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Combined the Data-driven with Model-driven Strategy: A Novel Framework for Mixed Noise Removal in Hyperspectral Image

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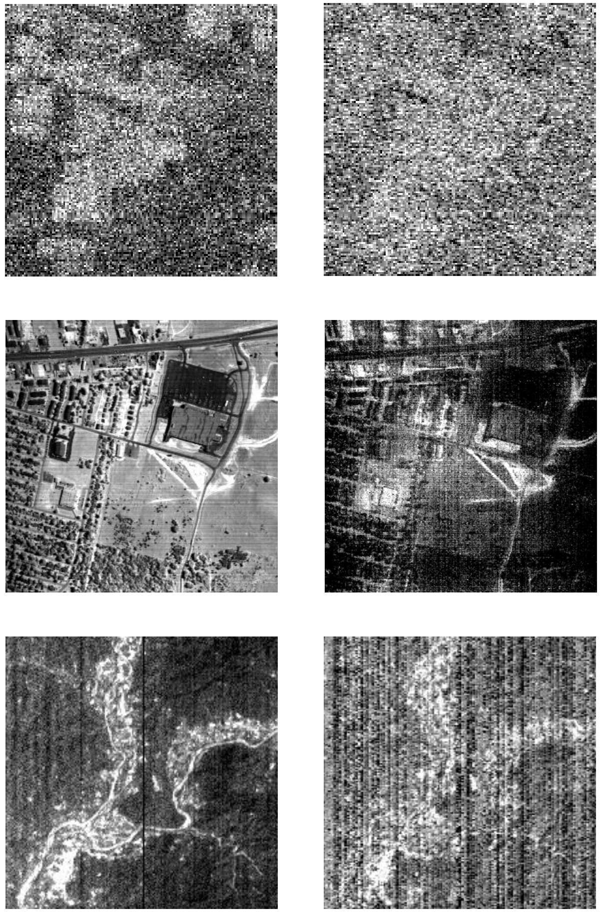
Outline

1 Background

HSI Mixed Noise Removal



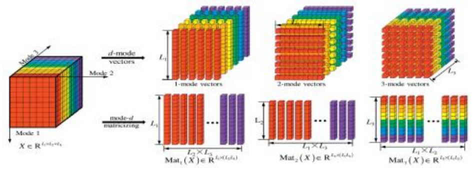
Mild, Middle, Severe...

Noise Levels

Varying in Different Bands!

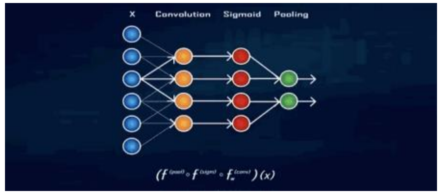
Noise types

Gaussian, Poisson, Stripe, Deadline...



- **Model-driven Methods**:
  Total Variation
  Low Rank Matrix/Tensor
  Spare Representation

- **Data-driven Methods**:
  HSID-CNN (Yuan et al, 2018)
  HSI-DeNet (Chang et al., 2018)
  SSGN (Zhang et al., 2019)



How about Combined the Data-driven with Model-driven Strategy?

Outline

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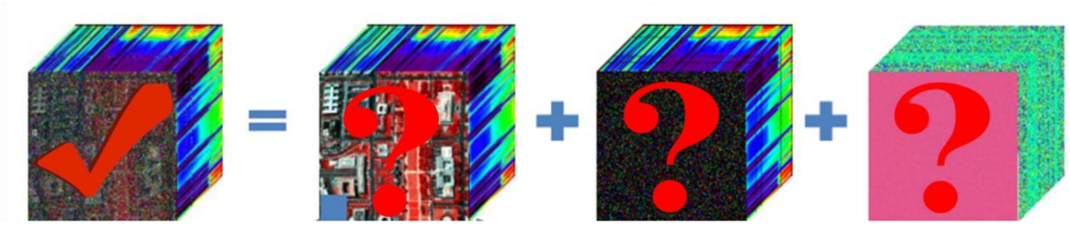
2 **Methodology**

3 Experiments

4 Conclusion

2 Methodology

1) Problem Formulation



Noisy HSI = Clean HSI + Sparse Noise + Non-i.i.d. Noise

$$\mathbf{Y} = \mathbf{X} + \mathbf{S} + \mathbf{N}$$

Latent Clean HSI

Noise Variance

$$\mathbf{Y}_i \sim \mathcal{N}(\mathbf{Y}_i \mid \mathbf{Z}_i, \sigma_i^2), \ i = 1, 2, \cdots b$$

$$\mathbf{Z}_i \sim \mathcal{N}(\mathbf{Z}_i \mid \mathbf{X}_i, \varepsilon_0^2), \ i = 1, 2, \cdots b$$

$$\sigma_i^2 \sim \mathcal{IG}(\sigma_i^2 \mid \frac{p^2}{2} - 1, \frac{p^2 \xi_i}{2}), \ i = 1, 2, \cdots b$$

$$\mathbf{S}_i \sim \mathcal{K}(\mathbf{S}_i \mid Y_i, \mathbf{Y}), \ i = 1, 2, \cdots b$$

Bayesian Posterior Framework:

$$q(\mathbf{Z}_i, \sigma_i^2, \mathbf{S}_i \mid \mathbf{Y}) = q(\mathbf{Z}_i \mid \mathbf{Y}) q(\sigma_i^2 \mid \mathbf{Y}) q(\mathbf{S}_i \mid \mathbf{Y})$$

How to infer the three variables ?

$$q(\mathbf{Z}_i \mid \mathbf{Y}) = \mathcal{N}(\mathbf{Z}_i \mid \varphi_i(Y_i, \mathbf{Y}_s; W_E), m_i^2(Y_i, \mathbf{Y}_s; W_E))$$

Non-i.i.d. noise estimation

$$q(\sigma_i^2 \mid \mathbf{Y}) = \mathcal{IG}(\sigma_i^2 \mid \alpha_i(Y_i, \mathbf{Y}_s; W_D), \beta_i(Y_i, \mathbf{Y}_s; W_D))$$

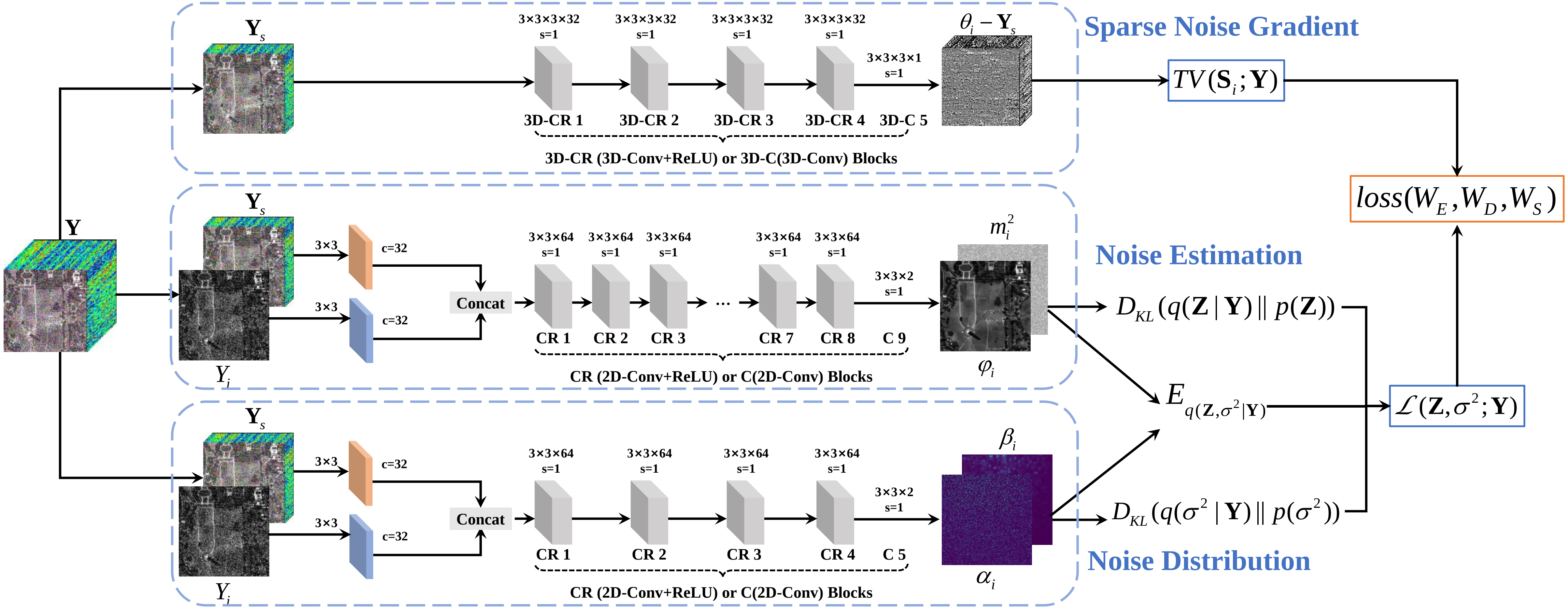
Non-i.i.d. noise distribution

$$q(\mathbf{S}_i \mid \mathbf{Y}) = TV(\mathbf{S}_i \mid \mathbf{K}_s(\nabla \mathbf{Y}_s; W_s))$$

Sparse noise spatio-spectral gradient

2 Methodology

2) Flowchart



Deep Spatio-Spectral Network + Bayesian Posterior

2 Methodology

3) Model Optimization

The lower bound of the non-i.i.d. noise

$$\mathcal{L}(\mathbf{Z},\sigma^2;\mathbf{Y}) = E_{q(\mathbf{Z},\sigma^2|\mathbf{Y})} - D_{KL}(q(\mathbf{Z}\,|\,\mathbf{Y})\,\|\,p(\mathbf{Z})) - D_{KL}(q(\sigma^2\,|\,\mathbf{Y})\,\|\,p(\sigma^2))$$

*** More details can be found in the following reference**

Anisotropic TV term for sparse noise

$$TV(\mathbf{S}_i;\mathbf{Y}) = \underbrace{\|\nabla_v \mathbf{K}_s\|_1}_{\text{Vertical gradient of spectral difference}} + \underbrace{\|\nabla_h \mathbf{K}_s\|_1}_{\text{Horizontal gradient of spectral difference}}$$

$$loss(W_E, W_D, W_S) = -\mathcal{L}(\mathbf{Z},\sigma^2;\mathbf{Y}) + \eta \cdot TV(\mathbf{S}_i;\mathbf{Y})$$

Using BP to optimize W_E, W_D, W_S

Zhang *et al.*, Deep spatio-spectral Bayesian posterior for hyperspectral image non-i.i.d noise removal. ISPRS P&RS, 2020.

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3 Experiments

Simulated Experiments

	Noisy	HSSNR	BM4D	LRMR	NMoG	SSGN	Proposed
Case 1: i.i.d. Gaussian noise							
MPSNR	23.27	27.25	28.62	33.21	34.51	34.37	**34.53**
MSSIM	0.769	0.923	0.941	0.981	**0.983**	0.982	0.982
MSA	19.47	9.083	5.116	4.628	**4.127**	4.241	4.129
Time/s	-	304.4	461.8	449.6	513.8	**7.3**	14.8
Case 2: non-i.i.d. Gaussian noise							
MPSNR	19.78	23.51	24.24	28.73	29.76	25.90	**30.88**
MSSIM	0.654	0.84	0.856	0.958	0.962	0.896	**0.976**
MSA	23.72	11.34	10.37	6.14	5.73	9.21	**5.102**
Time/s	-	312.6	479.5	437.9	538.2	**7.2**	15.0
Case 3: non-i.i.d. Gaussian noise + stripe noise							
MPSNR	20.82	25.64	26.39	28.35	29.98	27.35	**30.67**
MSSIM	0.669	0.893	0.938	0.957	0.967	0.948	**0.974**
MSA	22.47	10.92	7.87	6.142	6.298	6.565	**5.436**
Time/s	-	314.8	486.3	440.7	542.5	**7.3**	15.1

Quantitative Evaluation of the W. DC HSI data

Model-driven:

- **HSSNR (TGRS, 2006)**
- **BM4D (TIP, 2012)**
- **LRMR (TGRS, 2014)**
- **NMoG (TCYB, 2018)**

Data-driven:

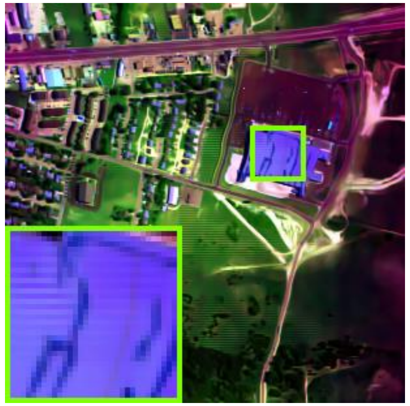
- **SSGN (TGRS, 2019)**

3 Experiments

Real Experiments

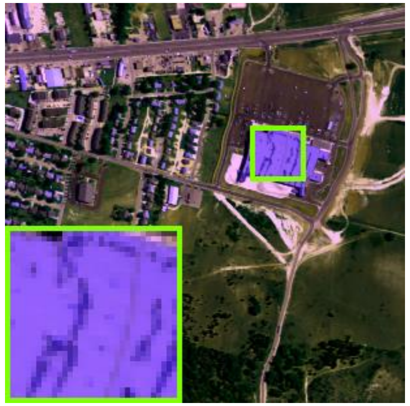
(a) Noisy (24, 104, 187)

(b) HSSNR



(c) BM4D

(d) LRMR



(e) NMoG

(f) SSGN

(g) Proposed

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4 Conclusion

- Combine the model-driven and data-driven based strategy
- Deep spatio-spectral Bayesian posterior framework
- Aiming at mixed noise in hyperspectral image

Paper & Code & Dataset

Thanks!

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