

VISIONARY: Novel Spatial-Spectral Attention Mechanism for Hyperspectral Image Denoising

Aditya Dixit

IIT Indore, India

phd2201101009@iiti.ac.in

Nischit Hosamani

IIT Indore, India

cse200001054@iiti.ac.in

Puneet Gupta

IIT Indore, India

puneet@iiti.ac.in

Ankur Garg

SAC, Ahmedabad, India

agarg@sac.isro.gov.in

Qualitative denoising results of real data for various band combinations are presented in Fig. 1, where it is shown that our proposed method surpasses existing methods in terms of visual quality. We also perform experiments using the Urban [4] and RealHSI datasets [9]. The visual results is shown in Fig. 4. It's clear that VISIONARY delivers cleaner and sharper images.

For a thorough evaluation, we compared HSI classification accuracy before and after denoising using various methods Fig. 2 shows SVM classification results for the IP and PU datasets and Fig. 5 shows SVM classification results for the Urban dataset, while Table 1 provides the quantitative results of the same dataset. Post-denoising, our proposed method surpasses existing methods in terms of visual quality, indicating superior denoising performance. Additionally, Fig. 3 provides spectral profiles to assess further the potency of different denoising methods in the spectral domain, showing that our method outperforms all others in spectral performance and closely matches the ground truth.

1. Computational Efficiency

We give an overview of the computational efficiency of our proposed method in terms of GFLOPs, number of parameters, and inference/training time. The GFLOP for VISIONARY is 144.47, which is relatively lesser than the GFLOPs of state-of-the-art methods like SERT with values of 1018.9 and comparable to UNFOLD's value of 141.5. Additionally, the parameter count is relatively comparable but gives better results as a trade-off. Moreover, the average inference time of VISIONARY is 5.1 seconds, which is better than UNFOLD [9] and relatively comparable to SERT [17], which have average inference times of 5.8 and 3.2 seconds, respectively. The training time of VISIONARY is 15 hours.

References

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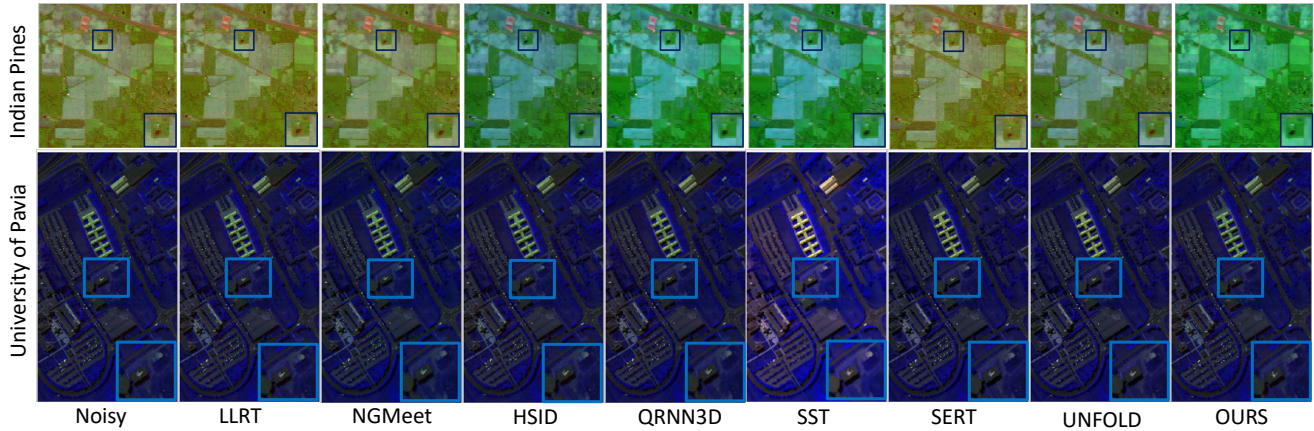


Figure 1. Real denoised results on IP and PU datasets for bands (3, 103, 203) and (5, 13, 95), respectively.

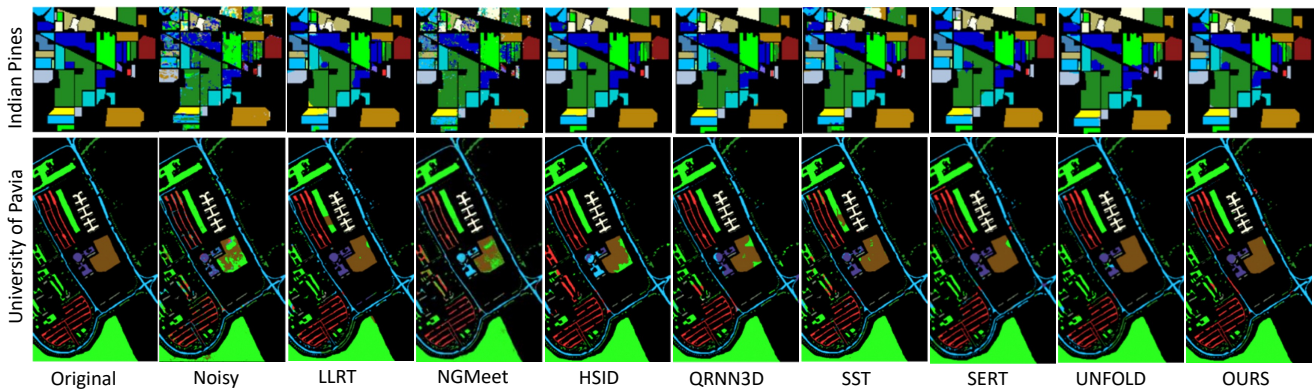


Figure 2. Classification outcomes for IP and PU datasets.

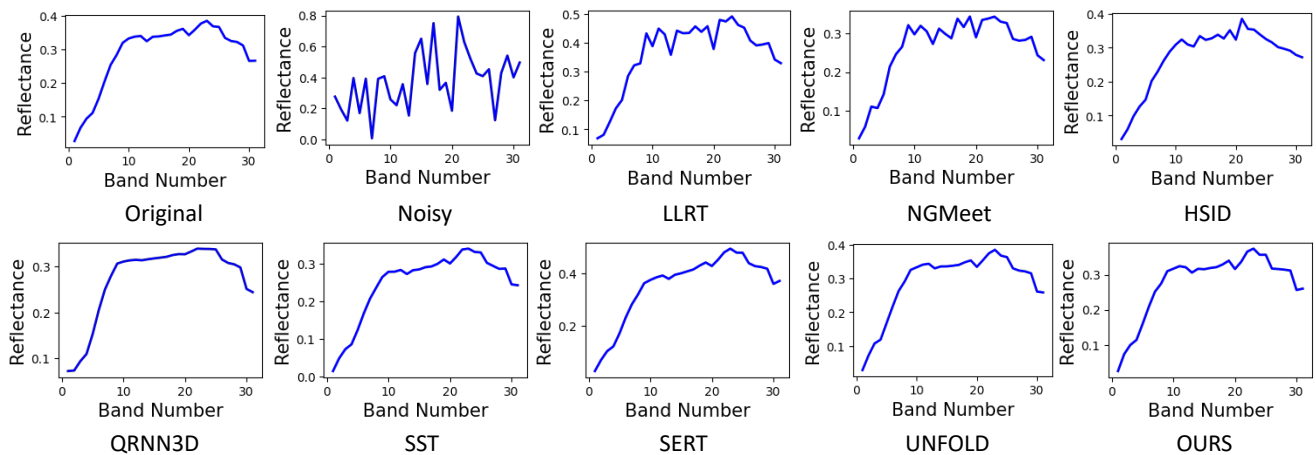


Figure 3. Spectral curves of the ICVL dataset at coordinates (110, 110) under Gaussian noise ($\sigma = 50$).

Table 1. Classification outcomes on Urban Dataset Pre- and Post-HSI Denoising

Dataset	Index	Noisy	[1]	[3]	[8]	[7]	[5]	[6]	[2]	OURS
Urban	OA	86.11	91.27	92.33	92.76	92.99	94.17	94.91	95.13	96.02
	Kappa	0.8385	0.8847	0.8909	0.9088	0.9086	0.9189	0.9267	0.9405	0.9528

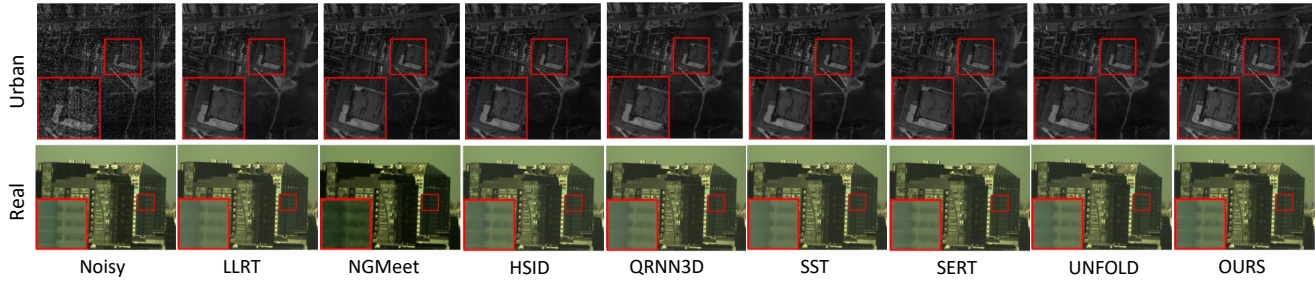


Figure 4. Visual outcomes for real-world noise reduction on the Urban [4] and Real [9] Datasets.

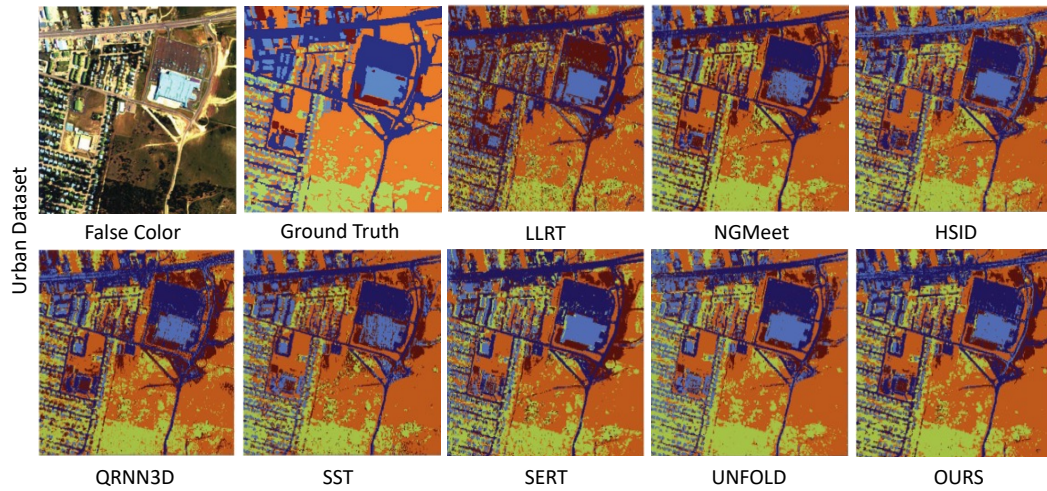


Figure 5. Classification outcomes for Urban [4] dataset.