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Comparative Study of the Performance of Seismic Waveform Denoising Methods Using Local and Near-Regional Data

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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 remain 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.

Introduction

- We implemented and applied 3 classes of noise suppression methods using seismic data recorded at local to near-regional distances in Utah.
- 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.

Thresholding of Continuous Wavelet Transforms (CWT Denoising)

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

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

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, $\beta(a) = \text{mean}(|W(a,\tau)|) + c\,\text{std}_{\text{v}}(|W(a,\tau)|) \qquad (5)$

- Assuming noise coefficients follow Gaussian distribution (Donoho & Johnstone, 1994, DONO):

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

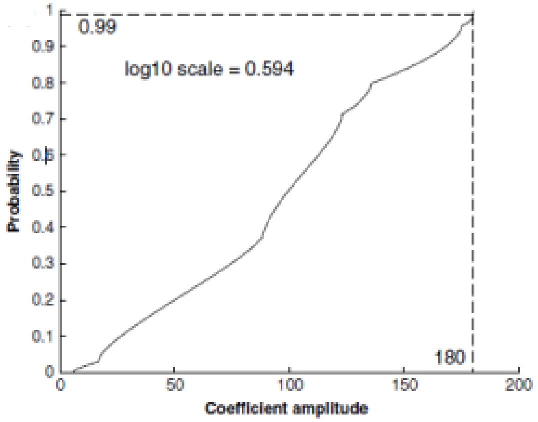
with N being the number of noise samples at each scale.

Thresholding of Continuous Wavelet Transforms (CWT denoising)

- 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.



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

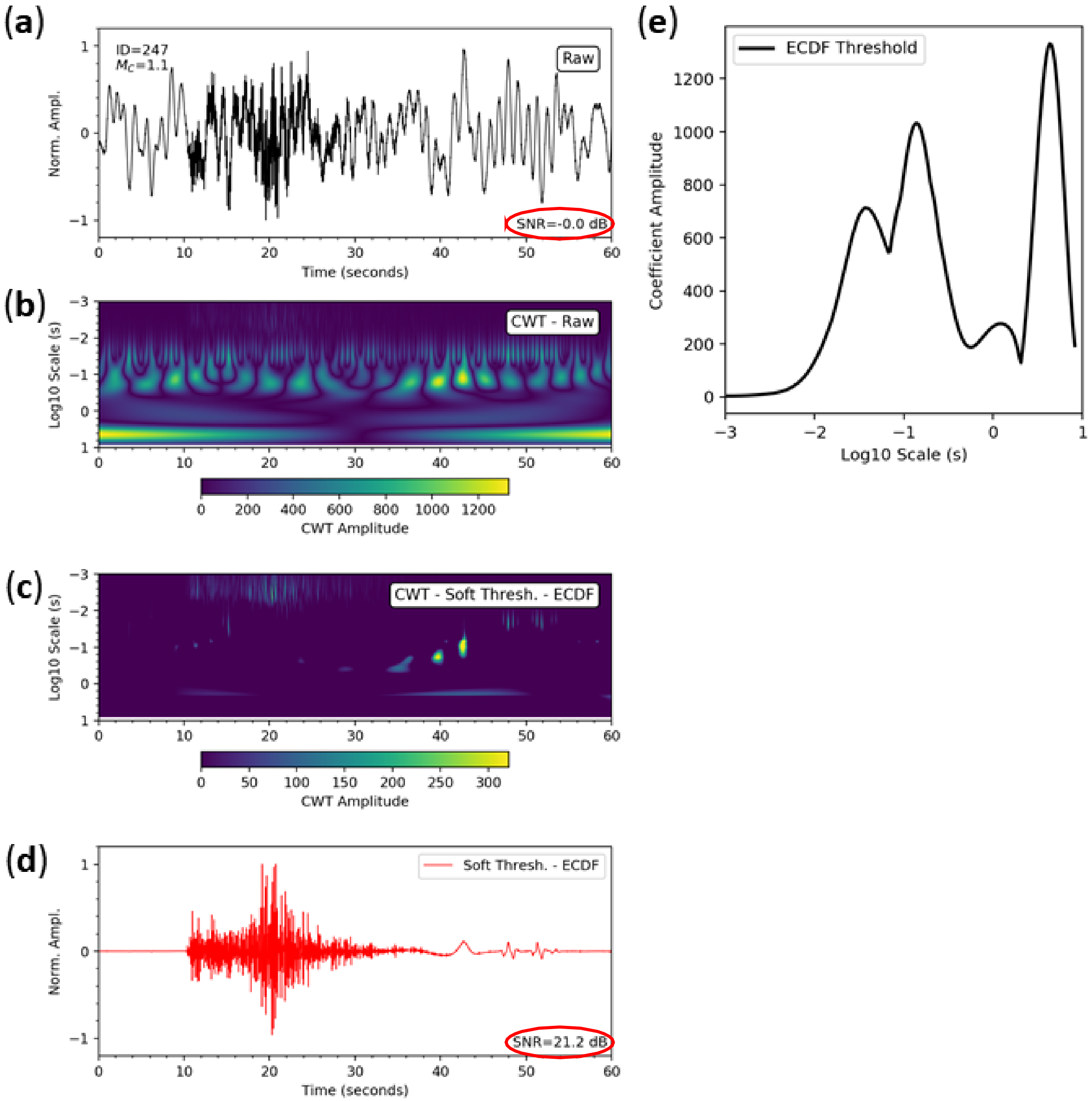
$$\tilde{x}(t) = \frac{1}{C}\int_0^{+\infty}\int_{-\infty}^{+\infty}\frac{1}{\sqrt{a}}\widetilde{W}(a,\tau)\psi\left(\frac{t-\tau}{a}\right)\frac{da\,d\tau}{a^2}, \qquad (8)$$

where

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

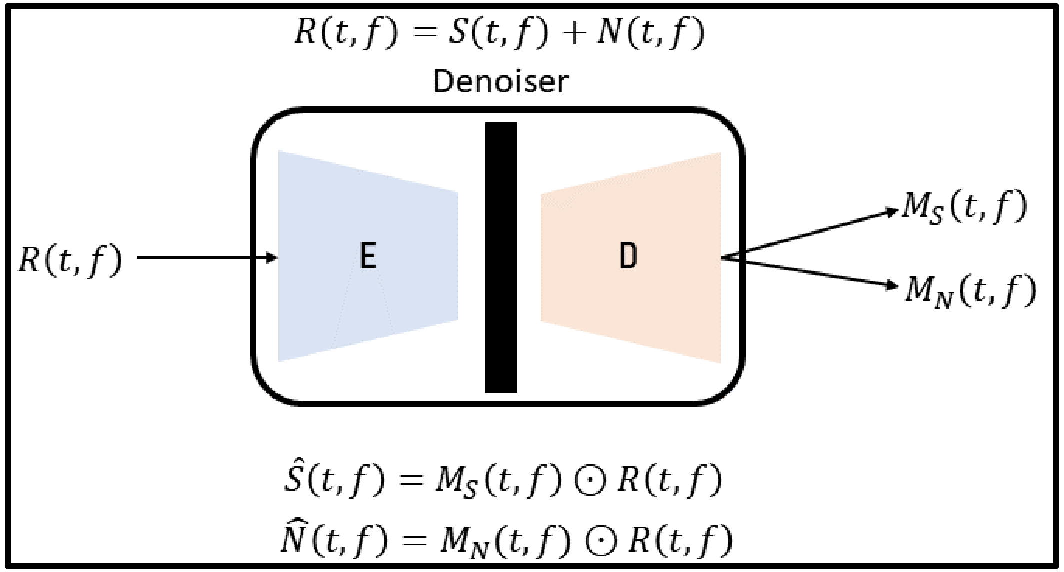
in which $\widehat{\psi}(\omega)$ is the Fourier transform of $\psi(t)$.

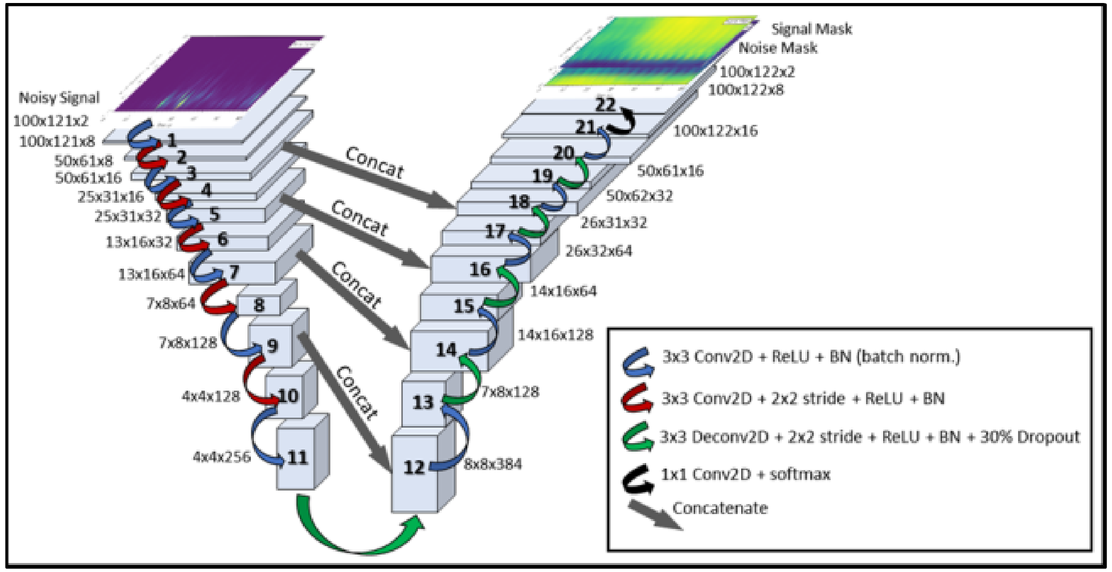
Thresholding of Continuous Wavelet Transforms (CWT Denoising)



Deep Learning Denoising (CNN Denoising)

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

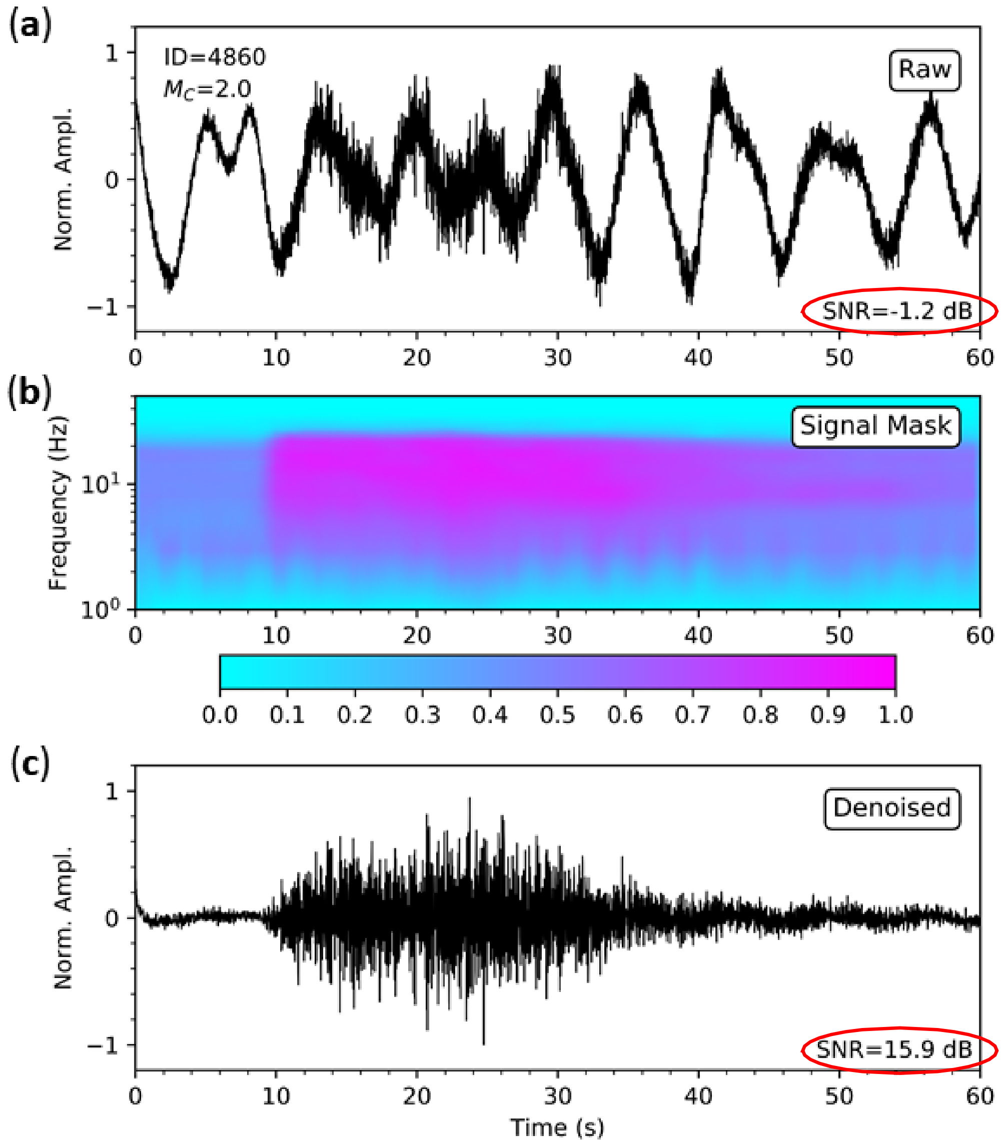




- For an input $R(t,f)$, the network provides a signal mask ($M_S(t,f)$) and a noise mask ($M_N(t,f)$).
- The estimated 'clean' signal ($\hat{S}(t,f)$) is obtained by multiplying $M_S(t,f)$ with $R(t,f)$; and the estimated noise ($\hat{N}(t,f)$) is obtained by multiplying $M_N(t,f)$ with $R(t,f)$.

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

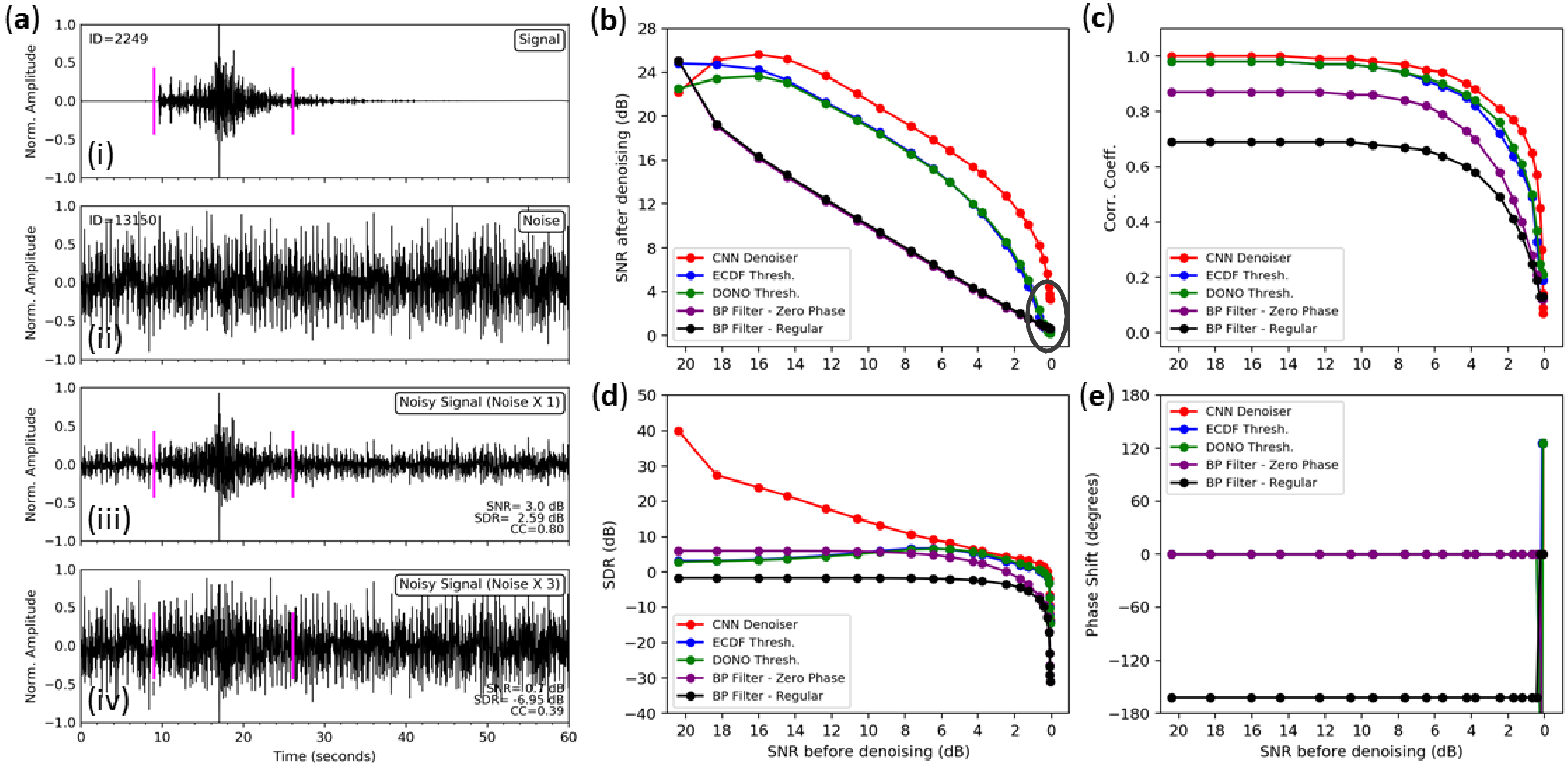
Deep Learning Denoising (CNN Denoising)



Elements of the mask operator vary with both time & frequency in the range of 0–1.

Effect of Input Seismogram Quality

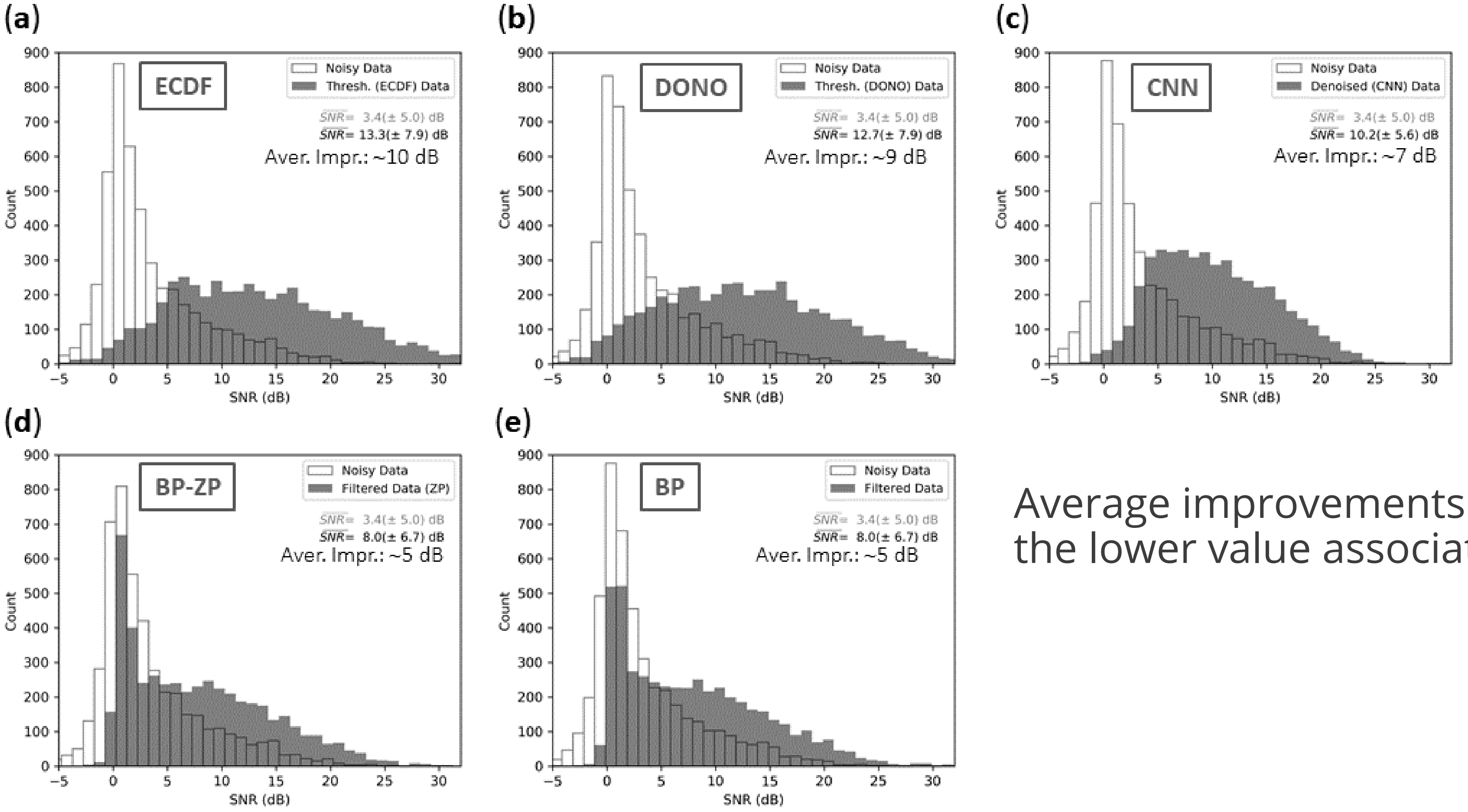
- Evaluation based on constructed (noisy) data because the underlying components (signal and noise) are perfectly known



- For frequency filtering, the SNR of the processed waveform decreases significantly faster with decreasing SNR of the input seismogram.
- Deep Denoiser is capable of denoising a waveform with a SNR floor of approx. 0 dB.
- Causal filtering is associated with significant changes in waveform shape (CC of ~ 0.7).
- CNN denoising has unrivaled capability of conserving the amplitude information at input SNRs > 7 dB.
- In contrast to causal filtering, zero-phase filtering and the other methods do not result in phase change.

Improvement in Seismogram Quality

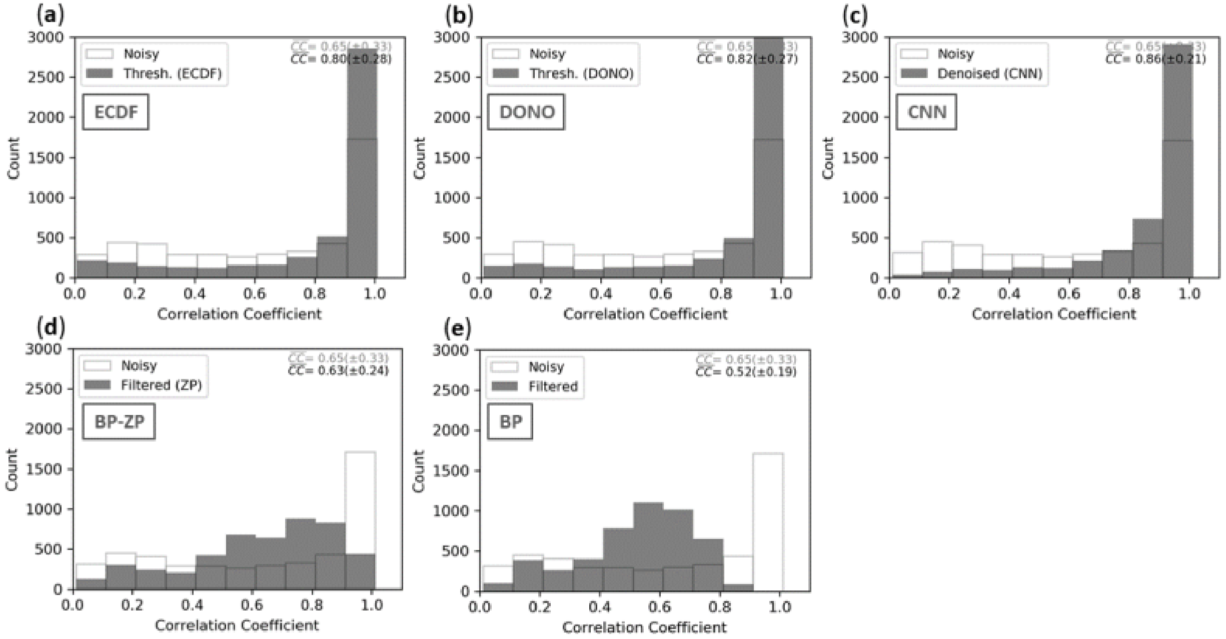
We processed 4780 constructed waveforms with components (signal & noise) recorded at local to near-regional distances.



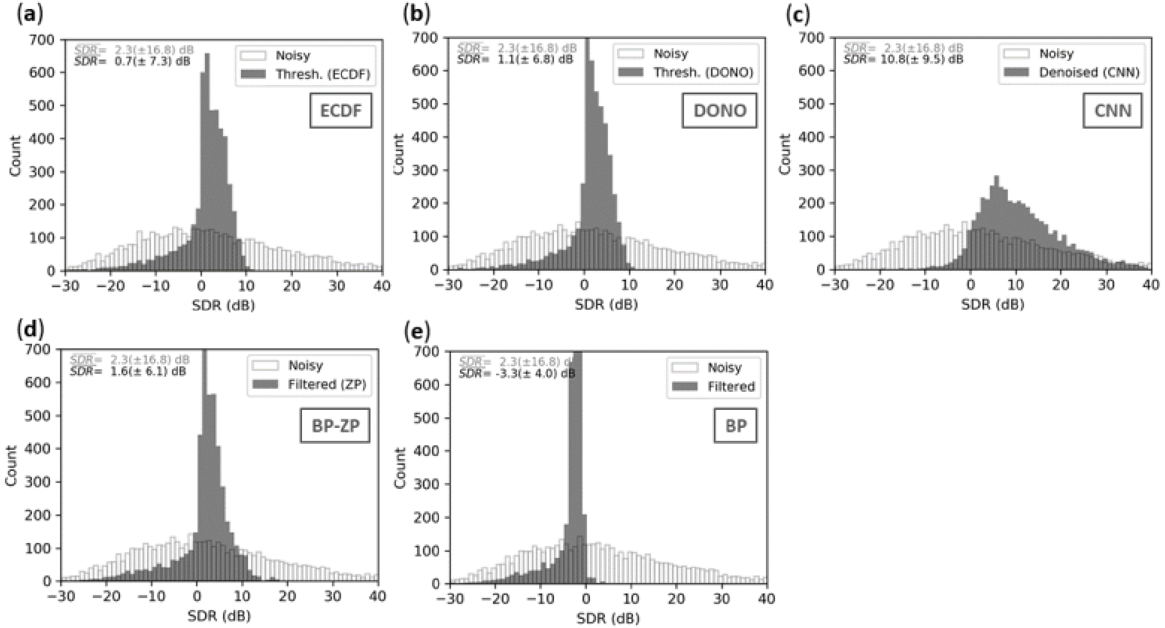
Average improvements in SNR are ~5–10 dB, with the lower value associated with frequency filtering

Degrees of Fidelity to Ground Truth Waveforms

Waveform Similarity

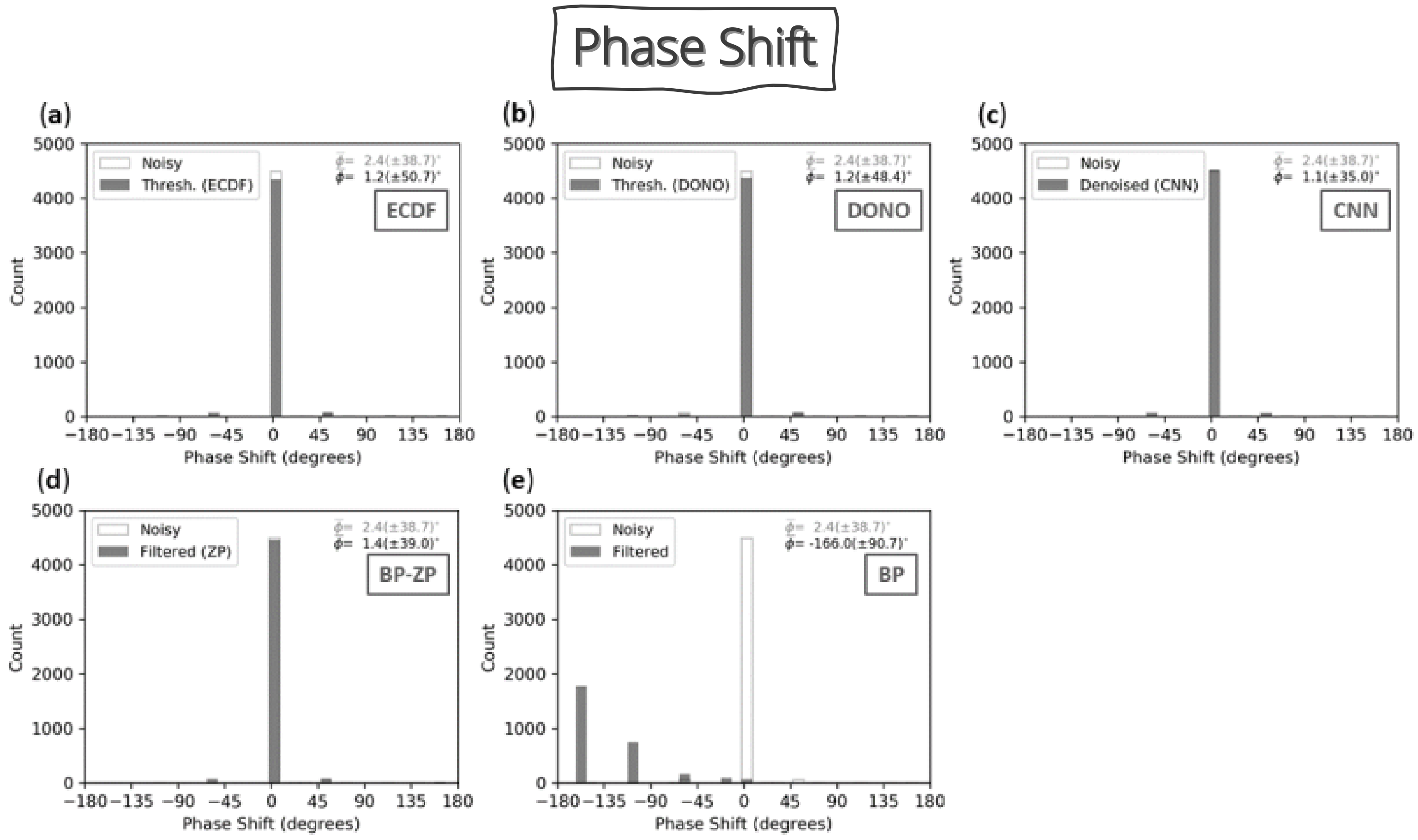


Amplitude Distortion



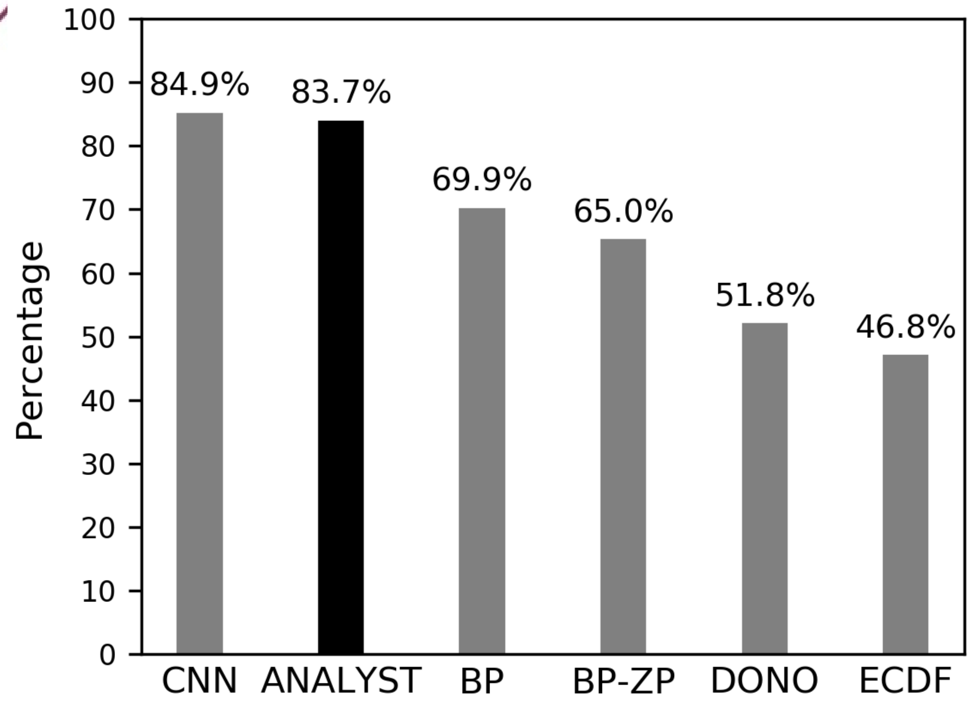
- In terms of preservation of both waveform shape and amplitude information, CNN denoising outperforms both CWT thresholding and frequency filtering.
- The average CC of ~0.5 for causal BP filtering indicates that waveform shapes underwent significant changes.

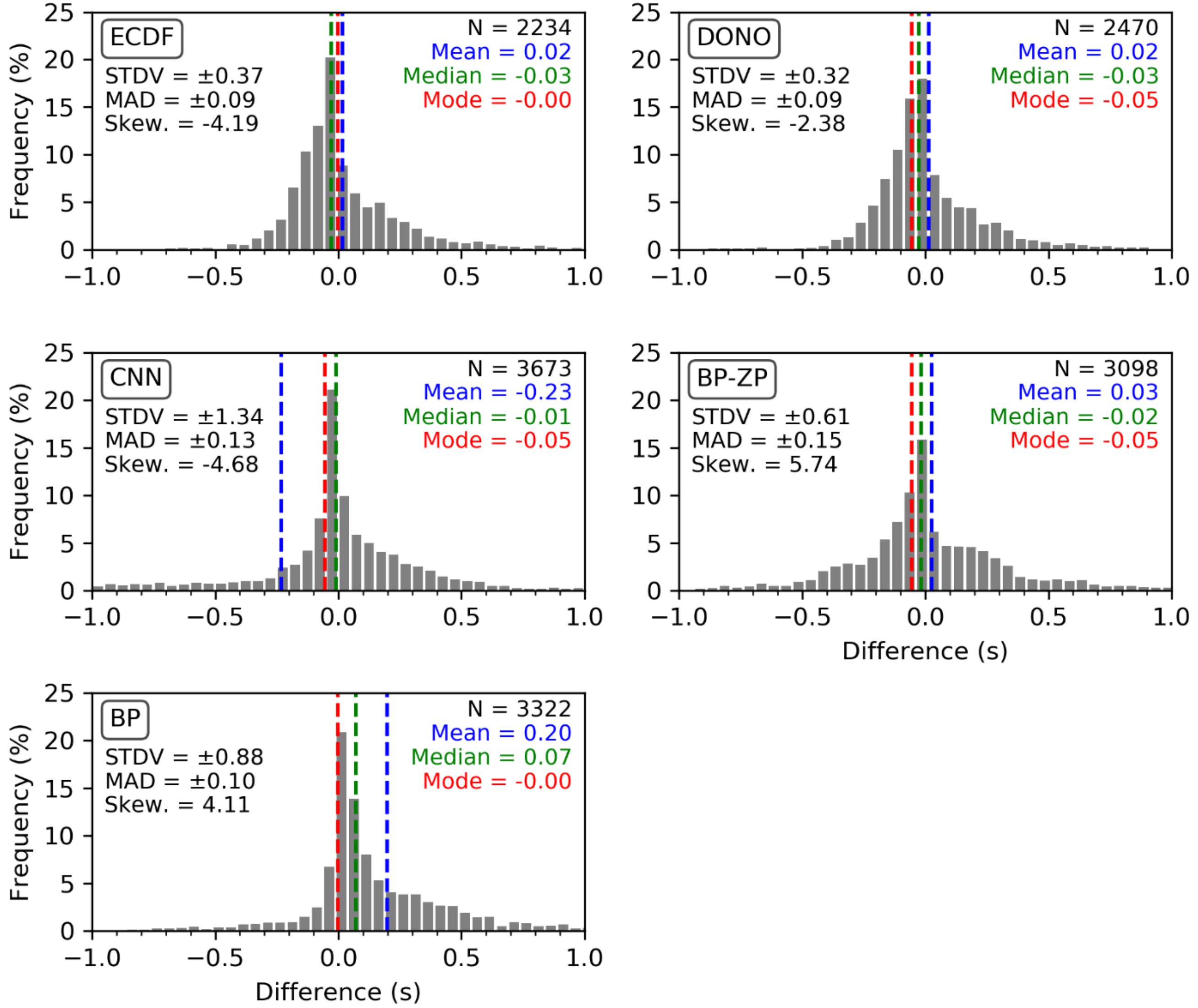
Degrees of Fidelity to Ground Truth Waveforms



- Like zero-phase filtering, little to no phase change occurs for CWT thresholding and CNN denoising.
- This contrasts to causal filtering that shows and average phase shift of -166°.

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.
- Most of the picks determined for each method are consistent with the expert analyst’s best filters.

Conclusions

- For all approaches the quality (SNR) of the output waveform is dependent on the input SNR; however, for frequency filtering the output SNR decreases significantly faster with decreasing input SNR.
- On average CWT and CNN denoising, and bandpass filtering improve the 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.
- 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.

Implications

Purpose	CNN Denoising	CWT Thresholding	Zero-Phase Frequency Filtering	Causal Frequency Filtering
Improve SNR (e.g., for signal detection)	✓	✓	✓ if input is of sufficient SNR (≥ 3dB)	✓ if input is of sufficient SNR (≥ 3dB)
Exploit amplitude information (e.g., for magnitude, yield or moment tensor estimation)	✓ (most suitable approach)	✗ (significant amplitude distortion)	✗ (significant amplitude distortion)	✗ (significant amplitude distortion, changes in waveform shape & phase)

Thank you for you attention

Evaluation Metrics

- Based on constructed (noisy) data because the characteristics of their components (signal and noise) are known
- Comparison Metrics:
  - Correlation Coefficient (CC)
    - 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

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

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

$$SDR = 10\log_{10}\frac{\|W_{GT}\|^2}{\|\widehat{W}-W_{GT}\|^2} \qquad (11)$$

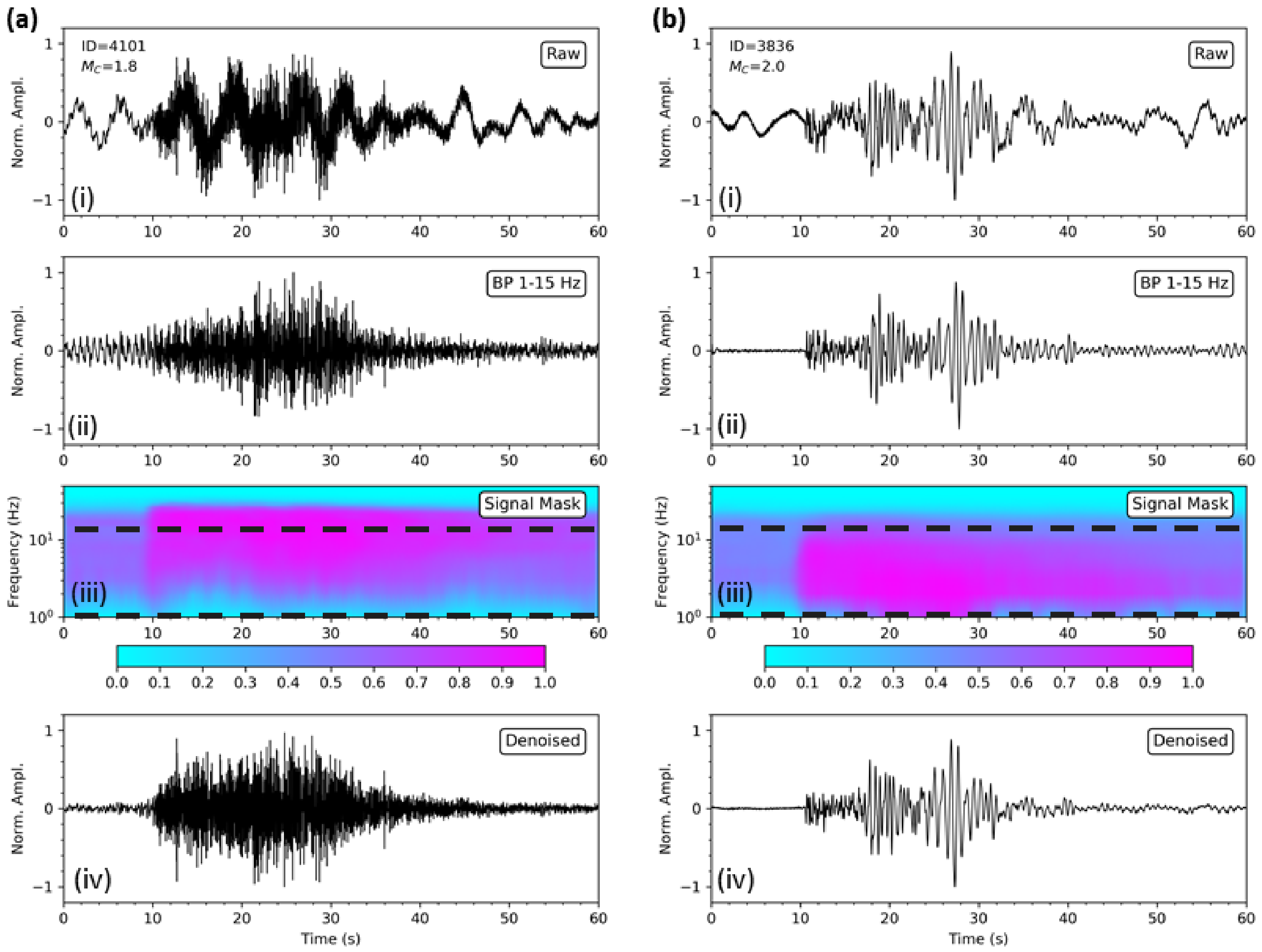
W_{GT} - Ground truth waveform; $\widehat{W}$ - Recovered (denoised) waveform

  - Phase change (ϕ in radians)

$$\phi = 2\pi f\delta t \qquad (12)$$

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

Why Does CNN Denoising Outperforms Frequency Filtering



- 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.
- The mask operator adapts to the changing characteristics of the input signal.