Hyperspectral Image Reconstruction using Hierarchical Neural Architecture Search from a Snapshot Image

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Research Background and Purpose:

RGB Image

3 spectral bands only

Hyperspectral Image

More than tens of spectra

Abundance Spectral information
->Benefiting for many fields
- Remote Sensing
- Agriculture
- Medical diagnosis

Hyperspectral Imaging: Aims to capture 3D cube

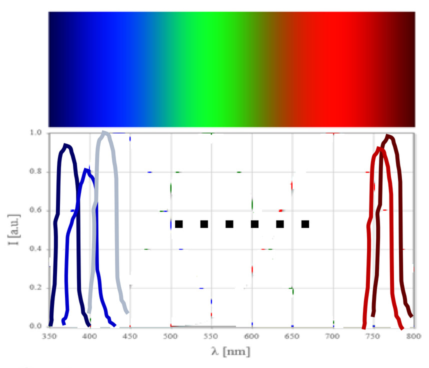
2D detector: Conventional scanning method

Challenge to capture 3D HSI in dynamic world

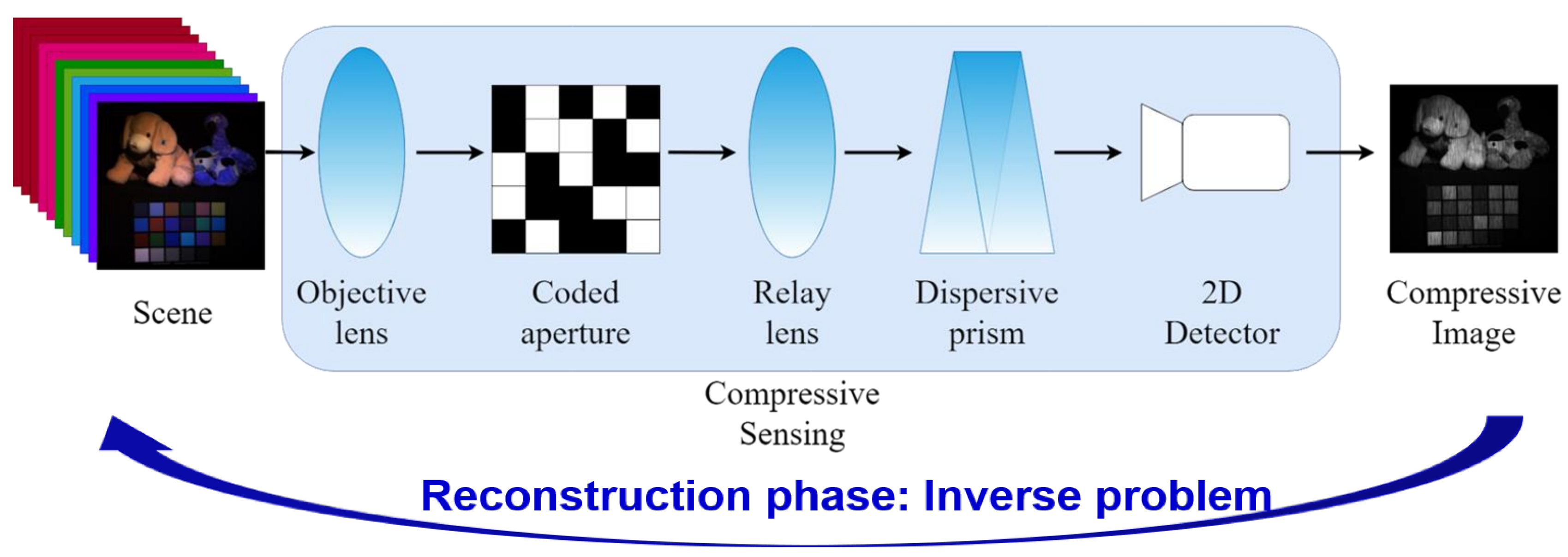
Coded aperture snapshot spectral imaging (CASSI)

Detect a 2D snapshot measurement using compressive theory

The spectral sensitivity function of HSI camera (Narrow spectral bands)



CASSI: Detection Phase

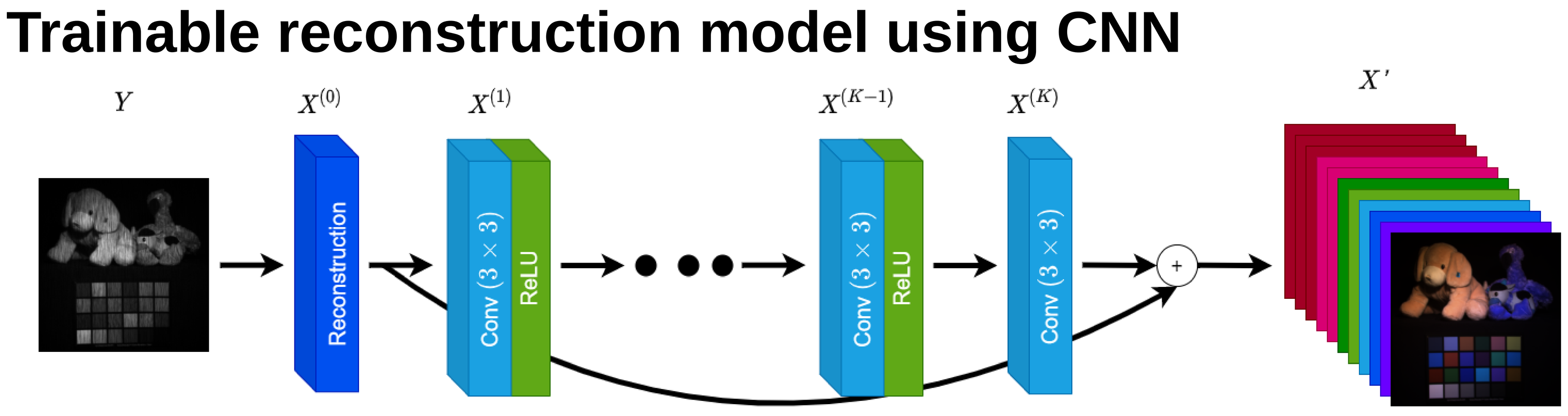


Reconstruct the underlying 3D HS images from the measure snapshot

- **Challenge task with high compressive rate**
- **HSI reconstruction performance: Bottleneck of the CASSI**
- **Require reconstruction in the CASSI sensor: High-speed**

Related Work: Deep learning-based methods

Trainable reconstruction model using CNN



Learning the mapping function from the training data
→Fast and high restoration performance after training

Current effort: Manually design network architecture according to the insight of **natural image vision**

Deep and complicate network architecture: Massive-computational models

→Difficult for being embedding in the real imaging systems

Proposed Method: NAS for architecture design

Leverage network architecture search:
->Automatically design effective and efficient network architectures for HSI reconstruction

Main Efforts

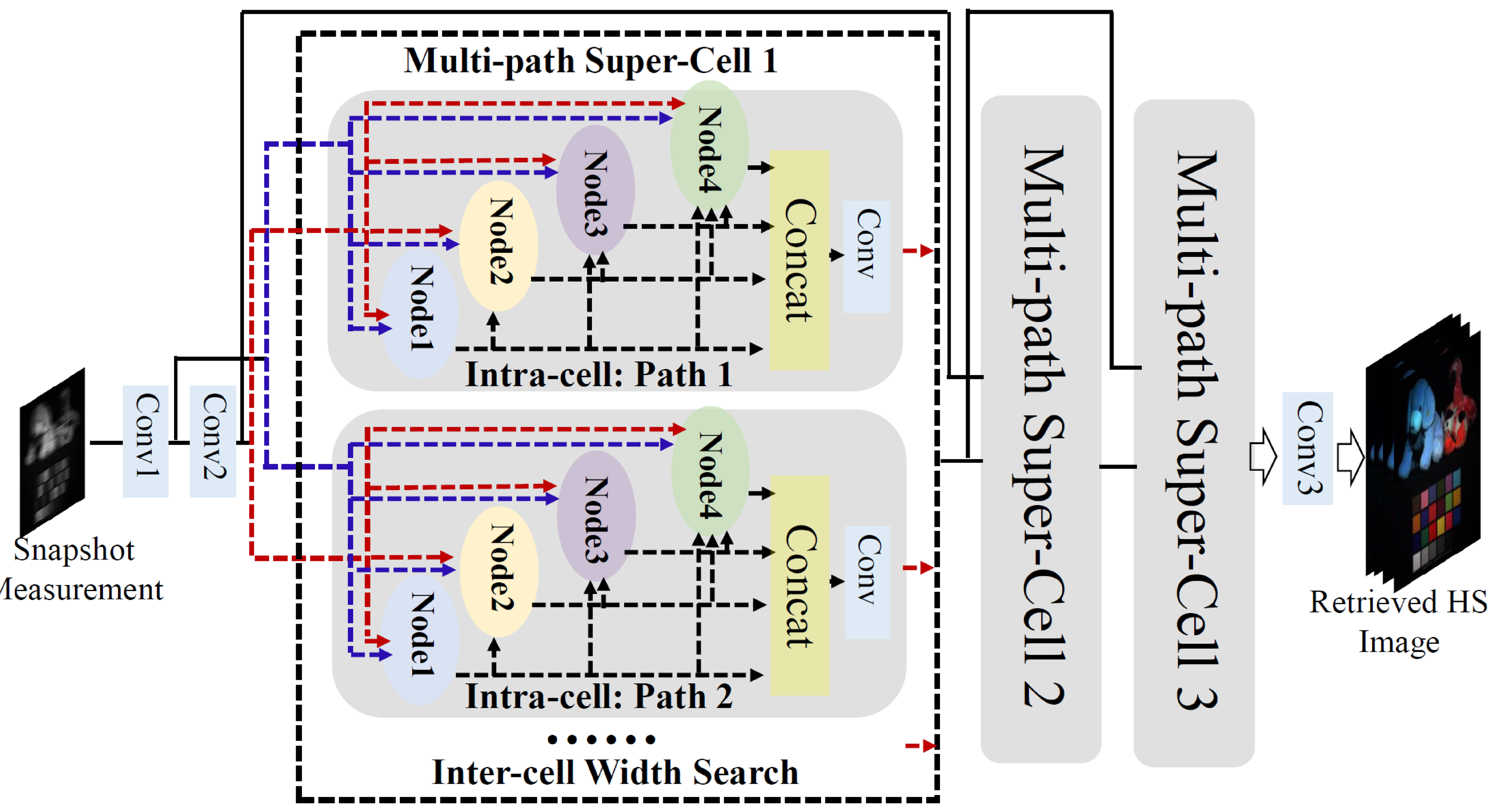
1) Prepare optional operations (cells) with adaptive receptive field
Dilate/deformable conv layers

2) **A flexible hierarchical search space**
A. Intra-cell architecture search: Optional operations
(1) 3×3 convolution (conv), (2) separable convolution (sep),
(3) 3×3 dilated convolution with rate of 2 (dil),
(4) Deformable convolution (def), (5) Mix convolution (mix)
(6) skip connection (skip).
B. Inter-cell width search: Adaptively select optimal path

3) Share cells within different levels of features
Early stopping technique
→ **Computational and memory efficient NAS**

4) Gradient-based search strategy
→ **Efficient learning**

The conceptual scheme of the proposed architecture search



1) Two initial convolution layers for shallow feature extraction
2) three multi-path super-cells with hierarchical search space of various operations (nodes)
3) A reconstruction module with the convolution

◆ Search the suitable operation or connections of intra-cell
◆ Find the adaptive path width of inter-cell

Experimental Results:

Datasets: **CAVE (32 HS Images) 512x512x31**
16 training images; 4 Val images; 12 test images

Harvard (50 HS Images) 1042x1392x31
22 training images; 8 Val images; 20 test images

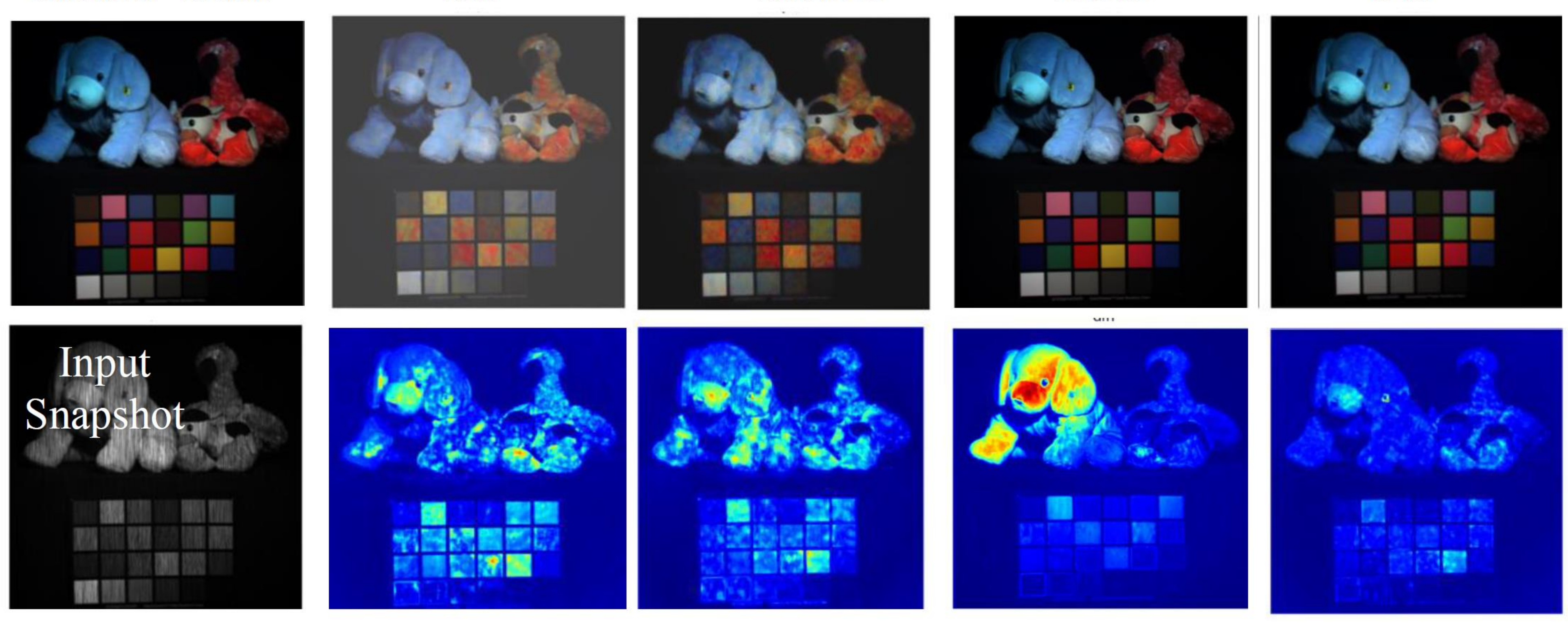
Validation images: decide the search epoch number

Sensing masks: randomly generated binary matrix in a Bernoulli distribution with p = 0.5

Comparison with SoTA methods

Dataset	Metrics	HS [16]	HRNet [19]	DSSP [20]	HMNet [21]	our
CAVE	PSNR↑	23.22	25.82	24.82	25.88	**25.98**
	SSIM↑	0.720	0.829	0.807	0.814	**0.853**
	SAM↓	0.475	0.305	0.392	**0.259**	0.299
	Para. (MB)↓	312	581	341	167	**138**
	GMACS↓	86.9	152.1	89.4	65.4	**28.3**
Harvard	PSNR↑	34.93	36.04	36.77	36.81	**37.06**
	SSIM↑	0.916	0.938	0.934	0.947	**0.955**
	SAM↓	0.120	0.166	**0.099**	0.119	0.109
	Para. (MB)↓	312	581	341	**167**	188
	GMACS↓	86.9	152.1	89.4	65.4	**47.8**

Visualization Results



Ablation Study:

1) Optional layers in IAS **Set1** (conv, sep, dil, def, skip) **Set2** (conv sep, mix, skip) **Set3** (conv, sep, dil, skip),

2) With or Without inter-cell width search (IWS)

IAS	Set1	Set1	set2	set3
IWS		✓	✓	✓
PSNR↑	25.47	25.98	25.04	25.19
SSIM↑	0.829	0.853	0.803	0.826
SAM↓	0.305	0.299	0.323	0.308