



RUB



EUROPÄISCHE UNION
Investition in unsere Zukunft
Europäischer Fonds
für regionale Entwicklung



EFRE.NRW
Investitionen in Wachstum
und Beschäftigung

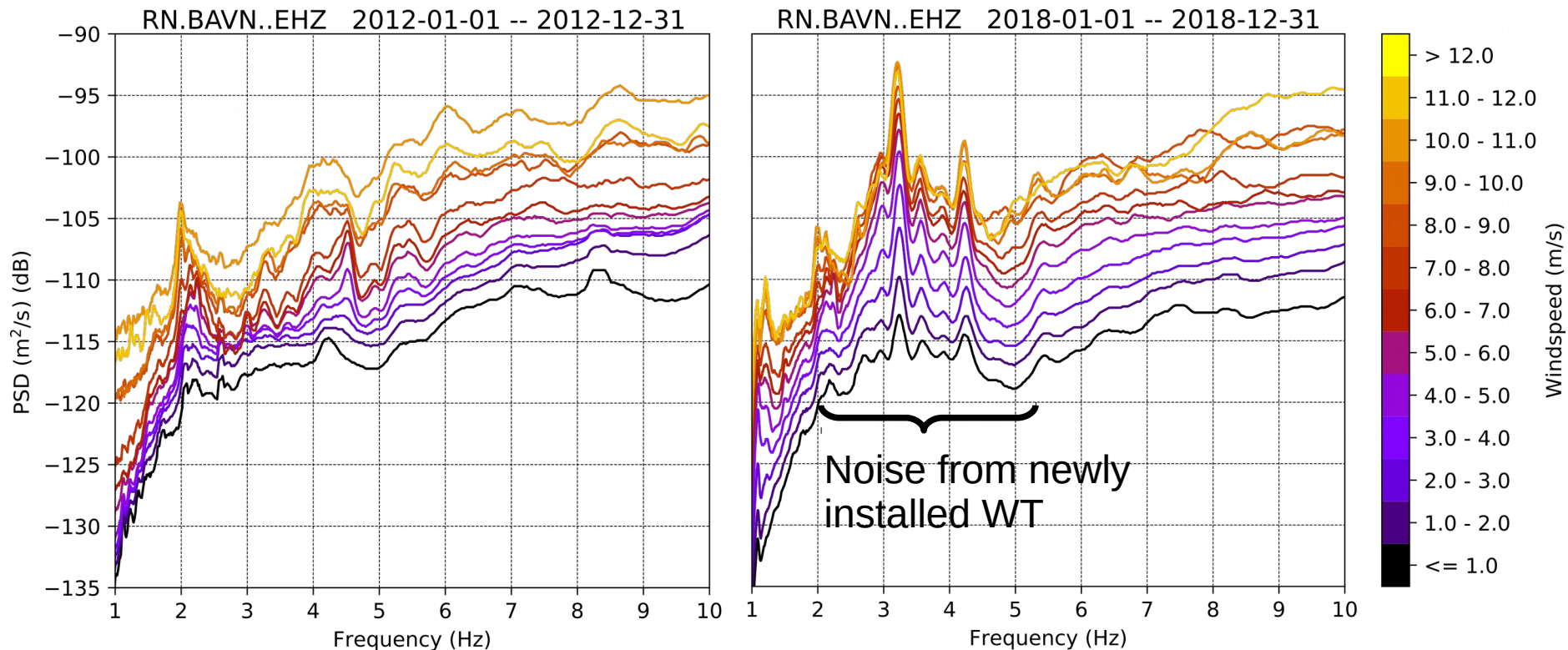
RUHR-UNIVERSITÄT BOCHUM

Wind Turbine Noise Reduction from Seismological Data

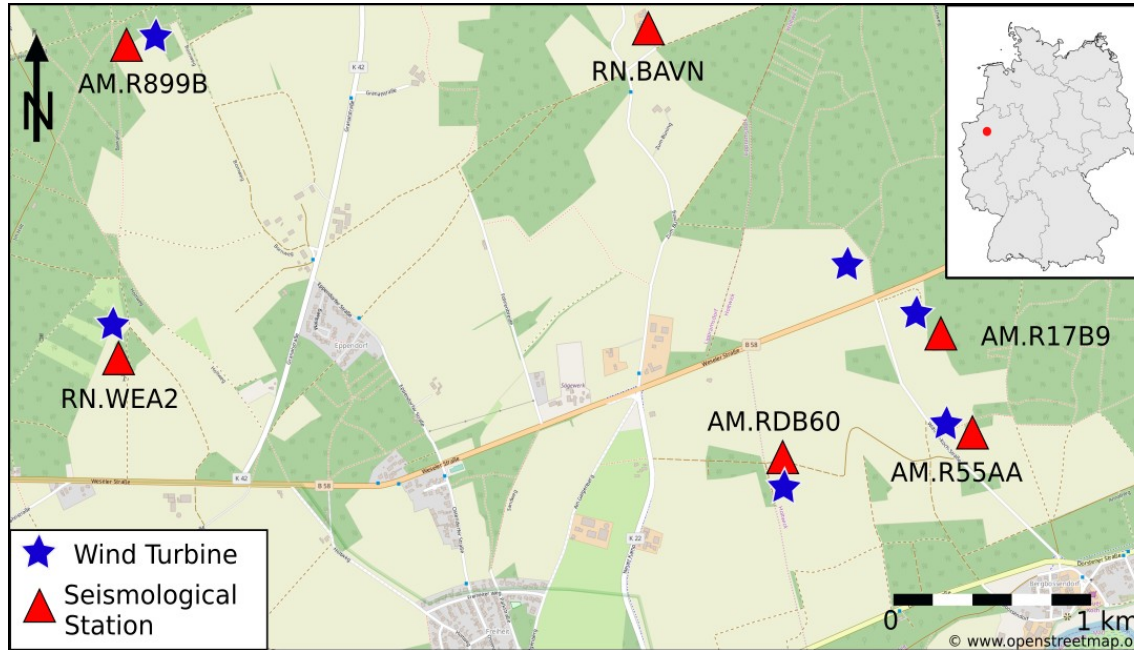
Janis Heuel, Wolfgang Friederich
Email: janis.heuel@rub.de

Introduction

- Installation of Wind Turbines (WT) close to seismological stations lead to a worsening in station quality (e.g. Stammer & Ceranna, 2016)
- WT noise and earthquake signals have overlapping frequency bands, therefore spectral filtering suppresses both signal and noise

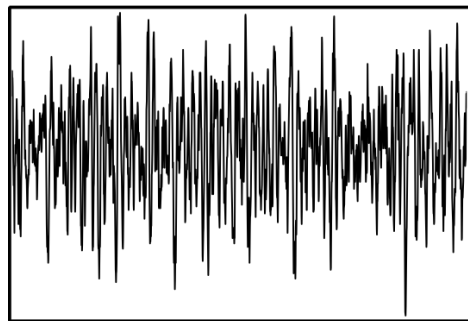


Introduction



Development of a tool to suppress WT Noise:

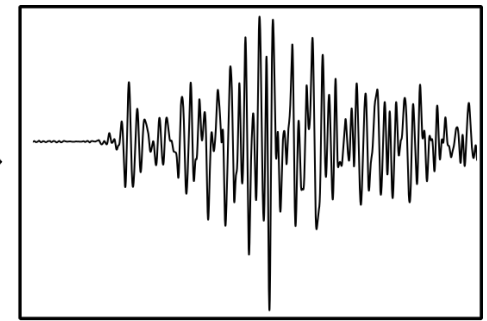
1. Select affected site (RN.BAVN)
2. Installed new seismometers close to each WT to record noise sources
3. Testing different tools to suppress WT noise



seismological signal
corrupted by WT noise

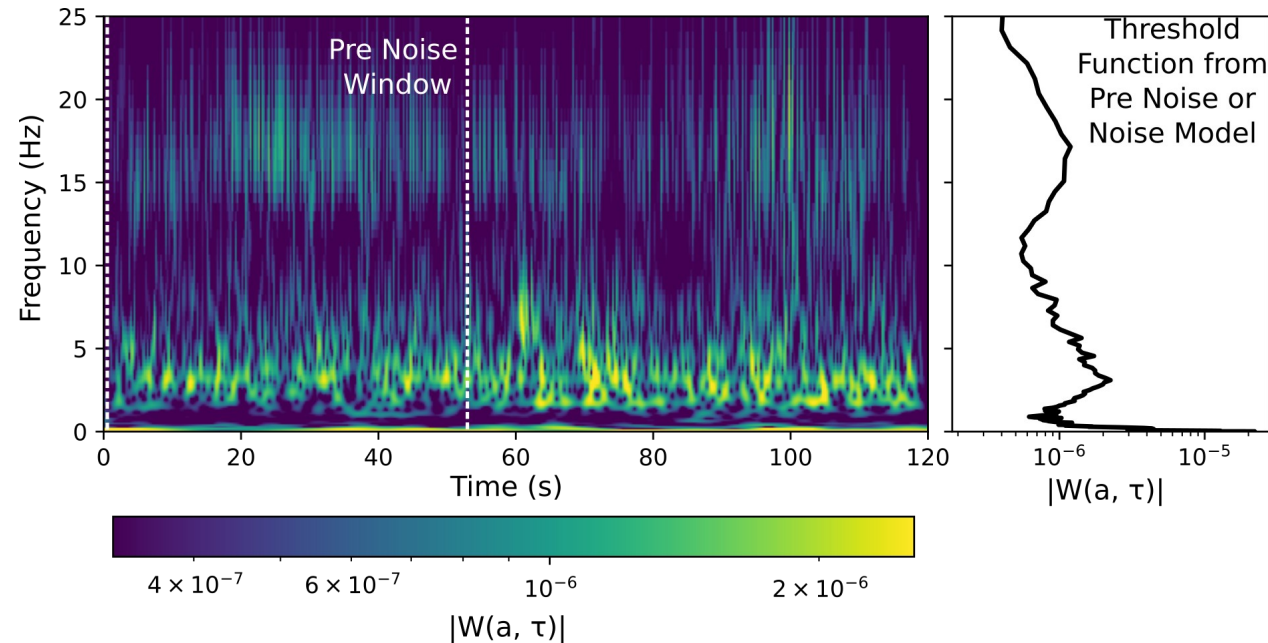


Denoising
Toolbox



denoised signal

Denoising Methods | Nonlinear Thresholding



- Transforming corrupted signal into time-scale domain using Continuous Wavelet Transform (CWT)
- Defining a noise level $\beta(a)$ either from the noise before the expected event or from a noise model:

$$\beta(a) = |W(a, \tau)|_{p=0.99}$$

- Shrinkage of all CWT coefficients that are above the noise level $\beta(a)$ (Langston & Mousavi, 2019)

$$\tilde{W}(a, \tau) = \begin{cases} \frac{W(a, \tau)}{|W(a, \tau)|} (|W(a, \tau)| - \beta(a)) & \text{if } |W(a, \tau)| \geq \beta(a), \\ 0 & \text{otherwise} \end{cases}$$

- Back transformation of the modified CWT into time domain to obtain a clean signal

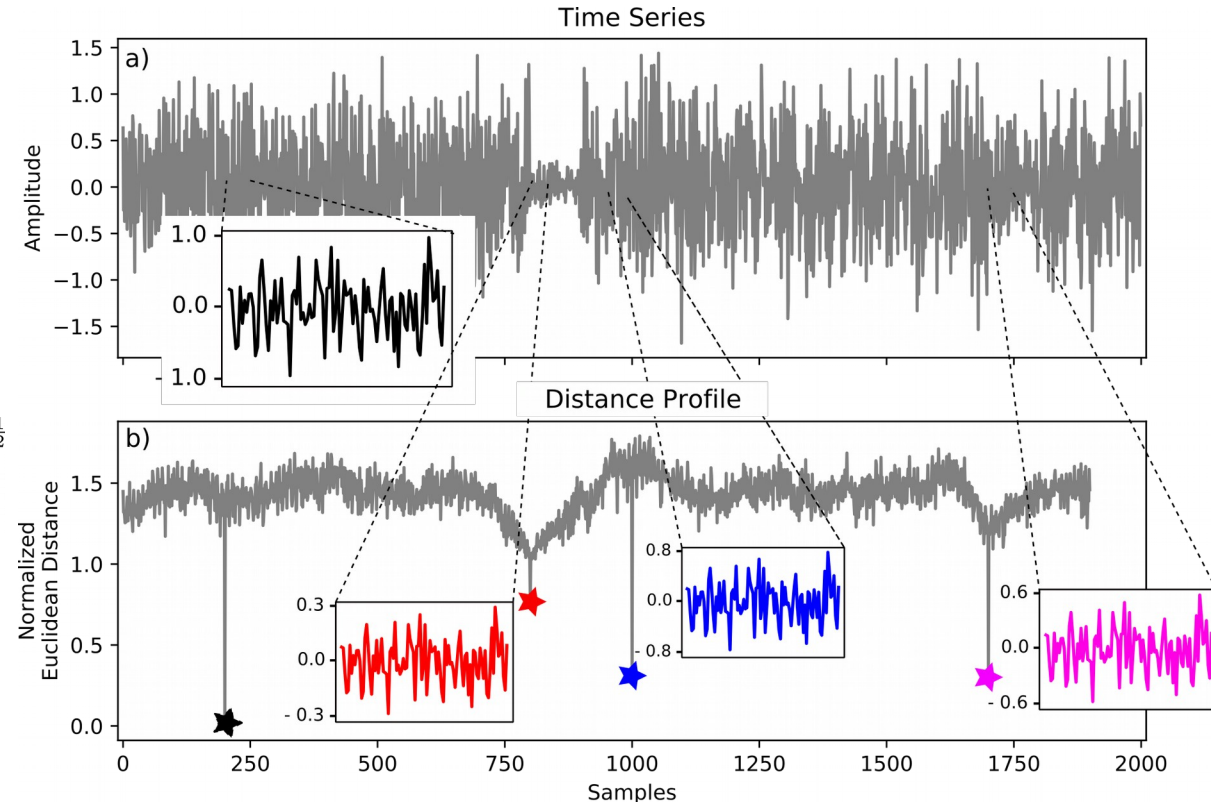
Denoising Methods | Nonlinear Thresholding

Obtaining Noise Model from new WT stations

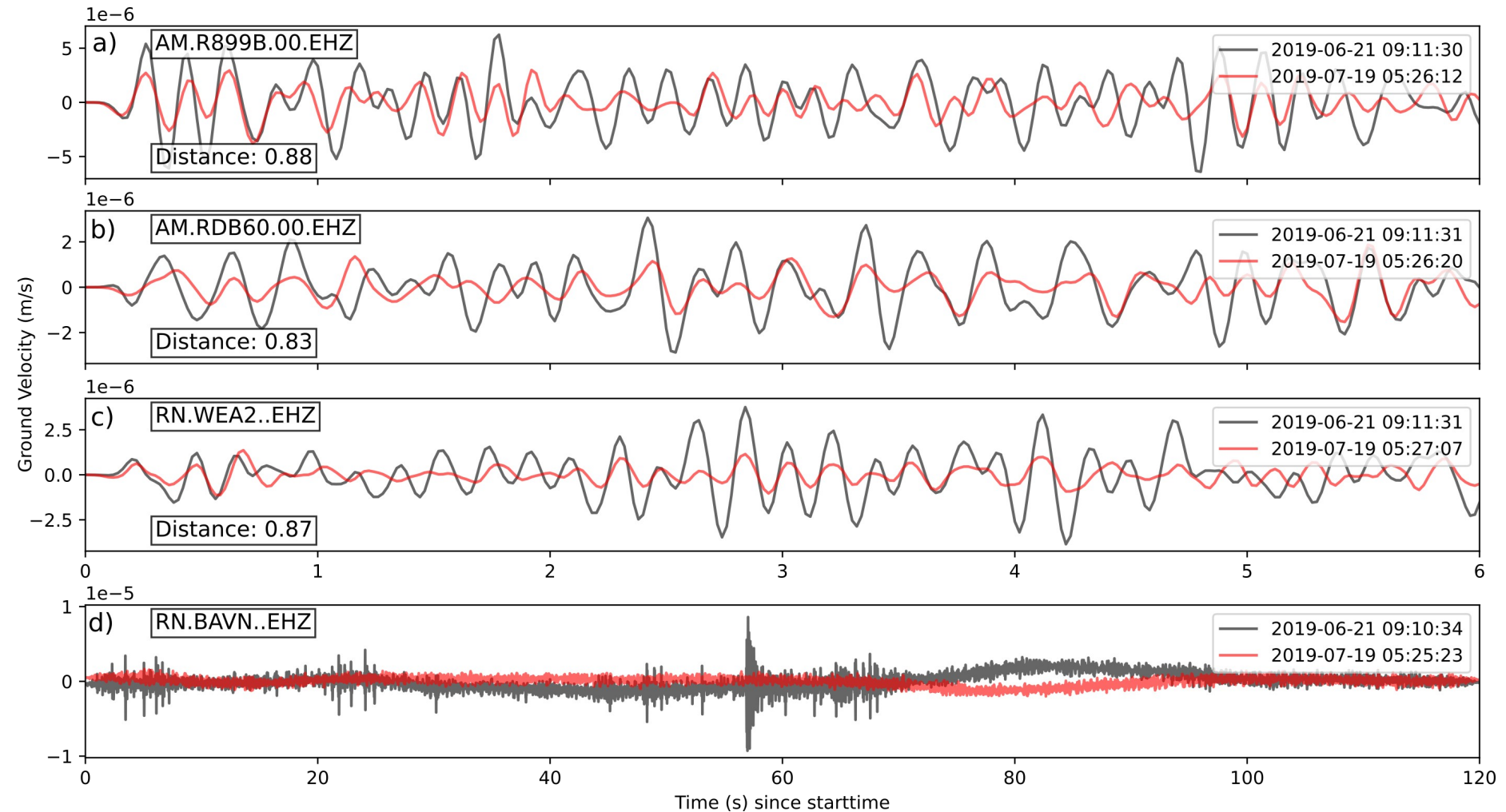
1. Taking Time Series of station at Wind Turbine
2. Computing Euclidean Distance of selected signal window t_i and windows in the continuous record t_j by

$$D_{i,j} = \left[\frac{\sum_{l=0}^{n-1} ((t_{i+l} - \mu_i) - (t_{j+l} - \mu_j))^2}{\sum_{l=0}^{n-1} (t_{i+l} - \mu_i)^2} \right]^{\frac{1}{2}}$$

3. Minima in resulting Distance Profile represent highly similar signals
4. Extracting signal at seismological station as Noise Model

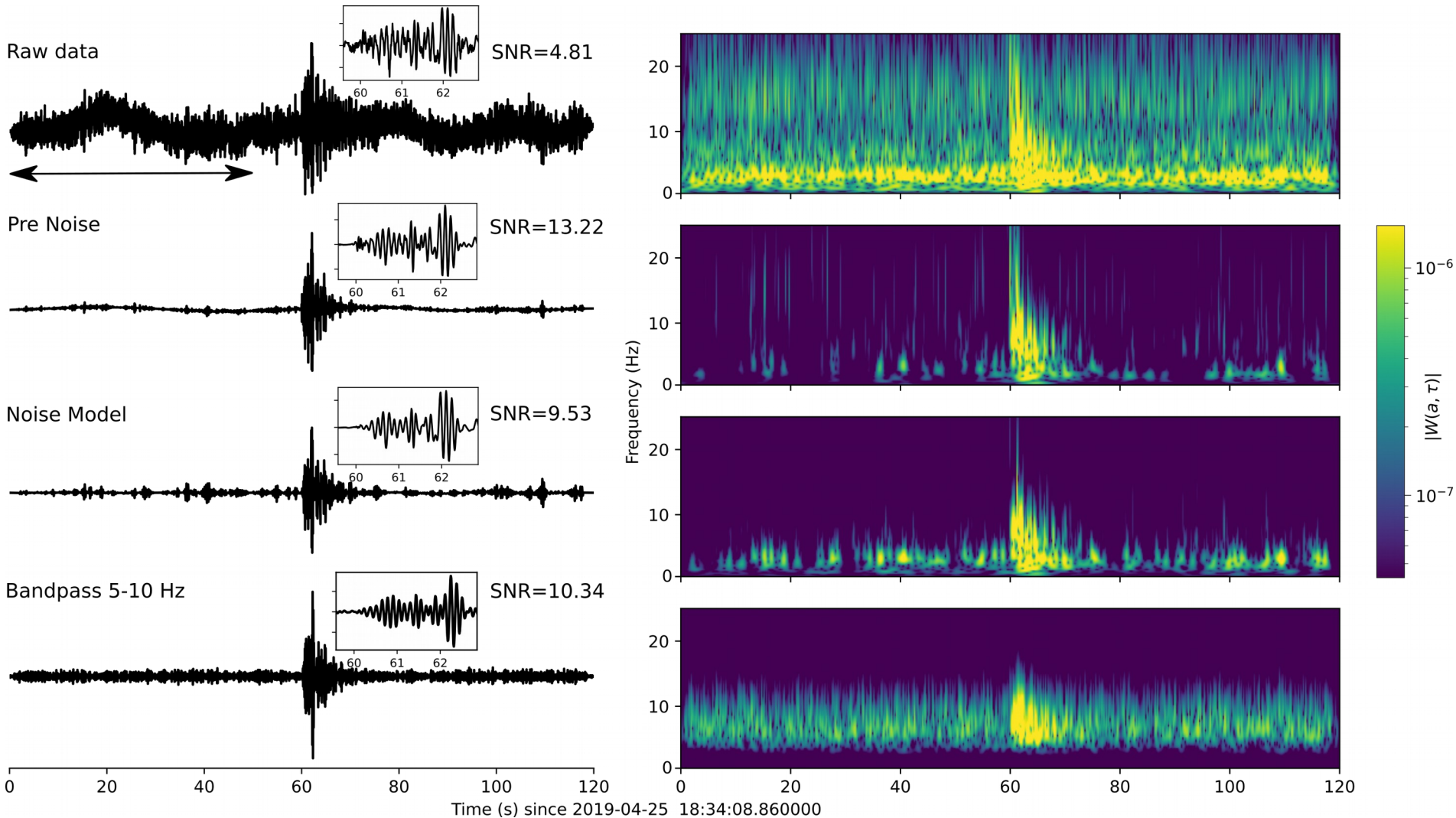


Denoising Methods | Nonlinear Thresholding

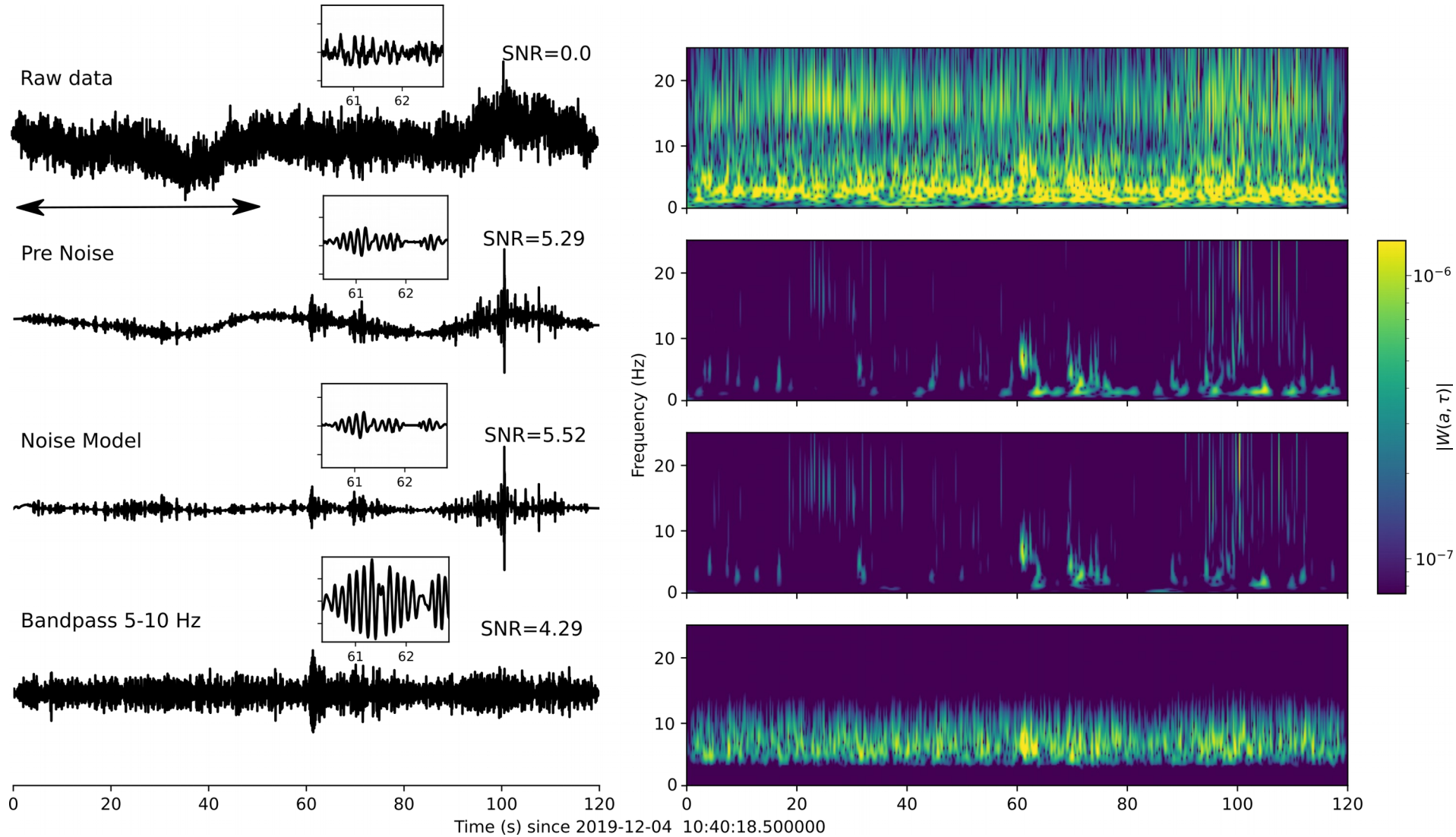


Similar signals found at each WT (red curve in a-c) for grey master trace using the distance profile, the corrupted signal (grey curve in d) and the extracted noise model (red curve in d)

Denoising Methods | Nonlinear Thresholding



Denoising Methods | Nonlinear Thresholding



Denoising Methods | Denoising Autoencoder (DAE)

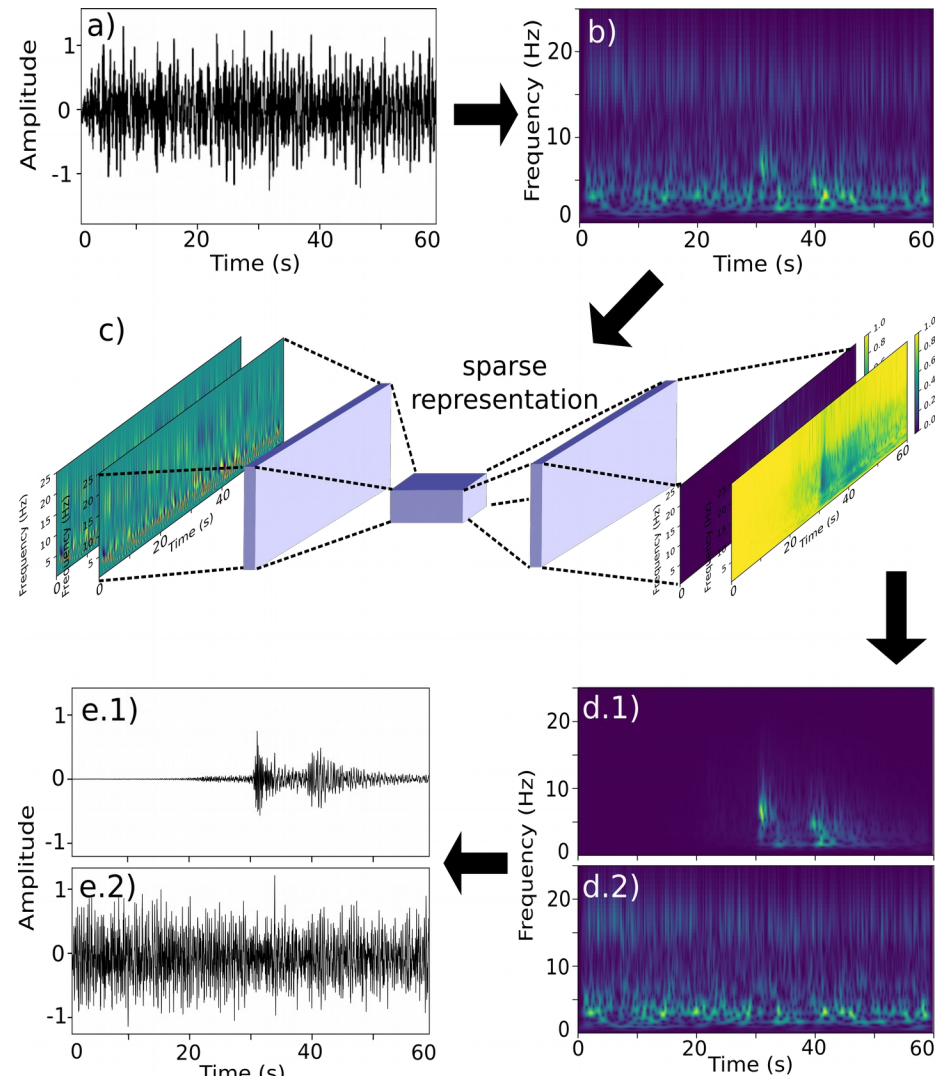
- DAE learns a sparse representation of the real and imaginary parts of the time-frequency (TF) coefficients and creates two individual masks for signal (S) and noise (N)

- Masking functions (Zhu et al., 2019):

$$M_S(t, f) = \frac{1}{1 + \frac{|N(t, f)|}{|S(t, f)|}}$$

$$M_N(t, f) = \frac{\frac{|N(t, f)|}{|S(t, f)|}}{1 + \frac{|N(t, f)|}{|S(t, f)|}}$$

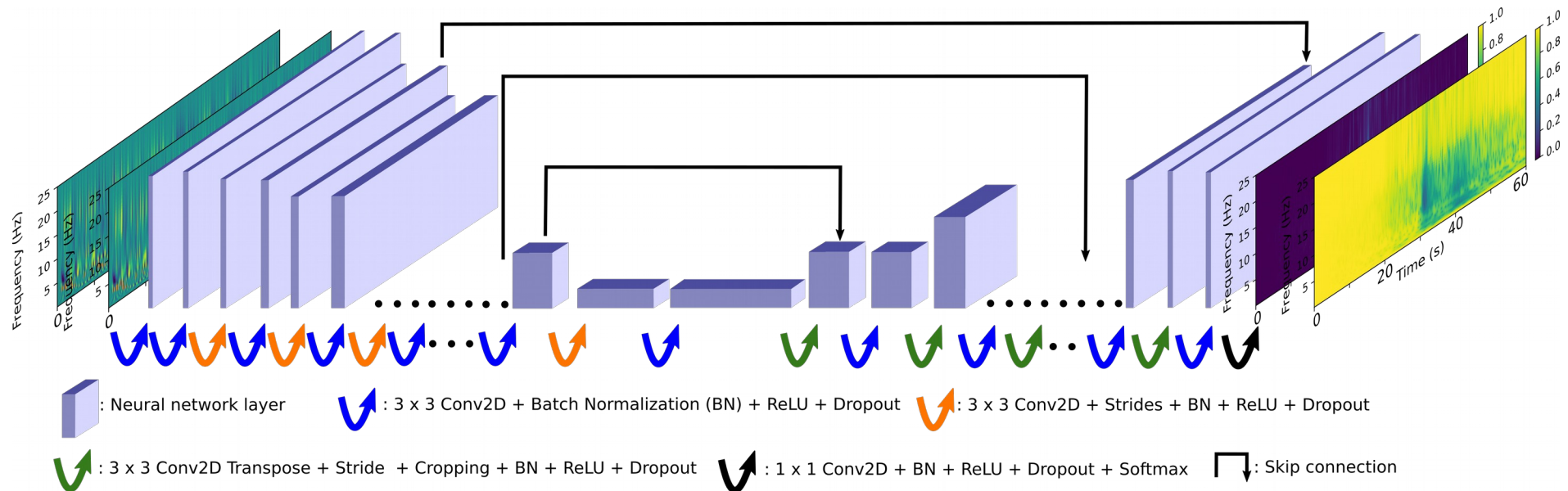
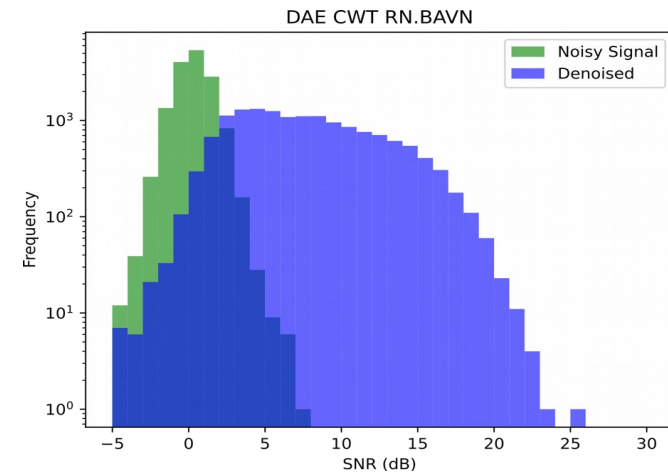
- Masking functions are multiplied element-wise with noisy TF coefficients to obtain TF coefficients for signal and noise
- Both modified TF coefficients are transformed back into time domain



After Zhu et al. (2019)

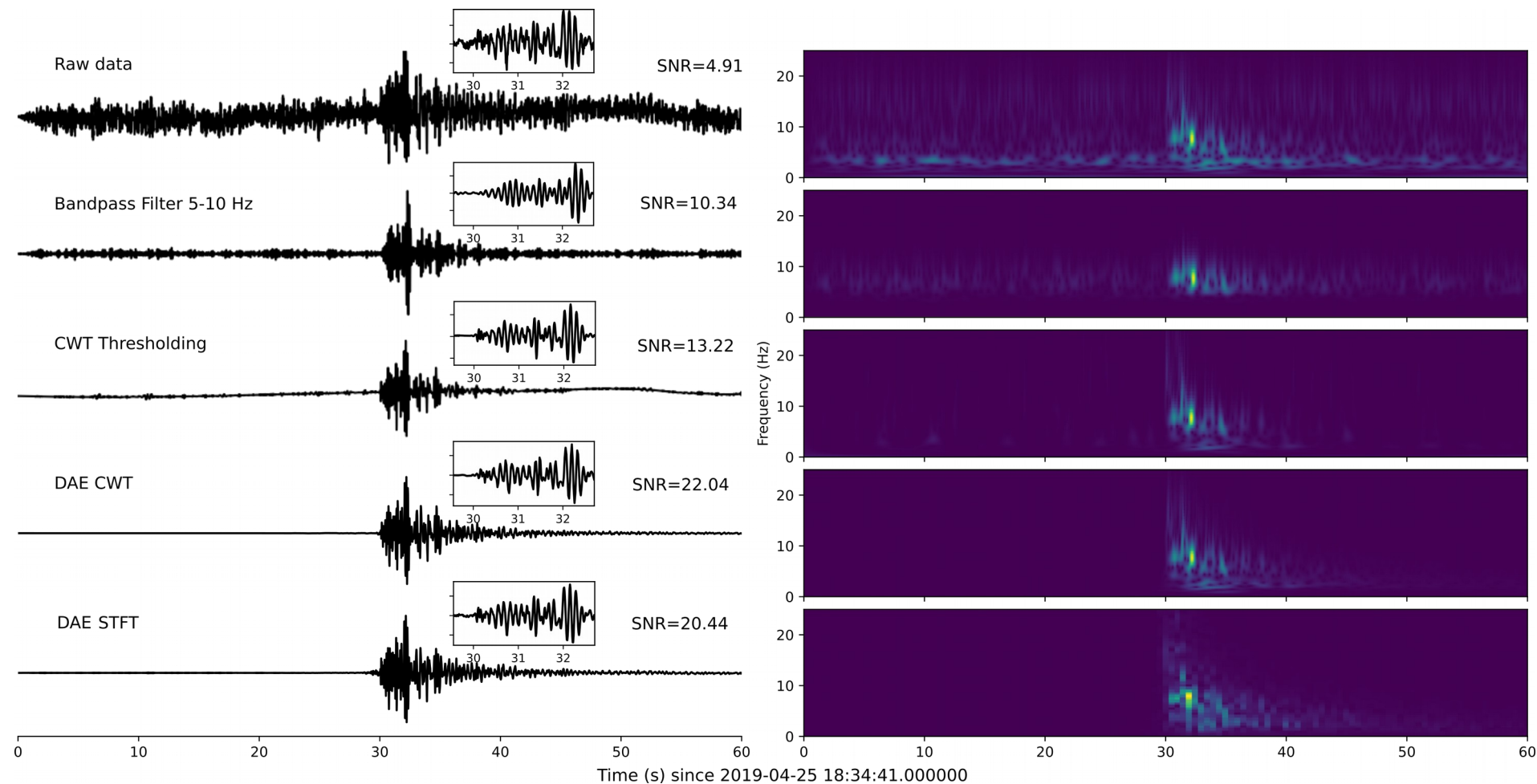
Denoising Methods | Denoising Autoencoder (DAE)

- DAE is trained using high SNR data from STEAD (Mousavi et al. 2019) and noise from station RN.BAVN
- A noisy test dataset is used to evaluate the performance of the neural network



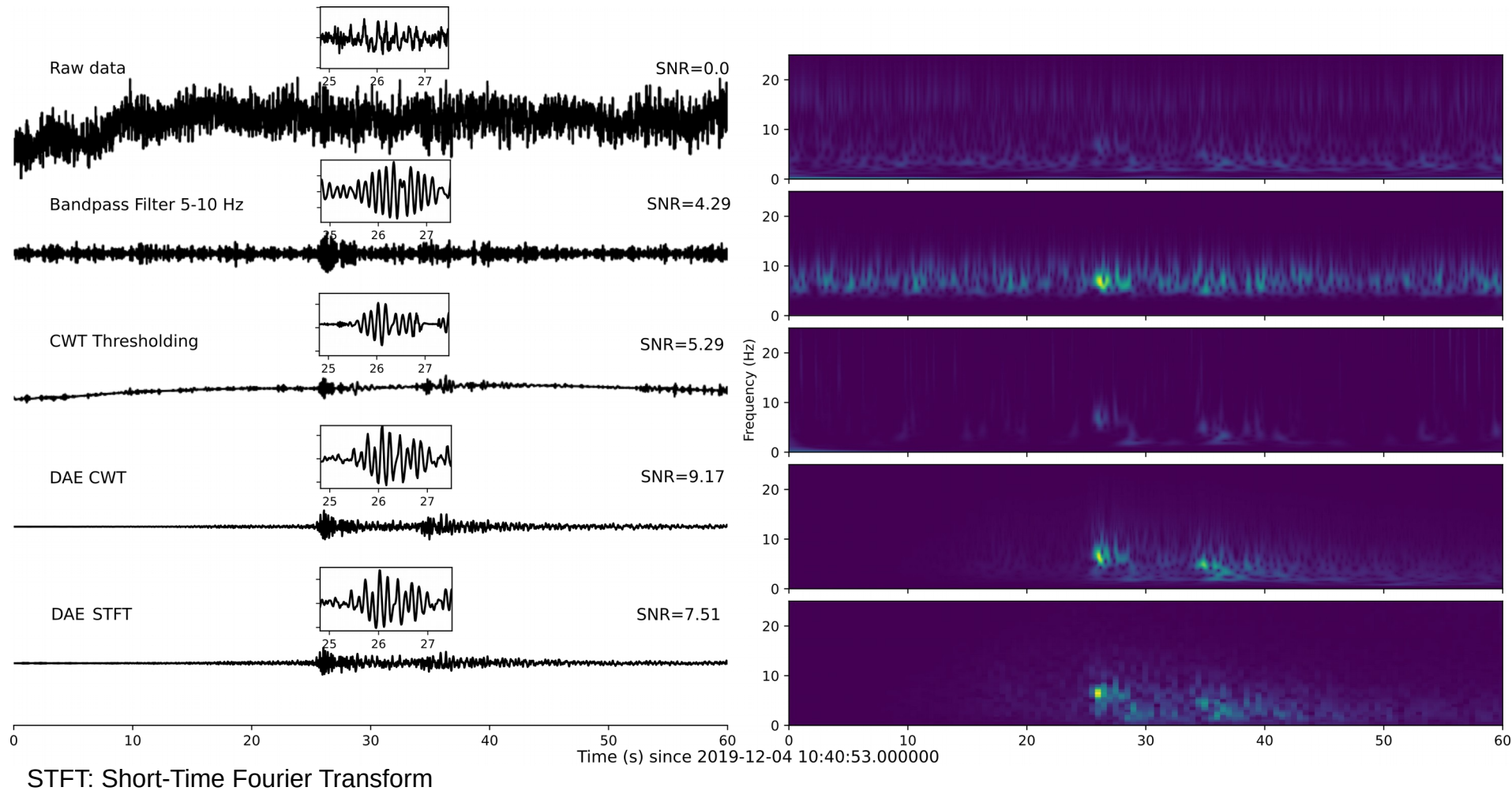
After Mandelli et al. (2019), Zhu et al. (2019) and Tibi et al. (2021)

Comparison of Denoising Methods

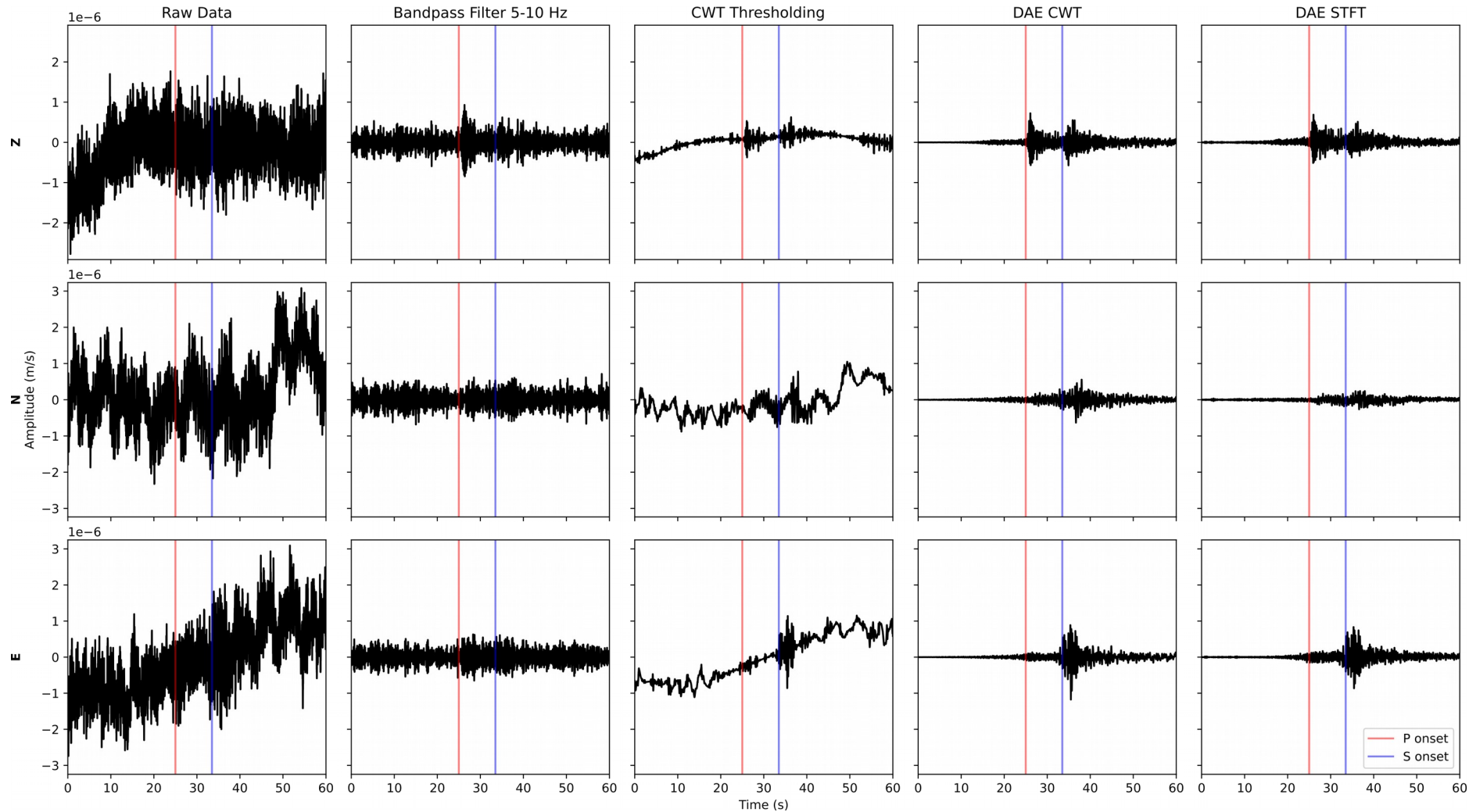


STFT: Short-Time Fourier Transform

Comparison of Denoising Methods



Comparison of Denoising Methods



Conclusions

- Nonlinear thresholding suppresses noise well if the TF coefficients are far above the threshold function
- For events covered by noise, nonlinear thresholding results in a spiky recovered signal
- Using pre noise is easier and computationally cheaper instead of finding a suitable noise model
- DAE separates signal and noise, even if both share a common frequency band and the event is covered by noise
- DAE is limited to recover signals larger than input noisy data because mask functions have values between $[0, 1]$
- Using CWT instead of STFT for the DAE is computationally more complex, but usually leads to a higher SNR
- Generally, training the DAE takes some time (depends on the length of the input signal and the depth of the neural network), but when it is trained for a station, denoising can be done immediately

References

Langston, C. A. & Mousavi, S. M. Separating Signal from Noise and from Other Signal Using Nonlinear Thresholding and Scale-Time Windowing of Continuous Wavelet Transforms Bulletin of the Seismological Society of America, Seismological Society of America, 2019, 109, 1691-1700

Mandelli, S.; Lipari, V.; Bestagini, P. & Tubaro, S. Interpolation and denoising of seismic data using convolutional neural networks arXiv preprint arXiv:1901.07927, 2019

Mousavi, S. M.; Sheng, Y.; Zhu, W. & Beroza, G. C. STanford EArthquake Dataset (STEAD): A Global Data Set of Seismic Signals for AI IEEE Access, IEEE, 2019a, 7, 179464-179476

Stammler, K. & Ceranna, L. Influence of wind turbines on seismic records of the Gräfenberg array Seismological Research Letters, Seismological Society of America, 2016, 87, 1075-1081

Tibi, R.; Hammond, P.; Brogan, R.; Young, C. J. & Koper, K. Deep Learning Denoising Applied to Regional Distance Seismic Data in Utah Bulletin of the Seismological Society of America, 2021

Zhu, W.; Mousavi, S. M. & Beroza, G. C. Seismic signal denoising and decomposition using deep neural networks IEEE Transactions on Geoscience and Remote Sensing, IEEE, 2019, 57, 9476-9488