

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