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Deep Residual Attention Network for Hyperspectral Image Reconstruction

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Research Background

- What is a hyperspectral image?

RGB Image
(3 spectral channels)

Hyperspectral Image
(Decades or hundreds of spectral channels)

Hyperspectral Image (HSI): 3D tensor image containing abundant spectral information

Different Applications:

1) Remote sensing   2) Medical daignostics

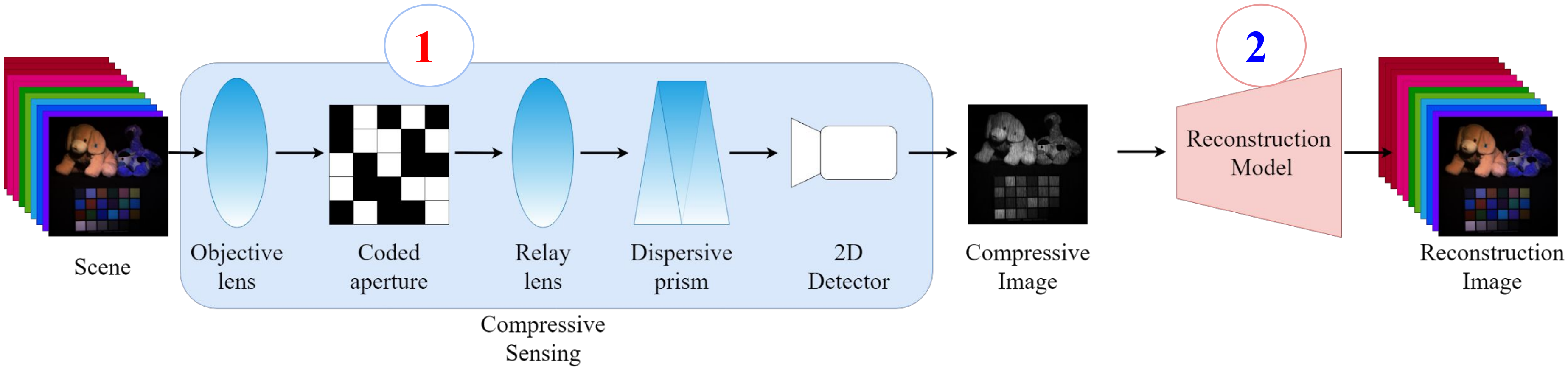
Research Background and purpose

- Imaging the 3D cubic data: Taking long time using 1D or 2D sensor

popularly used HS imaging system:

Coded Aperture snapshot spectral imaging (CASSI)

1. Measure phase: encoding the 3D HSI into a single 2D compressive image (**snapshot)**
   -->Imaging moving objects or capturing video at high-speed rates.
2. **Reconstruction phase**: employing an inverse optimization strategy to recover the underlying HSI



Research purpose: propose a novel deep learning based reconstruction model for effectively and efficiently restore HSI

Motivation

Recently method: Deep learning based method

- Automatically learn the image priors using DCNN
- High restoration ability and Low computational cost

Complicate and deep network architecture for performance boosting

A lot of redundant feature maps

Our Proposal:

1. Multi-stage reconstruction blocks with residual structure

   □**Hierarchically reconstruct the un-recovering**

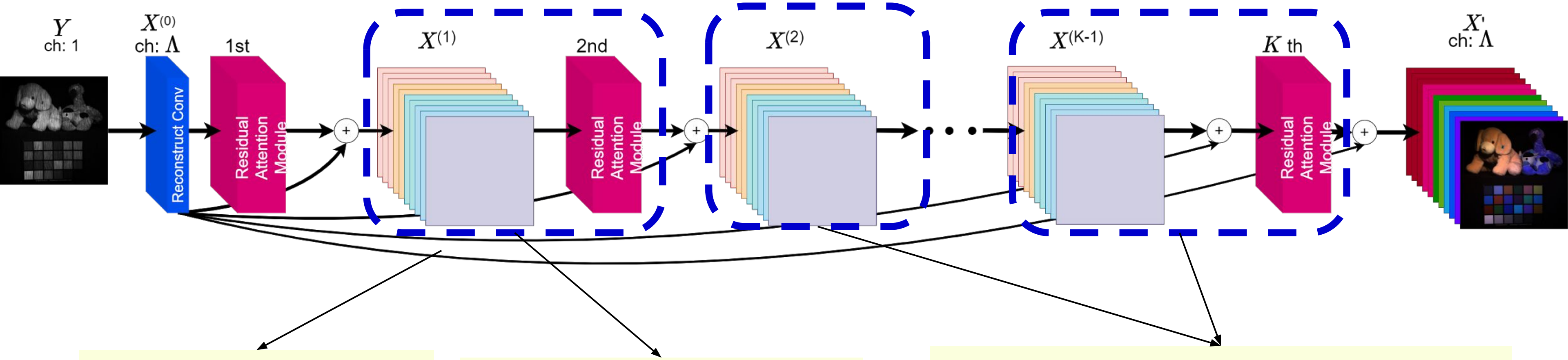
2. Attention module

   □**Automatically learn important features for both spatial and spectral reconstruction**

Proposed method:

Residual Attention HSI Reconstruction Model

The schematic concept of the reconstruction model



Residual Structure

Reuse the previous learned features

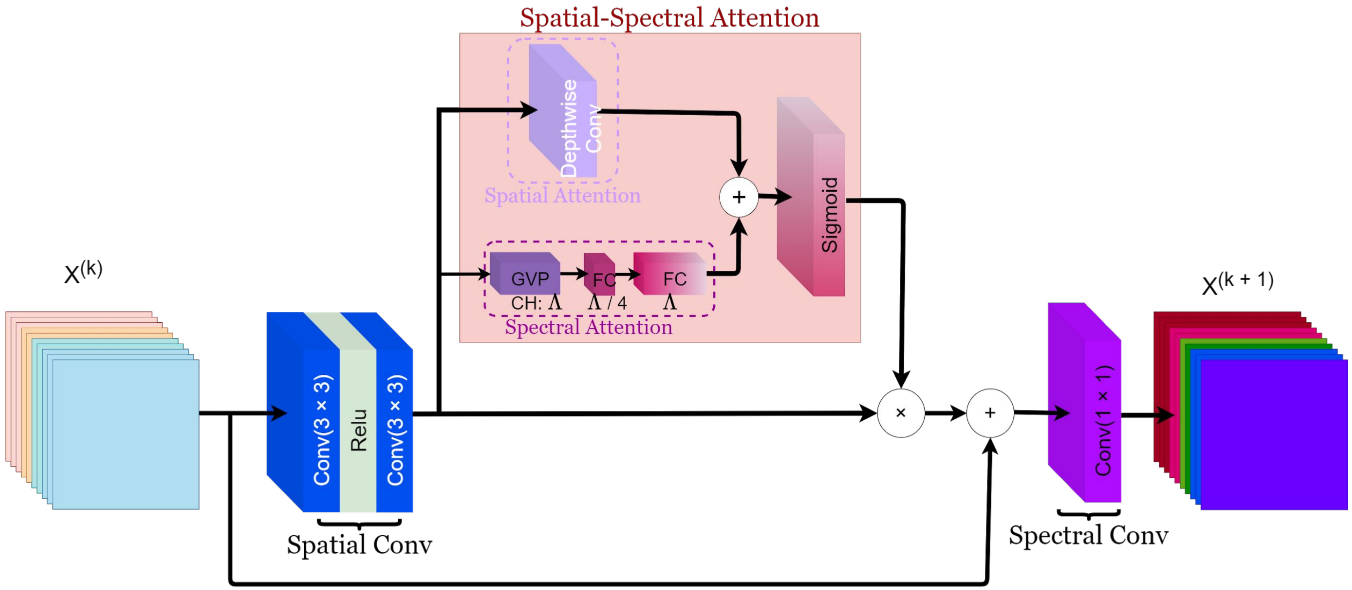
Attention Modules

Highlight important features

Multi-stage reconstruction blocks

Hierarchically reconstruct the un-recover regions

The reconstruction block



- Spatial Conv : Focus on spatial reconstruction from the recovered HIS of
  the previous block.
- Spatial-Spectral Attention (SS Attention):
  Emphasize the important features in both spatial and spectral directions
  Attenuate un-related feature
- Spectral Conv : Focus on spectral reconstruction from emphasized feature map of
  the Spatial Conv by the SS Attention module.

Experiment

To demonstrate the usefulness of the proposed model, we perform HSI reconstruction using two datasets.

Harvard Dataset: 50 HSIs

- Spectral range: 420nm to 720nm
- Training images: 40
- Test Images: 10

ICVL Dataset: 104 HSIs

- Spectral range: 400nm to 700nm
- Training images: 90
- Test Images: 14

Quantitative Evaluation:

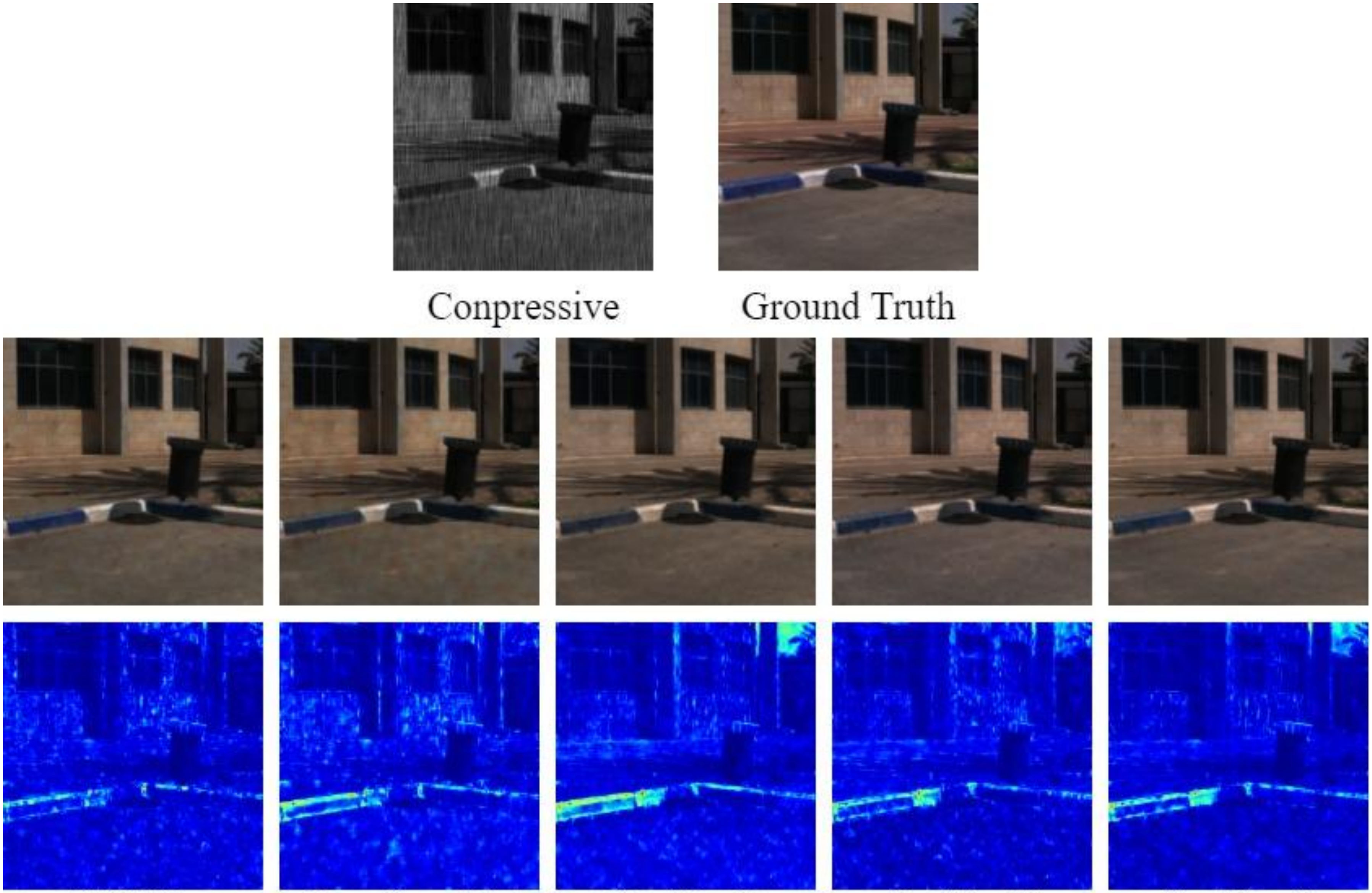
ICVL							
	TwIST	NSR	HSCNN[1]	Hyper ReconNet[2]	Our (K = 5)	Our (K = 7)	Our (K = 9)
PSNR	26.15	27.95	38.25	36.56	37.01	38.02	38.90
SSIM	0.936	0.958	0.971	0.962	0.975	0.977	0.980
SAM	0.053	0.051	0.060	0.075	0.064	0.061	0.056

Harvard							
	TwIST	NSR	HSCNN[1]	Hyper ReconNet[2]	Our (K = 5)	Our (K = 7)	Our (K = 9)
PSNR	27.16	28.51	35.09	34.29	35.04	35.33	35.69
SSIM	0.924	0.94	0.936	0.924	0.939	0.943	0.945
SAM	0.119	0.132	0.092	0.106	0.096	0.093	0.091

[1] Z. Xiong, Z. Shi, H. Li, L. Wang, D. Liu, and F. Wu, “Hscnn: Cnn-based hyperspectral image recovery from spectrally under- sampled projections,” 2017 IEEE International Conference on Computer Vision Workshops (ICCVW), pp. 518–525, 2017.

[2] L. Wang, T. Zhang, Y. Fu, and H. Huang, “Hyperreconnet: Joint coded aperture optimization and image reconstruction for compressive hyperspectral imaging,” IEEE Transactions on Image Processing, vol. 28, pp. 2257–2270, 2019.

Experimental Results (Visualization)



HSCNN (37.66, 0.973) | HyperReconNet (35.63, 0.965) | Our (K = 5) (36.07, 0.978) | Our (K = 7) (38.19, 0.980) | Our (K = 9) (38.84, 0.984)

Conclusion

- **Proposed a novel deep learning-based HSI reconstruction model**

1. Multi-stage reconstruction blocks:
   □Reciprocal spatial and spectral conv layer
2. Residual structure for
   □Reuse the reconstruction in the previous block
3. Attention modules:
   □Automatically learn important features

- **Conducted experiments on two HSI datasets**

Impressive performance compared with the SOTA methods