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Snapshot Hyperspectral Imaging Based on Weighted High-order Singular Value Regularization

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Introduction

Motivation

- The vectorization process ignores the high-dimensionality nature of hyperspectral image and breaks the original structure.
- High-order tensors can provide a more accurate representation to deliver the intrinsic structure of high-dimensionality signals.

Contributions

- We propose a high-order tensor optimization based method to boost the reconstruction performance for snapshot hyperspectral imaging reconstruction.
- We propose a weighted high-order singular value regularization, where the spatial self-similarity, spectral correlation and joint correlation will be fully exploited.
- We develop an general reconstruction framework for snapshot hyperspectral imaging, which can be effectively solved via an alternating minimization algorithm.

Related work

[1] Fu et al. Exploiting spectral-spatial correlation for coded hyperspectral image restoration. CVPR 2016.

[2] Choi et al. High-quality hyperspectral reconstruction using a spectral prior. TOG 2017.

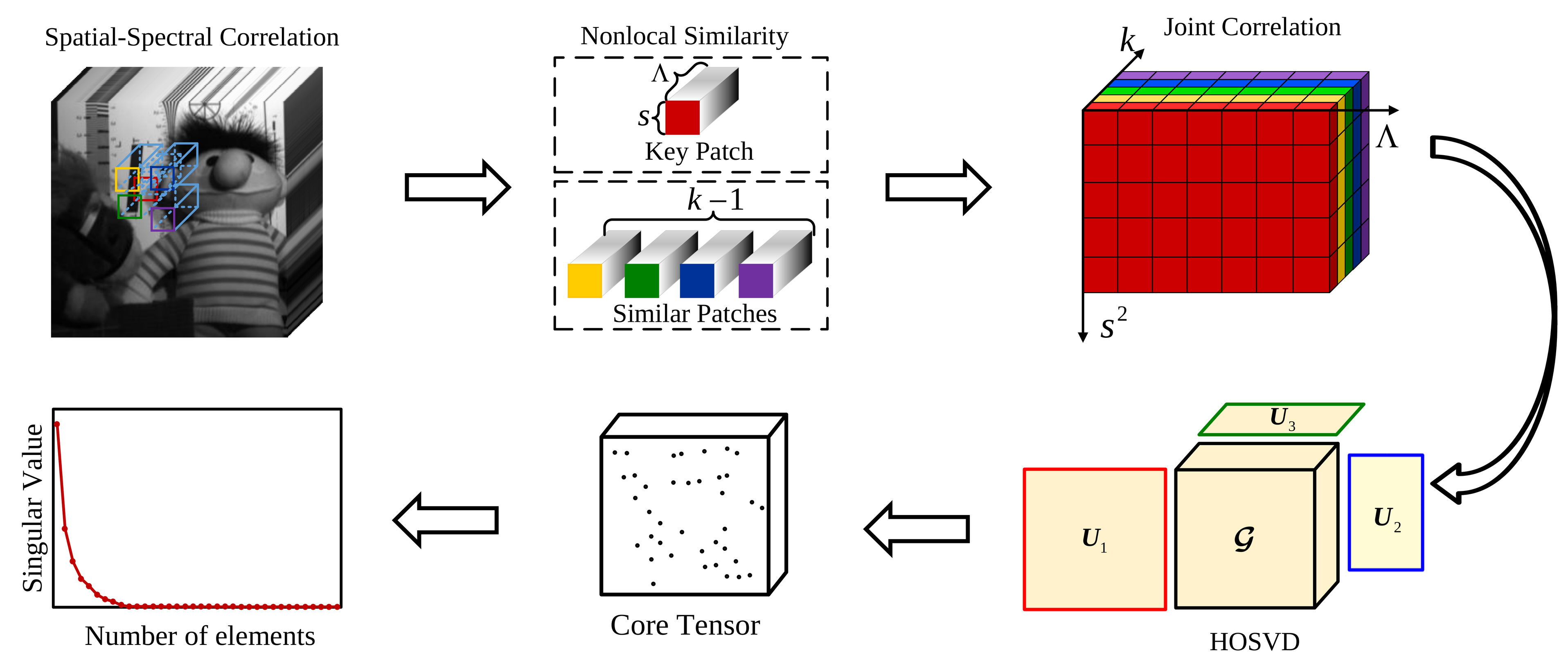
[3] Zhang et al. Ista-net: Interpretable optimization-inspired deep network for image compressive sensing. CVPR 2018.

[4] Xiong et al. Hscnn: Cnn-based hyperspectral image recovery from spectrally undersampled projections. CVPR 2017.

[5] Wang et al. Hyperspectral image reconstruction using a deep spatial-spectral prior. CVPR 2019.

Our approach

Weighted High-order Singular Value Regularization

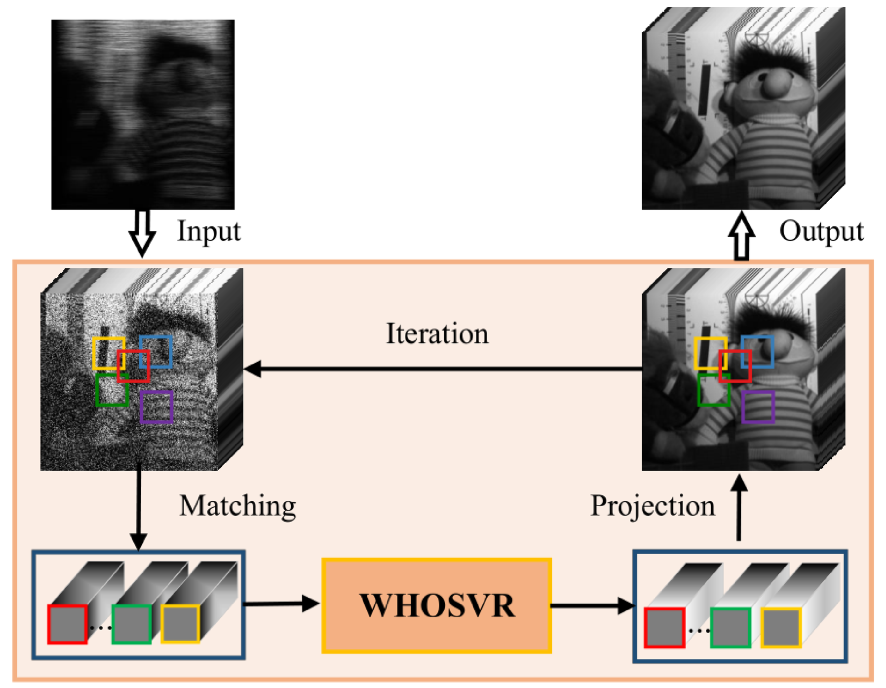


- Weighted high-order singular value regularization

$$\Gamma(\mathcal{G}) = \tau\|\mathbf{R}(\mathcal{X}) - \mathcal{G}\times_1 \boldsymbol{U}_1 \times_2 \boldsymbol{U}_2 \times_3 \boldsymbol{U}_3\|_F^2 + \|w \odot \mathcal{G}\|_1$$

$$w^{t+1} = c/(|w^t| + \varepsilon)$$

Model Based Reconstruction



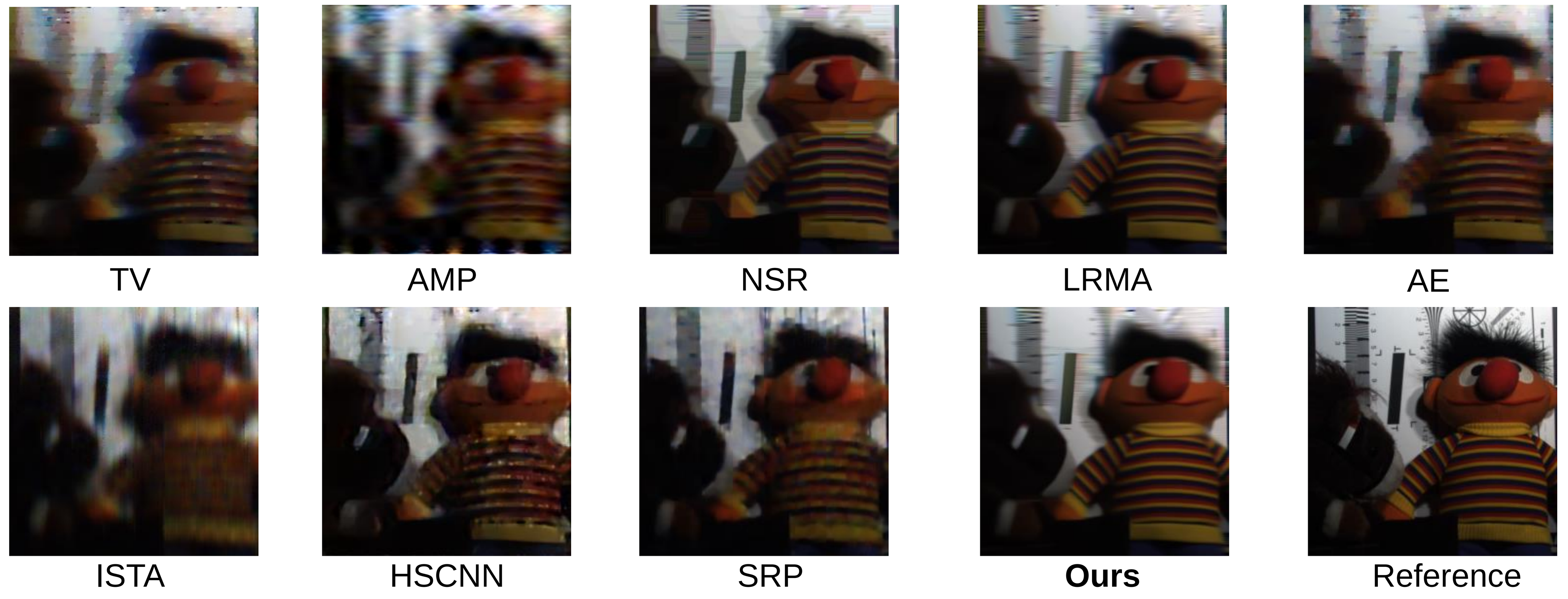
- Objective function

$$\min_{\mathcal{X},\mathcal{P}^l} \frac{1}{2}\|\boldsymbol{Y} - \Phi(\mathcal{X})\|_F^2 + \sum_{l=1}^{L}(\tau\|\mathbf{R}(\mathcal{X}) - \mathcal{G}\times_1 \boldsymbol{U}_1 \times_2 \boldsymbol{U}_2 \times_3 \boldsymbol{U}_3\|_F^2 + \|w \odot \mathcal{G}\|_1)$$

Experimental Results

Results on CASSI

Indexes	TV	AMP	NSR	LRMA[1]	AE[2]	ISTA[3]	HSCNN[4]	SPR[5]	Ours
PSNR	23.16	23.18	26.13	25.94	25.72	20.60	25.09	24.48	**28.05**
SSIM	0.7130	0.6600	0.7610	0.7930	0.7720	0.5499	0.7334	0.7395	**0.8302**
ERGAS	258.32	256.76	189.19	195.63	197.32	344.57	206.97	224.19	**153.06**



Results on DCCHI

Indexes	TV	AMP	NSR	LRMA	Ours
PSNR	28.51	28.52	32.58	37.45	**37.81**
SSIM	0.8938	0.8526	0.9377	0.9732	**0.9733**
ERGAS	167.14	140.75	107.71	57.30	**51.38**