SAND2021-15101C

SAND2021-

Comparative Study of the Performance of Seismic Denoising Methods Using Regional Data

Rigobert Tibi, Christopher Young, and Robert Porritt

Sandia National Laboratories

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525. This research was funded by the National Nuclear Security Administration, Defense Nuclear Nonproliferation Research and Development (NNSA DNN R&D). The authors acknowledge important interdisciplinary collaboration with scientists and engineers from LANL, LLNL, MSTS, PNNL, and SNL.”.

Abstract

Seismic waveform data are generally contaminated by noise from various sources, which interfere with the signals of interest. Thus, the efficiency of the noise suppression approach used early in the processing pipeline affects the quality of the downstream products. In this study, we implemented and applied different seismic denoising methods and their respective variants to data recorded by the regional network of the University of Utah Seismograph Stations. The denoising methods consist of frequency filtering, approaches based on nonlinear thresholding of continuous wavelet transforms (CWTs, e.g., Langston and Mousavi, 2019), and a convolutional neural network (CNN) denoiser (Tibi et al., 2021). Frequency filtering works by retaining signals within a predefined frequency band, while suppressing anything that lies outside that band. The CWT nonlinear soft thresholding involves first calculating a scale-dependent threshold using the characteristics of the pre-event noise, and assumes that the noise is stationary across the waveform. The denoising step subtracts off the threshold value from the CWT coefficients of the seismic waveform that are above the threshold, while setting to zero coefficients that are below the threshold. The CNN denoiser exploits a machine learning model trained using constructed noisy waveforms with known component (signal and noise) characteristics to process the input seismogram. Results involving 4780 constructed waveforms suggest that on average bandpass filter, the CWT, and CNN denoisers improve the signal-to-noise ratio (SNR) by about 5, 10, and 7 dB, respectively. In terms of waveform similarity and amplitude distortion for the recovered waveforms with respect to the ground truth (GT) seismograms, CNN denoising outperforms both frequency filtering and CWT denoising. The performance of all the approaches are depend on the SNR of the input waveforms; however, for frequency filtering the SNR of the processed waveform decreases significantly faster with decreasing SNR for the input seismogram. Also, we find that the average correlation coefficient value is about 0 for the seismograms processed with frequency filtering, which suggests that these

Denoising Methods – Thresholding of Continuous Wavelet Transforms (CWTs)

The wavelet transform of a continuous signal, *x(t)*, with respect to a wavelet function, *ψ(t)*, is defined as:

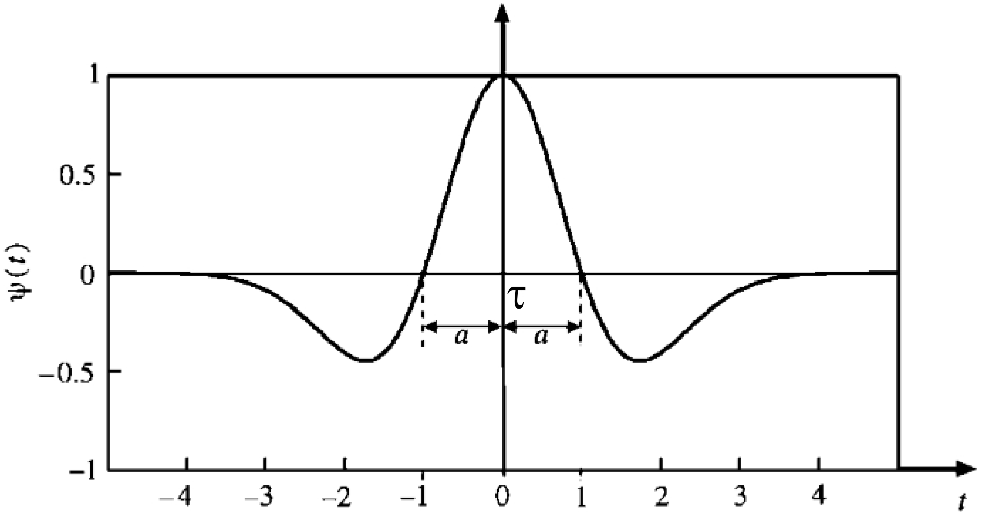
$$W(a,\tau) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-\tau}{a}\right)dt \qquad (1)$$

a - Scale

τ - Time lag or location

ψ^*- Complex conjugate of the wavelet function

As our mother wavelet, we used the Ricker wavelet, also known as the Mexican Hat wavelet



$$\psi(t) = (1-t^2)e^{-\frac{t^2}{2}} \qquad (2)$$

Denoising Methods – Thresholding of CWTs

Key Aspects of the Denoising Approach Based on the Thresholding of CWTs:

- Pre-event window is used to estimate the scale dependent (non-linear) threshold
- Noise is assumed to be stationary throughout the waveform

Soft-thresholding (≠ hard thresholding):

The thresholded wavelet coefficients, $\widetilde{W}(a,\tau)$ are defined as:

$$\widetilde{W}(a,\tau) = \begin{cases} sign[W(a,\tau)](|W(a,\tau)| - \beta(a)) \text{ if } |W(a,\tau)| \geq \beta(a), \\ 0 \text{ otherwise} \end{cases} \qquad (3)$$

in which

$$sign[W(a,\tau)] = \frac{W(a,\tau)}{|W(a,\tau)|} \qquad (4)$$

the threshold, $\beta(a) = \text{mean}(|W_n(a,\tau)|) + c\ \text{stdv}(|W_n(a,\tau)|), \qquad (5)$

where $W_n(a,\tau)$ is wavelet transform for the the noise window.

- Noise coefficients are assumed to follow a Gaussian distribution (Donoho & Johnstone, 1994, DONO):

$$c = \sqrt{2\log_{10} N}, \qquad (6)$$

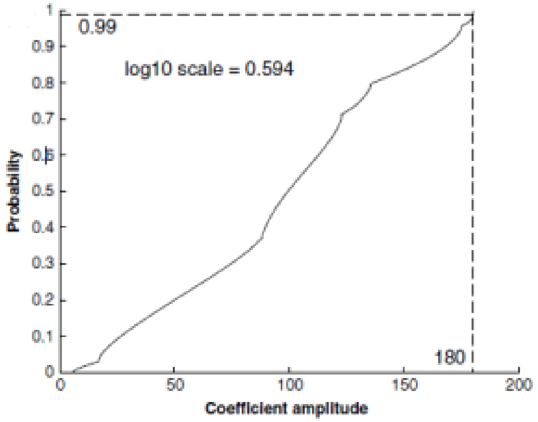
with N being the number of noise samples at each scale.

Denoising Methods – Thresholding of CWTs

- Seismic noise is rarely Gaussian. For that reason, Langston & Mousavi (2019) proposed ordering the N noise values and then assigning a probability jump of $1/N$ when a value is attained.

$$\beta(a) = ECDF_a^{-1}(\mathrm{P} = 0.99), \qquad (7)$$

in which $ECDF_a^{-1}$ is the inverse empirical cumulative distribution function.



Langston & Mousavi (2019)

Denoised (thresholded) waveform, $\tilde{x}(t)$, is estimated using the inverse transform as:

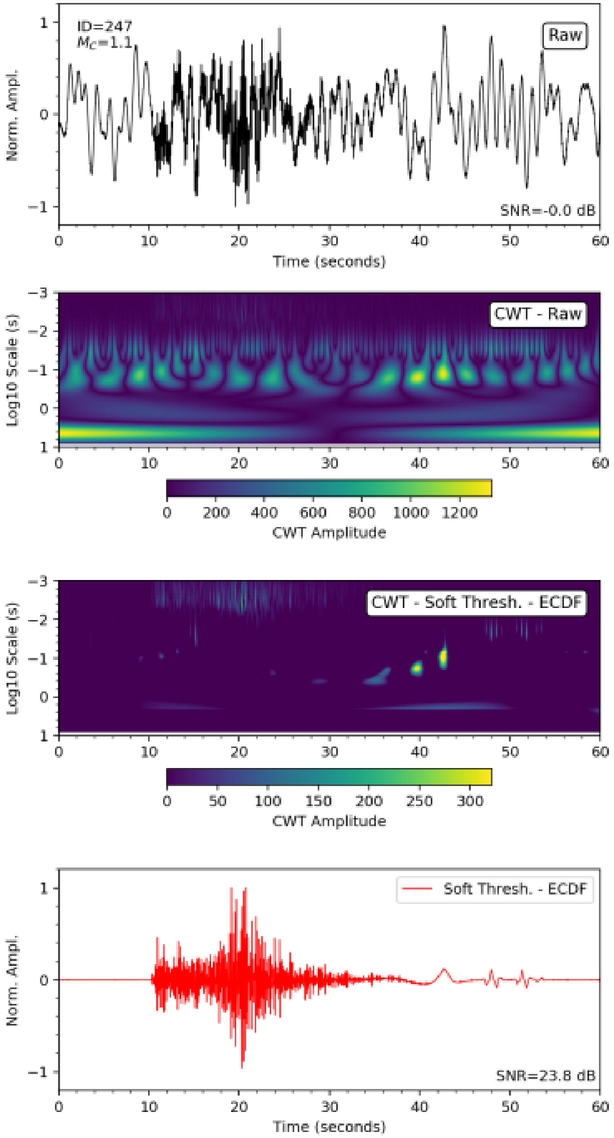
$$\tilde{x}(t) = \frac{1}{C}\int_0^{+\infty}\int_{-\infty}^{+\infty}\frac{1}{\sqrt{a}}\widetilde{W}(a,\tau)\psi\left(\frac{t-\tau}{a}\right)\frac{dt\,d\tau}{a^2}, \qquad (8)$$

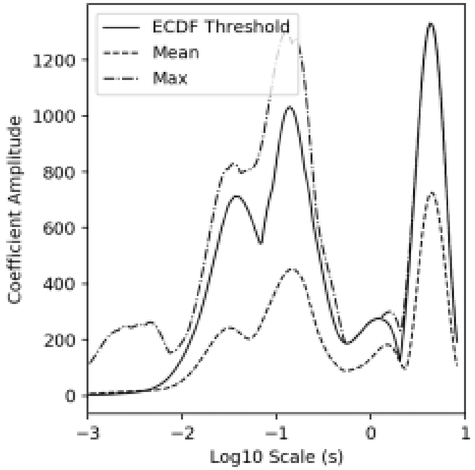
where

$$C = \int_0^{+\infty}\frac{\widehat{\psi}^*(\omega)\widehat{\psi}(\omega)}{\omega}d\omega, \quad (9)$$

in which $\widehat{\psi}(\omega)$ is the Fourier transform of $\psi(\mathrm{t})$.

Denoising Methods – Thresholding of CWTs

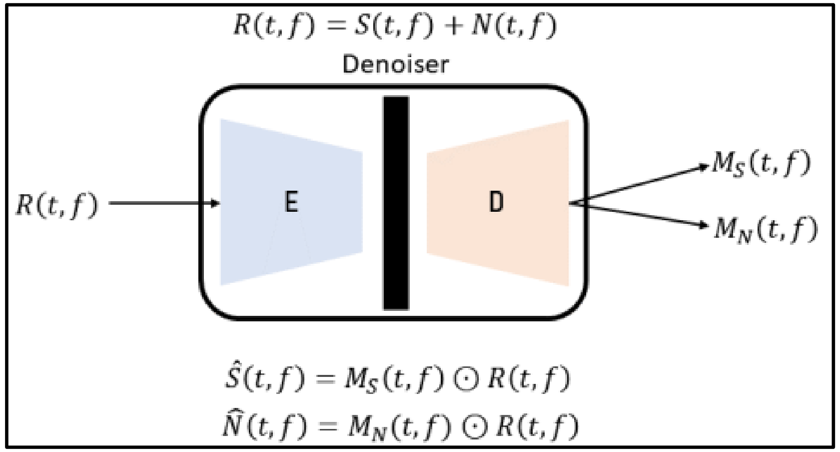




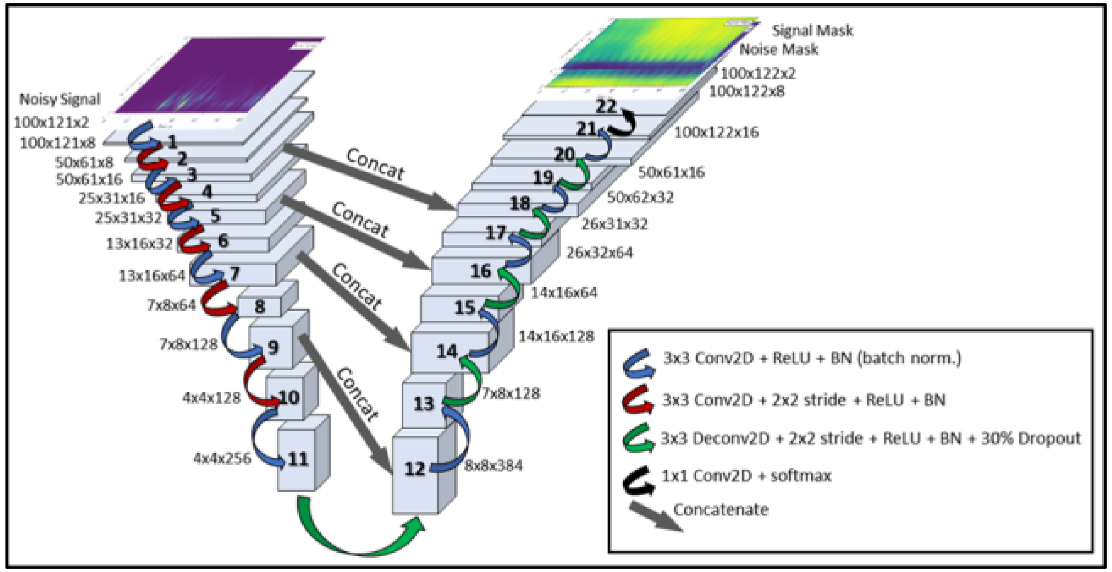
Threshold based on 9-sec window preceding the first *P* arrival

Denoising Methods – Deep Learning Denoising

The approach uses a trained deep convolutional neural network (CNN) model to decompose an input waveform into signal of interest and noise.



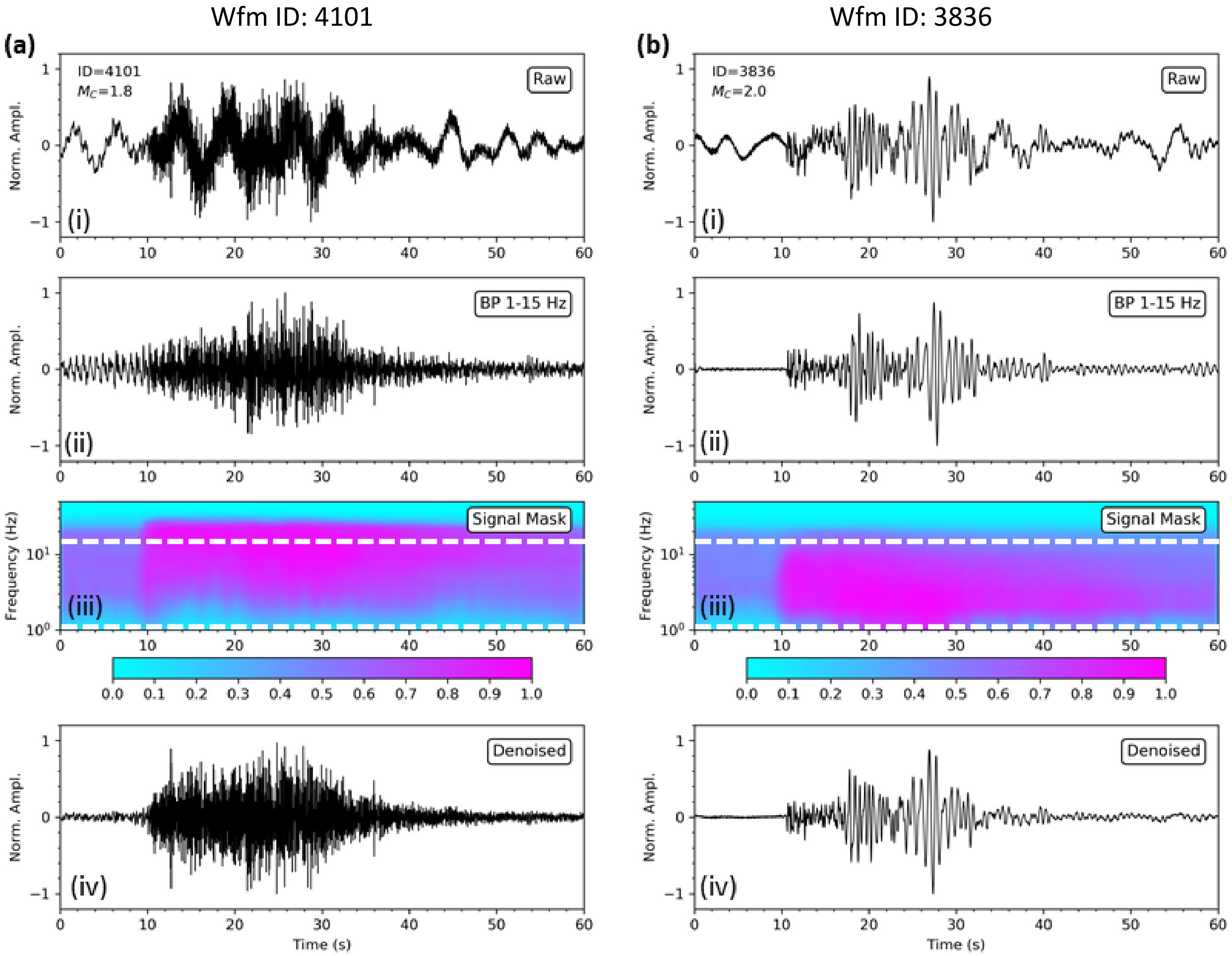
- For an input $R(t,f)$, the network provides a signal mask ($M_S(t,f)$) and a noise mask ($M_N(t,f)$).
- The estimated 'clean' signal ($\hat{S}(t,f)$) is obtained by multiplying $M_S(t,f)$ with $R(t,f)$; and the estimated noise ($\hat{N}(t,f)$) is obtained by multiplying $M_N(t,f)$ with $R(t,f)$.



- The network consists of 20 hidden layers.
- Half of the layers make up the encoder, and the other half the decoder.

Tibi, R., P. Hammond, R. Brogan, C. J. Young, and K. Koper (2021). Deep Learning Denoising Applied to Regional Distance Seismic Data in Utah, *Bull. Seismol. Soc. Am*. 111, 775–790, doi: 10.1785/0120200292.

Denoising Methods – Deep Learning Denoising

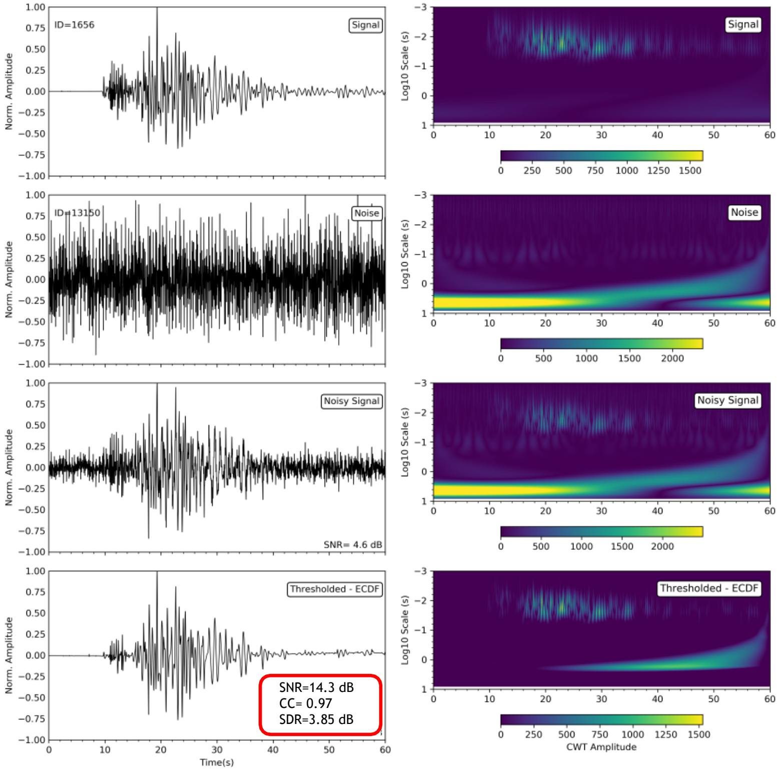


- The values of the elements of the mask operator vary with both time & frequency in the range of 0–1.
- The operator for a bandpass filter would appear as a streak of 1's within the passband.
- In contrast to the filter operator, the mask operator adapts to the changing characteristics of the input waveform.

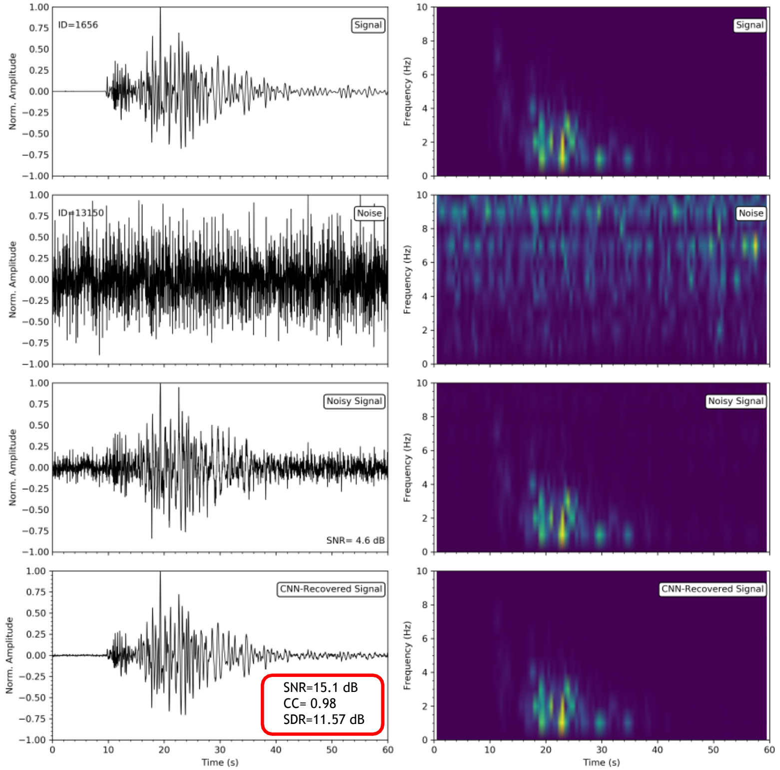
Tibi, R., P. Hammond, R. Brogan, C. J. Young, and K. Koper (2021). Deep Learning Denoising Applied to Regional Distance Seismic Data in Utah, *Bull. Seismol. Soc. Am*. 111, 775–790, doi: 10.1785/0120200292.

Comparison of the Denoising Methods

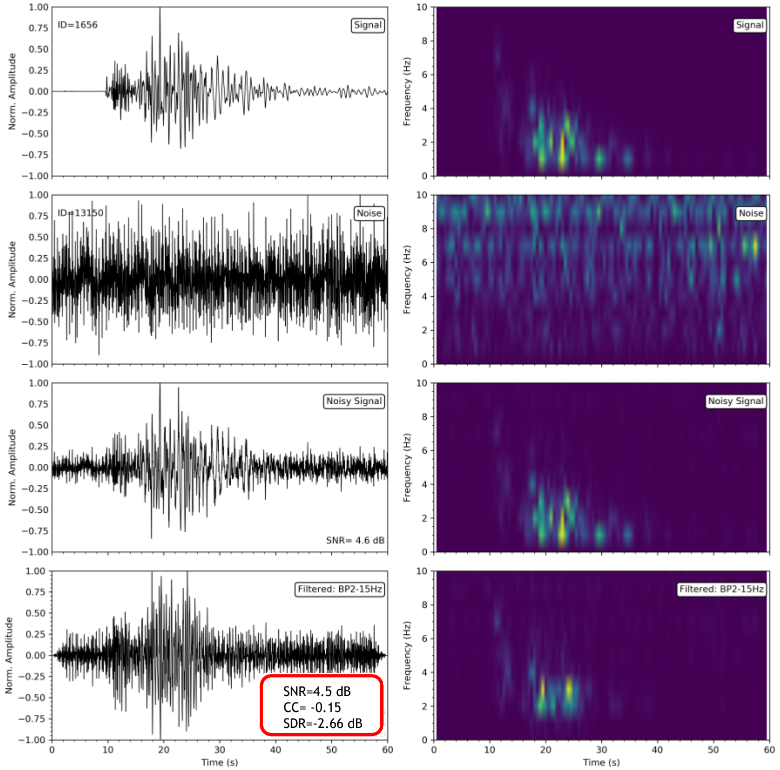
CWT Thresholding - ECDF



CNN Denoising

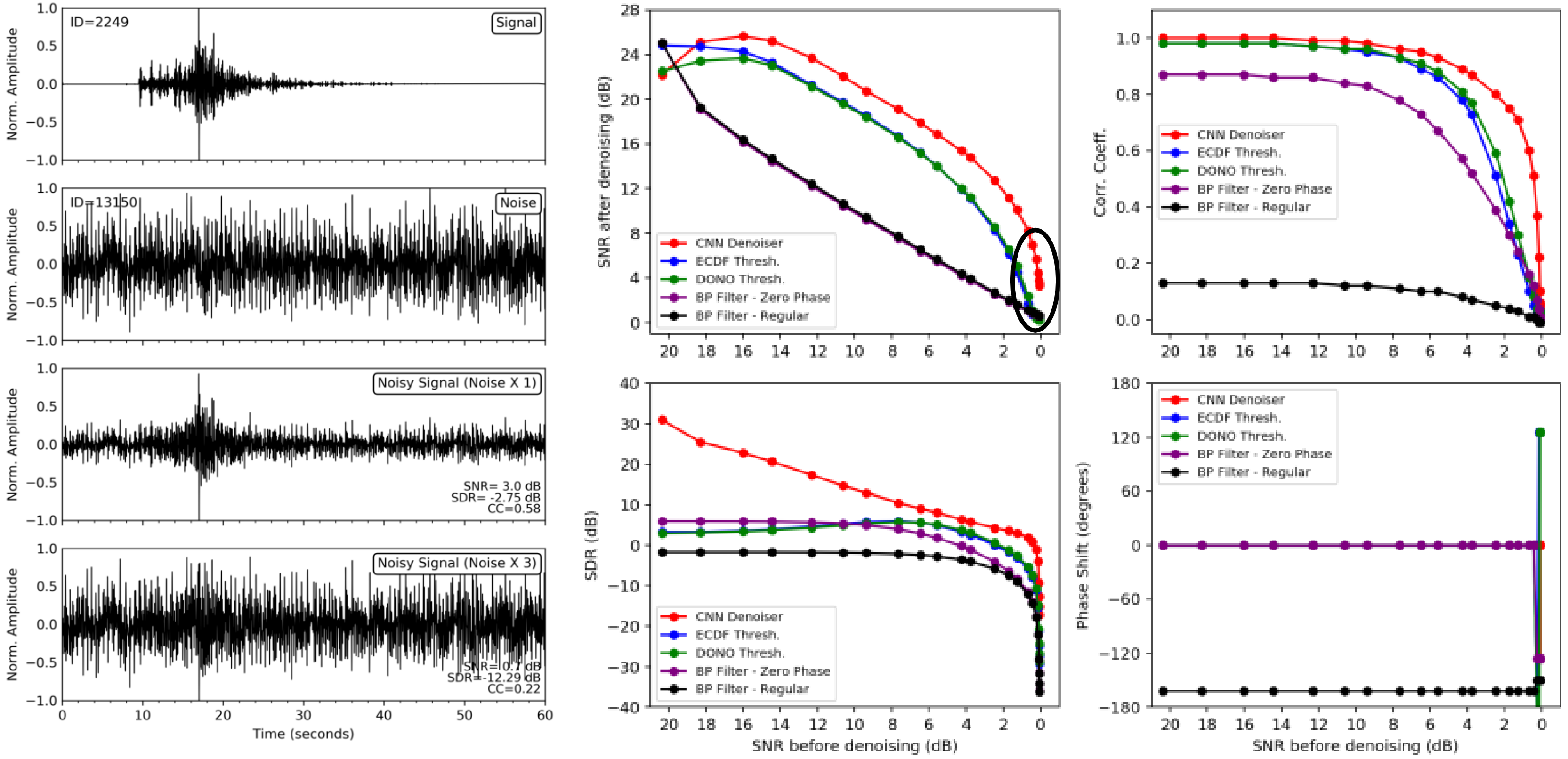


Regular BP Filtering (2–15 Hz)



- In this case, the CWT and CNN denoisers, and frequency filtering improve the SNR by about 10, 11 and 0 dB, respectively.
- The CC values of 0.97–0.98 indicate that the shape of the signal waveform remained nearly unchanged after CNN or CWT denoising (in contrast to frequency filtering, CC = -0.15).
- Also, frequency filtering results in significant amplitude distortion (SDR = -2.66 dB, compared with 3.85 and 11.57 for the CWT and CNN denoiser, respectively).

Comparison of the Denoising Methods – Dependence on Input SNR

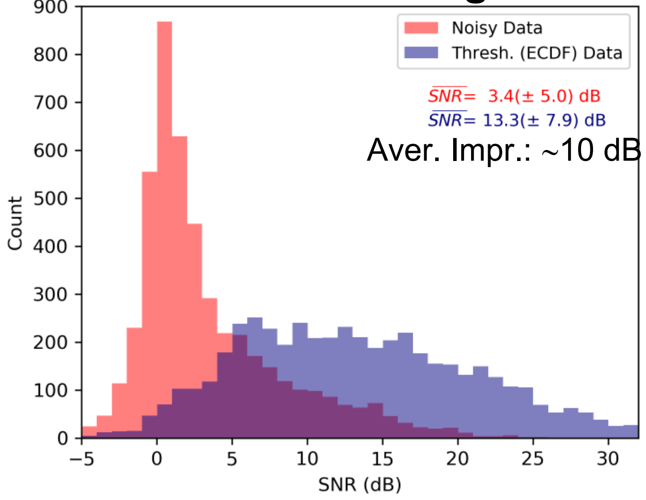


- For frequency filtering, the SNR of the processed waveform decreases significantly faster with decreasing SNR of the input seismogram.
- CNN denoiser is capable of denoising a waveform with a SNR floor of approx. 0 dB.
- In terms of waveform similarity and amplitude distortion, CNN denoising outperforms both frequency filtering and CWT denoising.
- Regular frequency filtering (causal) is associated with significant phase shift.

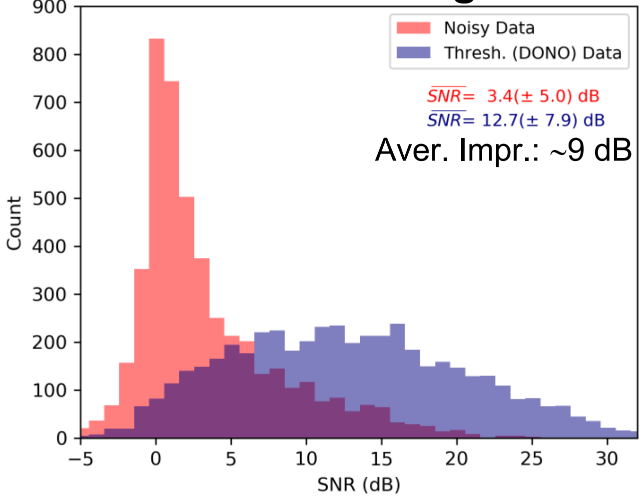
Comparison of the Denoising Methods – Output SNR

We processed 4780 constructed waveforms with components (signal & noise) recorded at local to near regional distances.

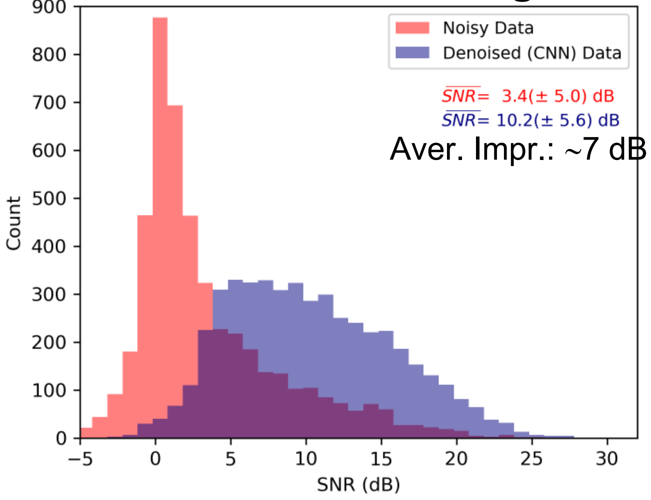
CWT Thresholding - ECDF



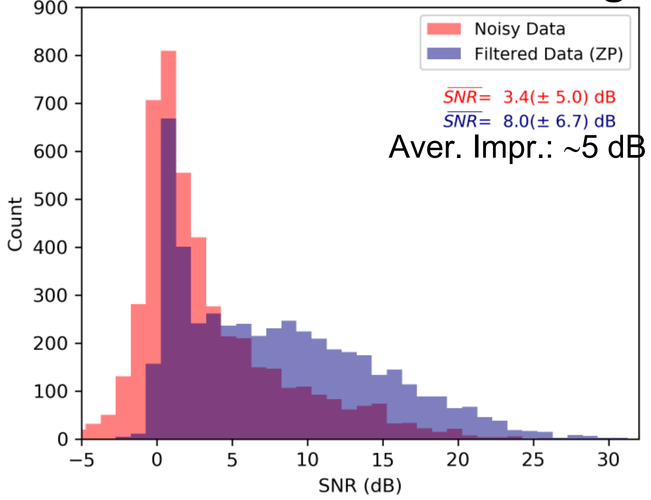
CWT Thresholding - DONO



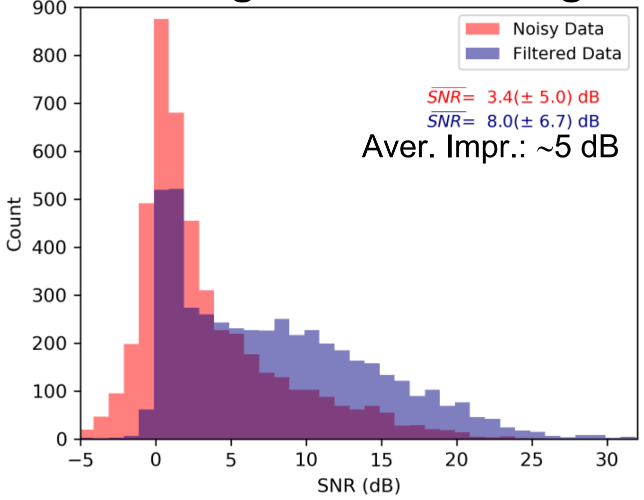
CNN Denoising



Zero-Phase BP Filtering



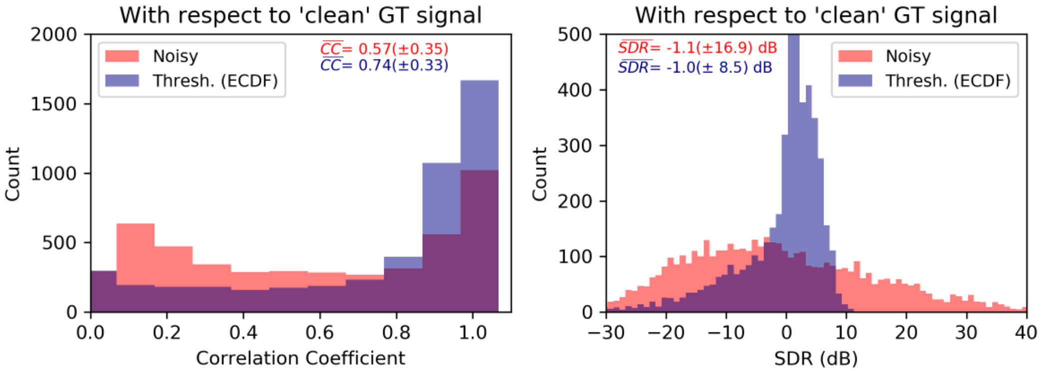
Regular BP Filtering



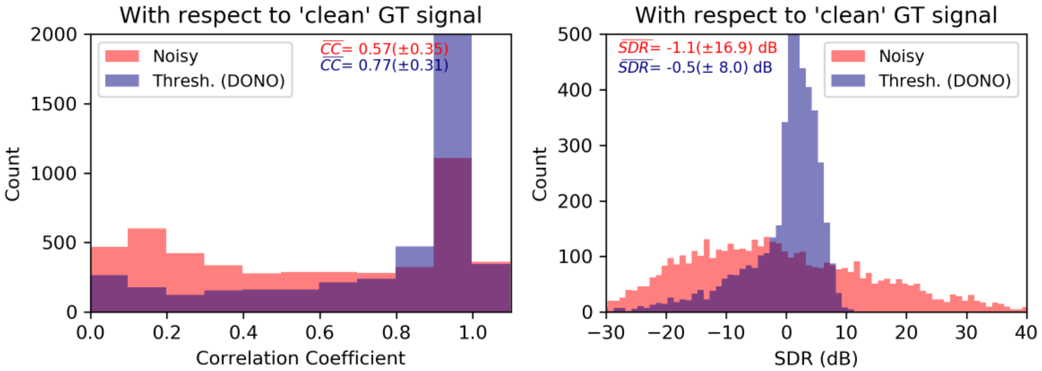
Average improvements in SNR are ~5–10 dB, with the lower value associated with frequency filtering

Comparison of the Denoising Methods – Output CC and SDR

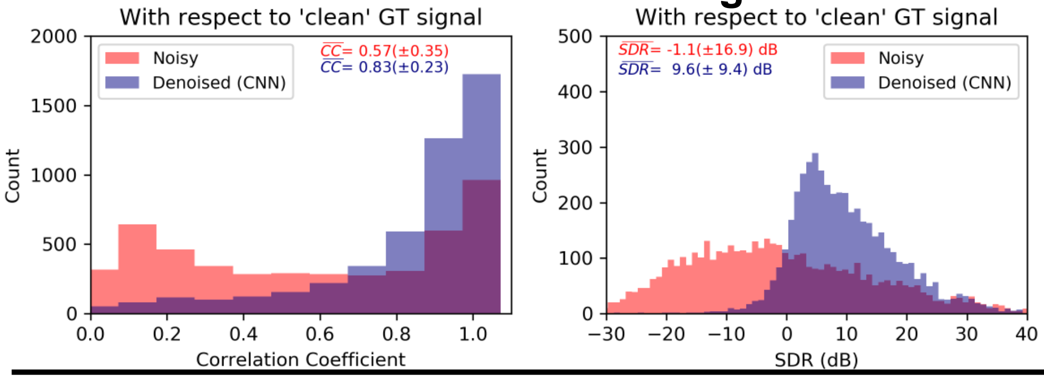
CWT Thresholding - ECDF



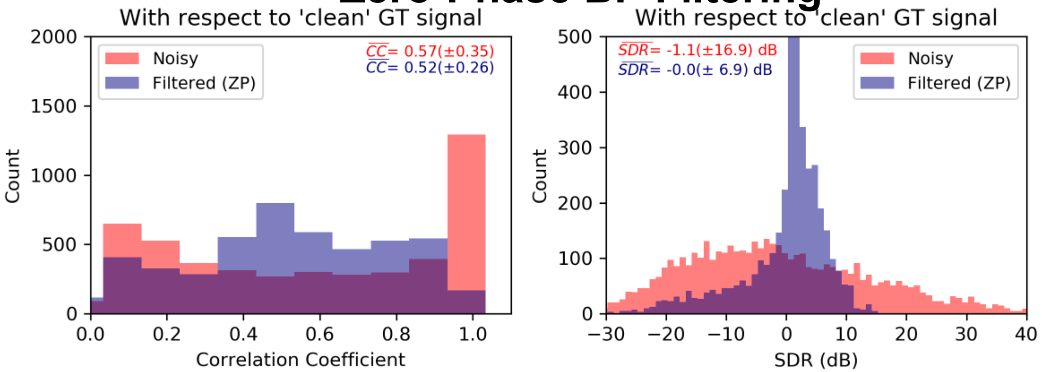
CWT Thresholding - DONO



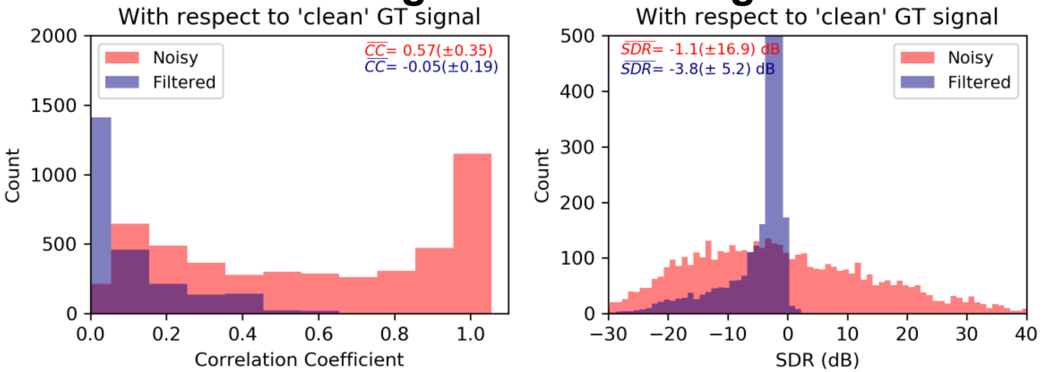
CNN Denoising



Zero-Phase BP Filtering



Regular BP Filtering



- In terms of waveform similarity and amplitude distortion with respect to GTs, CNN denoising outperforms both CWT denoising and frequency filtering.
- The average CC of ~0 for regular BP filtering indicates that waveform shapes underwent significant changes

Conclusions and Implications

- Results involving 4780 constructed waveforms suggest that on average the CWT and CNN denoisers, and bandpass filter improve the signal-to-noise ratio (SNR) by about 10, 7 dB and 5 dB, respectively.

- In terms of waveform similarity and amplitude distortion for the recovered waveforms with respect to the GT seismograms, CNN denoising outperforms both CWT denoising and frequency filtering.

- The performance of all the approaches are depend on the SNR of the input waveforms; however, for frequency filtering the SNR of the processed waveform decreases significantly faster with decreasing SNR for the input seismogram.

- Also, we find that the average correlation coefficient value is about 0 for the seismograms processed wit orms are significantly di vaveform shape have occurrec

- **Implications:**

Purpose	CNN Denoising	CWT Thresholding	Zero-Phase Frequency Filtering	Regular Frequency Filtering
Improve SNR (e.g., for signal detection)	✓	✓	✓ (if input is of sufficient SNR)	✓ (if input is of sufficient SNR)
Exploit amplitude information (e.g., for magnitude or moment tensor estimation)	✓ (most suitable approach)	✗ (significant amplitude distortion)	✗ (significant amplitude distortion)	✗ (significant amplitude distortion & changes in waveform shape)

References

Donoho, D., and I. Johnstone (1994). Ideal spatial adaptation via wavelet shrinkage, *Biometrika* **81,** 425–455.

Langston, C. A., and S. M. Mousavi (2019). Separating signal from noise and from other signal using nonlinear thresholding and scale-time windowing of continuous wavelet transforms, *Bull. Seismol. Soc. Am.* **109,** 1691–1700, doi: 10.1785/0120190073.

Tibi, R., P. Hammond, R. Brogan, C. J. Young, and K. Koper (2021). Deep Learning Denoising Applied to Regional Distance Seismic Data in Utah, *Bull. Seismol. Soc. Am.* **111,** 775–790, doi: 10.1785/0120200292.

Zhu, W., S. M. Mousavi, and G. C. Beroza (2019). Seismic signal denoising and decomposition using deep neural networks, *IEEE Trans. Geosci. Remote Sens.* **57,** no. 11, 9476–9488, doi: 10.1109/TGRS.2019.2926772.