MST++: Multi-stage Spectral-wise Transformer for Efficient Spectral Reconstruction

Winner of NTIRE 2022 Challenge on Spectral Reconstruction from RGB

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Overview

• Introduction

• Method

• Experiments

Introduction

Introduction

Application





Medical Imaging

Object Tracking





Coded Aperture Snapshot Spectral Imaging (CASSI) System



Model-based Methods

- Time consuming
- Poor representing capacity
- Unsatisfactory performance

CNN-based Methods

 Show limitations in capturing long-range dependencies

Method



Network Architecture

- Cascaded by N_s SSTs
- Each SST adopts a threelevel U-shaped structure

Spectral-wise MSA

- Based on HSI characteristic
- Treats each spectral feature map as $\mathbf{A}_j = \operatorname{softmax}(\sigma_j \mathbf{K}_j^{\mathrm{T}} \mathbf{Q}_j), \ head_j = \mathbf{V}_j \mathbf{A}_j$ a token to calculate self-attention $\operatorname{S-MSA}(\mathbf{X}) = \left(\operatorname{Concat}_{j=1}^{N}(head_j)\right)\mathbf{W} + f_p(\mathbf{V})$

 $\mathbf{Q} = \mathbf{X}\mathbf{W}^{\mathbf{Q}}, \mathbf{K} = \mathbf{X}\mathbf{W}^{\mathbf{K}}, \mathbf{V} = \mathbf{X}\mathbf{W}^{\mathbf{V}}$



We compare computational complexity of S-MSA, global MSA, and window-based MSA as

$$O(G - MSA) = 2(HW)^2C, \qquad O(W - MSA) = \frac{HW}{M^2}(2(M^2)^2C) = 2M^2HWC$$
$$O(S - MSA) = N((C/N)^2HW + (C/N)^2HW)^2 = \frac{2HWC^2}{N}$$

Only our S-MSA can enjoy linear computational complexity and global receptive fields jointly.

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NTIRE 2022 HSI Dataset - Valid							NTIRE 2022 HSI Dataset - Test				
Method	Params (M)	FLOPS (G)	MRAE	RMSE	PSNR	Username	MRAE	RMSE			
HSCNN+ [67]	4.65	304.45	0.3814	0.0588	26.36	pipixia	0.2434	0.0411			
HRNet [88]	31.70	163.81	0.3476	0.0550	26.89	uslab	0.2377	0.0391			
EDSR [45]	2.42	158.32	0.3277	0.0437	28.29	orange_dog	0.2377	0.0376			
AWAN [36]	4.04	270.61	0.2500	0.0367	31.22	askldklasfj	0.2345	0.0361			
HDNet [29]	2.66	173.81	0.2048	0.0317	32.13	HSHAJii	0.2308	0.0364			
HINet [21]	5.21	31.04	0.2032	0.0303	32.51	ptdoge_hot	0.2107	0.0365			
MIRNet [84]	3.75	42.95	0.1890	0.0274	33.29	test_pseudo	0.2036	0.0324			
Restormer [83]	15.11	93.77	0.1833	0.0274	33.40	gkdgkd	0.1935	0.0322			
MPRNet [85]	3.62	101.59	0.1817	0.0270	33.50	deeppf	0.1767	0.0322			
MST-L [13]	2.45	32.07	0.1772	0.0256	33.90	mialgo_ls	0.1247	0.0257			
MST++	1.62	23.05	0.1645	0.0248	34.32	MST++*	0.1131	0.0231			

Our MST++ significantly outperforms SOTA CNN-based methods with cheaper memory and computational costs

We plot PSNR-Params-FLOPS comparisons, where MST++ takes up the upper-left corner



RGB Image RGB Patch											
→ Ground Truth → EDSR, corr: 0.9980 → HDNet, corr: 0.9981 → HINet, corr: 0.9925 → HRNet, corr: 0.9979											
0.2 HSCNN+, corr: 0.9975 											
RGB Image RGB Patch		innilli F							IIIIIII F		
→ Ground Truth → EDSR, corr: 0.9980 → HDNet, corr: 0.9981 → HINet, corr: 0.9979		inininini f									
HSCNN+, corr: 0.9975 MIRNet, corr: 0.9977 MPRNet, corr: 0.9979 Restormer, corr: 0.9983 MST-L, corr: 0.9983 MST-L, corr: 0.9993 MST++, corr: 0.9993											
Wavelength (nm)	HSCNN+	HRNet	EDSR	HDNet	HINet	MIRNet	Restormer	MPRNet	MST-L	MST++	GT

Method	Baseline	SW-MSA	W-MSA	G-MSA	S-MSA	N_s	1	2		3
MRAE	0.3177	0.2839	0.2624	0.1821	0.1645	MRAE	0.1761	0.1716	0.16	45
RMSE	0.0453	0.0399	0.0375	0.0271	0.0248	RMSE	0.0266	0.0269	0.024	8
Params (M)	1.30	1.60	1.60	1.60	1.62	Params (M)	0.55	1.08	1.62	
FLOPS (G)	17.68	24.10	24.10	25.11	23.05	FLOPS (G)	8.10	15.57	23.05	

(a) Ablation study of different self-attention mechanisms.

(b) Ablation study of stage number N_s .

Ablation study of different MSA modules Our S-MSA achieves the most significant improvement while requiring cheapest memory and computational costs

Ablation study of stage number N_s The performance is improved as the stage number increases

Please note that MST++ is based on our previous work "Mask-guided Spectral-wise Transformer for Effcient Hyperspectral Image Reconstruction" that has been accepted by CVPR 2022 main conference

Thanks for Watching



MST : <u>https://github.com/caiyuanhao1998/MST</u>

MST++ : <u>https://github.com/caiyuanhao1998/MST-plus-plus</u>