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武漢大學 WUHAN UNIVERSITY

Hyperspectral Image Denoising via Noise-adjusted Iterative Randomized Singular Value Decomposition

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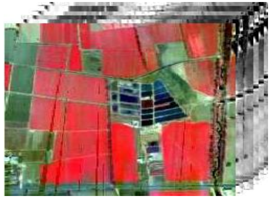
Content

Introduction of **H**yper**S**pectral **I**mage (HSI)

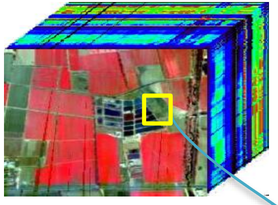
Development of optical remote sensing: the improvement of spectral resolution

Panchromatic

Color photography



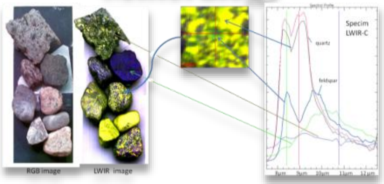
Multispectral



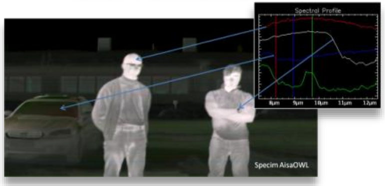
Hyperspectral

Mineralogy

…



Surveillance



Chemical imaging

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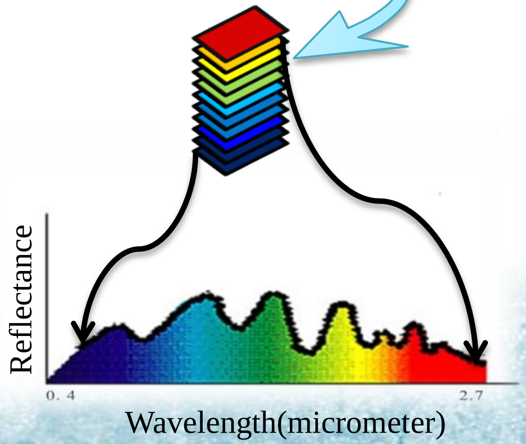
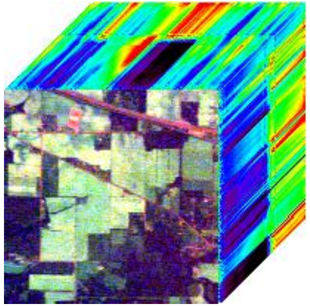
Agriculture

Applications



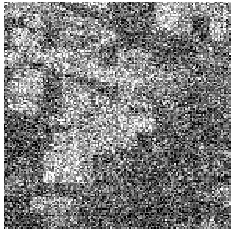
HSI Noise



AVIRIS Indian

Band 2

Band 144



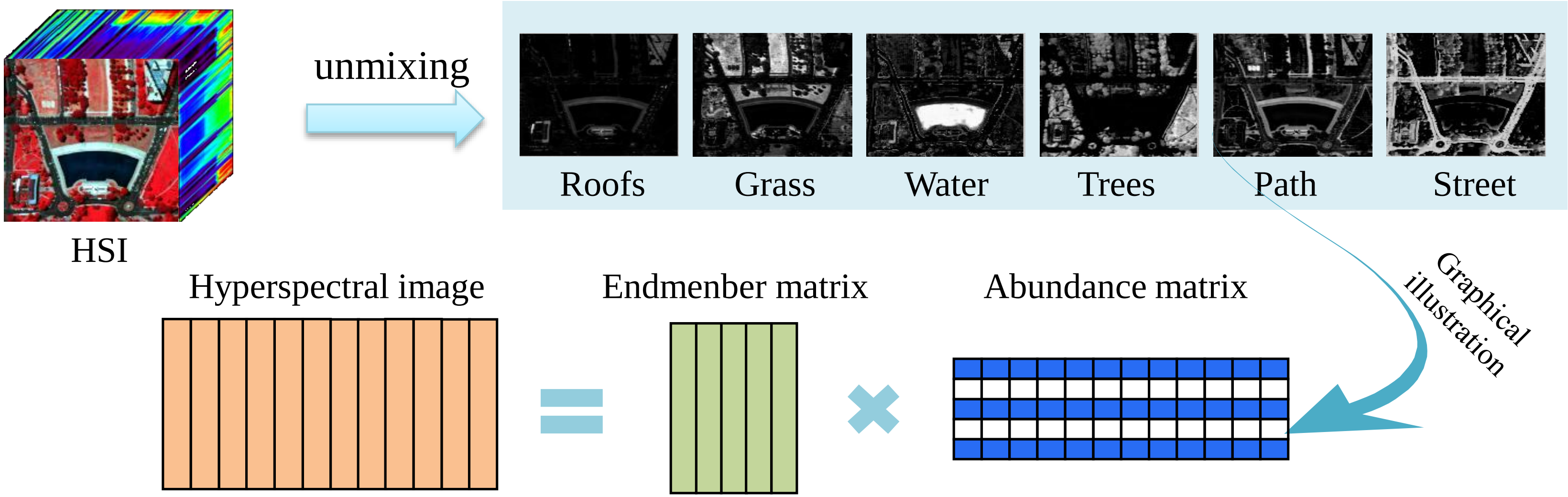
Band 220

- Challenges in HSI denoising
  - **High redundancy** in the spectral and spatial information
  - Noise intensity in different bands is **different**
- Our solution
  - Explore and utilize the **intrinsic characteristic** of the noise-free HSI
  - Adopt **Noise-adjusted iterative regularization** to handle different noise intensity in different bands

Content

Low-rank Property of HSI

❖ From view of unmixing: Linear mixing model

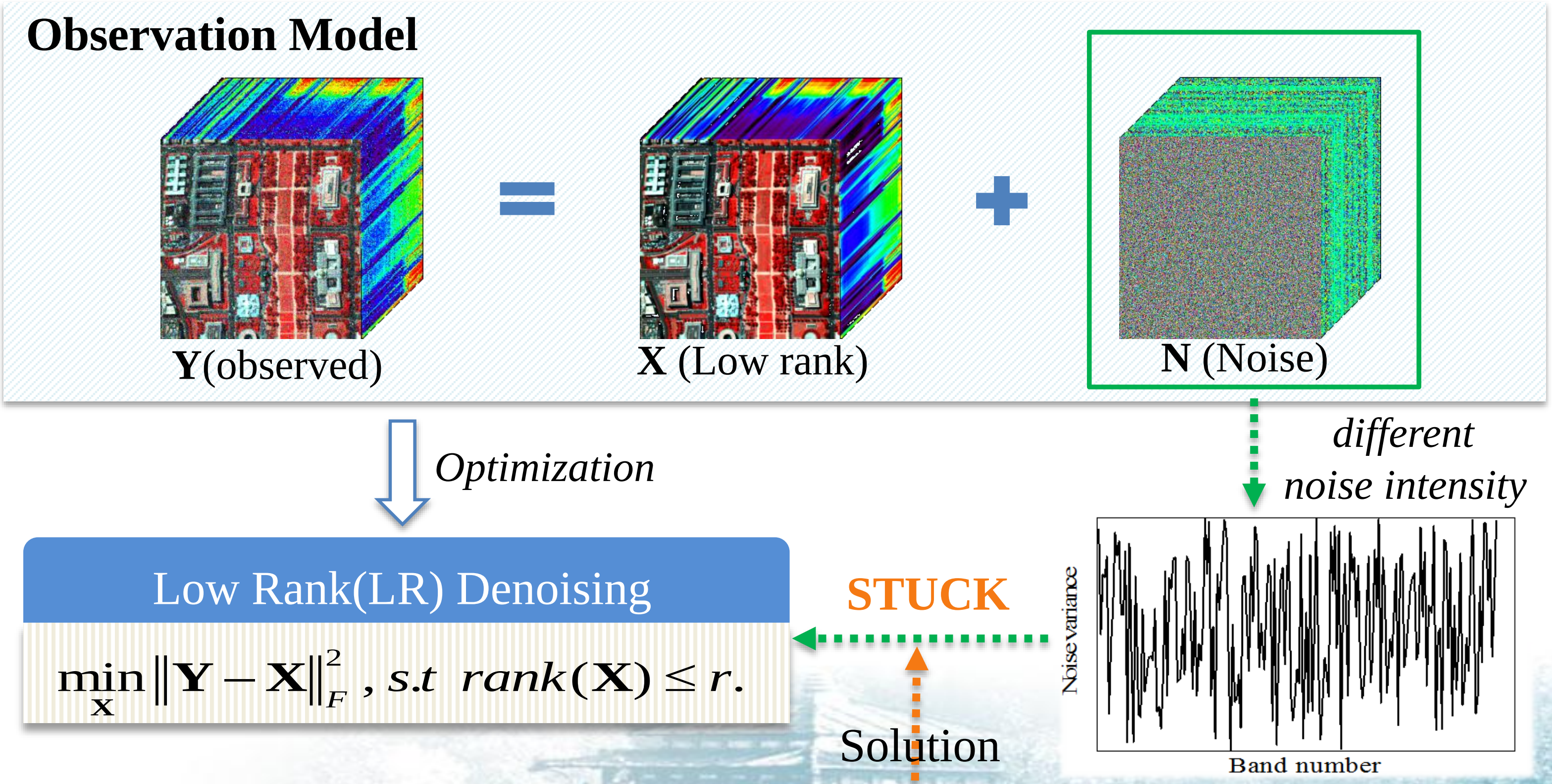


$Y=[Y_1,.....Y_n]\in\mathbb{R}^{d\times n}$ $\quad M=[x_1,......x_r]\in\mathbb{R}^{d\times r}$ $\quad S^T=[s_1,......s_r]^T\in\mathbb{R}^{r\times n}$

Comparision: Endmenber number *r* << HSI dimension *d*

⇒ Clean HSI lies in a low rank subspace

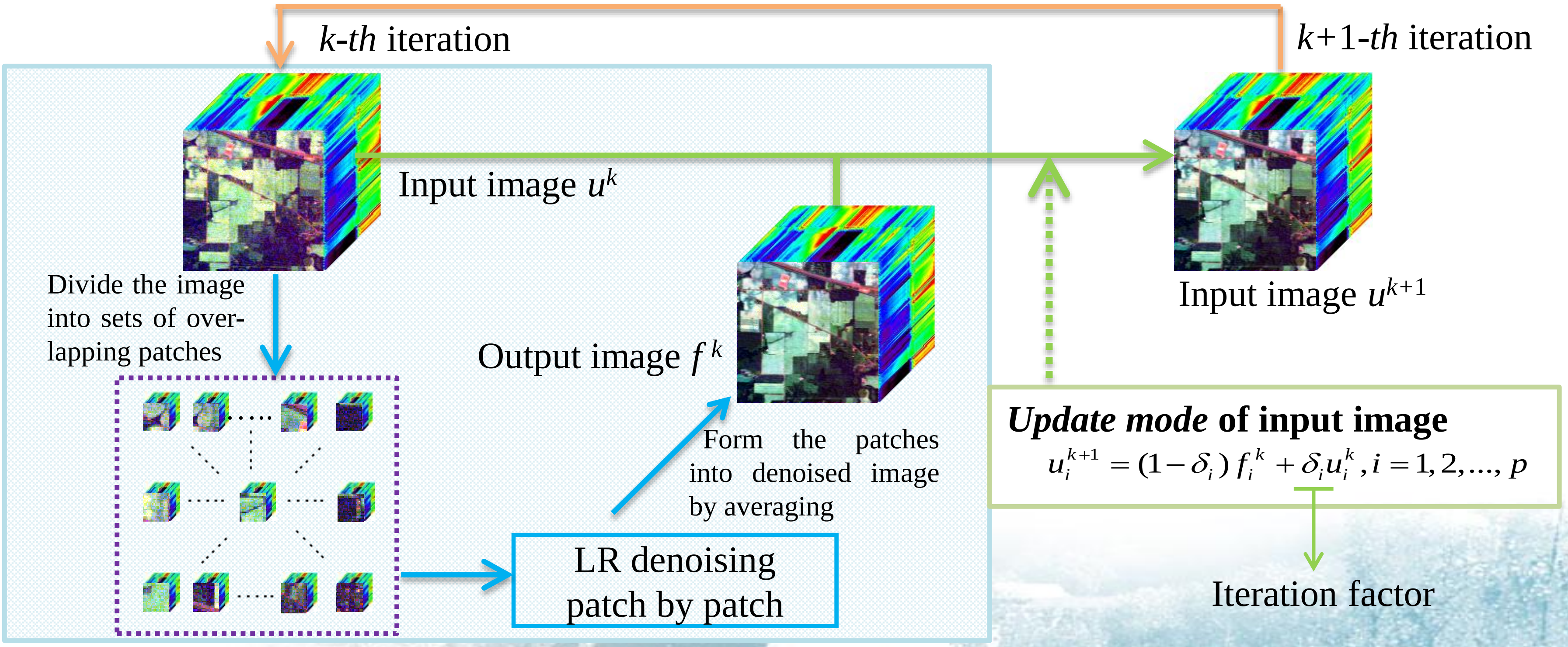
Low Rank based HSI Denoising Framework



Main contribution: Noise-adjusted iterative regularization

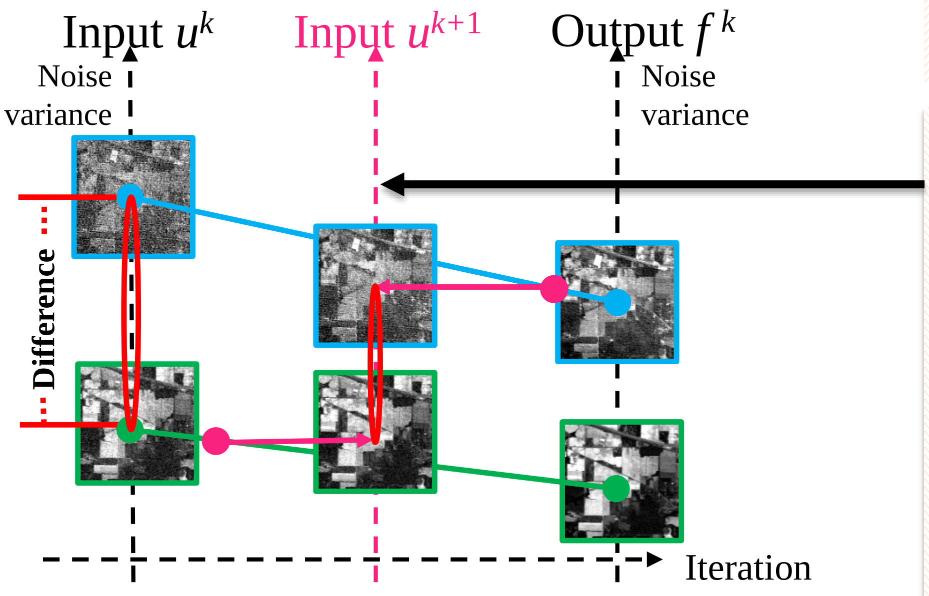
Noise-adjusted Iterative Regularization

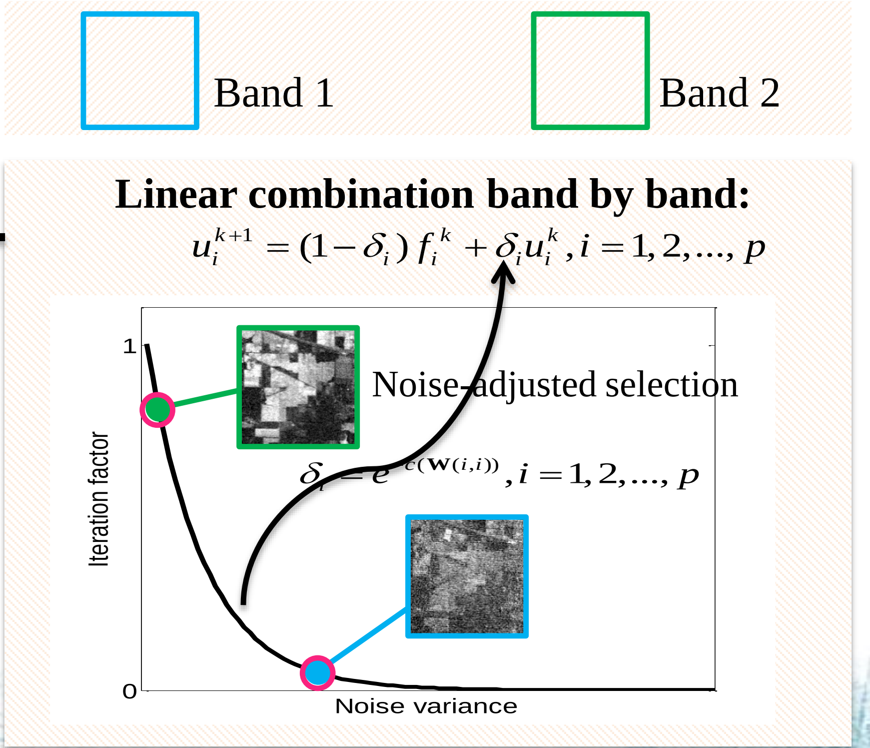
Flowchart of the proposed noise-adjusted iterative LR denoising



Zhang *et al*, 2014 && E. J. Candes *et al*, 2012

Noise-adjusted Iterative Regularization

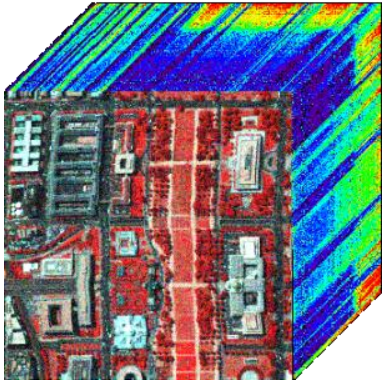




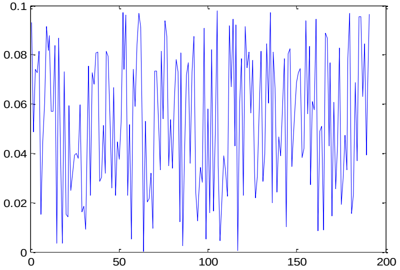
- Advantages of noise-adjusted iteration
  - ✓ Reduce the **noise variance difference** of each band
  - ✓ **Suppress noise** in strong noisy bands, meanwhile, **preserve details** in weak noisy bands.

Experimental Data

- Simulated data experiment

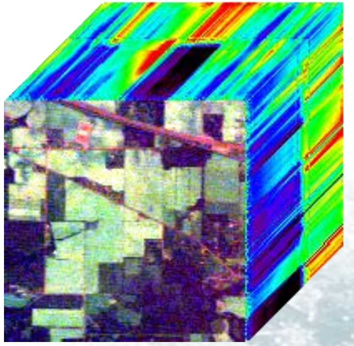


- Washington DC Mall
- HYDICE Data
- 256×256 pixels
- 191 bands



Simulated noise variance of each band

- Real data experiment



- Indian Pines data
- AVIRIS
- 145×145 pixels
- 220 bands

Ground truth for classification

Evaluation Indices & Benchmark

❖ Quantitative assessment indices

Peak Signal to Noise Ratio (PSNR)

$$PSNR = 10\log_{10}\frac{L^2 mn}{\sum_{x=1}^{m}\sum_{y=1}^{n}\left[\hat{z}(x-y)-z(x-y)\right]^2}$$

$$MPSNR = \frac{1}{p}\sum_{j=1}^{p} PSNR_j$$

Structural Similarity (SSIM)

$$SSIM = \frac{(2\mu_z\mu_{\hat{z}}+C_1)(2\sigma_{z\hat{z}}+C_2)}{(\mu_z{}^2+\mu_{\hat{z}}{}^2+C_1)(\sigma_z{}^2+\sigma_{\hat{z}}{}^2+C_2)}$$

$$MSSIM = \frac{1}{p}\sum_{j=1}^{p} SSIM_j$$

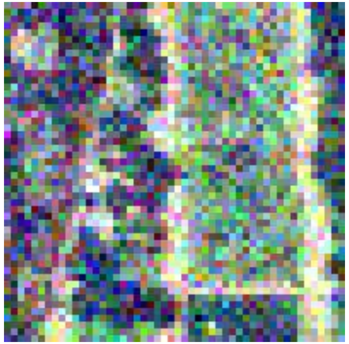
❖ Compared methods

- ✓ **SSAHTV** [Q. Yuan *et.al* "Hyperspectral image denoising employing a spectral-spatial adaptive total variation model," TGRS, vol. 50, no. 10, pp. 3660–3677, Oct. 2012.]
- ✓ **VBM3D** [K. Dabov *et.al* "Video denoising by sparse 3D transform-domain collaborative filtering," 2007.]
- ✓ **BM4D** [M. Maggioni *et.al* "Nonlocal transform-domain filter for volumetric data denoising and reconstruction," TIP, vol. 22, no. 1, pp. 119–133, Jan. 2013.]
- ✓ **SURE-SVT** [E. Candes *et.al* "Unbiased risk estimates for singular value thresholding and spectral estimators," arXiv preprint arXiv:1210.4139, 2012.]
- ✓ **LRMR** [Zhang et.al, 2014 "Hyperspectral image restoration using low-rank matrix recovery," TGRS, vol. 52, no. 8, pp. 4729–4743, Aug. 2014.]
- ✓ **NAIRSVD** [Proposed, noise-adjusted iterative low rank based method solved via randomized singular value decomposition]

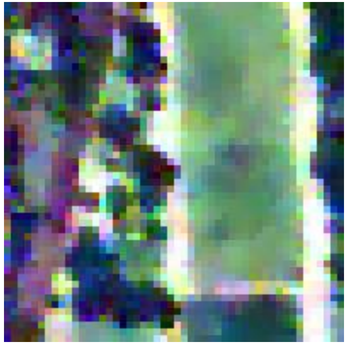
Simulated Experiment

- Denoised results of band 52, 105, and 191

Original

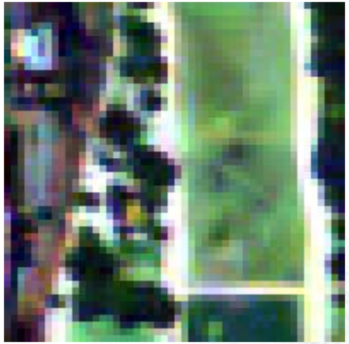


Noisy



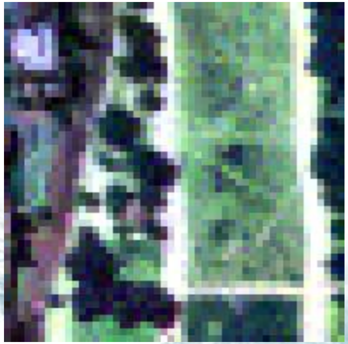
SSAHTV

VBM3D



BM4D

SURE-SVT



LRMR

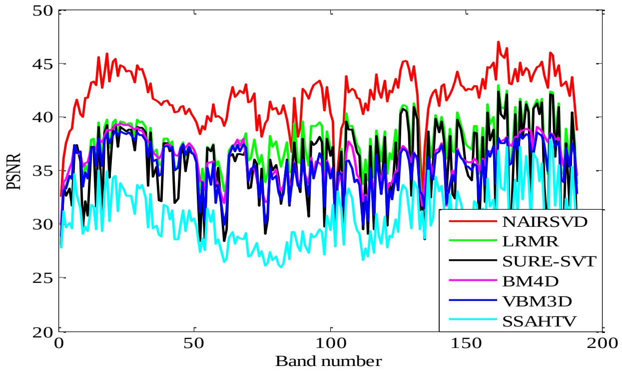
NAIRSVD

Simulated Experiment

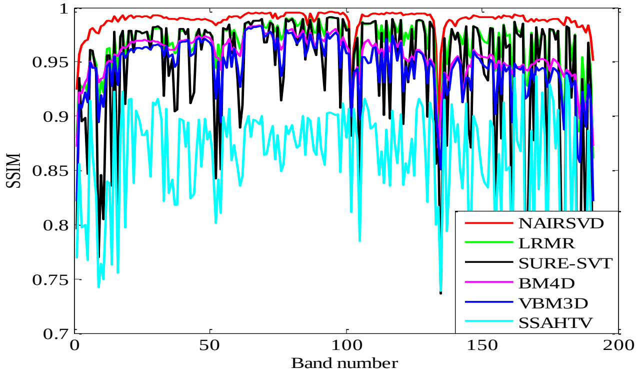
- MPSNR and MSSIM values of the denoised results

Data	Evaluation index	SSAHTV	VBM3D	BM4D	SURE-SVT	LRMR	NAIRSVD
Washington	MPSNR(dB)	30.59	35.35	35.98	35.61	37.64	**42.05**
DC Mall	MSSIM	0.8593	0.9459	0.9553	0.9405	0.9698	**0.9882**

- PSNR and SSIM values of each band



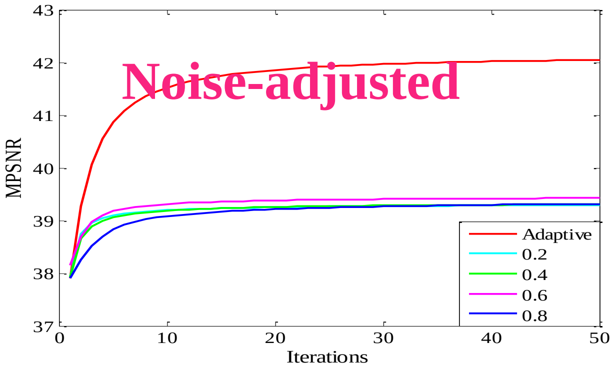
PSNR

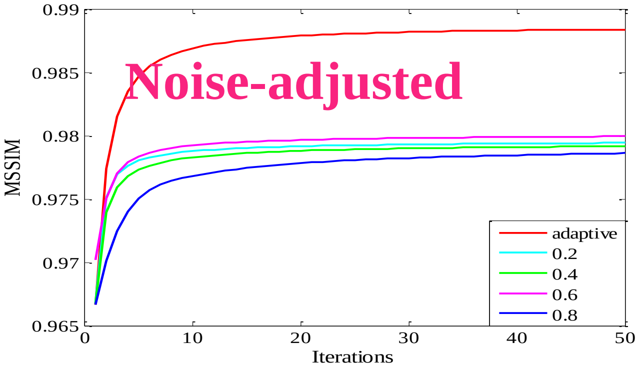


SSIM

Simulated Experiment

- Analysis of iteration factor





δ_i : Noise-adjusted selection

$$u_i^{k+1} = (1-\delta_i) f_i^k + \delta_i u_i^k, i = 1, 2, \ldots, p$$

Where $\delta_i = e^{-c(\mathbf{W}(i,i))}, i = 1, 2, \ldots, p$

VS

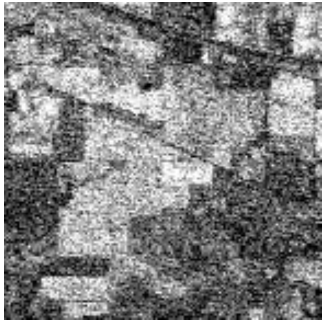
δ : Constant for all bands

$$u^{k+1} = (1-\delta) f^k + \delta u^k$$

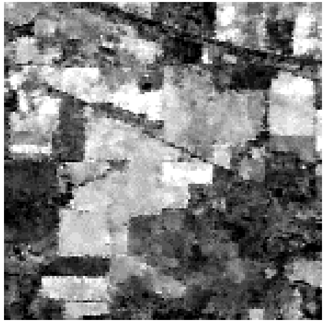
$$\delta = 0.2,\ 0.4,\ 0.6,\ 0.8$$

Real Data Experiment

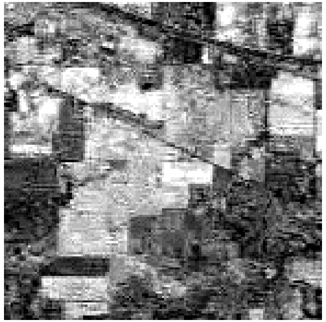
- Denoised results of band 103



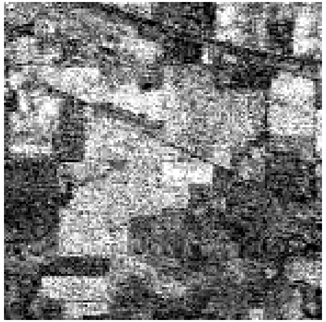
Noisy



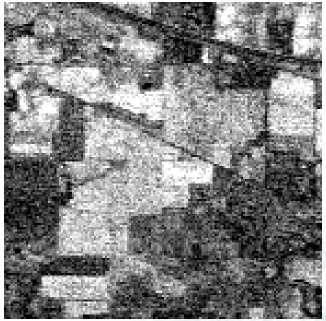
SSAHTV



VBM3D



BM4D



SURE-SVT

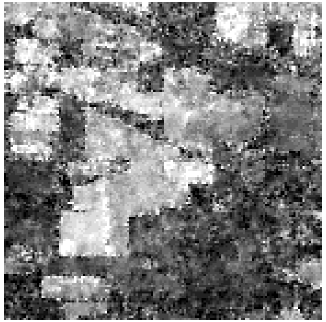
LRMR

NAIRSVD

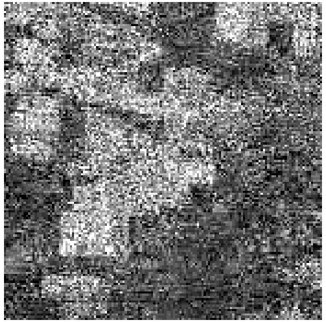
Real Data Experiment

- Denoised results of band 220

Original



SSAHTV



VBM3D

BM4D

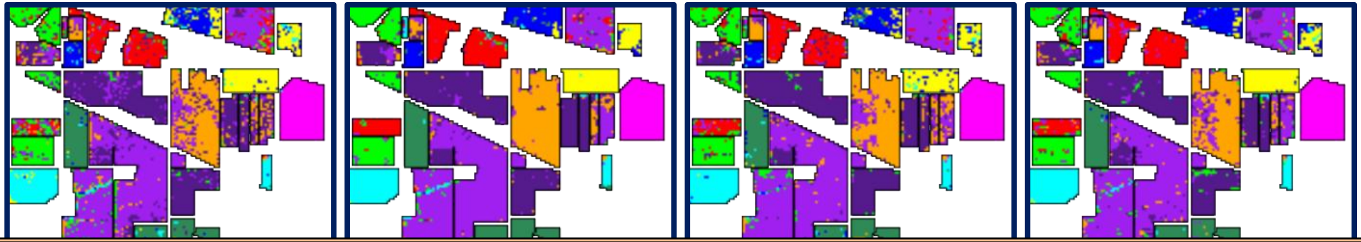
SURE-SVT

LRMR

NAIRSVD

Real Data Experiment

- Observation: the better classification result, the lower noise of input image.



	Origin	SSAHTV	VBM3D	BM4D	SURE-SVT	LRMR	NAIRSVD
OA	0.7618	0.9123	0.8562	0.8689	0.8757	0.9406	**0.9615**
Kappa	0.7398	0.9009	0.8394	0.8536	0.8604	0.9323	**0.9558**

SURE-SVT LRMR NAIRSVD

Conclusions

- Hyperspectral image (HSI) lies in a low dimensional subspace, and low rank approximation method is appropriate for HSI processing.

- The proposed noise-adjusted iterative randomized singular value decomposition (NAIRSVD) method is useful for different intensity noise removal in HSI.

- The parameters are adaptively determined in the proposed method. Especially, noise variance is estimated via multiple regression theory-based method and the rank is estimated via SVD.

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[2] C.-I. Chang and Q. Du, “Interference and noise-adjusted principal components analysis,” *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 5, pp. 2387–2396, Sept. 1999.

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[6] K. Dabov, A. Foi, and K. Egiazarian, “Video denoising by sparse 3D transform-domain collaborative filtering,” presented at the European Signal Processing Conf., Poznan, Poland, Sept. 2007.

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THANK YOU FOR YOUR ATTENTION!