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Comparative Study of the Performance of Seismic Waveform Denoising Methods

Rigobert Tibi, Christopher Young, and Robert Porritt
Sandia National Laboratories

Sandia National Laboratories

National Nuclear Security Administration

INTRODUCTION

Seismic waveforms are generally contaminated by noise from various sources, which interfere with signals of interest. We implemented and applied several noise suppression methods. That were all subjected to the same analyses and level of scrutiny using the same set of metrics.

METHODS/DATA

The denoising methods consist of nonlinear thresholding of continuous wavelet transforms (CWT), convolutional neural network denoising (CNN denoising), and frequency filtering (acausal & causal). The data we used are local and near regional data recorded by the University of Utah Seismograph Stations (UUSS) network.

START

RESULTS

On average CWT and CNN denoising, and bandpass filtering improve the SNR by about 20, 14 dB and 9 dB, respectively. CNN denoising has unrivaled capability of conserving the amplitude information. In contrast to causal filtering, zero-phase filtering and the other methods do not result in phase change. CNN denoising allow more picks to be made compared with other approaches.

CONCLUSION

In terms of degree of fidelity to the ground truth waveforms, CNN denoising outperforms both CWT denoising and frequency filtering. If the purpose of the analysis is to exploit amplitude information for magnitude, yield, or moment tensor estimation, CNN denoising would be the most suitable approach.

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INTRODUCTION

- Recorded seismic data are generally contaminated by various types of noise (cultural or natural).
- Despite significant progress in seismic data analysis, the separation of signal and noise remains a fundamental problem.
- In the seismology community, frequency filtering is the most commonly used method for noise suppression.
- Frequency filtering can be problematic when the signal of interest and noise occupy the same region in the frequency domain.
- We implemented and applied 3 classes of noise suppression methods using seismic data recorded at local to near-regional distances.
- The methods consist of approaches based on:
    - *Non-linear thresholding of continuous wavelet transforms (CWT),*
    - *Convolutional Neural network (CNN) denoising, and*
    - *Frequency filtering (causal & acausal).*
- The denoising approaches are compared by subjecting them to the same analyses and level of scrutiny using the same set of evaluation metrics.

OBJECTIVES AND EVALUATION METRICS

Objectives

- To explore which noise suppression methods work best, using data recorded at local and near-regional distances in Utah, we implemented and applied 5 denoisers based on CWT nonlinear thresholding, CNN deep denoising, or frequency filtering.
- We used a set of metrics, criteria, and the same dataset to evaluate and compare the performance of these noise suppression approaches.
- The implications of the obtained results are discussed in relationship with the end goals of potential analyses.
- We believe that the findings discussed in this paper will guide analysts in choosing the suitable noise suppression method that is appropriate for the end goal of their analyses.

Evaluation Metrics

- Correlation Coefficient (CC) from non-zero lag cross correlation
  - Measures the similarity between the recovered waveform and the ground truth (GT)
- Signal-to-Noise Ratio (SNR in dB)
  - Using 9-sec window for both signal and noise

$$SNR = 20\log_{10}\frac{A_S}{A_N} \qquad (1)$$

- Signal-to-Distortion Ratio (SDR in dB)
  - Measures the amplitude distortion with respect to GT

$$SDR = 10\log_{10}\frac{\|W_{GT}\|^2}{\|\widehat{W}-W_{GT}\|^2} \qquad (2)$$

W_{GT} - Ground truth waveform; $\widehat{W}$ - Recovered (denoised) waveform, corrected for time shift

- Phase change (ϕ in radians)

$$\phi = 2\pi f\delta t \qquad (3)$$

δt – Estimated time shift in seconds; f – Frequency set to 15 Hz (high-cut of chosen BP filter)

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METHODS AND DATA

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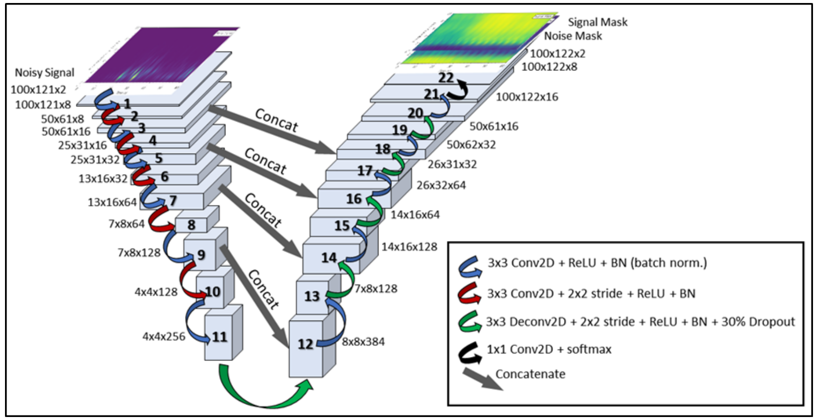
Methods

- **CWT Denoising**
  - Noise is assumed to be stationary throughout the waveform
  - Pre-event window is used to estimate the scale dependent (non-linear) threshold
- **CNN Denoising**
  - The approach uses a trained deep convolutional neural network model to decompose an input waveform into signal of interest and noise.



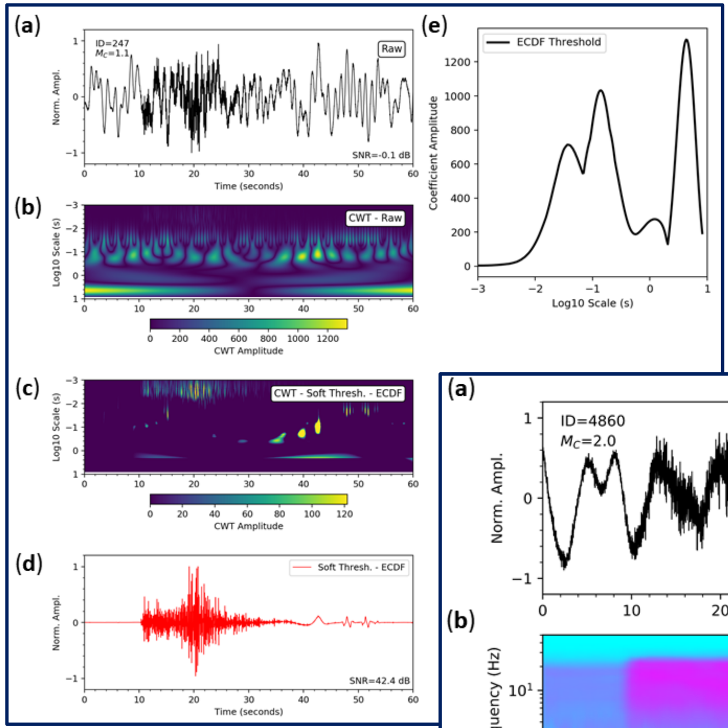
- **Frequency Fileting**
  - We used a 4-pole Butterworth-bandpass filter (2–15 Hz), as implemented in Obspy (Beyreuther et al., 2010).

Data

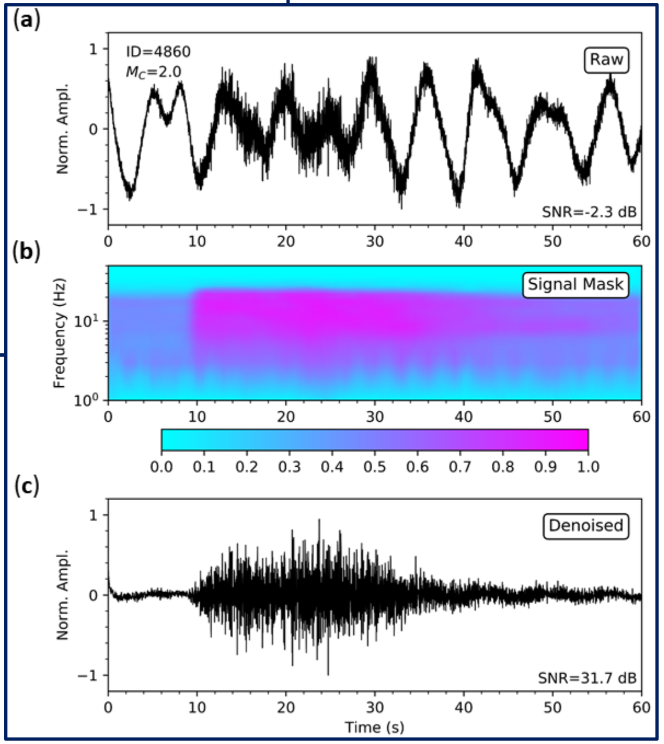
To evaluate the denoising methods, we used constructed noisy waveforms, each generated by summing a high-SNR seismogram and a randomly selected noise waveform

- Pure signal waveforms consists of local and near-regional recordings from the UUSS
- Noise waveforms also from UUSS, carefully curated to not contain event signals

CWT Denoising



CNN Denoising



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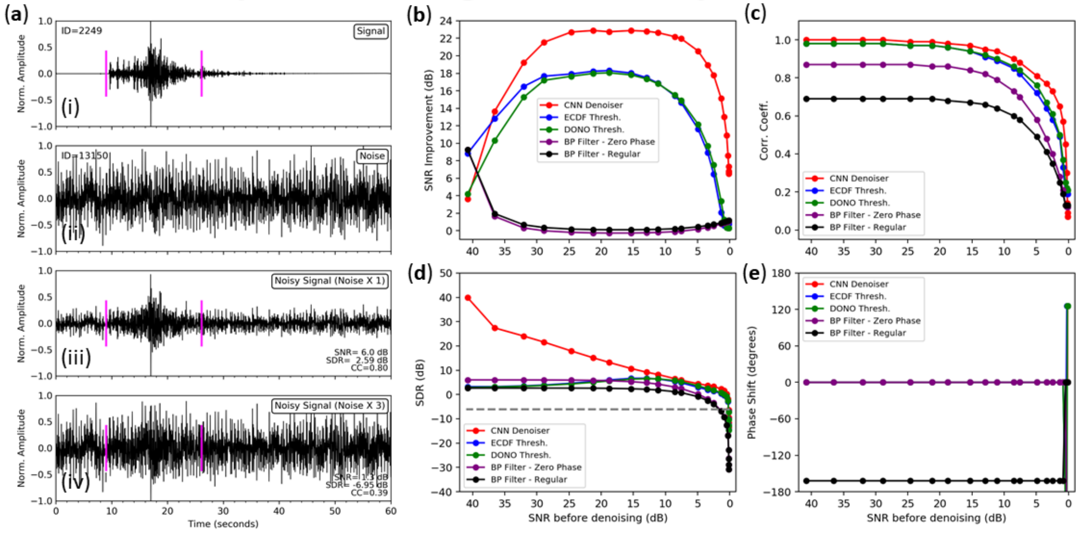
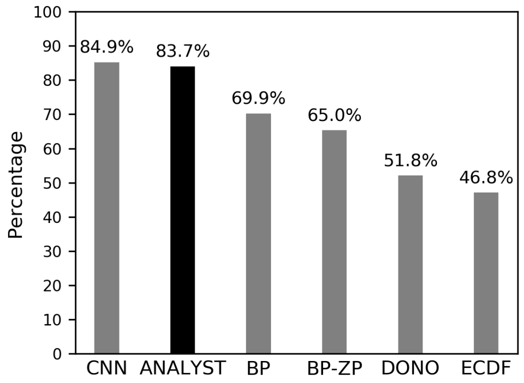
RESULTS

Effect of Input Seismogram Quality



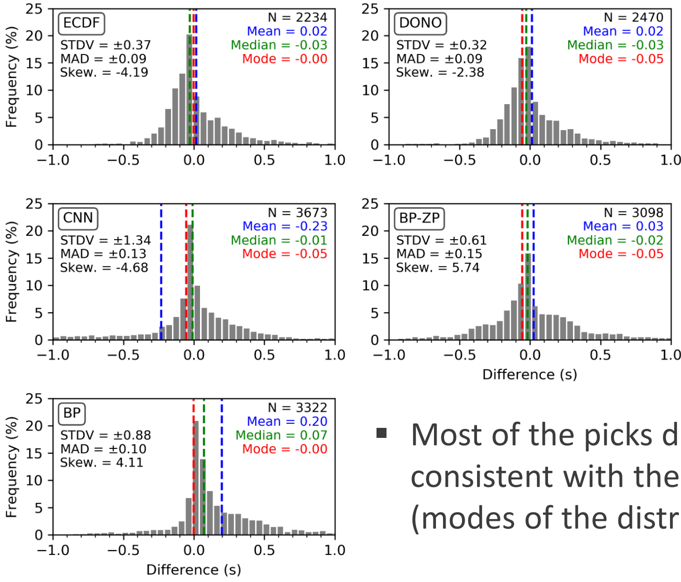
- For frequency filtering (purple & black), the SNR gain of the processed waveform decreases quickly with decreasing SNR of the input seismogram **(b)**.
- CNN denoiser (red) is capable of denoising a waveform with a SNR floor of approx. 0 dB **(b)**.
- Causal filtering (black) is associated with significant changes in waveform shape (CC of only ~ 0.7) **(c)**.
- CNN denoising (red) has unrivaled capability of conserving the amplitude information at input SNRs > 14 dB (See signal-to-distortion (SDR) values in **(d)**).
- In contrast to causal filtering (black), zero-phase filtering (purple) and the other methods do not result in phase change **(e)**.

Onset-time Determination



- CNN denoising allows more picks to be made compared with other approaches, and is on par with the expert-analyst's best filters (bar labeled ANALYST).
- The CWT techniques are more likely to introduce artifacts that made the waveforms unusable.

This is reflected in the low proportion (~47–52%) of picks that our expert-analyst was able to make for these methods.



- The larger mean differences (0.20–0.23 s in absolute sense) and standard deviations (±0.88–1.34 s), which contrasts to the median values of ~0 s, suggest that the estimated differences for CNN denoising and causal bandpass filtering contain non-negligible numbers of outliers.
- Most of the picks determined for each method are consistent with the expert- analyst's best filters (modes of the distributions are all close to 0).

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CONCLUSIONS AND IMPLICATIONS

- For frequency filtering, the improvement in SNR decreases quickly with decreasing input SNR and below an input SNR of ~32 dB the improvement is relatively marginal.
- On average CWT and CNN denoising, and bandpass filtering improve the SNR by about 20, 14 dB and 9 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 CWT denoising and frequency filtering.
- Also, the average correlation coefficient value is low for the seismograms processed with causal frequency filtering, which suggests that these waveforms are different from their respective GTs, i.e., significant changes in waveform shape have occurred.
- Like zero-phase filtering, little to no phase shift occurs for CWT and CNN denoising. This contrasts to causal filtering that is associated with significant phase shifts.
- CNN denoising allows more picks to be made compared with frequency filtering or CWT denoising, and is on par with the expert-analyst's processing, which is consistent with the current operational procedure.

Example of Analysis Purposes	CNN Denoising	CWT Thresholding	Zero-Phase Frequency Filtering BP 2–15 Hz	Causal Frequency Filtering BP 2–15 Hz
Improve SNR for signal detection	✓	✓	✓ if input is of sufficient SNR (≥ 6 dB)	✓ if input is of sufficient SNR (≥ 6 dB)
Array Analysis	✓	✓	✓	✗ significant changes in phase
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 & phase

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