Hyperspectral image super-resolution via non-local sparse tensor factorization

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1. Abstract:

Hyperspectral image (HSI) super-resolution, which fuses a low res-olution (LR) HSI with a high-resolution (HR) multispectral image (MSI), has recently attracted much attention. Most of the current HSI super-resolution approaches are based on matrix factorization, which unfolds the threedimensional HSI as a matrix before processing. In general, the matrix data representation obtained after the matrix unfolding oper-ation makes it hard to fully exploit the inherent HSI spatial-spectral structures.

In this paper, a novel HSI super-resolution method based on non-local sparse tensor factorization (called as the NLSTF) is pro-posed. The sparse tensor factorization can directly decompose each cube of the HSI as a sparse core tensor and dictionaries of three modes, which reformulates the HSI super-resolution problem as the estimation of sparse core tensor and dictionaries for each cube. To further exploit the non-local spatial self-similarities of the HSI, similar cubes are grouped together, and they are assumed to share the same dictionaries. The dictionaries are learned from the LR-HSI and HR-MSI for each group, and corresponding sparse core tensors are estimated by sparse coding on the learned dictionaries for each cube.

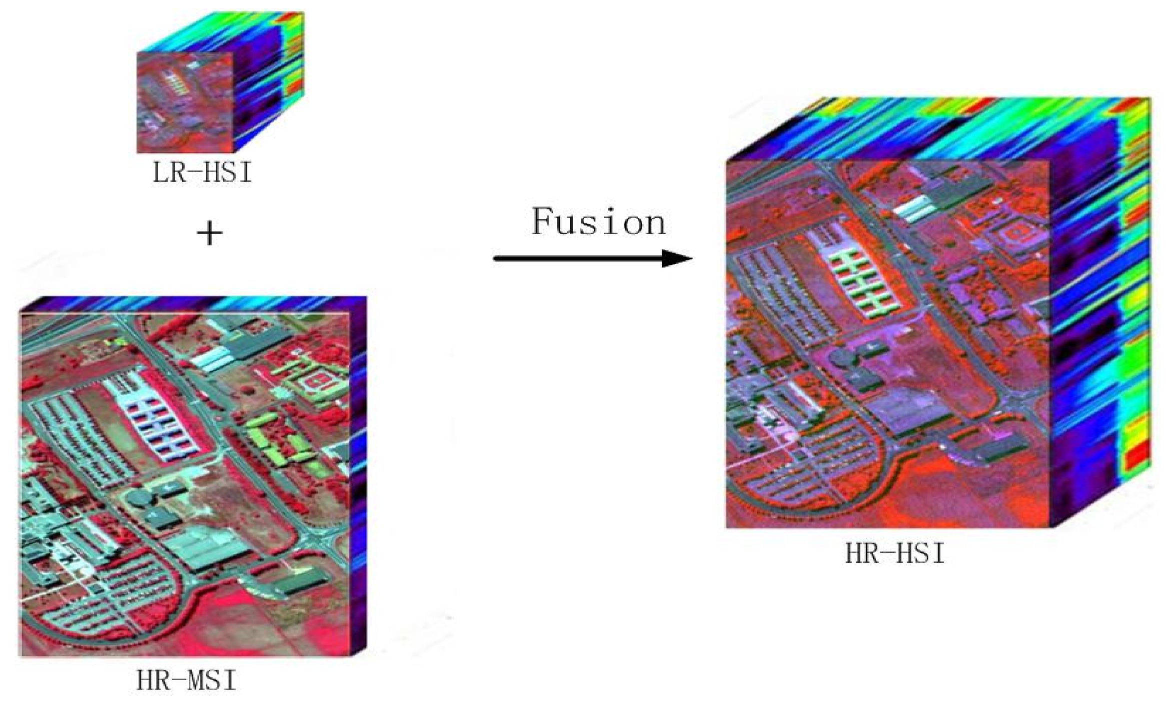

Fig. 1 Fusion based HSI superresolution.

2. Problem Formulation

2.1 Preliminaries

$\mathcal{X} \in R^{W\times H\times S}$: Unknown HR-HSI

$\mathcal{Y} \in R^{w\times h\times S}$: Acquired LR-HSI

$\mathcal{Z} \in R^{W\times H\times s}$: Acquired HR-MSI

Goal : Estimate $\mathcal{X}$ by fusing $\mathcal{Y}$ and $\mathcal{Z}$

2.2 Matrix factorization based HSI-super-resolution

Linear mixing based HSI decompostion:

$$\mathbf{X}_{(3)} = \mathbf{DA}$$

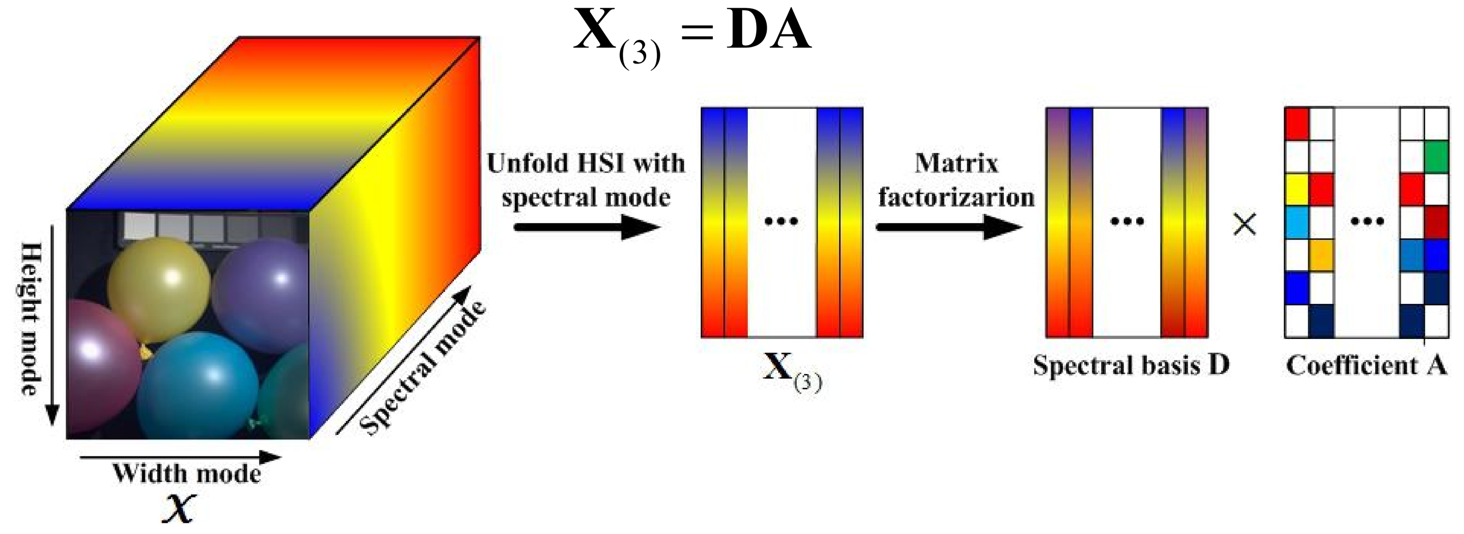

Fig. 2 Matrxi factorization based HR-HSI decomposition.

$$LR-HSI: \mathbf{Y}_{(3)} = \mathbf{X}_{(3)}\mathbf{M} = \mathbf{DAM} = \mathbf{DA}^*$$

$$HR-MSI: \mathbf{Z}_{(3)} = \mathbf{P_3 X}_{(3)} = \mathbf{P_3 DA} = \mathbf{D}^*\mathbf{A}$$

M is spatial downsampling matrix, **P3** is spectral downpling matrix. The goal is to estimate **D** and **A**

3. Tensor factorization based HSI super-resolution

Tucker fatorization based HR-HSI decomposition:

$$\mathcal{X} = \mathcal{C} \times_1 \mathbf{W} \times_2 \mathbf{H} \times_3 \mathbf{S}$$

W : dictionary of the width mode **H** : dictionary of the height mode

S : dictionary of the spectral mode $\mathcal{C}$**:** core tensor, it models the correlation of the dictionaries three modes. Since the high spatial-spectral correlation exists in the HR-HSI, the sparse prior is incoporated into the core tensor

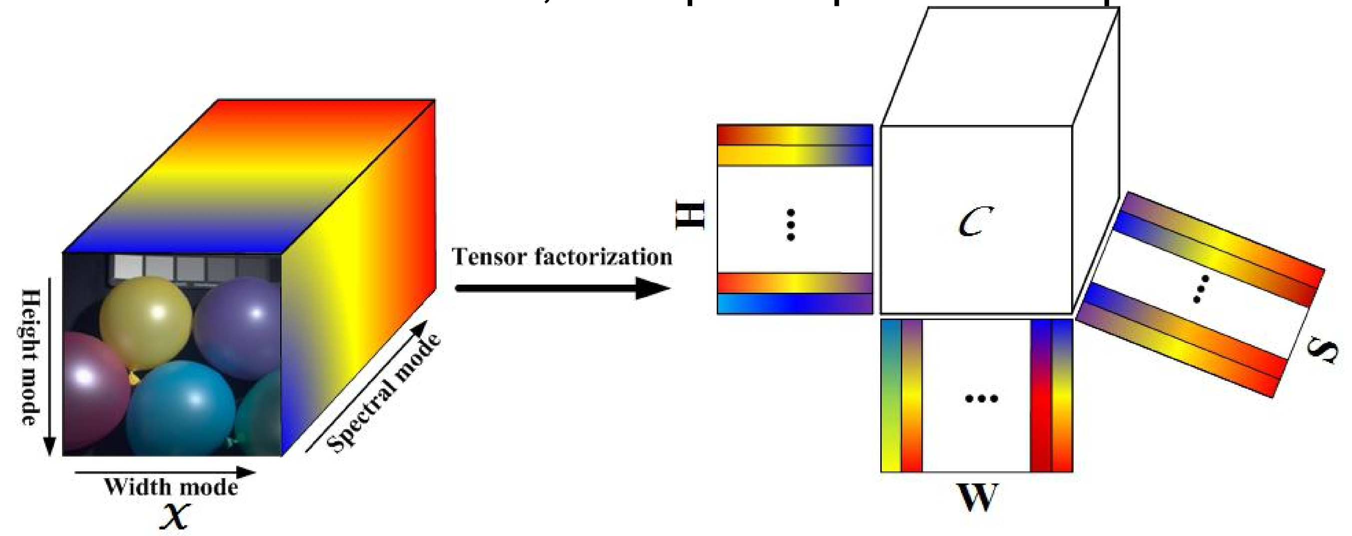

Fig. 3 Tensor factorization based HR-HSI decomposition.

$$LR-HSI: \mathcal{Y} = \mathcal{X} \times_1 \mathbf{P}_1 \times_2 \mathbf{P}_2 = \mathcal{C} \times_1 \mathbf{W} \times_2 \mathbf{H} \times_3 \mathbf{S} \times_1 \mathbf{P}_1 \times_2 \mathbf{P}_2$$
$$= \mathcal{C} \times_1 (\mathbf{P}_1\mathbf{W}) \times_2 (\mathbf{P}_2\mathbf{H}) \times_3 \mathbf{S}$$
$$HR-MSI\, \mathcal{Z} = \mathcal{X} \times_3 \mathbf{P}_3 = \mathcal{C} \times_1 \mathbf{W} \times_2 \mathbf{H} \times_3 \mathbf{S} \times_3 \mathbf{P}_3$$
$$= \mathcal{C} \times \mathbf{W} \times \mathbf{H} \times_3 (\mathbf{P}_3\mathbf{S})$$

P1 and P2 is the downsampling matrix of the width and height modes, respectively.

3. Proposed method

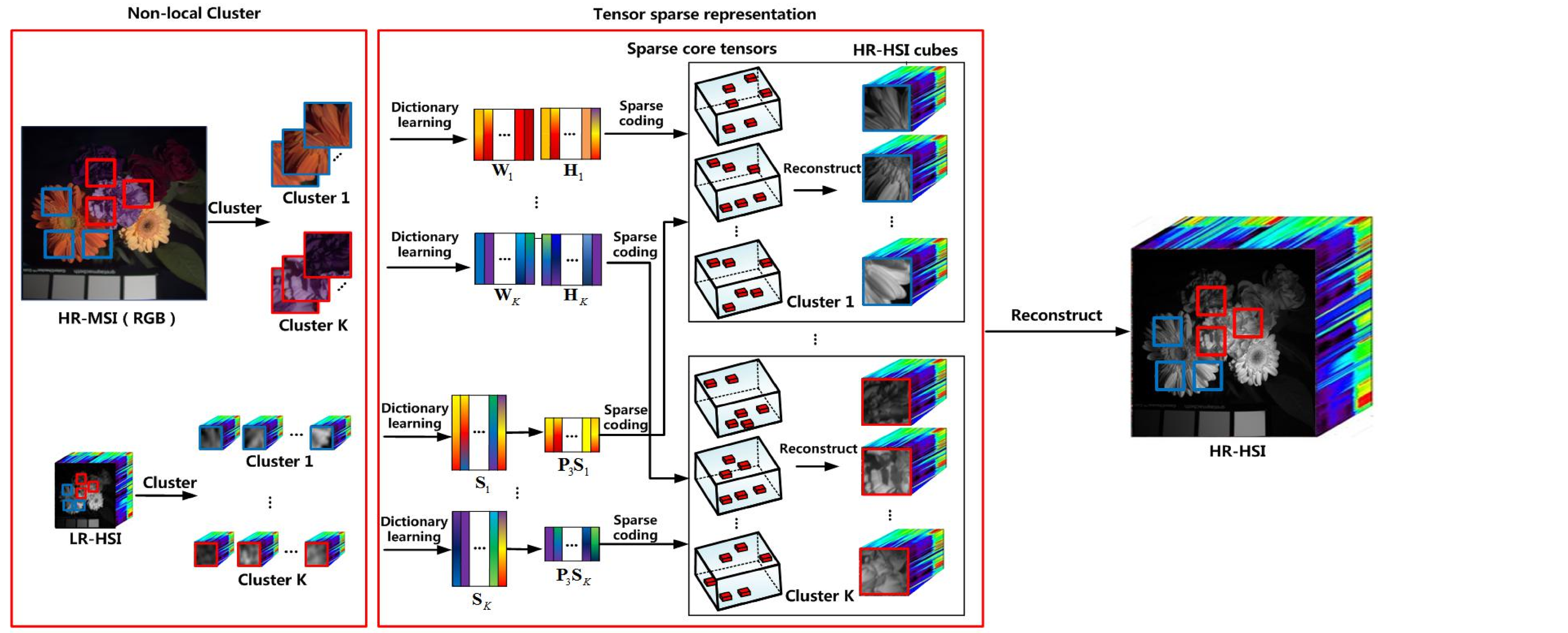

Fig. 4 The scheme of the proposed NLSTF method

Step 1. Cluster: Conduct non-local cluster on the HR-MSI, and the LR-HSI is also grouped into several groups according to corresponding spatial location.

Step 2. Dictionary learning: For each group, dictionaries **W** and **H** are learned from the HR-MSI, and the dictionary **S** is learned from the LR-HSI.

Step 3. Sparse coding: Estimate the sparse core tensor $\mathcal{C}$ over the learned dictionaries for each cube.

Table 1. Quantitative results of the test methods on the CAVE database. (Downsample factor 32)

	RMSE	SAM	SSIM	ERGAS
SNNMF (ICASSP 2013)	4.38	17.85	0.918	0.773
GSOMP (ECCV 2014)	5.73	12.19	0.960	0.815
SSR (TGRS 2015)	4.71	22.00	0.945	0.796
BSR (CVPR 2015)	5.19	12.93	0.955	0.787
Proposed NLSTF	2.60	6.83	0.980	0.858

Table 2. Quantitative results of the test methods on the Harvard database. (Downsample factor 32)

	RMSE	SAM	SSIM	ERGAS
SNNMF (ICASSP 2013)	2.46	4.93	0.973	0.381
GSOMP (ECCV 2014)	3.10	4.34	0.971	0.449
SSR (TGRS 2015)	3.08	5.59	0.820	0.459
BSR (CVPR 2015)	2.64	4.48	0.974	0.453
Proposed NLSTF	1.78	3.12	0.982	0.261