Paper ID:4141

Hyperspectral Image Super-resolution with Deep Priors and Degradation Model Inversion

Xiuheng Wang, Jie Chen†, Cédric Richard**

* Université Côte d'Azur, CNRS, OCA, France.

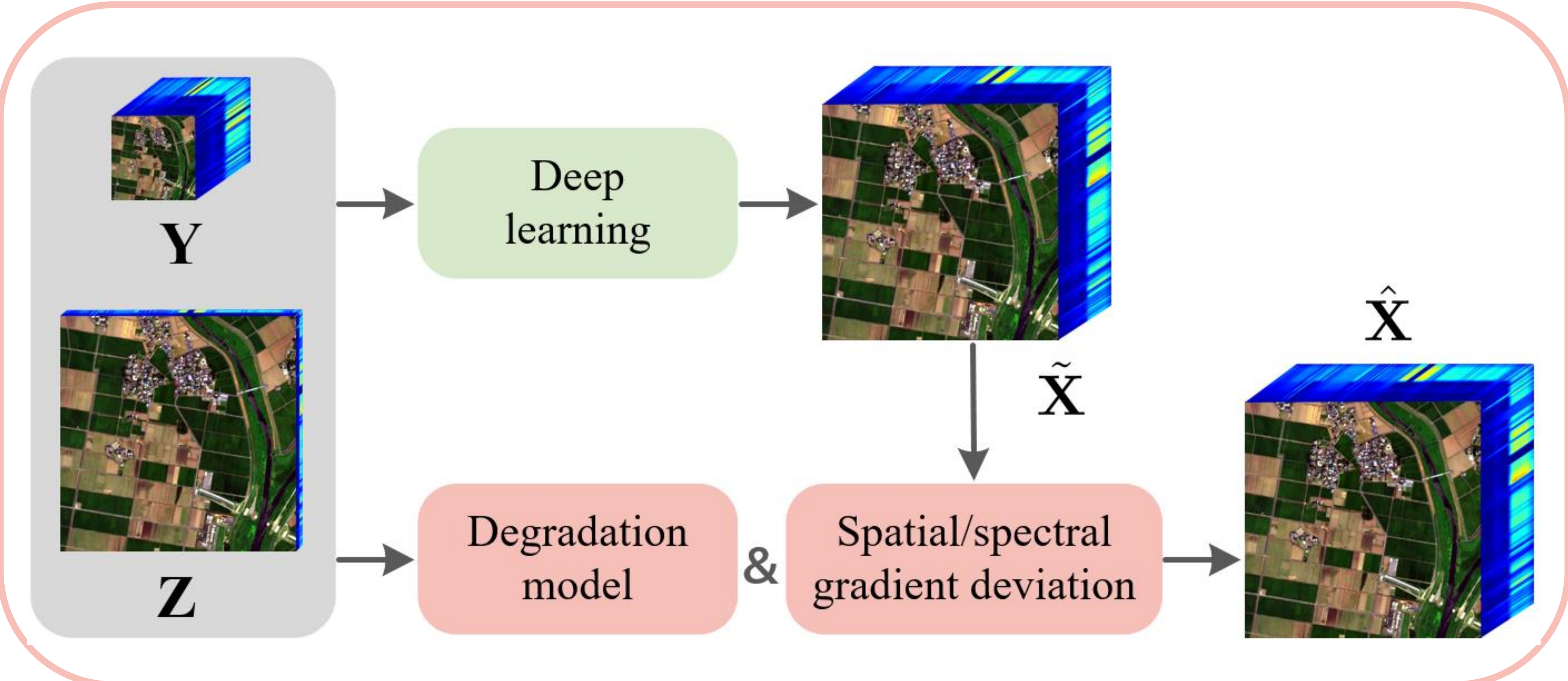
†School of Marine Science and Technology, Northwestern Polytechnical University, China

Introduction

1. We introduce a novel strategy for HSI super-resolution that
   - makes use of the physical linear degradation model in the data-fidelity term of the objective function;
   - exploits the spectral-spatial gradient difference of HSIs using a *deep prior regularizer* from the output of an CNN.
2. Experimental results show the performance improvement achieved with this strategy.

The Proposed Method

The scheme of our method:



Object function:

$$J(\mathbf{X}) = \|\mathbf{Y} - \mathbf{XBS}\|_F^2 + \|\mathbf{Z} - \mathbf{RX}\|_F^2 + \varphi(\mathbf{X})$$

$$\text{with } \varphi(\mathbf{X}) = \mu\|\mathbf{D}(\mathbf{x} - \tilde{\mathbf{x}})\|^2 + \nu\|\mathbf{E}(\mathbf{x} - \tilde{\mathbf{x}})\|^2$$

$$\text{and} \quad \tilde{\mathbf{X}} = \mathtt{CNN}(\mathbf{Y}, \mathbf{Z})$$

- $\|\mathbf{Y} - \mathbf{XBS}\|_F^2$ and $\|\mathbf{Z} - \mathbf{RX}\|_F^2$ guarantee that the candidate solution is consistent with the degradation model
- $\|\mathbf{D}(\mathbf{x} - \tilde{\mathbf{x}})\|^2$ and $\|\mathbf{E}(\mathbf{x} - \tilde{\mathbf{x}})\|^2$ are regularization terms exploiting deep priors, with positive hyper-parameters μ and ν.

References:

[1] Q. Wei, N. Dobigeon, and J.-Y. Tourneret, "Fast fusion of multi-band images based on solving a sylvester equation," TIP, 2015

[2] S. Henrot, C. Soussen, and D. Brie, "Fast positive deconvolution of hyperspectral images," TIP, 2012.

[3] F. Yasuma et al., "Generalized assorted pixel camera: postcapture control of resolution, dynamic range, and spectrum," TIP, 2010.

[4] A. Chakrabarti and T. Zickler, "Statistics of real-world hyperspectral images," CVPR, 2011.

[5] L. Zhang et al., "Unsupervised adaptation learning for hyperspectral imagery super-resolution," CVPR, 2020

[6] W. Dong et al., "Hyperspectral image super-resolution via non-negative structured sparse representation," TIP, 2016.

[7] R. Dian, S. Li, and L. Fang, "Learning a low tensor-train rank representation for hyperspectral image super-resolution," TNNLS, 2019.

Numerical Optimization

Variable splitting based on HQS:

$$\hat{\mathbf{X}} = \min_{\mathbf{X}} \|\mathbf{Y} - \mathbf{XBS}\|_F^2 + \|\mathbf{Z} - \mathbf{RX}\|_F^2 + \mu\|\mathbf{D}(\mathbf{v} - \tilde{\mathbf{x}})\|^2 + \nu\|\mathbf{E}(\mathbf{v} - \tilde{\mathbf{x}})\|^2 \quad \text{s.t.} \quad \mathbf{V} = \mathbf{X}.$$

⇓

$$\mathbf{X}_{k+1} = \min_{\mathbf{X}} \|\mathbf{Y} - \mathbf{XBS}\|_F^2 + \|\mathbf{Z} - \mathbf{RX}\|_F^2 + \rho\|\mathbf{X} - \mathbf{V}_k\|_F^2$$

$$\mathbf{v}_{k+1} = \min_{\mathbf{v}} \rho\|\mathbf{x}_{k+1} - \mathbf{v}\|^2 + \mu\|\mathbf{D}(\mathbf{v} - \tilde{\mathbf{x}})\|^2 + \nu\|\mathbf{E}(\mathbf{v} - \tilde{\mathbf{x}})\|^2$$

Optimization w.r.t. X:

$\mathbf{X}_{k+1}$ is the solution of the Sylvester equation:

$$\mathbf{C}_1\mathbf{X}_{k+1} + \mathbf{X}_{k+1}\mathbf{C}_2 = \mathbf{C}_3$$

where

$$\mathbf{C}_1 = \mathbf{R}^T\mathbf{R} + \mu\mathbf{I}_B$$

$$\mathbf{C}_2 = (\mathbf{BS})(\mathbf{BS})^T$$

$$\mathbf{C}_3 = \mathbf{R}^T\mathbf{Z} + \mathbf{Y}(\mathbf{BS})^T + \rho\mathbf{V}_k$$

For a fast algorithm solving this equation, refer to [1].

Optimization w.r.t. v:

The problem is decomposed in the Fourier domain [2] as

$$\min_{\mathbf{v}_\mathbf{f}} \|\mathbf{x}_{k+1,\mathbf{f}} - \mathbf{v}_\mathbf{f}\|^2 + \mu'\|\Delta_\mathcal{D}(\mathbf{f})(\mathbf{v}_\mathbf{f} - \tilde{\mathbf{x}}_\mathbf{f})\|^2 + \nu'\|\mathbf{E}_0(\mathbf{v}_\mathbf{f} - \tilde{\mathbf{x}}_\mathbf{f})\|^2$$

with the solution for each spatial frequency **f** :

$$\mathbf{v}_\mathbf{f} = \mathbf{T}_\mathbf{f}^{-1}(\mathbf{x}_{k+1,\mathbf{f}} + \mu'\Delta_\mathcal{D}(\mathbf{f})^*\Delta_\mathcal{D}(\mathbf{f})\tilde{\mathbf{x}}_\mathbf{f} + \nu'\mathbf{E}_0^*\mathbf{E}_0\tilde{\mathbf{x}}_\mathbf{f})$$

Finally, we can obtain $\mathbf{v}_{k+1}$ by the inverse 2D DFT.

Experimental Results

Table: Averaged RMSE, PSNR, SAM, ERGAS and SSIM of different methods on the CAVE and Harvard data sets.

Methods	CAVE data set					Harvard data set				
	RMSE	PSNR	ERGAS	SAM	SSIM	RMSE	PSNR	ERGAS	SAM	SSIM
UAL	1.854	44.656	0.196	4.33	0.9910	1.833	45.807	0.323	3.58	0.9832
UAL + Ours	**1.587**	**45.939**	**0.171**	**4.08**	**0.9917**	**1.784**	**46.034**	**0.316**	**3.54**	**0.9833**
NSSR	2.236	43.439	0.244	5.22	0.9849	1.874	45.540	0.363	3.73	0.9821
NSSR + Ours	**2.068**	**44.044**	**0.230**	**5.19**	**0.9854**	**1.844**	**45.649**	**0.357**	**3.69**	**0.9822**
LTTR	2.300	43.277	0.249	5.50	0.9848	1.914	45.251	0.375	3.81	0.9813
LTTR + Ours	**2.235**	**43.613**	**0.243**	**5.27**	**0.9851**	**1.887**	**45.392**	**0.374**	**3.77**	**0.9915**

The code is made available at github.com/xiuheng-wang

Datasets:

CAVE [3] and Harvard [4].

Baselines:

UAL [5], NSSR [6] and LTTR [7].

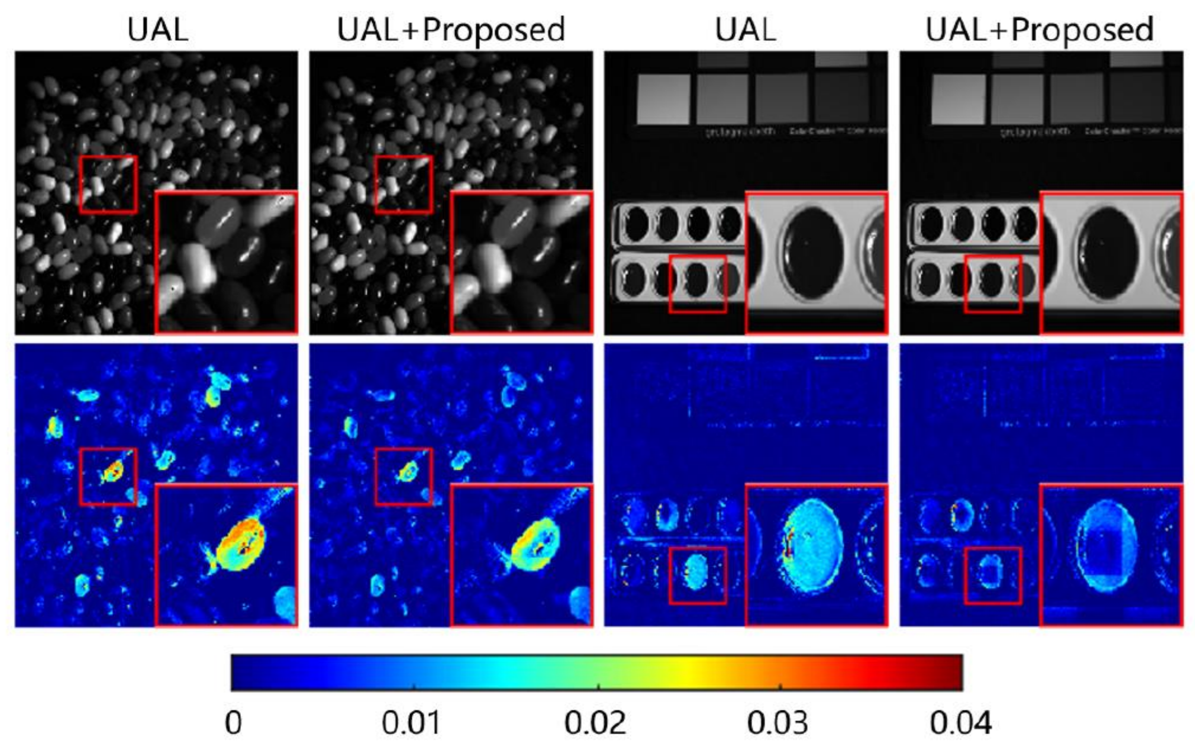


Figure: Reconstructed images and corresponding error maps of two images from the CAVE data set in the 540 nm band

- Table shows that our algorithm significantly improved the performance of the baselines.
- Figure confirms that our approach produced smaller reconstruction errors than the UAL.

Conclusion

In this paper, we introduced an HSI super-resolution method which makes use of a degradation model in the data-fidelity term of the objective function and, on the other hand, utilizes the spectral-spatial gradient deviation of latent HSIs and the output of a convolutional neural network as a deep prior regularizer.