

Local-Global Transformer Enhanced Unfolding Network for Pan-sharpening

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Summary

- ➤ **Task description:** *Pan-sharpening* aims to increase the spatial resolution of the low-resolution multispectral (LrMS) image with the guidance of the corresponding panchromatic (PAN) image.
- Input: The coupled LrMS image and PAN image.
- Output: A high-resolution multispectral (HrMS) image.
- > Existing two-fold deficiency:
- Model Interpretability
- Local and Global Dependencies
- > Our main contributions:
- We customize a transformer module LGT as an image denoiser to efficiently model local and global dependencies at the same time and sufficiently mine the potential of the proposed unfolding pan-sharpening framework.
- We develop an interpretable transformer-based deep unfolding network, LGTEUN.
- To the best of our knowledge, LGTEUN is the first transformer-based deep unfolding network for the MS pan-sharpening, and LGT is also the first transformer module to perform spatial and frequency dual-domain learning.
- Code: https://github.com/lms-07/LGTEUN

Proposed Method

Model formulation and optimization

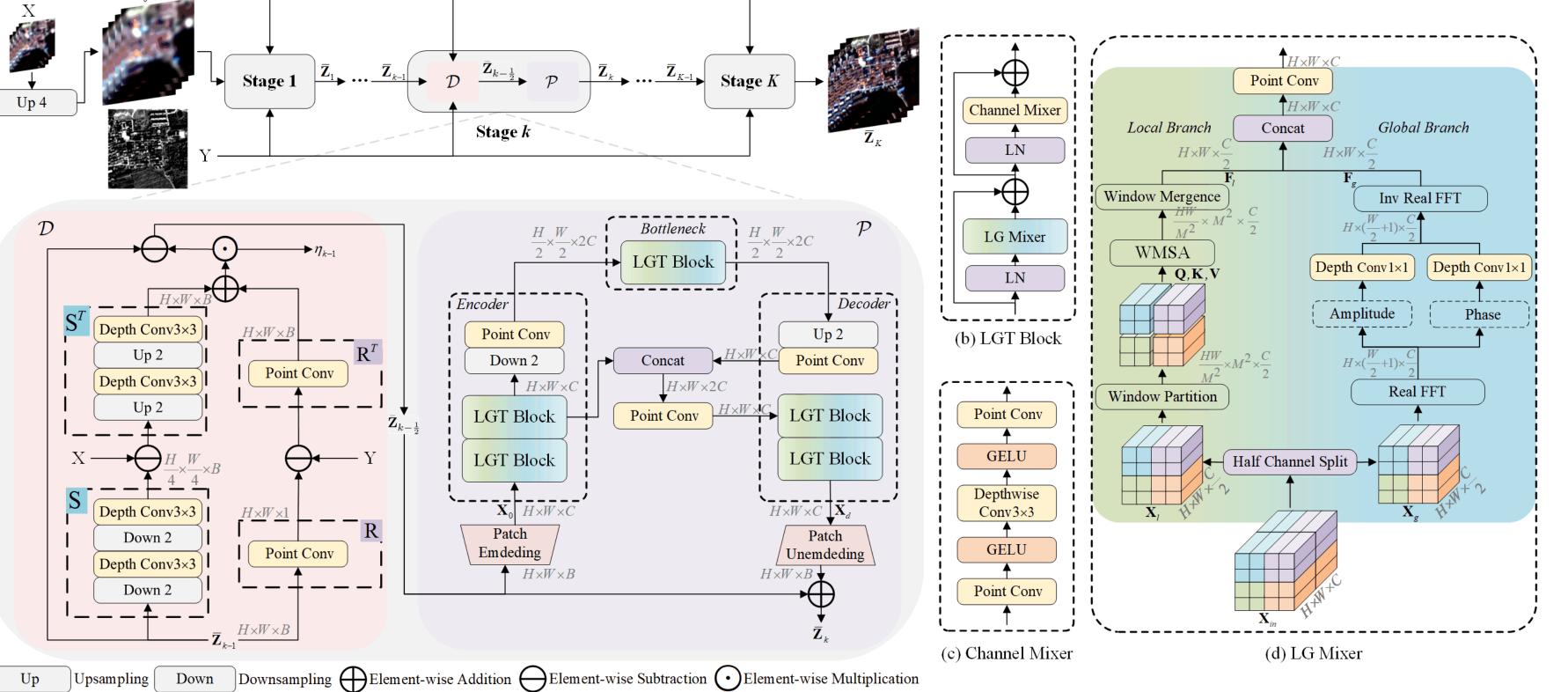
The degradation process of the HrMS image **Z**:

 $\mathbf{X} = \mathbf{SZ} + \mathbf{N}_x, \ \mathbf{Y} = \mathbf{ZR} + \mathbf{N}_y,$

The energy function under MAP framework:

$$ar{\mathbf{Z}} = argmin \frac{1}{2} \| \mathbf{X} - \mathbf{SZ} \|^2 + \frac{1}{2} \| \mathbf{Y} - \mathbf{ZR} \|^2 + \lambda J(\mathbf{Z}),$$





Employing proximal gradient descent (PGD) algorithm:

$$\bar{\mathbf{Z}}_{k} = argmin\frac{1}{2} \| \mathbf{Z} - (\bar{\mathbf{Z}}_{k-1} - \eta \nabla_{f}(\bar{\mathbf{Z}}_{k-1}) \|^{2} + \lambda J(\mathbf{Z}),$$

The data terms oriented differentiable operator:

$$\nabla_f(\bar{\mathbf{Z}}_{k-1}) = \mathbf{S}^T(\mathbf{S}\bar{\mathbf{Z}}_{k-1} - \mathbf{X}) + (\bar{\mathbf{Z}}_{k-1}\mathbf{R} - \mathbf{Y})\mathbf{R}^T.$$

The data subproblem and the prior subproblem:

$$egin{align} ar{\mathbf{Z}}_{k-rac{1}{2}} &= ar{\mathbf{Z}}_{k-1} - \eta
abla (ar{\mathbf{Z}}_{k-1}), \ ar{\mathbf{Z}}_{k} &= prox_{\eta,J}(ar{\mathbf{Z}}_{k-rac{1}{2}}), \end{aligned}$$

Prior module: $\bar{\mathbf{Z}}_k = \mathcal{P}(\bar{\mathbf{Z}}_{k-\frac{1}{2}})$.

Deep unfolding network

Data module: $\bar{\mathbf{Z}}_{k-\frac{1}{2}} = \mathcal{D}(\bar{\mathbf{Z}}_{k-1}, \mathbf{X}, \mathbf{Y}, \eta_{k-1}).$

■ Local-Global Transformer: LGT

• Local branch calculates local window based self-attention in spatial domain.

$$\mathbf{F}_a^i = Softmax(rac{\mathbf{Q}^i \mathbf{K}^{i^T}}{\sqrt{d}} + \mathbf{P}^i) \mathbf{V}^i, \ i = 1, ..., h,$$

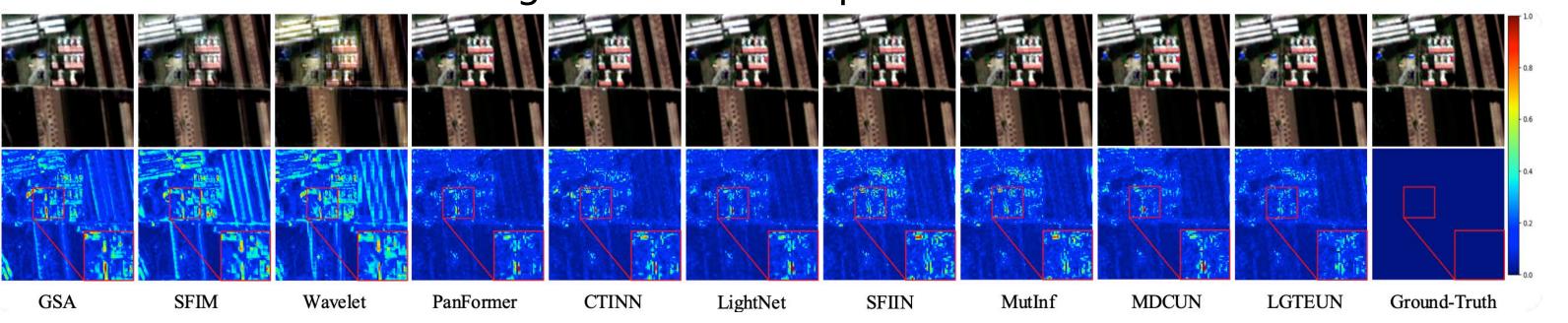
• Global branch extracts global contextual feature representation in frequency domain.

$$\mathcal{F}(\mathbf{X}_g)(u,v) = \frac{1}{\sqrt{HW}} \sum_{h=0}^{H-1} \sum_{w=0}^{W-1} \mathbf{X}_g(h,w) e^{-j2\pi(\frac{h}{H}u + \frac{w}{W}v)},$$

$$\mathcal{A}(\mathbf{X}_g)(u,v) = \sqrt{R^2(\mathbf{X}_g)(u,v) + I^2(\mathbf{X}_g)(u,v)}, \ \mathcal{P}(\mathbf{X}_g)(u,v) = arctan[rac{I(\mathbf{X}_g)(u,v)}{R(\mathbf{X}_g)(u,v)}].$$

$$\mathbf{F}_g = \mathcal{F}^{-1}(DConv(\mathcal{A}(\mathbf{X}_g)), DConv(\mathcal{P}(\mathbf{X}_g))),$$

Fig: Qualitative comparison



Experiments

Quantitative comparison

Method	WorldView-3				WorldView-2				GaoFen-2						
	PSNR↑	SSIM↑	Q8↑	SAM↓	ERGAS↓	PSNR↑	SSIM↑	Q4↑	SAM↓	ERGAS↓	PSNR↑	SSIM↑	Q4↑	SAM↓	ERGAS
GSA	22.5164	0.6343	0.5742	0.1106	7.8267	33.5975	0.8899	0.5681	0.0573	2.5402	36.0557	0.8838	0.5517	0.0641	3.5758
SFIM	21.4154	0.5415	0.4525	0.1147	8.8553	32.6334	0.8728	0.5159	0.0597	3.1919	34.7715	0.8572	0.4584	0.0657	4.2073
Wavelet	21.4464	0.5656	0.5271	0.1503	9.1545	32.1992	0.8500	0.4577	0.0638	3.3799	33.9208	0.8197	0.4033	0.0695	4.6445
PanFormer	30.4772	0.9368	0.9316	0.0672	3.1830	41.3581	0.9731	0.8236	0.0241	1.0617	44.8540	0.9805	0.8865	0.0271	1.3334
CTINN	31.8564	0.9518	0.9460	0.0660	2.7421	41.2015	0.9735	0.8149	0.0246	1.0880	44.2942	0.9784	0.8716	0.0293	1.4148
LightNet	32.0018	0.9525	0.9472	0.0639	2.6853	41.5589	0.9739	0.8220	0.0237	1.0382	44.6876	0.9787	0.8741	0.0279	1.3510
SFIIN	31.6587	0.9492	0.9435	0.0652	2.8016	41.9489	0.9752	0.8108	0.0229	1.0084	44.7248	0.9802	0.8721	0.0280	1.3361
MutInf	31.8298	0.9523	0.9469	0.0636	2.7526	41.9522	0.9760	0.8258	0.0227	1.0153	44.8305	0.9800	0.8836	0.0277	1.3394
MDCUN	31.2978	0.9429	0.9363	0.0661	2.9295	42.3351	0.9772	0.8370	0.0216	0.9638	45.5677	0.9825	0.8915	0.0252	1.2249
LGTEUN	32.2188	0.9545	0.9494	0.0605	2.6286	42.6837	0.9786	0.8415	0.0208	0.9280	45.8364	0.9840	0.8973	0.0247	1.1824

A key hyperparameter setting

7 110	, , pc.	Para		. 500	9
Data Set	Metric	Stage 1	Stage 2	Stage 3	Stage 4
	PSNR↑	32.0339	32.2188	32.068	32.0042
	SSIM↑	0.9532	0.9545	0.9535	0.9527
	Q8↑	0.9481	0.9494	0.9487	0.9480
IonIdVious 2	SAM↓	0.0605	0.0605	0.0603	0.0612
VorldView-3	ERGAS↓	2.6765	2.6286	2.6678	2.6898
	Time (s/img)	0.0070	0.0133	0.0205	0.0262
	Params (KB)	270.2	540.0	809.9	1079.7
	FLOPs (GB)	9.52	19.04	28.56	38.08
	PSNR↑	42.600	42.6837	42.4771	42.1634
	SSIM↑	0.9784	0.9786	0.9781	0.9767
	Q4↑	0.8398	0.8415	0.8383	0.8329
71-1377: 2	SAM↓	0.0209	0.0208	0.0213	0.0222
/orldView-2	ERGAS↓	0.9358	0.928	0.9573	0.9787
	Time (s/img)	0.0065	0.0137	0.0204	0.0254
	Params (KB)	101.2	202.2	303.2	404.2
	FLOPs (GB)	2.57	5.14	7.71	10.28
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Full-resolution test > Performance-efficiency

tion	Test	CC	omparis	on	
\downarrow	QNR↑	42.8	LGTEUN OURS		
76	0.8839	42.6	(202.2 KB)		
61	0.8854	42.4			
30	0.8193	72.7			MDCUN CVPR 2022 (98.4 KB)
16	0.9400	42.2			(20.4 KB)
42	0.9440	<u>a</u> 42 0	SFIIN	MutInf	
82	0.9539	B 42.0	ECCV 2022 (85.3 KB)	CVPR 2022 (185.5 KB)	
52	0.9457	PSNR (dB) 41.8			
20	0.9423	41.6	LightNet		
73	0.7708	41.0	IJCAI 2022 (15.8 KB)		
10	0.9532	41.4		PanFormer ICME 2022 (1525.1 KB)	
		41.2	CTINN AAAI 2022 (37.8 KB)		
		$41.0 \frac{1}{10^{0}}$		101	102
				FLOPs (GB)	

> Efficiency comparison

Data Set	Metric	GSA	SFIM	Wavelet	PanFormer	CTINN	LightNet	SFIIN	MutInf	MDCUN	LGTEUN
	Time (s/img)	0.0482	0.0591	0.0562	0.0160	0.0426	0.0019	0.0529	0.1083	0.1747	0.0133
WorldView-3	Params (KB)	_	_	_	1532.8	38.3	16.3	85.8	185.8	140.9	540.0
	FLOPs (GB)	_	_	_	11.92	2.68	2.02	5.25	9.87	479.54	19.04
GaoFen-2	Time (s/img)	0.0216	0.0301	0.0271	0.0257	0.0431	0.0017	0.0528	0.1141	0.1017	0.0129
	Params (KB)	_	_	_	1530.3	37.8	15.8	85.3	185.5	98.3	202.2
	FLOPs (GB)	_	_	_	11.77	2.65	1.95	5.22	9.85	473.19	5.14

Ablation study

Set		Full-resolution Test							
Local Branch	Global Branch	PSNR↑	SSIM↑	Q 8↑	SAM↓	ERGAS↓	$D_{\lambda}{\downarrow}$	$D_S {\downarrow}$	QNR↑
×	√	31.9309	0.9519	0.9468	0.0636	2.7102	0.0177	0.0364	0.9465
\checkmark	×	31.9742	0.9525	0.9468	0.0618	2.7029	0.0170	0.0349	0.9486
\checkmark	\checkmark	32.2188	0.9545	0.9494	0.0605	2.6286	0.0162	0.0310	0.9532

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