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Noise2Noise Denoising of CRISM Hyperspectral Data

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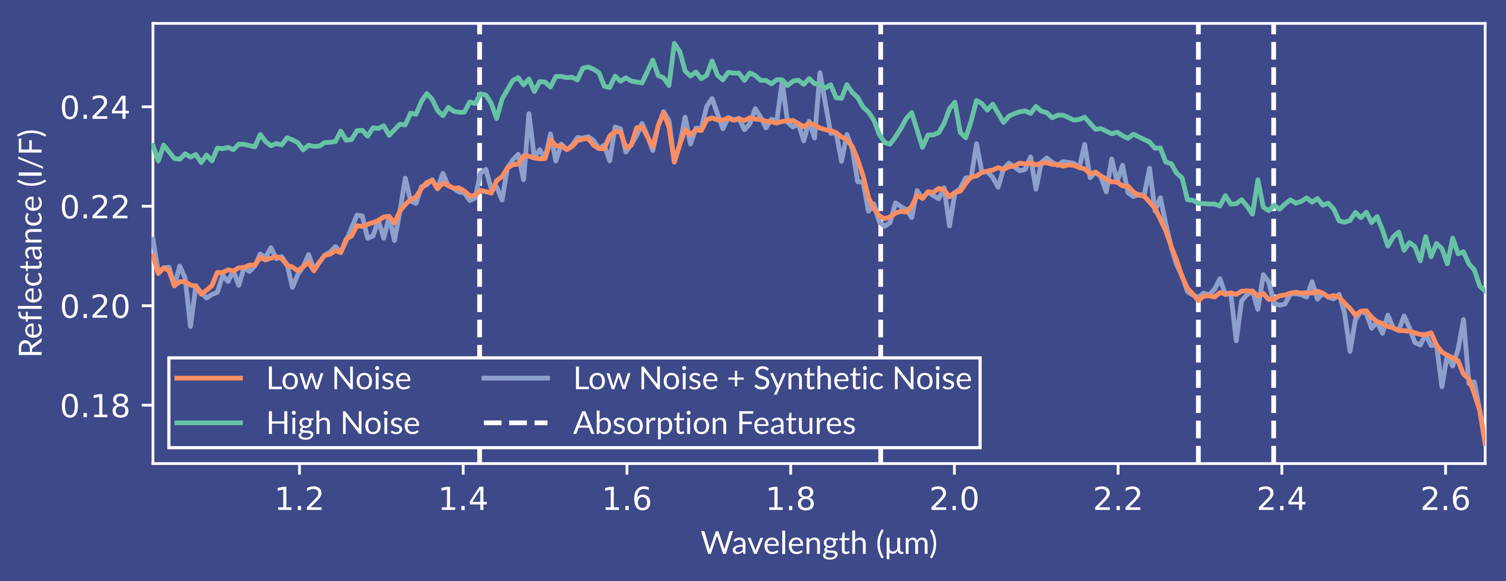

Figure 1: Example low-noise and high-noise spectra, and low-noise with added synthetic noise.

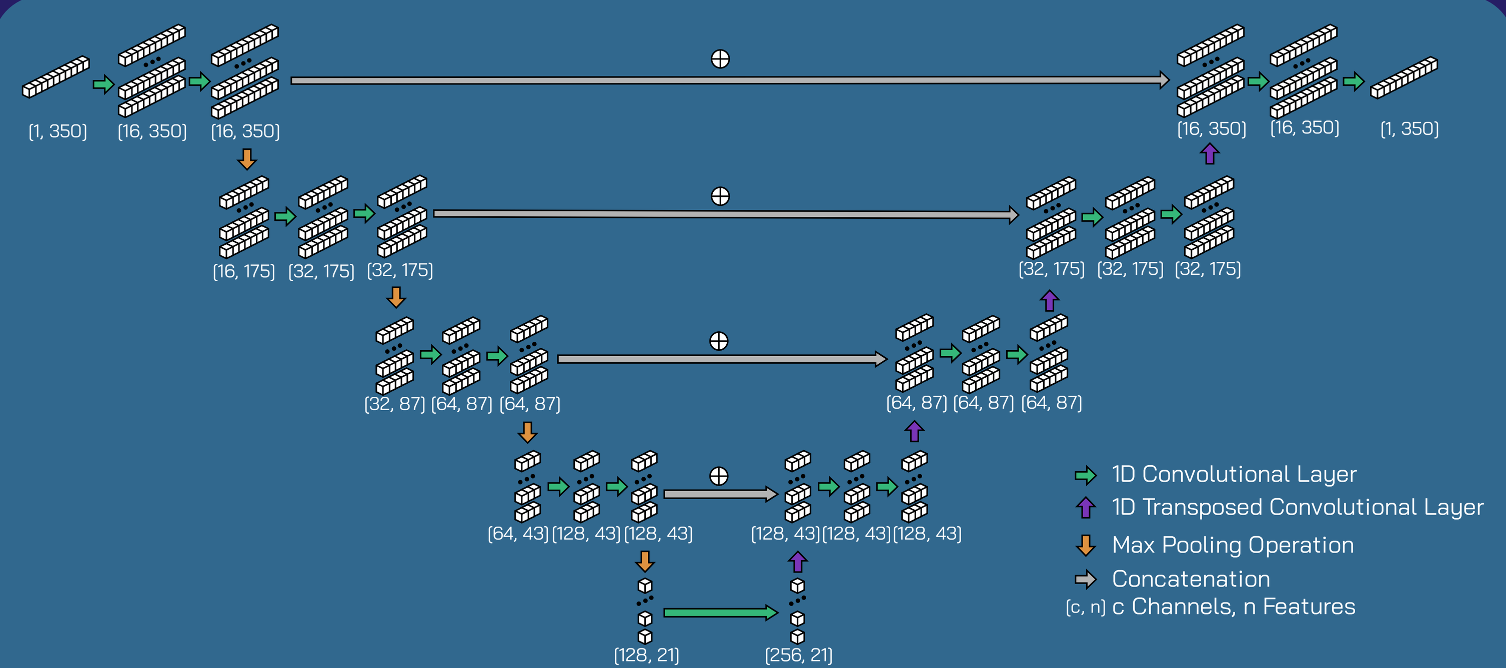

Figure 2: N2N4M Network Architecture.

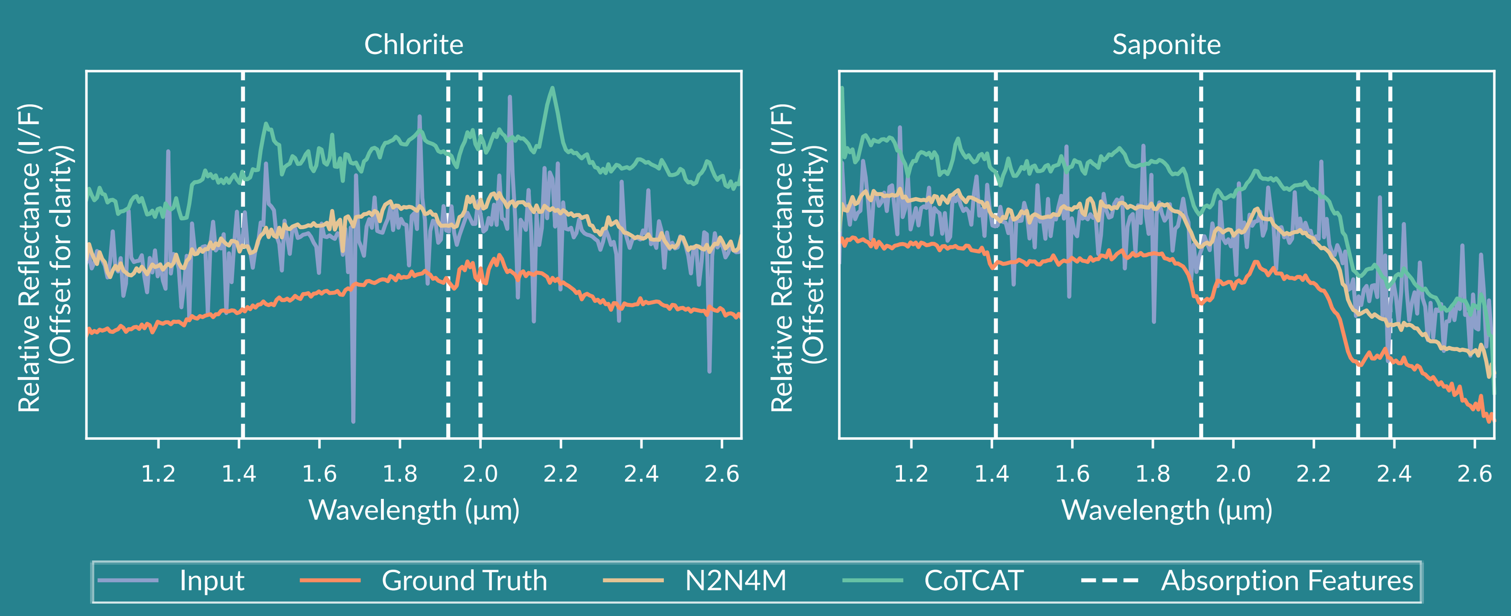

Figure 3: Denoising results on synthetic noise data.

Data	Denoising Task MSE	Downstream Classification Task Relative Accuracy	Relative F1 Score	Relative Precision	Relative Recall
Ground Truth	N/A	1.00	1.00	1.00	1.00
Savitzky-Golay Filter	2.8×10^{-5}	0.01	0.00	0.42	0.09
CoTCAT (Bultel et al. 2015)	5.0×10^{-6}	0.35	0.43	**0.50**	0.41
N2N4M (Ours)	$\mathbf{4.7 \times 10^{-6}}$	**0.52**	**0.48**	**0.50**	**0.64**

Table 1: Benchmarking results for denoising, and downstream classification task using HBM from Plebani et al. (2022).

Introduction

CRISM hyperspectral data allows for detailed mineralogy mapping of Martian surface (Carter et al. 2013).
Significant noise increase over time limits use of imagery (Mandon et al. 2021), including over Oxia Planum, landing site for ESA's ExoMars mission.
Here a self-supervised deep learning method is proposed to denoise CRISM imagery.

Methods

Data from the CRISM Machine Learning Toolkit dataset (Plebani et al. 2022).
Synthetic noise added to spectra to form training data (Fig. 1)
1D Convolutional U-Net (Fig. 2) is trained to denoise synthetic noise CRISM spectra.

Synthetic Results

N2N4M significantly lower reconstruction error than benchmark methods (Table 1). Synthetic results (Fig. 3) show N2N4M removes more noise than benchmarks, whilst retaining key absorption features.

Downstream Classification Results

HBM from Plebani et al. (2022) used for downstream classification, to predict pixel mineralogy. N2N4M denoising (Table 1) results in a significant increase in most metrics over benchmark denoising method CoTCAT (Bultel et al. 2015).

Real Image Results

2 noisy images denoised (Fig. 4) using N2N4M show clear improvement in image quality over original and benchmark, comparable to low noise reference images taken of same area.

Discussion and Conclusions

Our model shows strong results on both synthetic and real hyperspectral CRISM imagery. N2N4M denoised data shows significant improvement over the benchmark in enabling downstream classification. This will allow for further study of the ExoMars landing site before launch.

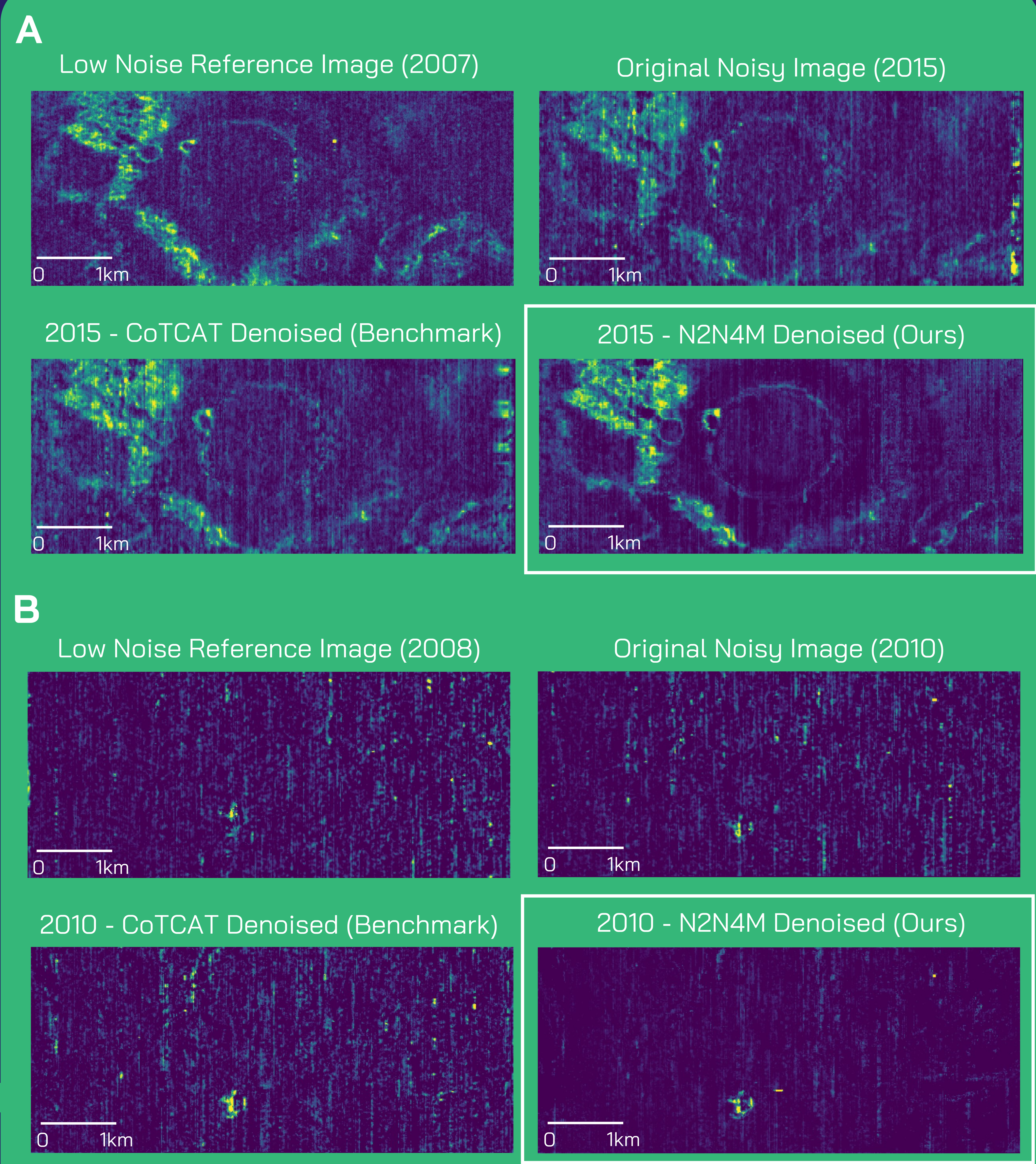

Figure 4: 2 examples (A and B) of paired CRISM images acquired at different times over the same area. Displayed summary parameters highlight mineralogy of interest (Hydrated Fe/Mg clays, and Gypsum respectively).

References

Plebani, E., Ehlmann, B. L., Leask, E. K., Fox, V. K. & Dundar, M. M. A machine learning toolkit for CRISM image analysis. *Icarus* **376**, 114849 (2022).
Carter, J., Poulet, F., Bibring, J.-P., Mangold, N. & Murchie, S. Hydrous minerals on Mars as seen by the CRISM and OMEGA imaging spectrometers: Updated global view. *Journal of Geophysical Research: Planets* **118**, 831–858 (2013).
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