Spectrum-aware and Transferable Architecture Search for Hyperspectral Image Restoration

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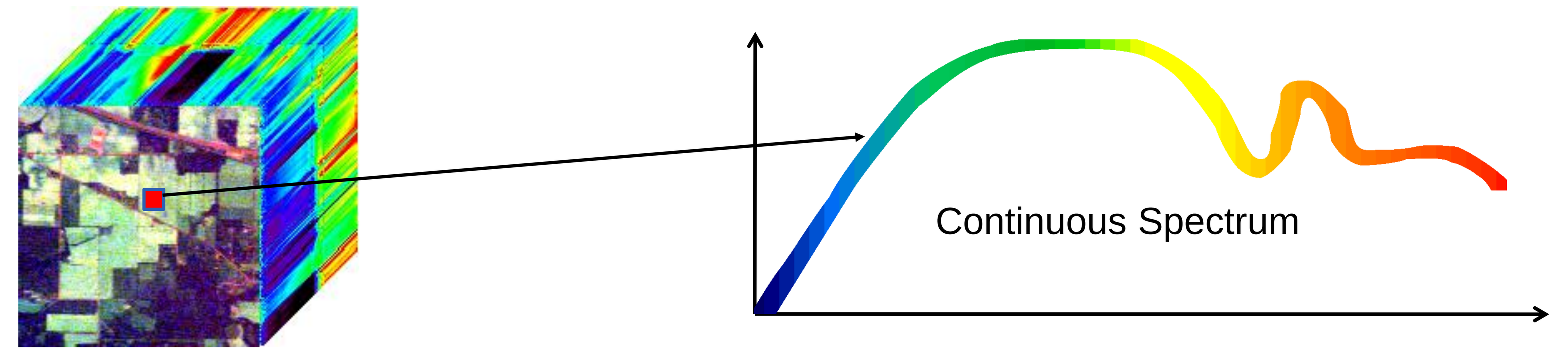
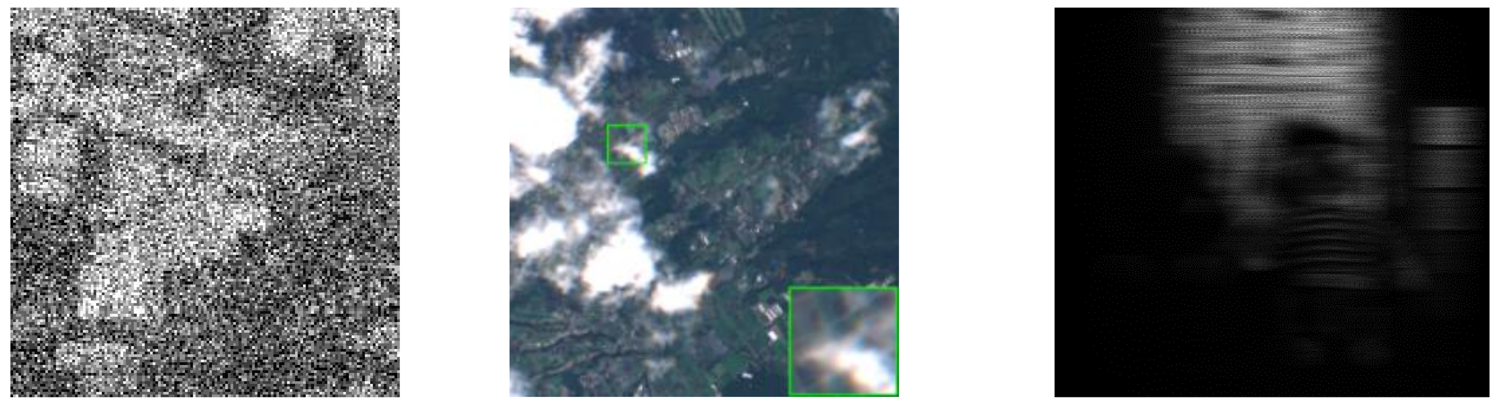
Background:

- Remote sensing hyperspectral image (HSI) has a high spectral resolution, it can imaging at every 10nm.
- HSIs always suffer from various degradations, such as noise, cloud/shadow, compressing, *etc*.
- The HSIs from different sensors differ significantly.

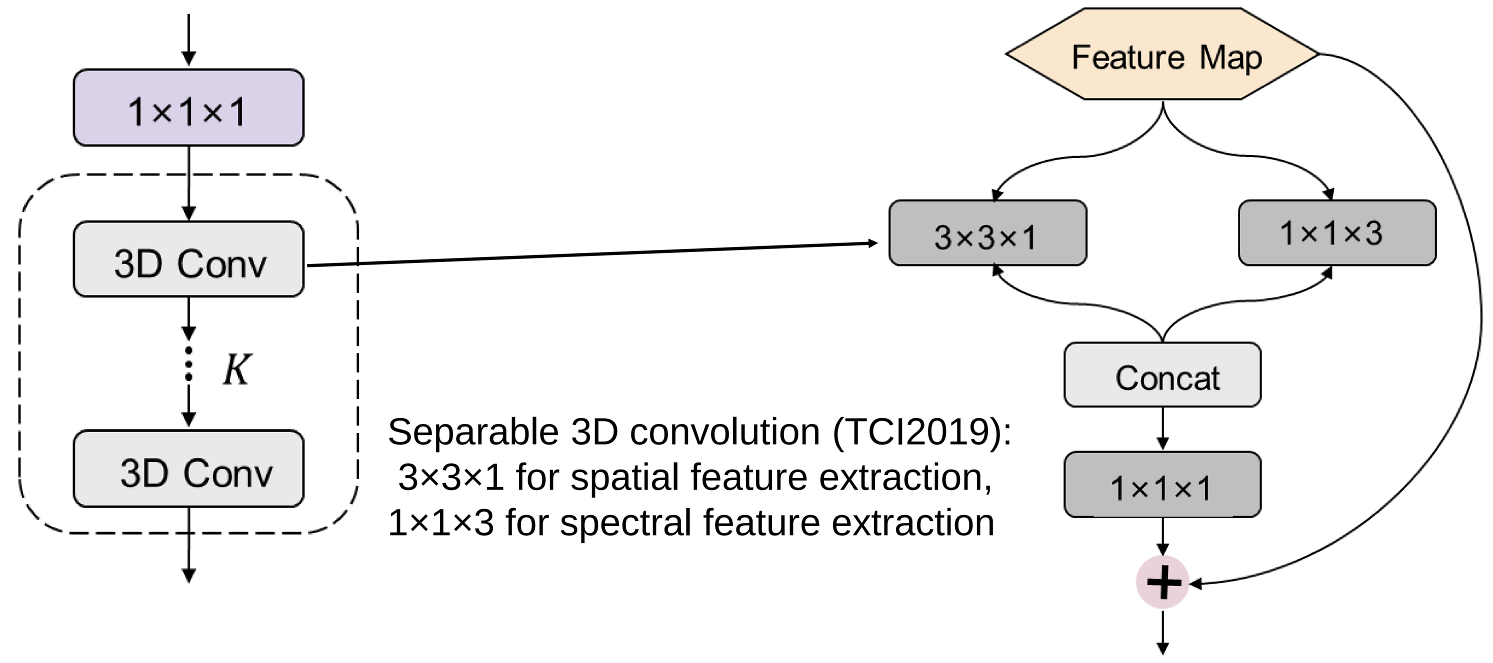




Noise　　Cloud corruption　　Compressing

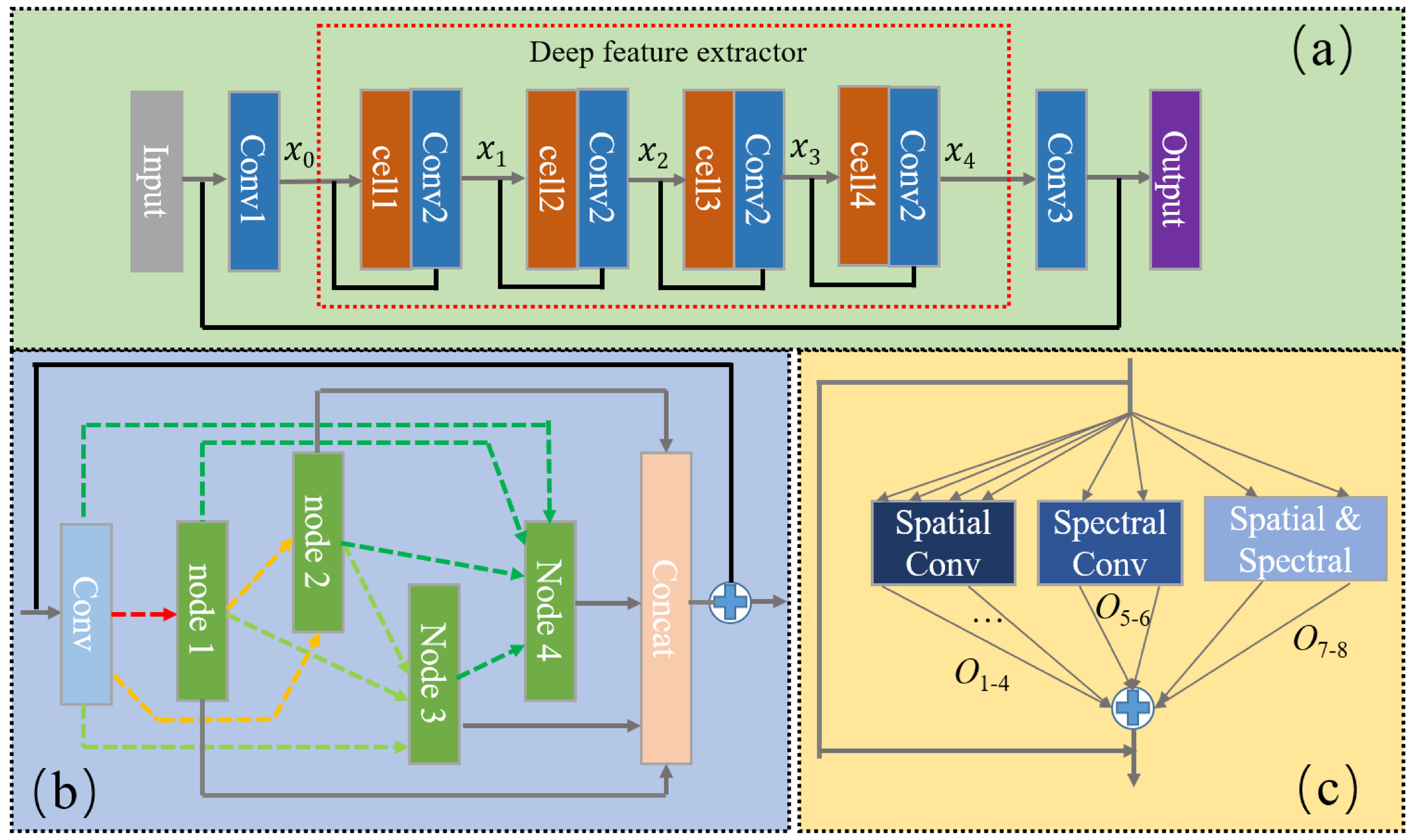
HSI restoration: spatial-spectral analysis

- At the beginning, the spatial based methods, such as HSI-DeNet, HSID-CNN are utilized to restore the HSIs from degraded image.
- Subsequently, 3D convolution, spatial-spectral attention, play-and-plug framework are introduced to explore the spectral information.
- Separable 3D convolution is efficient for spatial-spectral features exploration, but the balance analysis between the two is missing. Therein, most HSI restoration works simply focus on one specific task and lose the transferability across different sensors.



Spectrum-aware and Transferable Architecture Search

- Utilize One-shot neural architecture search [1] to design efficient architecture for various HSI restoration tasks across different sensors.
  - Build the global architecture (a) and micro cell architecture (b)
  - The mixed residual block (MRB) to connect the two possible tow nodes consists of 4 spatial Conv, 2 spec Conv, and 2 spatial-spectral Conv, shown in (c).



- To resist various degradations in different HSI restoration tasks, we introduce noise level independent search algorithm, with the following objective function. α and θ stand for the architecture parameter and network parameter, respectively, σ is the noise variance.

$$\mathcal{L}(\theta,\alpha,\mathcal{D}) = {}^{1}\!/_{2}\sum\nolimits_{y\in\mathcal{D}}\left\|\mathtt{net}_{\alpha}(x(\sigma);\theta)-y\right\|_2^2.$$

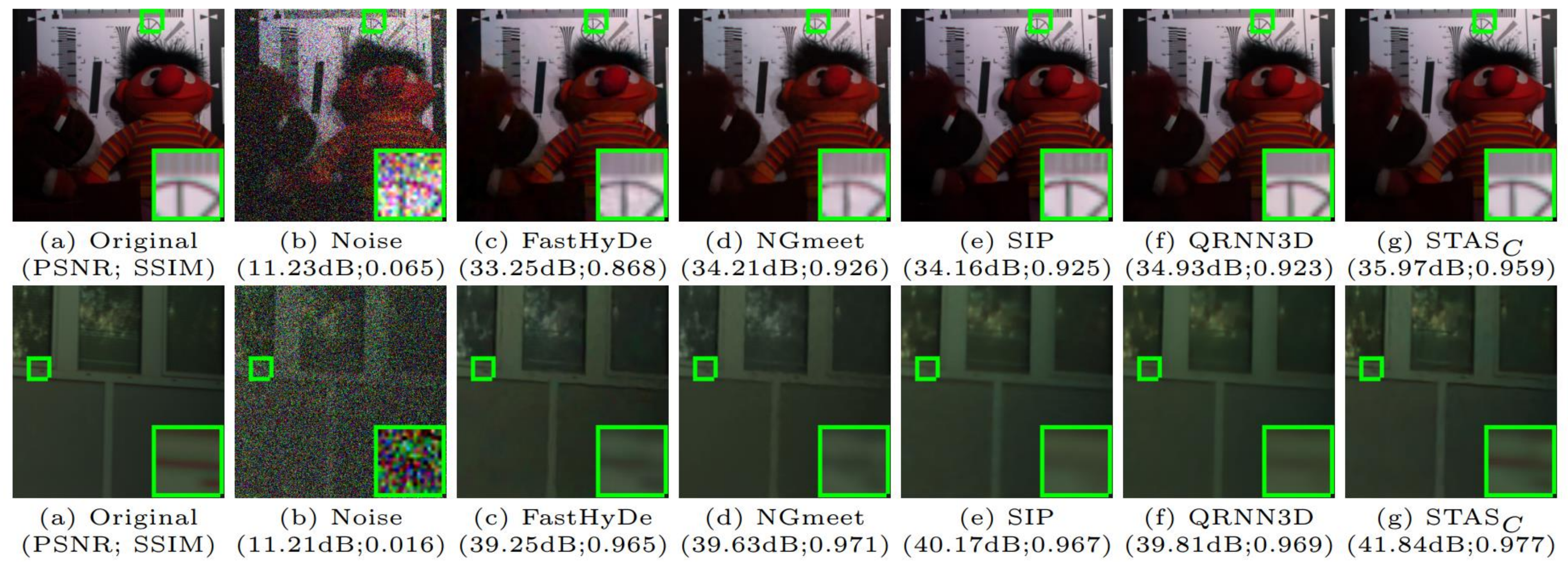
During the training, σ changes for different batch and epoch.

- Finally, we achieve the architecture a. The learned architecture is utilized for various HSI restoration tasks.

Experiments

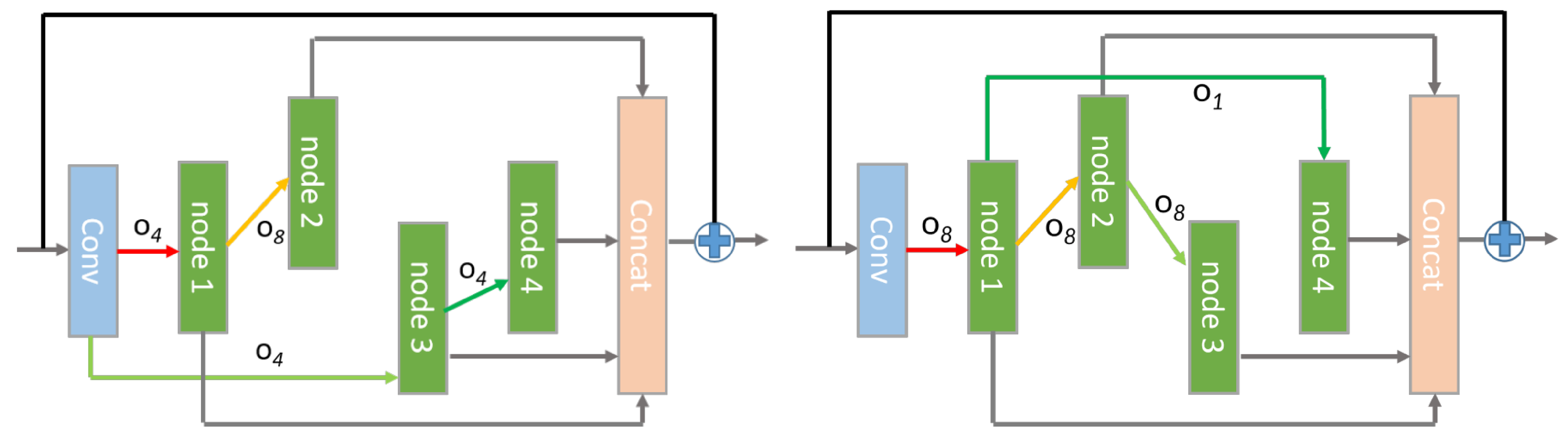
- Dataset: Network search experiments are implemented on CAVE and Pavia images, respectively. The learned architectures are used for CAVE denoising, ICVL denoising, and KAIST imaging reconstruction.
- The proposed STAS is compared to model based HSI denoising NGmeet[2], and learning based methods SIP[3] and QRNN3D[4]. STAS can achieve better quantitative and visual results, regarding different dataset/noise-level restoration.

	method / noise	FastHyDe PSNR	FastHyDe SSIM	NGmeet PSNR	NGmeet SSIM	SIP PSNR	SIP SSIM	QRNN3D PSNR	QRNN3D SSIM	$STAS_C$ PSNR	$STAS_C$ SSIM
CAVE	30	38.00	0.949	**39.05**	**0.963**	36.97	0.948	37.65	0.957	38.39	0.961
	50	35.53	0.911	36.38	0.941	35.81	0.937	35.84	0.935	**36.80**	**0.949**
	70	33.70	0.871	34.34	0.916	34.64	0.929	34.96	0.927	**35.83**	**0.940**
ICVL	30	42.96	0.971	43.42	0.973	41.58	0.960	42.08	0.967	**43.92**	**0.978**
	50	40.58	0.958	40.85	0.962	40.03	0.950	40.62	0.959	**42.01**	**0.969**
	70	38.86	0.941	39.21	0.950	38.88	0.930	39.21	0.943	**41.13**	**0.961**



- The learned $STAC_C$ can achieve better results on CAVE denoising; $STAC_p$ can achieve better on Pavia denoising.

Method	Index	FastHyDe	NGmeet	$STAS_C$	$STAS_P$
CAVE	PSNR	33.53	36.38	**36.80**	35.92
	SSIM	0.911	0.941	**0.949**	0.936
	MSA	9.33	6.12	**5.34**	6.04
Pavia	PSNR	33.93	34.80	33.10	**34.96**
	SSIM	0.913	0.926	0.917	**0.933**
	MSA	4.86	3.98	4.20	**3.64**



- Left side is the learned cell block of $STAC_C$ trained on CAVE dataset; right side is the cell block of $STAC_p$ from Paiva dataset.

Conclusion:

- For CAVE with fewer spectral bands, spatial convolution is effective. For Pavia with larger spectral bands, spatial-spectral convolution is effective.
- The transferability of searched architecture is dependent on the spectral information and independent of the noise levels.

Reference:

[1] Liu, H., Simonyan, K., Yang, Y.: Darts: Differentiable architecture search. ICLR, 2019.

[2] He, W., Yao, Q., Li, C., Yokoya, N., Zhao, Q., Zhang, H., Zhang, L.: Non-local meets global: An integrated paradigm for hyperspectral image restoration. IEEE TPAMI, 2022.

[3] Imamura, R., Itasaka, T., Okuda, M.: Zero-shot hyperspectral image denoising with separable image prior. ICCVW, 2019.

[4] Wei, K., Fu, Y., Huang, H.: 3d quasi recurrent neural network for hyperspectral image denoising. IEEE TNNLS, 2021.