Residual Degradation Learning Unfolding Framework with Mixing Priors across Spectral and Spatial for Compressive Spectral Imaging

Yubo Dong, Dahua Gao*, Tian Qiu, Yuyan Li, Minxi Yang, Guangming Shi

Xidian University, School of Artificial Intelligence, China

Poster: THU-PM-158

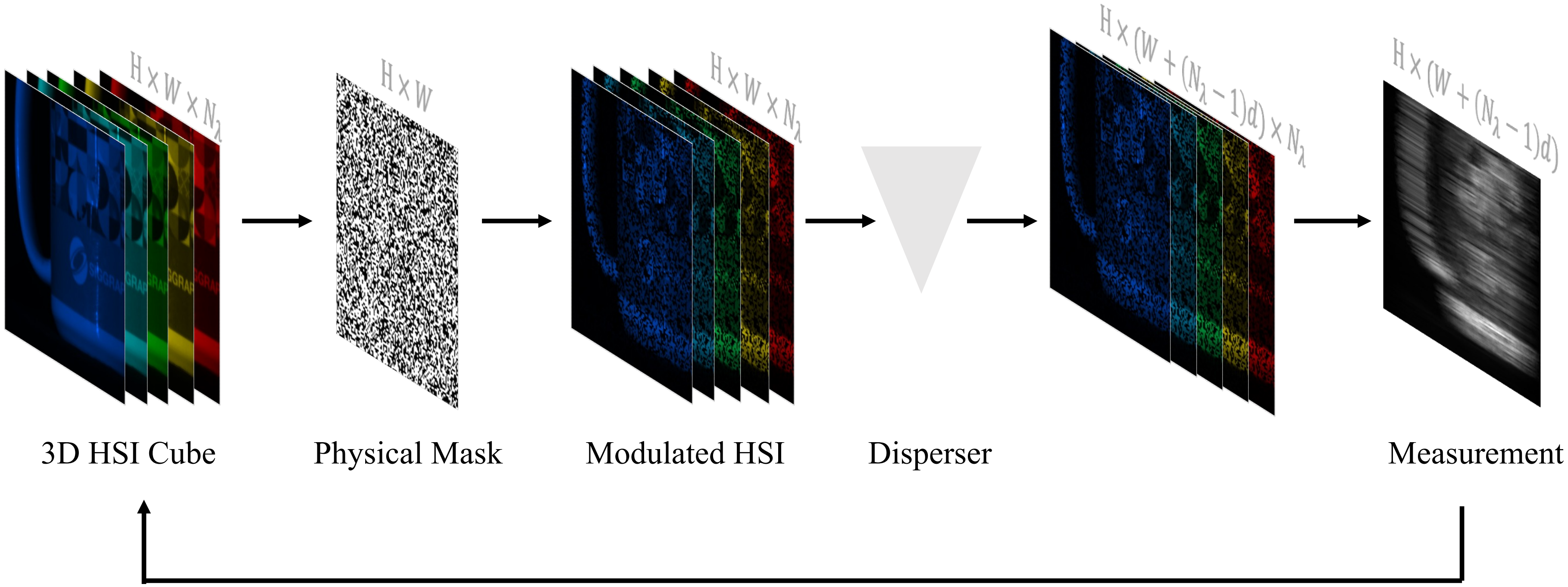
Paper: https://arxiv.org/abs/2211.06891

Code: https://github.com/ShawnDong98/RDLUF_MixS2

Overview

JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

Coded Aperture Snapshot Spectral Imaging (CASSI)

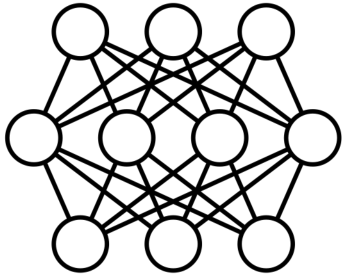


Core Problem: How to recover 3D spectral cube from the 2D measurement?

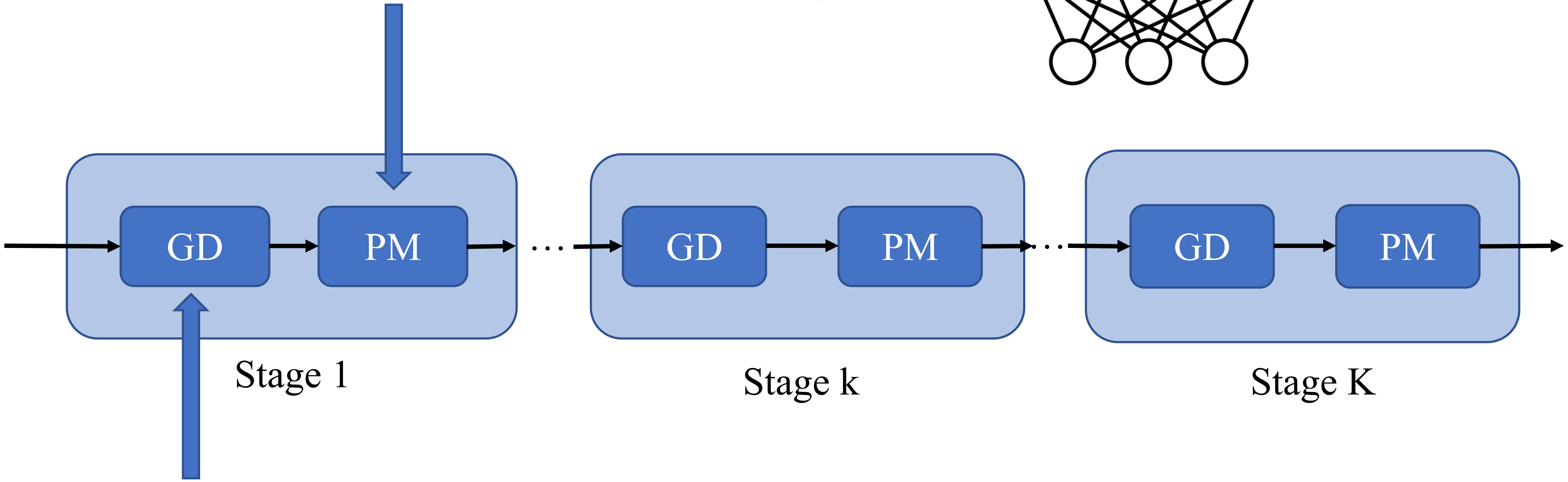
Overview

Deep Unfolding Methods

Prior Subproblem $\hat{x}^k = \mathbf{prox}_{\lambda,J}(v^k)$



Data-driven priors



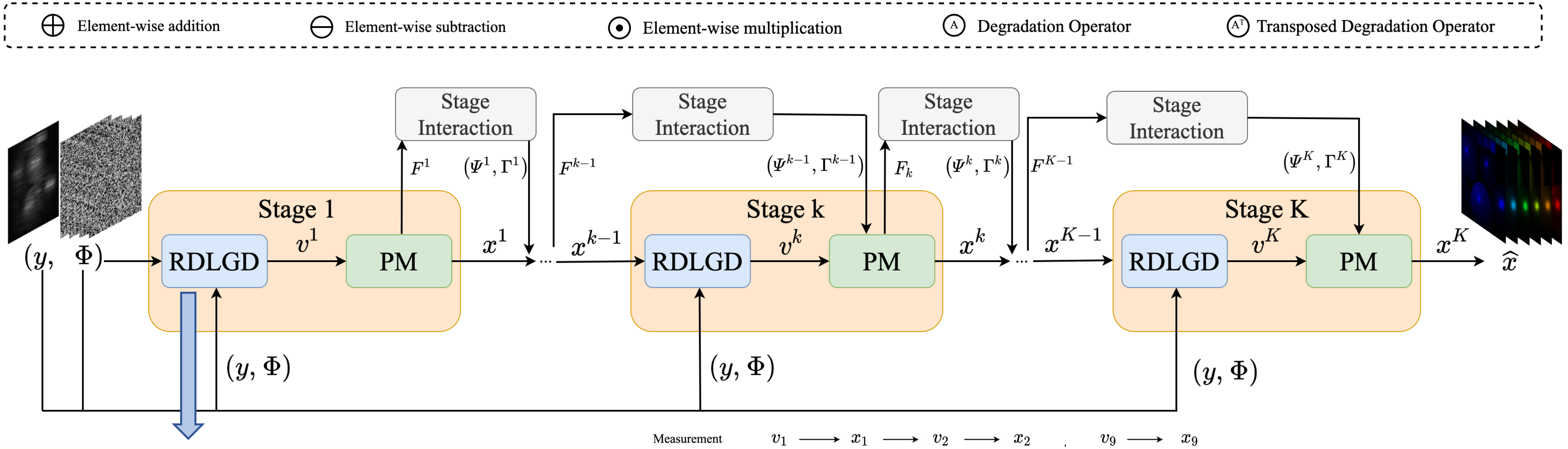
Data Subproblem $v^k = \hat{x}^{k-1} - \rho^k \hat{\Phi}^{\top k}(\hat{\Phi}^k \hat{x}^{k-1} - y)$

Degradation Matrix

Overview

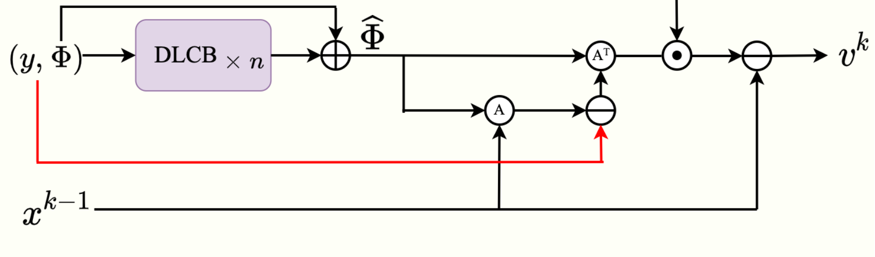
Data Subproblem $v^k = \hat{x}^{k-1} - \rho^k \hat{\Phi}^{\top k}(\hat{\Phi}^k \hat{x}^{k-1} - y)$

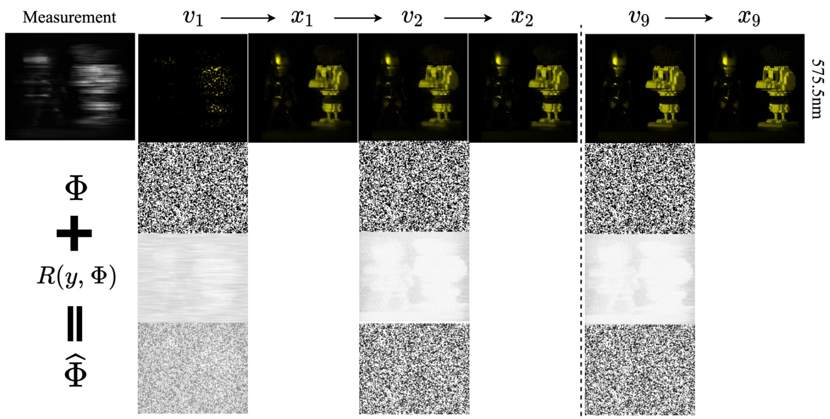
Residual Degradation Learning Unfolding Framework (RDLUF)



Residual Degradation Learning Gradient Descent (RDLGD)

$\hat{\Phi} = \Phi + R(y, \Phi)$

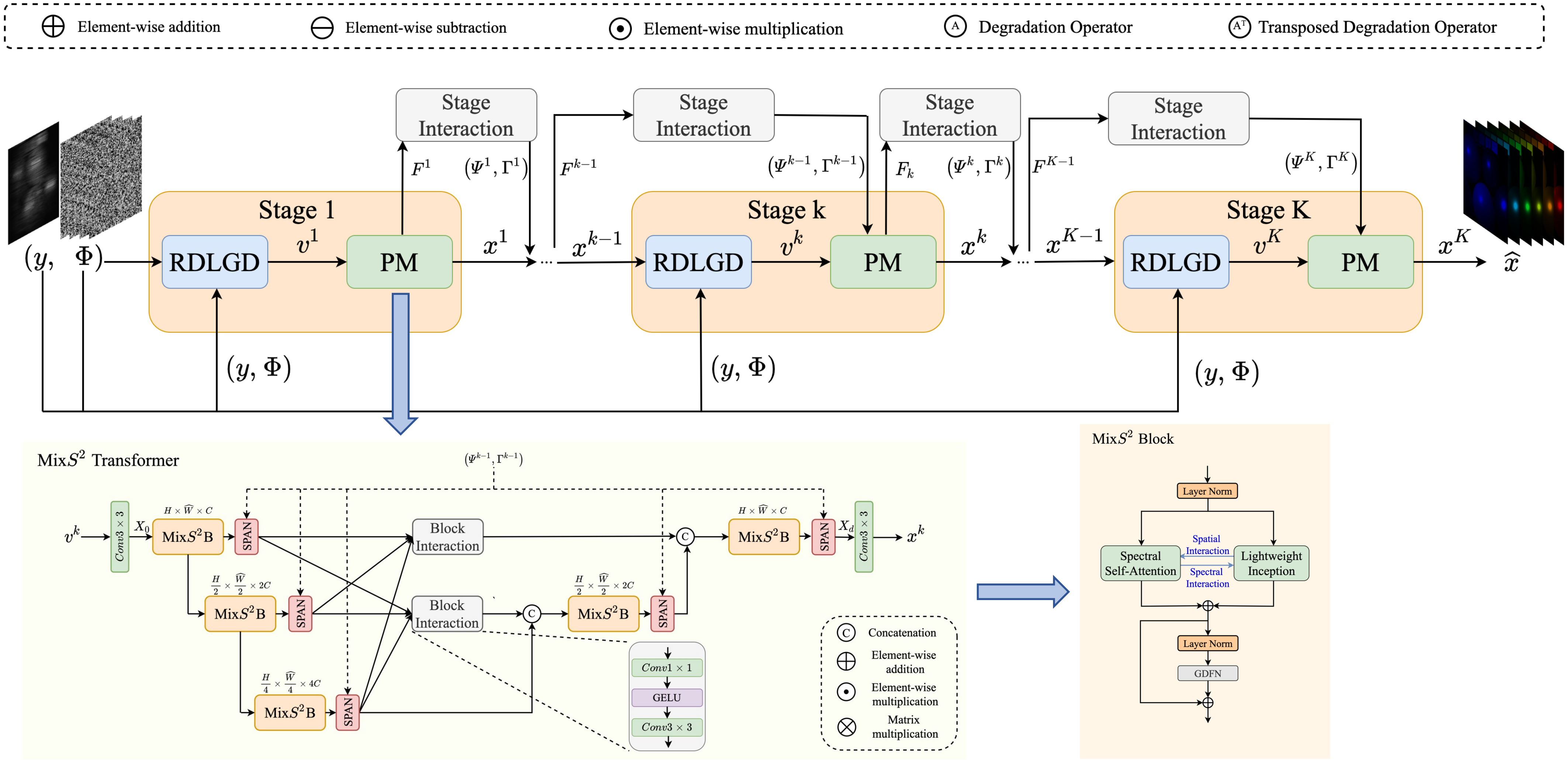




Overview

Prior Subproblem $\hat{x}^k = \mathrm{prox}_{\lambda,J}(v^k)$

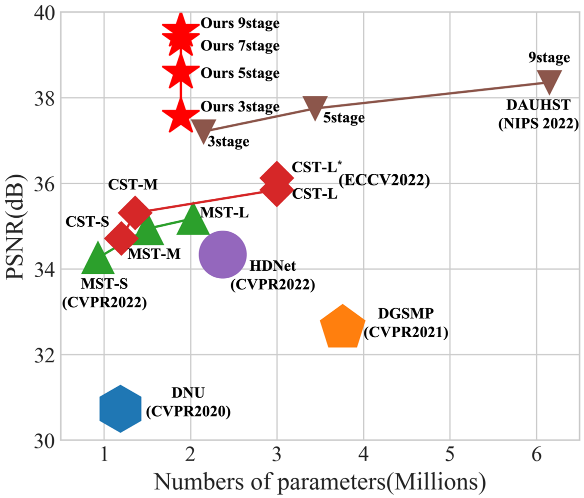
Residual Degradation Learning Unfolding Framework (RDLUF)



Overview

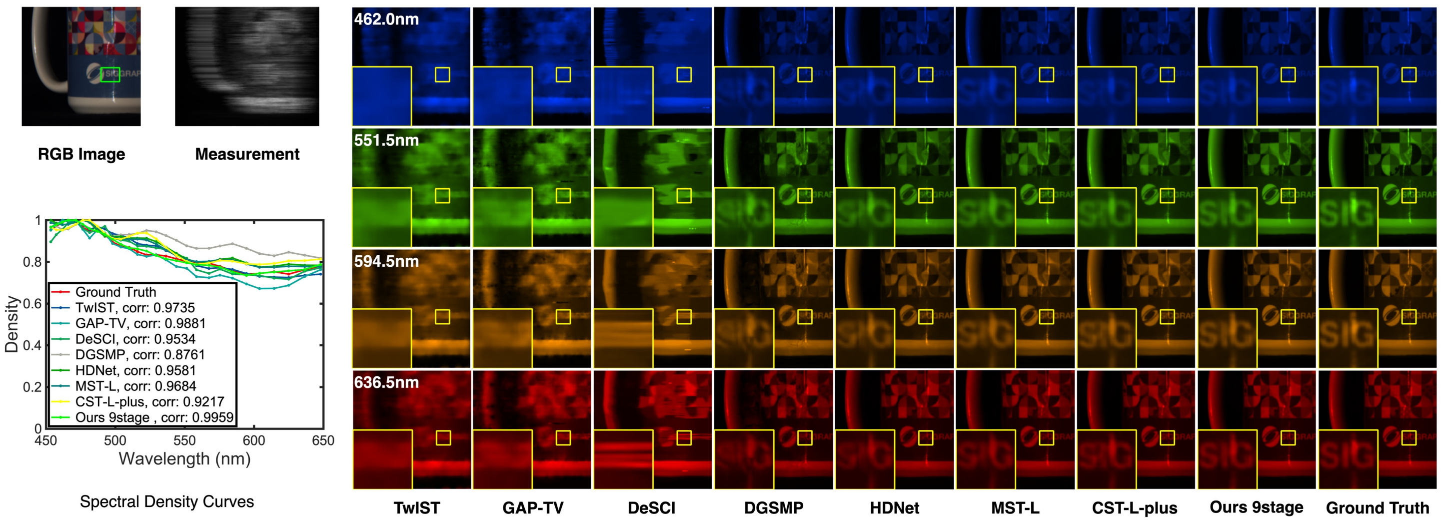
JUNE 18-22, 2023
CVPR
VANCOUVER, CANADA

Quantitative Results:



Scene	TwIST [3] PSNR	TwIST [3] SSIM	GAP-TV [44] PSNR	GAP-TV [44] SSIM	DeSCI [22] PSNR	DeSCI [22] SSIM	DGSMP [16] PSNR	DGSMP [16] SSIM	HDNet [15] PSNR	HDNet [15] SSIM	MST-L [6] PSNR	MST-L [6] SSIM	CST-L* [20] PSNR	CST-L* [20] SSIM	Ours 3stage PSNR	Ours 3stage SSIM	Ours 5stage PSNR	Ours 5stage SSIM	Ours 7stage PSNR	Ours 7stage SSIM	Ours 9stage PSNR	Ours 9stage SSIM
1	25.16	0.700	26.82	0.754	27.13	0.748	33.26	0.915	34.95	0.948	35.40	0.941	35.96	0.949	36.67	0.953	37.30	0.960	37.65	0.963	**37.94**	**0.966**
2	23.02	0.604	22.89	0.610	23.04	0.620	32.09	0.898	32.52	0.953	35.87	0.944	36.84	0.955	38.48	0.965	39.39	0.971	40.45	0.976	**40.95**	**0.977**
3	21.40	0.711	26.31	0.802	26.62	0.818	33.06	0.925	34.52	0.957	36.51	0.953	38.16	0.962	40.63	0.971	42.06	0.975	43.00	0.978	**43.25**	**0.979**
4	30.19	0.851	30.65	0.852	34.96	0.897	40.54	0.634	43.00	0.981	42.27	0.973	42.44	0.975	46.04	0.986	46.89	0.988	47.40	0.990	**47.83**	**0.990**
5	21.41	0.635	23.64	0.703	23.94	0.706	28.86	0.882	32.49	0.957	32.77	0.947	33.25	0.955	34.63	0.963	35.74	0.969	36.78	0.974	**37.11**	**0.976**
6	20.95	0.644	21.85	0.663	22.38	0.683	33.08	0.937	35.96	0.965	34.80	0.955	35.72	0.963	36.18	0.966	37.03	0.971	**37.56**	0.974	37.47	**0.975**
7	22.20	0.643	23.76	0.688	24.45	0.743	30.74	0.886	29.18	0.937	33.66	0.925	34.86	0.944	35.85	0.951	37.05	0.959	38.25	0.967	**38.58**	**39.69**
8	21.82	0.650	21.98	0.655	22.03	0.673	31.55	0.923	34.00	0.961	32.67	0.948	34.34	0.961	34.37	0.963	35.18	0.968	**35.86**	**0.971**	35.50	0.970
9	22.42	0.690	22.63	0.682	24.56	0.732	31.66	0.911	34.56	0.957	35.39	0.949	36.51	0.957	38.98	0.966	40.64	0.973	41.71	0.978	**41.83**	**0.978**
10	22.67	0.569	23.10	0.584	23.59	0.587	31.44	0.925	32.22	0.950	32.50	0.941	33.09	0.945	33.73	0.950	34.58	0.957	34.83	0.959	**35.23**	**0.962**
Avg	23.12	0.669	24.36	0.669	25.27	0.721	32.63	0.917	34.34	0.957	35.18	0.948	36.12	0.957	37.56	0.963	38.59	0.969	39.35	0.973	**39.57**	**0.974**

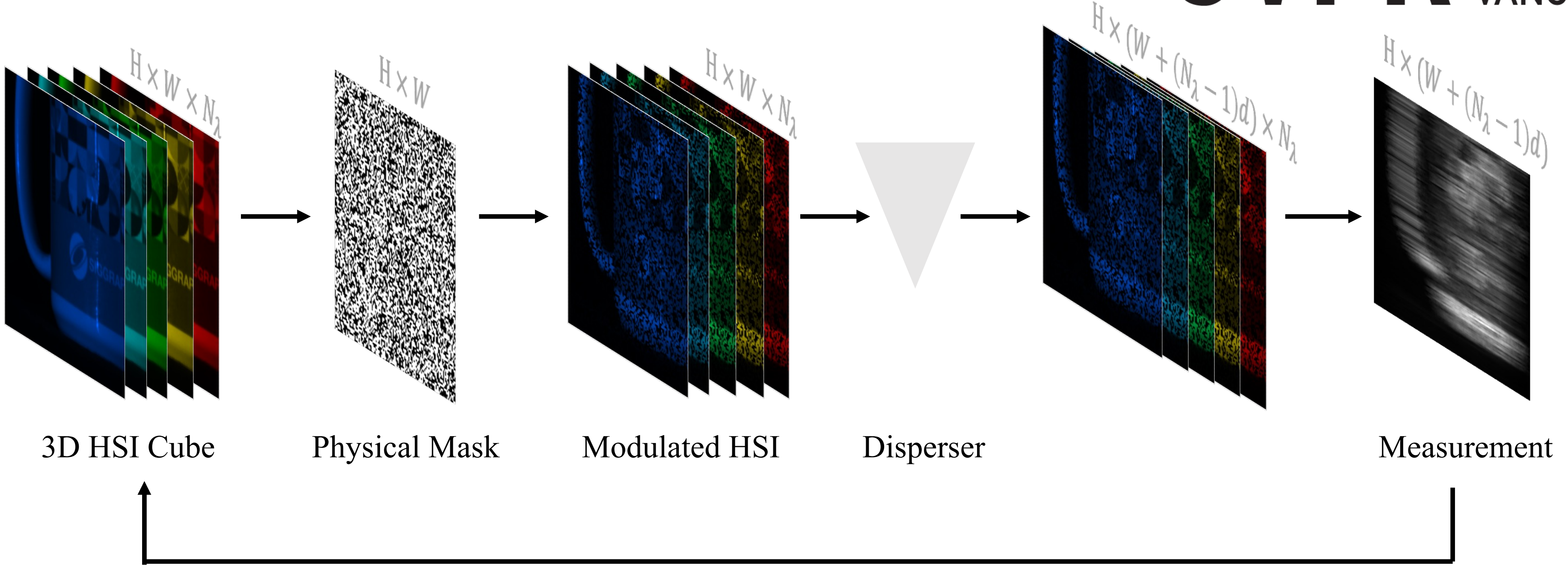
Qualitative Results:



Introduction

JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

Coded Aperture Snapshot Spectral Imaging (CASSI)



Core Problem: How to recover 3D spectral cube from the 2D measurement?

Existing methods

- Model-based methods: handcrafted priors result in limited modeling capabilities.
- End-to-End Neural Networks: powerful modeling ability, but design a powerful architecture is non-trivial.
- Deep Unfolding methods: heuristically design a neural network using the model-based method .

Introduction

JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

The reconstruction problem of the CASSI system is a ill-posed problem:

$$y = \Phi x + b$$

Where Φ is the sensing matrix, typically treated as the sum of the shifted mask, implemented in a operator.

Deep unfolding methods typically solve the problem under a MAP framework:

$$\hat{x} = \mathrm{argmax}_{\mathrm{x}} \log \mathrm{p}(\mathrm{x} \mid \mathrm{y}) = \mathrm{argmax}_{\mathrm{x}}\, \mathrm{p}(\mathrm{y} \mid \mathrm{x}) - \mathrm{argmax}_{\mathrm{x}}\, \mathrm{p}(\mathrm{y})$$

Energy function:

$$\hat{x} = argmin_x \frac{1}{2} \|y - \Phi x\|_2^2 + \lambda J(x)$$

Deep unfolding methods decouple it into a data subproblem and a prior subproblem:

$$\hat{x}^k = \underset{x}{\mathrm{argmin}} \frac{1}{2}\|x - (\hat{x}^{k-1} - \rho\Phi^T(\Phi\hat{x}^{k-1} - y))\|_2^2 + \lambda J(x)$$

Introduction

$$\hat{x}^k = \underset{x}{\operatorname{argmin}} \frac{1}{2}\|x-(\hat{x}^{k-1} - \rho\Phi^T(\Phi\hat{x}^{k-1} - y))\|_2^2+\lambda J(x)$$

Data subproblem and **Prior subproblem** corresponding to the **Gradient Descent** and **Proximal Mapping** of PGD

$$v^k = \hat{x}^{k-1} - \rho\Phi^T(\Phi\hat{x}^{k-1} - y)$$
$$\hat{x}^k = \operatorname{prox}_{\lambda,J}(v^k)$$

Data subproblem is highly related to the degradation process $\widehat{\Phi}$, the ways current methods acquiring the degradation matrix can be classified into two types:

- Treat sensing matrix Φ as the degradation matrix $\widehat{\Phi}$ → **There exist a gap between sensing matrix Φ and degradation matrix $\widehat{\Phi}$ due to device errors**
- Using a network to estimate the degradation matrix $\widehat{\Phi}$ → **It is challenging to directly estimate degradation matrix $\widehat{\Phi}$**

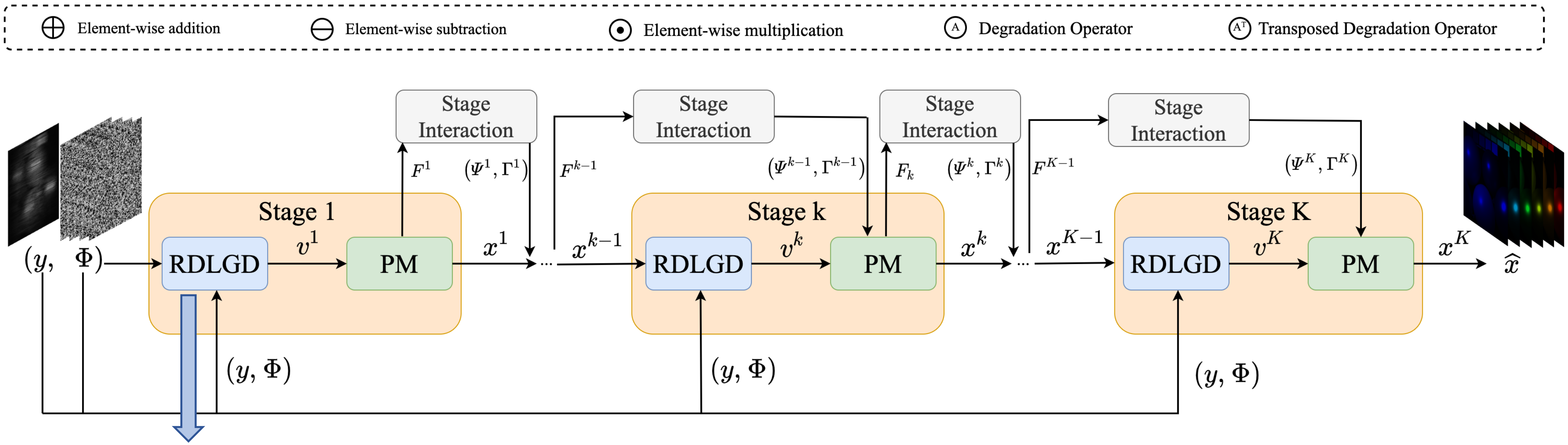
In the **prior subproblem**, it is important to design a suitable model to jointly exploit both spatial and spectral priors.

Method

JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

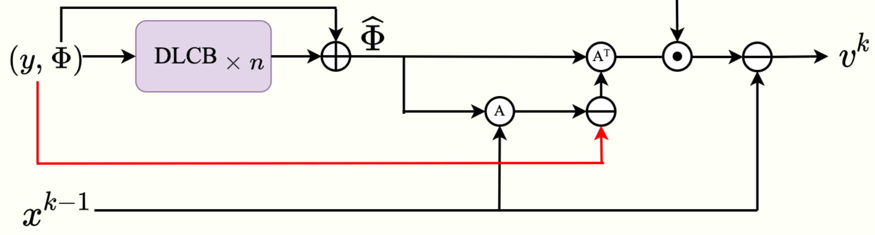
Data subproblem(Gradient Descent， GD):

Residual Degradation Learning Unfolding Framework (RDLUF)

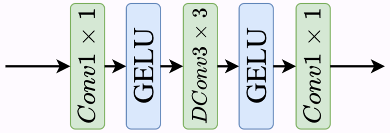


Residual Degradation Learning Gradient Descent (RDLGD)

$$\widehat{\Phi} = \Phi + R(y, \Phi)$$



Degradation Learning Convolution Block (DLCB)



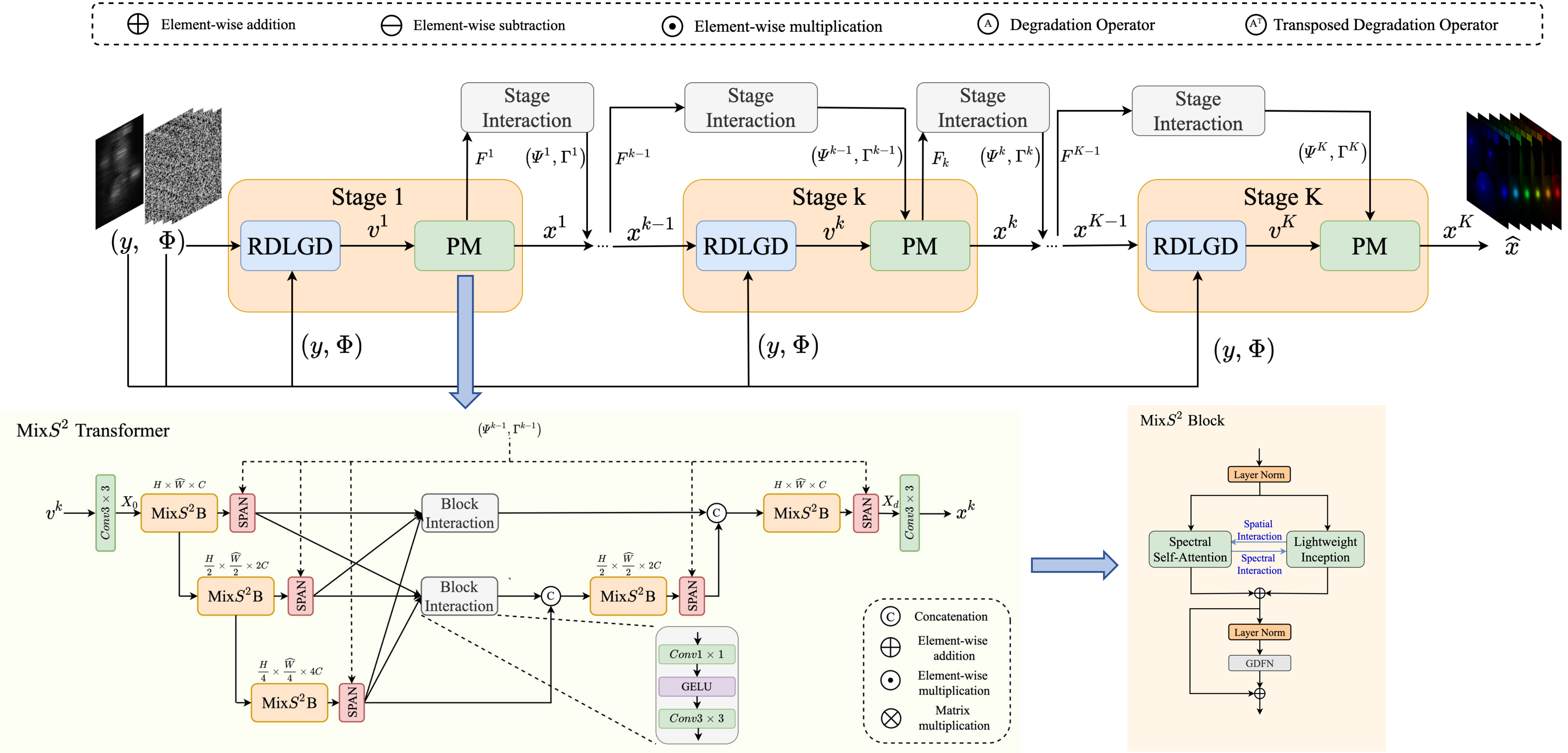
$$v^k = \hat{x}^{k-1} - \rho^k \hat{\Phi}^{\top k}(\hat{\Phi}^k \hat{x}^{k-1} - y)$$

Method

JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

Prior subproblem(Proximal Mapping， PM):

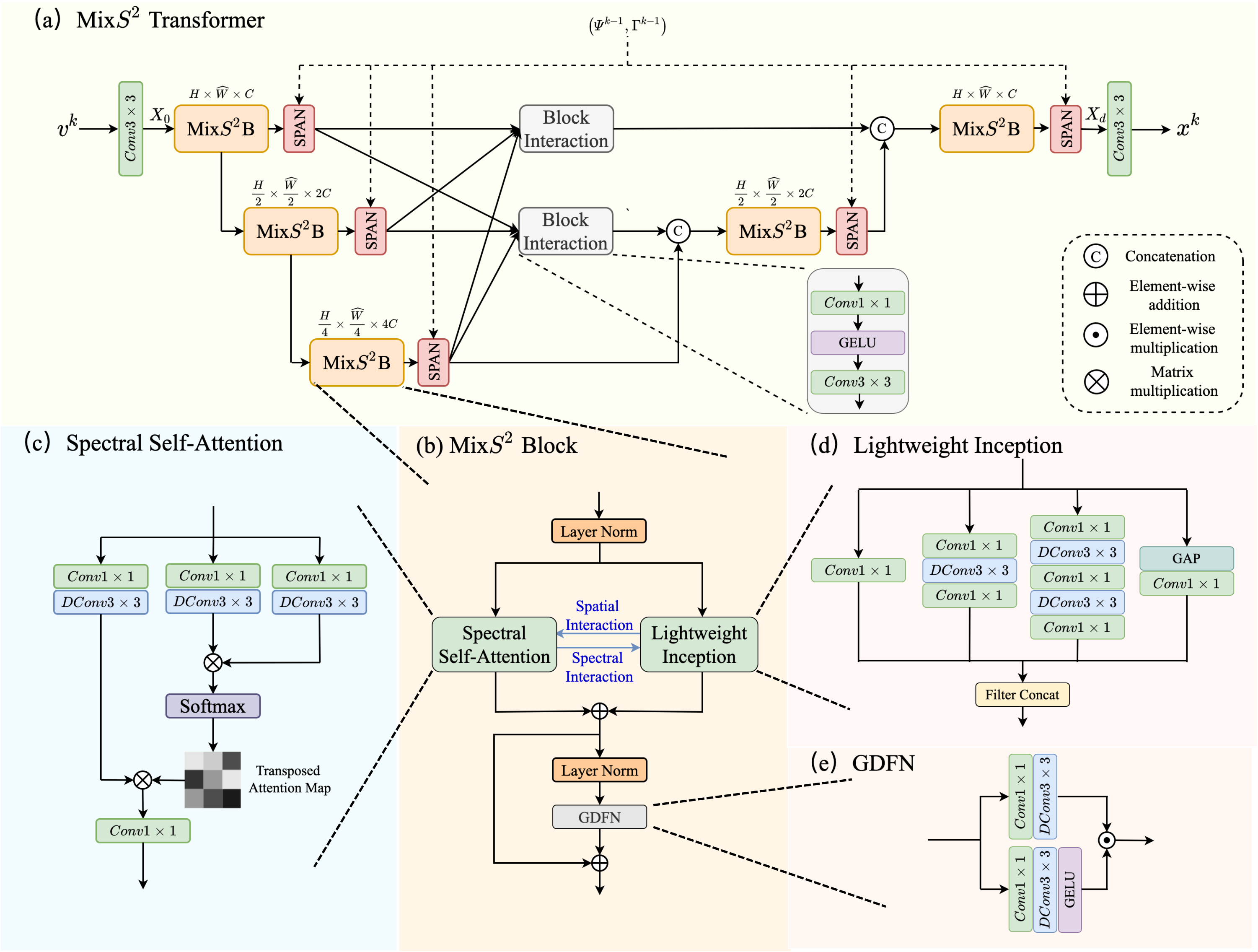
Residual Degradation Learning Unfolding Framework (RDLUF)



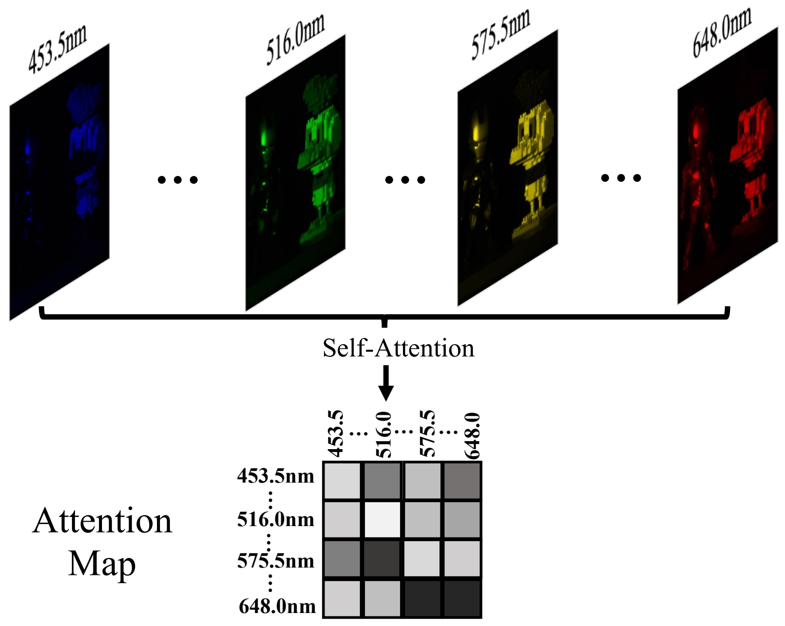
Method

JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

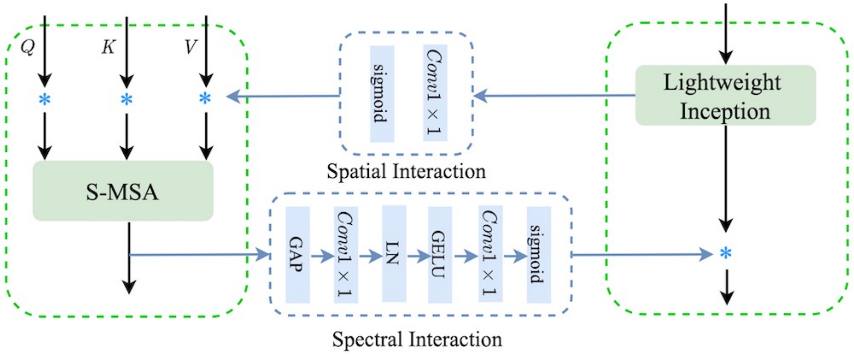
Prior subproblem(Proximal Mapping， PM):



Spectral Self-Attention:



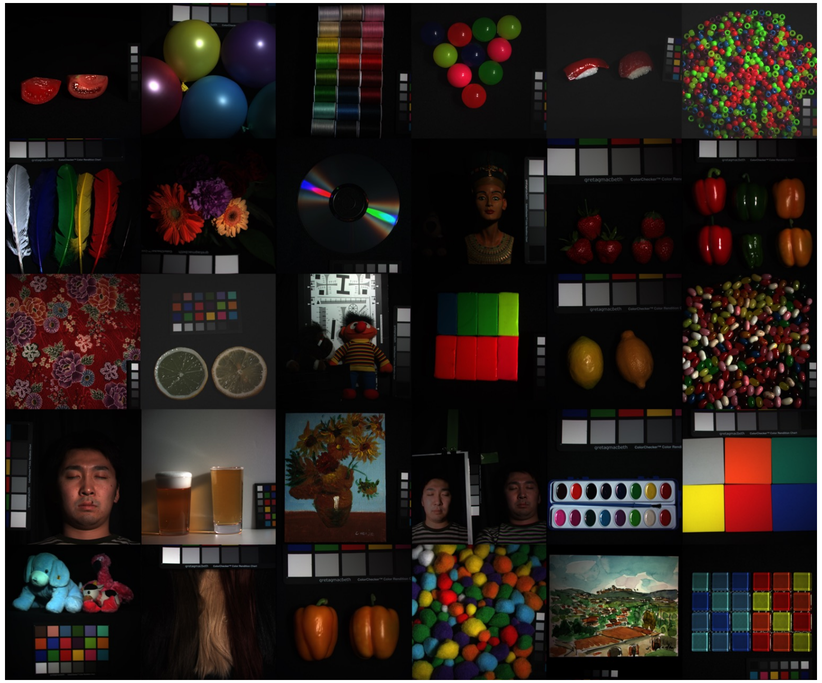
Bi-directional Interaction



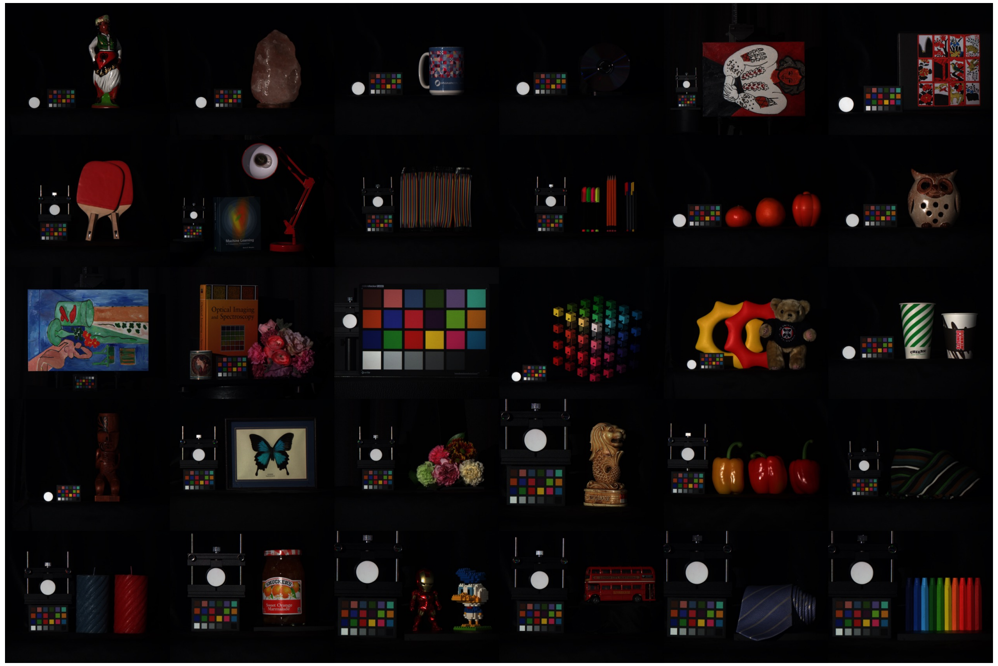
Experiments

Simulation Experiments	Training on simulation data: **CAVE** datasets, 28 wavelength, 450nm to 650nm Testing on simulation data: 10 scenes from **KAIST** datasets
Real Experiments	Training on simulation data: **CAVE** and **KAIST** datasets, 28 wavelength, 450nm to 650nm Testing on real data: Real measurements are captured by SD-CASSI system

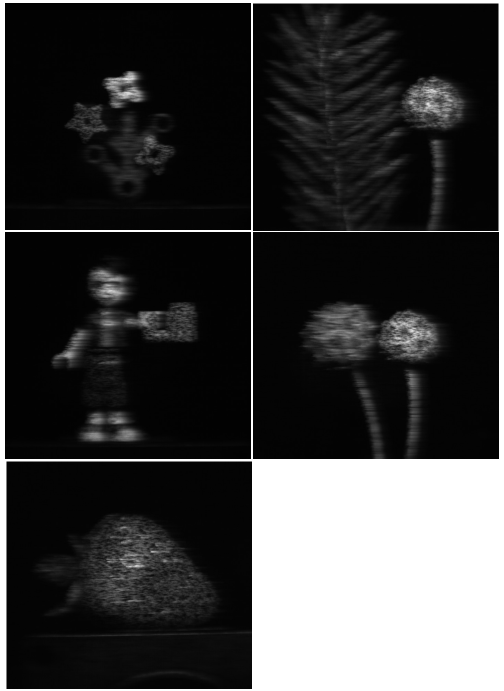
CAVE



KAIST



Real Measurements



Experiments

JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

Simulation Results

Algorithms	Scene1	Scene2	Scene3	Scene4	Scene5	Scene6	Scene7	Scene8	Scene9	Scene10	Avg
TwIST	25.16 0.700	23.02 0.604	21.40 0.711	30.19 0.851	21.41 0.635	20.95 0.644	22.20 0.643	21.82 0.650	22.42 0.690	22.67 0.569	23.12 0.669
GAP-TV	26.82 0.754	22.89 0.610	26.31 0.802	30.65 0.852	23.64 0.703	21.85 0.663	23.76 0.688	21.98 0.655	22.63 0.682	23.10 0.584	24.36 0.669
DeSCI	27.13 0.748	23.04 0.620	26.62 0.818	34.96 0.897	23.94 0.706	22.38 0.683	24.45 0.743	22.03 0.673	24.56 0.732	23.59 0.587	25.27 0.721
HSSP	31.48 0.858	31.09 0.842	28.96 0.823	34.56 0.902	28.53 0.808	30.83 0.877	28.71 0.824	30.09 0.881	30.43 0.868	28.78 0.842	30.35 0.852
DNU	31.72 0.863	31.13 0.846	29.99 0.845	35.34 0.908	29.03 0.833	30.87 0.887	28.99 0.839	30.13 0.885	31.03 0.876	29.14 0.849	30.74 0.863
DGSMP	33.26 0.915	32.09 0.898	33.06 0.925	40.54 0.964	28.86 0.882	33.08 0.937	30.74 0.886	31.55 0.923	31.66 0.911	31.44 0.925	32.63 0.917
HDNet	35.14 0.935	35.67 0.940	36.03 0.943	42.30 0.969	32.69 0.946	34.46 0.952	33.67 0.926	32.48 0.941	34.89 0.942	32.38 0.937	34.97 0.943
MST-L	35.40 0.941	35.87 0.944	36.51 0.953	42.27 0.973	32.77 0.947	34.80 0.955	33.66 0.925	32.67 0.948	35.39 0.949	32.50 0.941	35.18 0.948
CST-L*	35.96 0.949	36.84 0.955	38.16 0.962	42.44 0.975	33.25 0.955	35.72 0.963	34.86 0.944	34.34 0.961	36.51 0.957	33.09 0.945	36.12 0.957
DAUHST-9stg	37.25 0.958	39.02 0.967	41.05 0.971	46.15 0.983	35.80 0.969	37.08 0.970	37.57 0.963	35.10 0.966	40.02 0.970	34.59 0.956	38.36 0.967
Ours 3stage	36.67 0.953	38.48 0.965	40.63 0.971	46.04 0.986	34.63 0.963	36.18 0.966	35.85 0.951	34.37 0.963	38.98 0.966	33.73 0.950	37.56 0.963
Ours 5stage	37.30 0.960	39.39 0.971	42.06 0.975	46.89 0.988	35.74 0.969	37.03 0.971	37.05 0.959	35.18 0.968	40.64 0.973	34.58 0.957	38.59 0.969
Ours 7stage	37.65 0.963	40.45 0.976	43.00 0.978	47.40 0.990	36.78 0.974	**37.56** 0.974	38.25 0.967	**35.86** **0.971**	41.71 0.978	34.83 0.959	39.35 0.973
Ours 9stage	**37.94** **0.966**	**40.95** **0.977**	**43.25** **0.979**	**47.83** **0.990**	**37.11** **0.976**	37.47 **0.975**	**38.58** **0.969**	35.50 0.970	**41.83** **0.978**	**35.23** **0.962**	**39.57** **0.974**

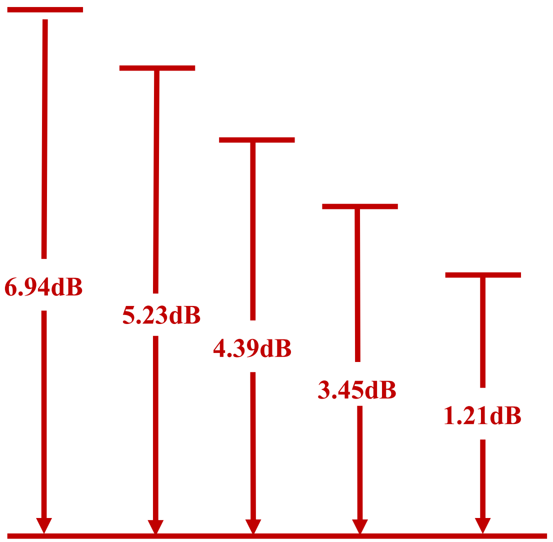


Table 1. The PSNR (upper entry in each cell) in dB and SSIM (lower entry in each cell) results of the test methods on 10 scenes. RDLUF- MixS[2] significantly surpasses other competitors.

Experiments

JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

Simulation Results

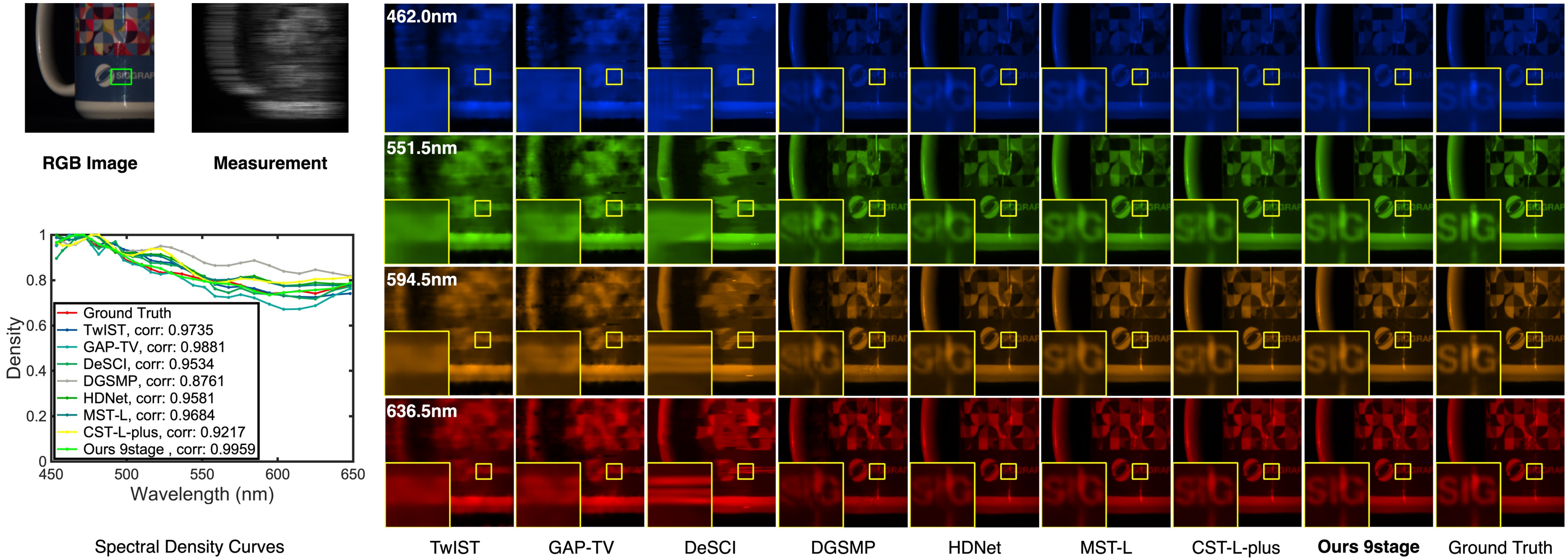


Figure 5. Comparisons of reconstructed HSIs use 4 out of 28 spectral channels in Scene 5. We evaluated 7 SOTA methods alongside the proposed approach RDLUF-MixS^2 with 9stage. Our method's results are most clear. The region within the green box was chosen for the analysis of the reconstructed spectra. Zoom in for a more detailed examination.

Experiments

JUNE 18-22, 2023
CVPR
VANCOUVER, CANADA

Simulation Results

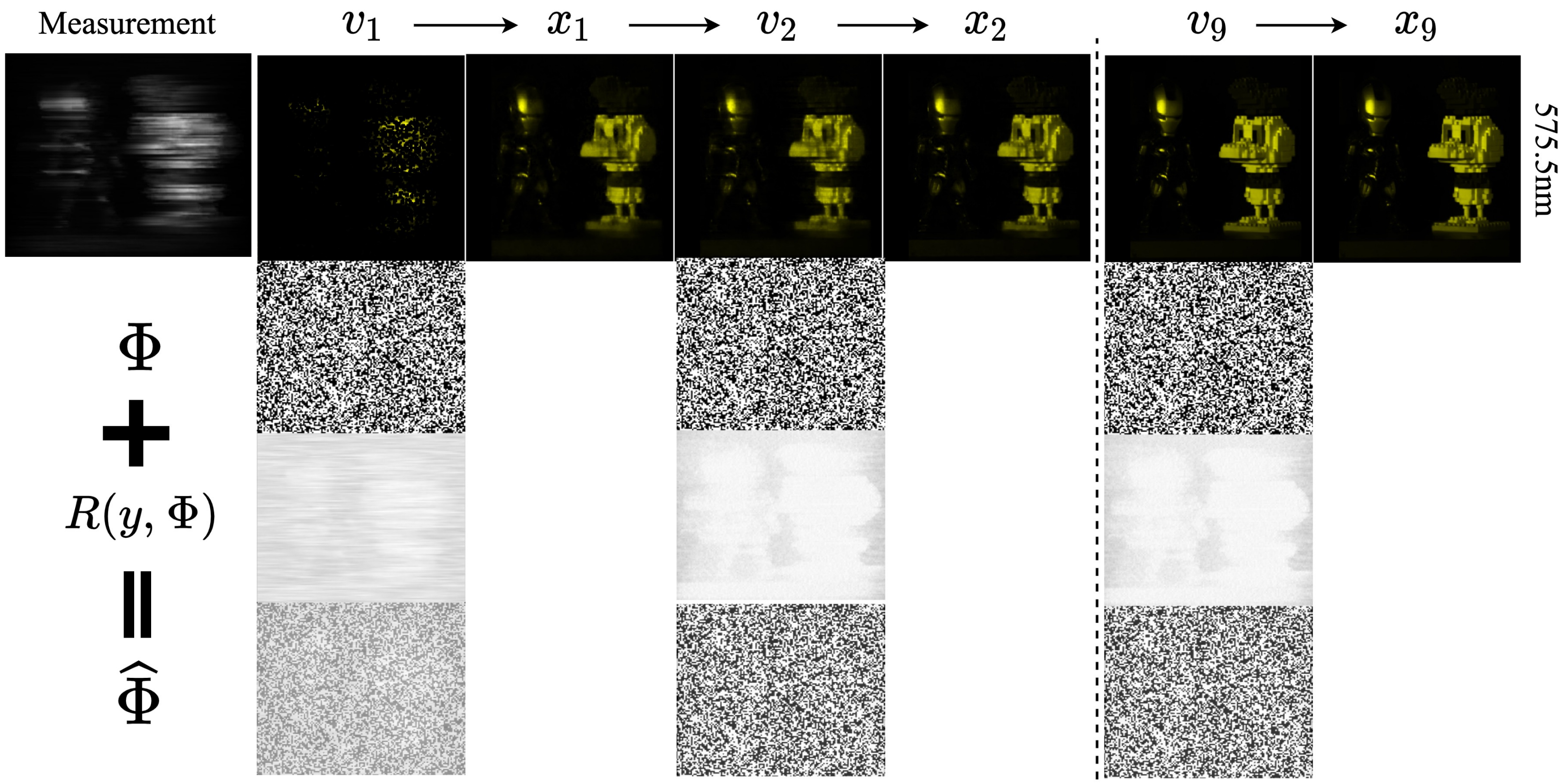


Figure 7. The results of the reconstruction, the visualizations of Φ, the residual $R(y, \Phi)$, and the corrected $\widehat{\Phi}$ are presented. Please note that the visualizations are normalized and the residual response is actually small.

Experiments

JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

Real Results

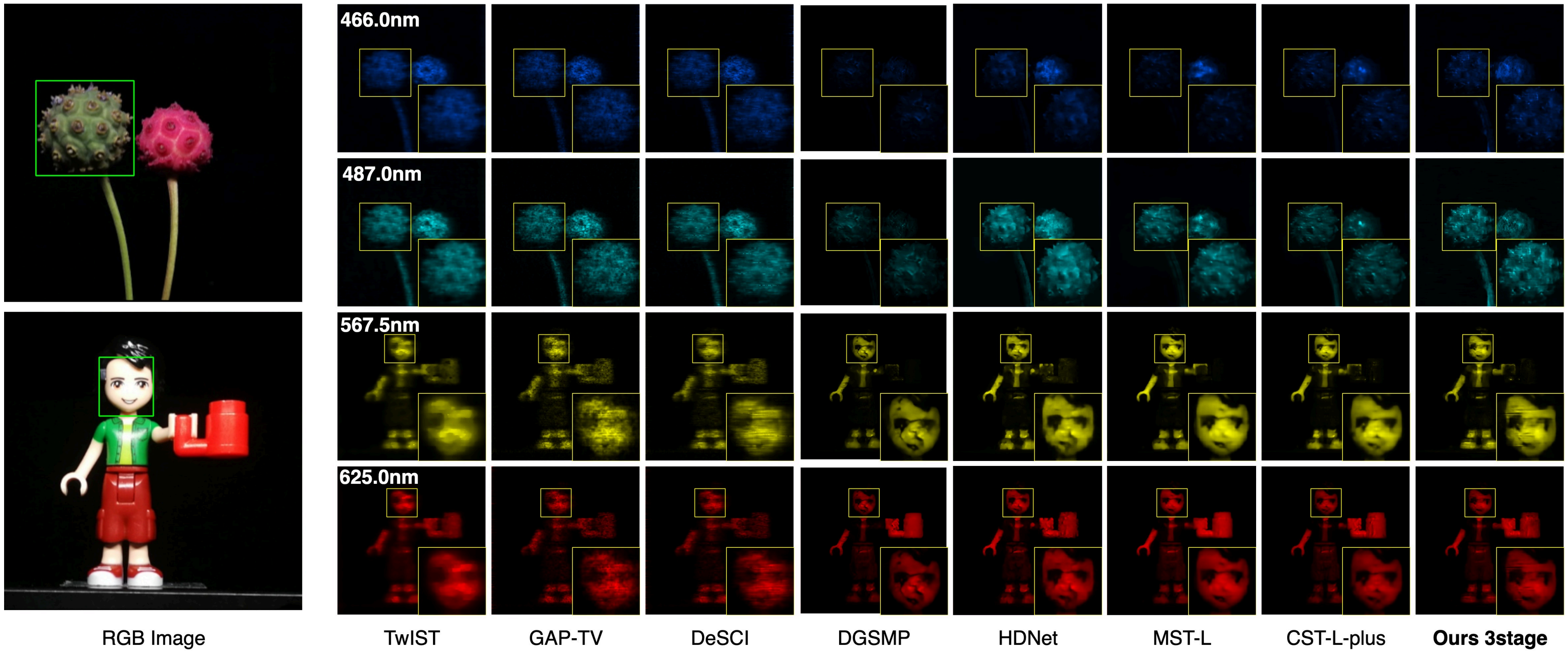


Figure 6. Real HSI reconstruction comparison of Scene 3 and Scene 4. 4 out of 28 spectra are randomly selected.

Thanks!