Unmixing Diffusion for Self-Supervised Hyperspectral Image Denoising

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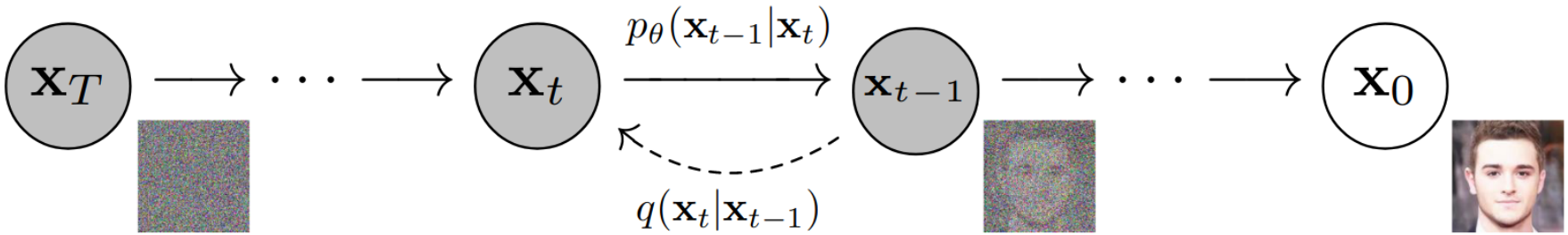
A method addressing spectral image reconstruction challenges using a diffusion model pre-trained on large-scale RGB images!

Denoising Diffusion Model



Denoising Diffusion Probabilistic Models, NeurIPS 2020

Denoising Diffusion Model

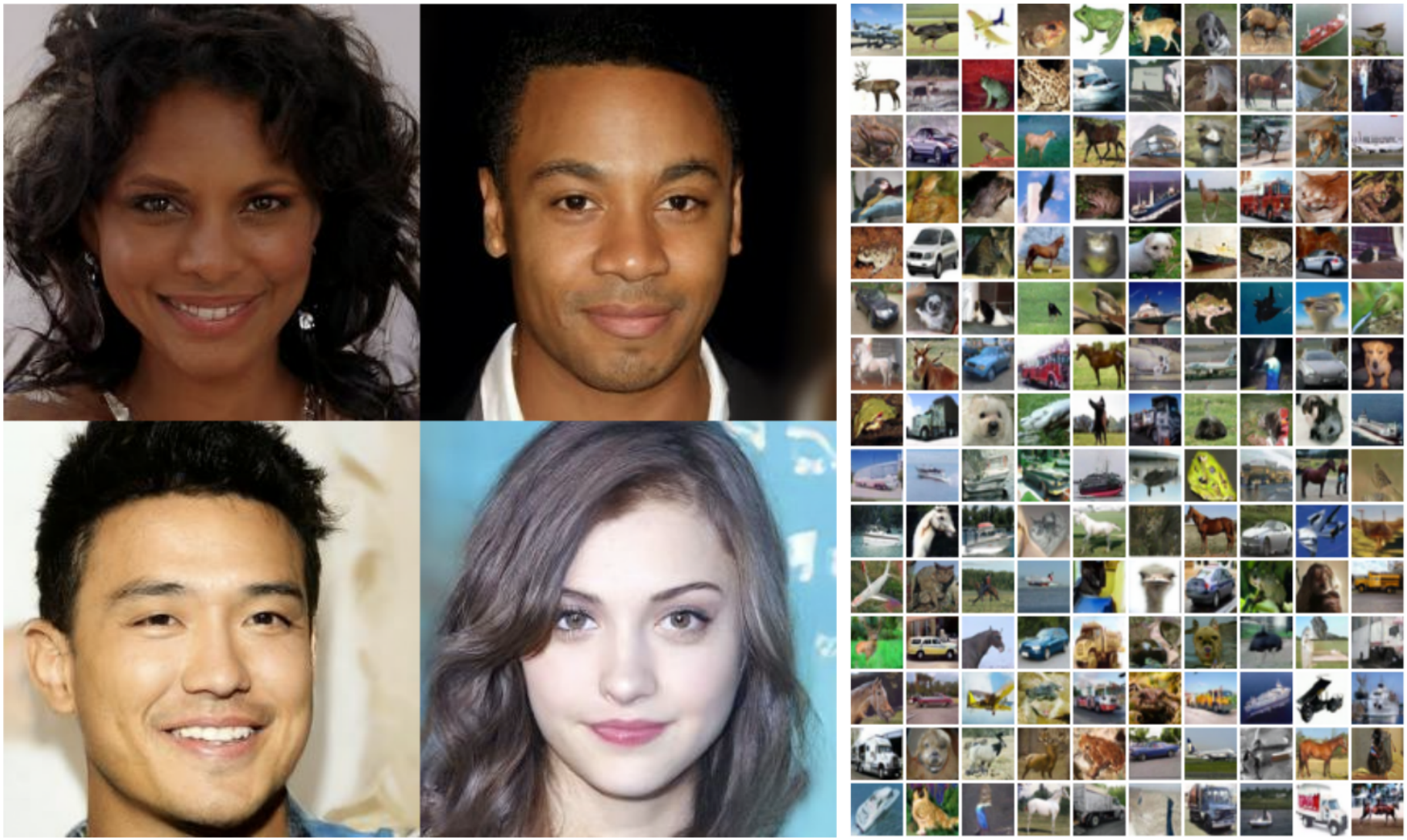
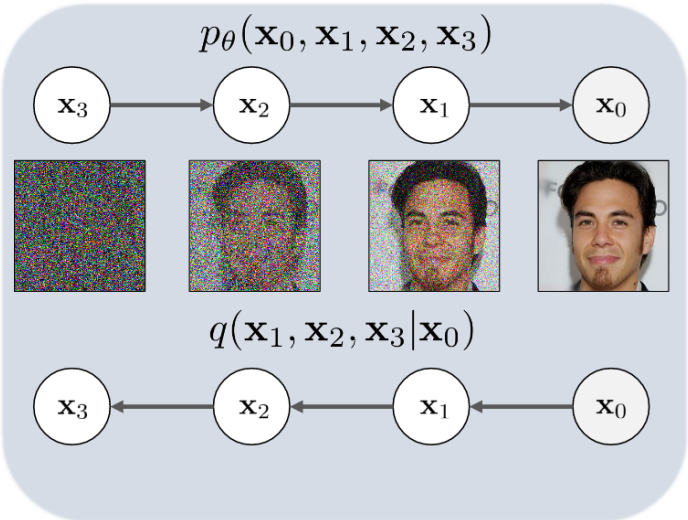


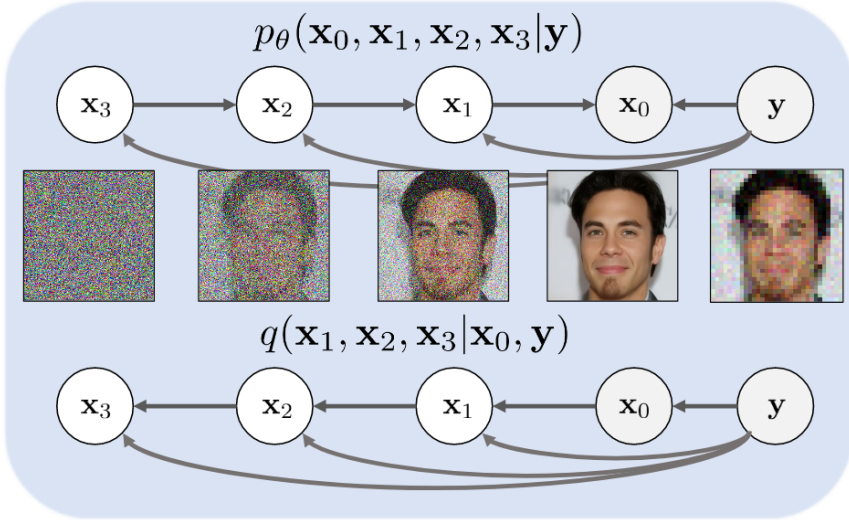
Figure 1: Generated samples on CelebA-HQ 256×256 (left) and unconditional CIFAR10 (right)

Denoising Diffusion Restoration Model



Denoising Diffusion Probabilistic Models
(Independent of inverse problem)

Use pre-trained models for linear inverse problems



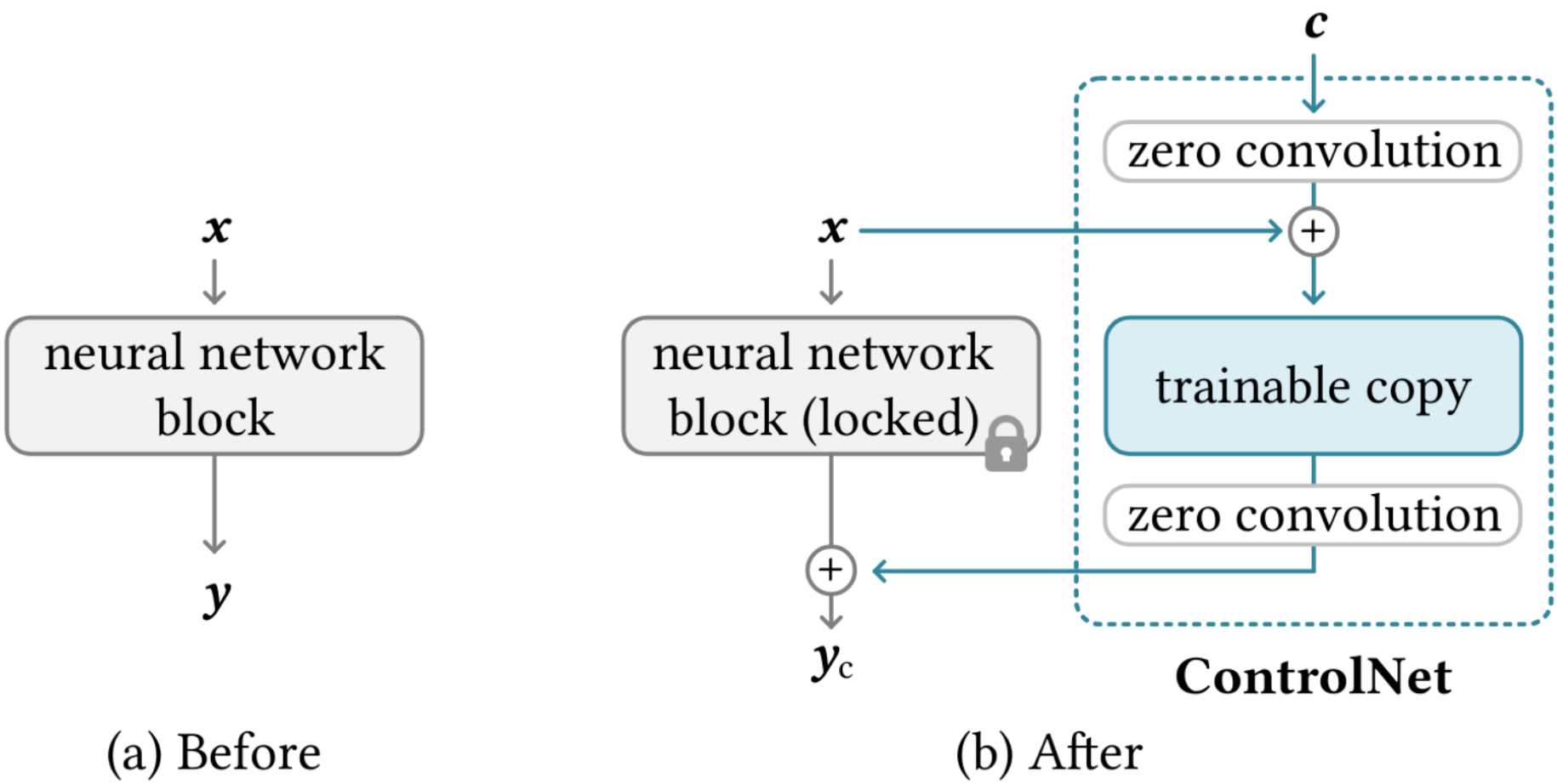
Denoising Diffusion Restoration Models
(Dependent on inverse problem)

DDRM, NeurIPS 2022

Control Diffusion Model

Adding Conditional Control to Text-to-Image Diffusion Models, 2023

Control Diffusion Model



Adding Conditional Control to Text-to-Image Diffusion Models, 2023

Get the generative power to Hyperspectral Image

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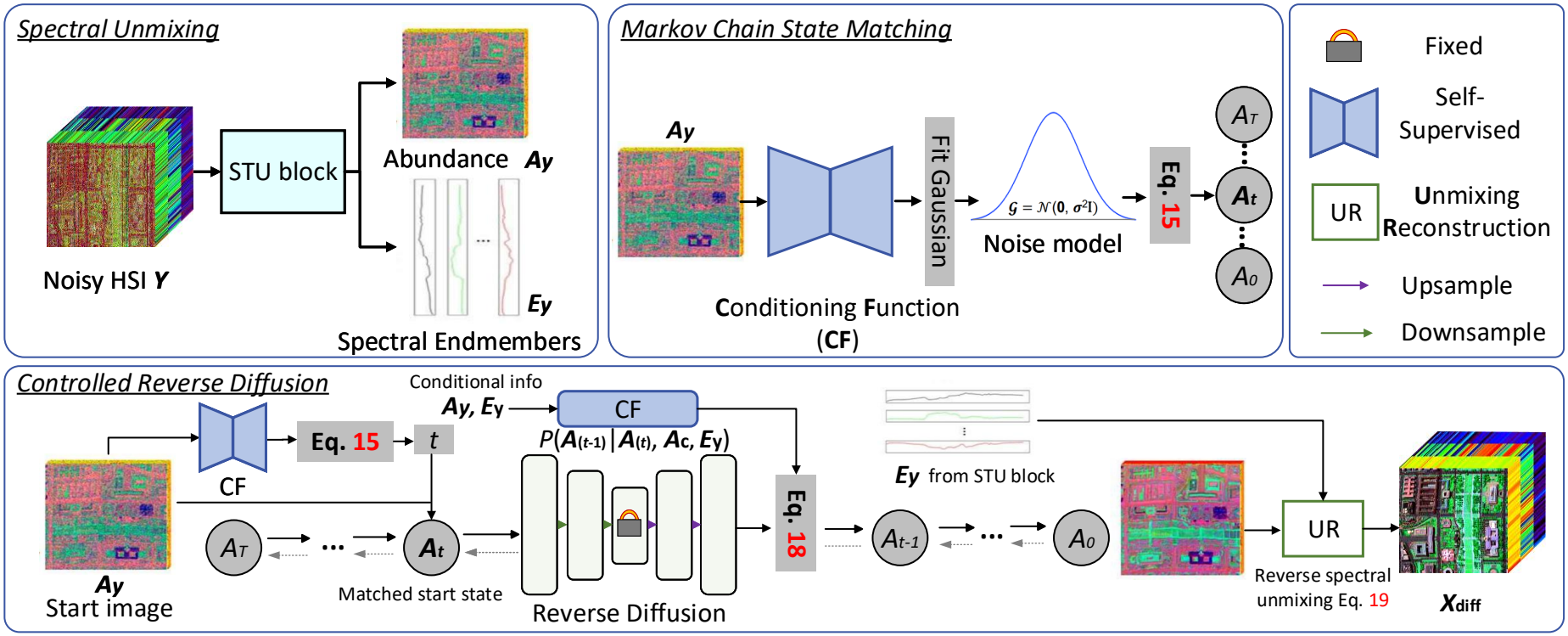
C We do not have lots of GPU or any big GPU.

D Big RGB datasets pretrained diffusion models are free lunch.

Pre-trained RGB Diffusion Models for Hyperspectral Image



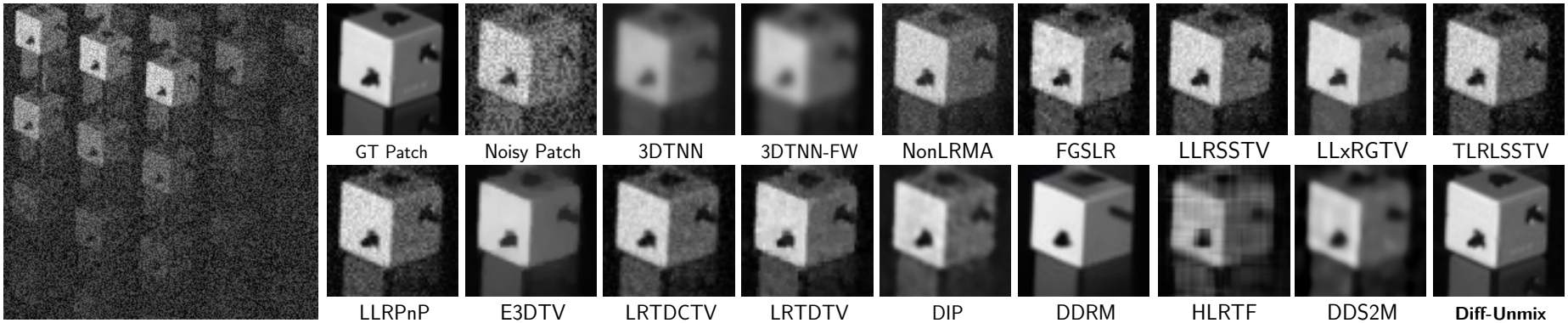
Diff-Unmix for hyperspectral Image Denoising

Results on Synthetic Noise

Quantitative results on KAIST dataset, PSNR, SSIM, FSIM, SAM and running time are reported.

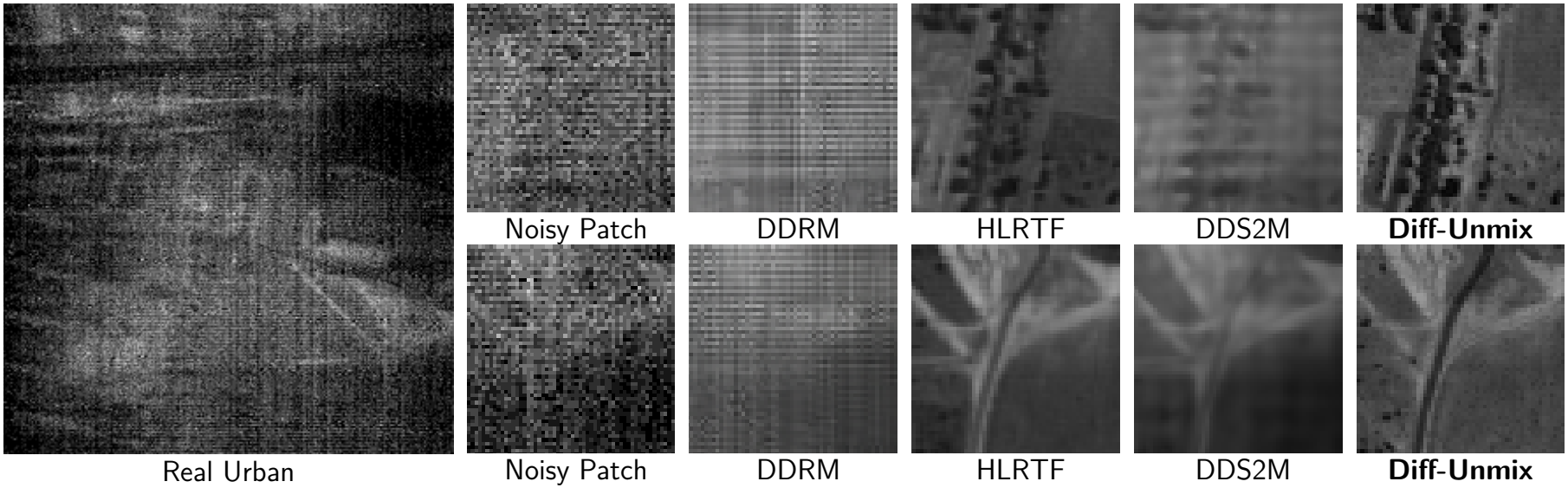
Method	**Reference**	**PSNR** ↑	**SSIM** ↑	**FSIM** ↑	**SAM** ↓	**Time (s)**
Noisy	None	16.175	0.115	0.401	0.801	None
NonLRMA	TGRS 2017	21.259	0.414	0.803	0.882	11
LRTDTV	JSTAR 2017	31.061	0.772	0.882	0.297	38
LLRSSTV	JSTAR 2018	28.145	0.682	0.814	0.432	36
TLR_LSSTV	TGRS 2021	24.875	0.532	0.767	0.395	76
LLxRGTV	SP 2021	31.152	0.802	0.917	0.205	38
3DTNN	IS 2020	25.477	0.668	0.887	0.227	16
3DTNN_FW	TGRS 2019	28.035	0.780	0.881	0.197	20
LRTDCTV	JSTAR 2023	25.952	0.658	0.816	0.406	43
E3DTV	TIP 2020	30.335	0.868	0.926	0.221	10
FGSLR	TGRS 2021	30.126	0.737	0.878	0.262	249
DIP	ICCV 2019	24.181	0.608	0.825	0.475	72
LLRPnP	IA 2020	28.664	0.748	0.861	0.379	240
HLRTF	CVPR 2022	33.011	0.808	0.925	0.275	23
DDRM	NeurIPS 2022	29.412	0.865	0.922	0.293	20
DDS2M	ICCV 2023	32.804	0.786	0.895	0.334	354
Diff-Unmix	Ours	**33.059**	**0.964**	**0.940**	**0.116**	37

Results on Synthetic Noise



Visual comparison of HSI denoising methods on KAIST dataset with noise $\mathcal{N}(0, 0.3)$.

Results on Real-World Noise



Visual comparison on HSI Urban with real-world noise.

Thank You