Denoising 3-component seismic data using deep neural network

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Abstract

Earthquake signals in seismic data are inevitably contaminated with signals from unwanted sources. Separating noise from earthquake signals can greatly improve the analysis of the seismic data, such as earthquake characterization and ambient noise analysis. In this work, we develop a new auto-encoder to extract transient signals from ambient signals directly in the time domain for 3-component seismograms. We benchmark our architecture development and performance against a time-frequency counterpart (similar to the DeepDenoisier). We explore the generalization of our time-domain denoiser by training on various scales of seismic data. First, we train purely on observed seismograms of local ($<$ 350 km) events using the STandford EArthquake Dataset (STEAD) data set. Second, we generate a data set of observed seismograms from regional earthquakes (350 km-2000 km), which we complement with seismograms generated by hybrid low-frequency deterministic, high-frequency stochastic synthetic waveforms. We explore the robustness of the denoiser on various noise structures. Finally, we explore the quality of the extracted signals, for earthquake characterization and for ambient noise seismology.

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Separation of seismic signal and ambient noise using deep neural network

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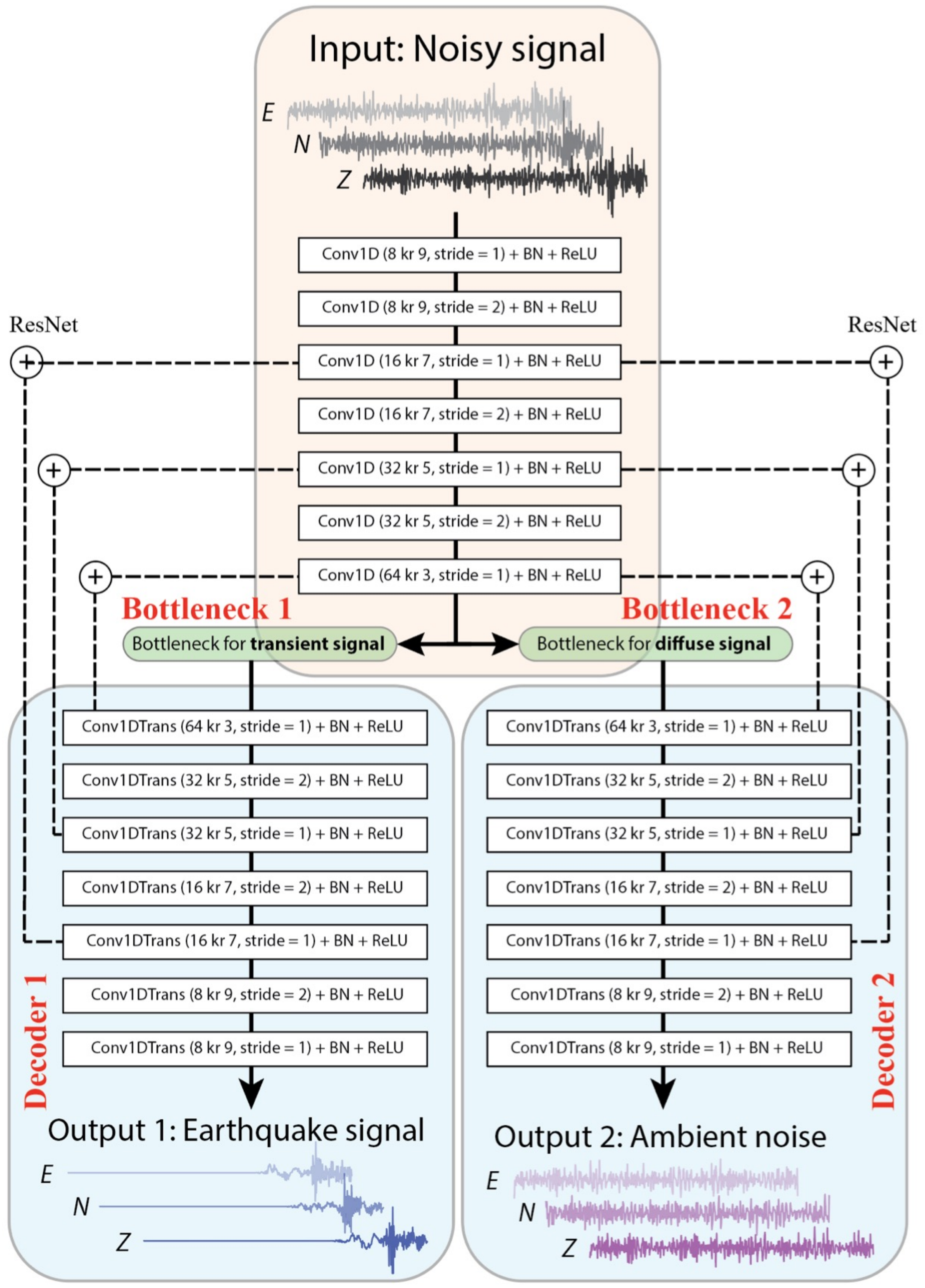
Summary

- We develop a machine learning method to separate the earthquake signal and noise signal in time domain.
- We systematically compare different network structures and find LSTM bottleneck outperforms others.
- We apply our network to continous seismic data and show improvement on the quality of both earthquake signals and ambient noise signals.

Network architecture



"x kr y, stride=z" refers to x kernels with y features and stride of z

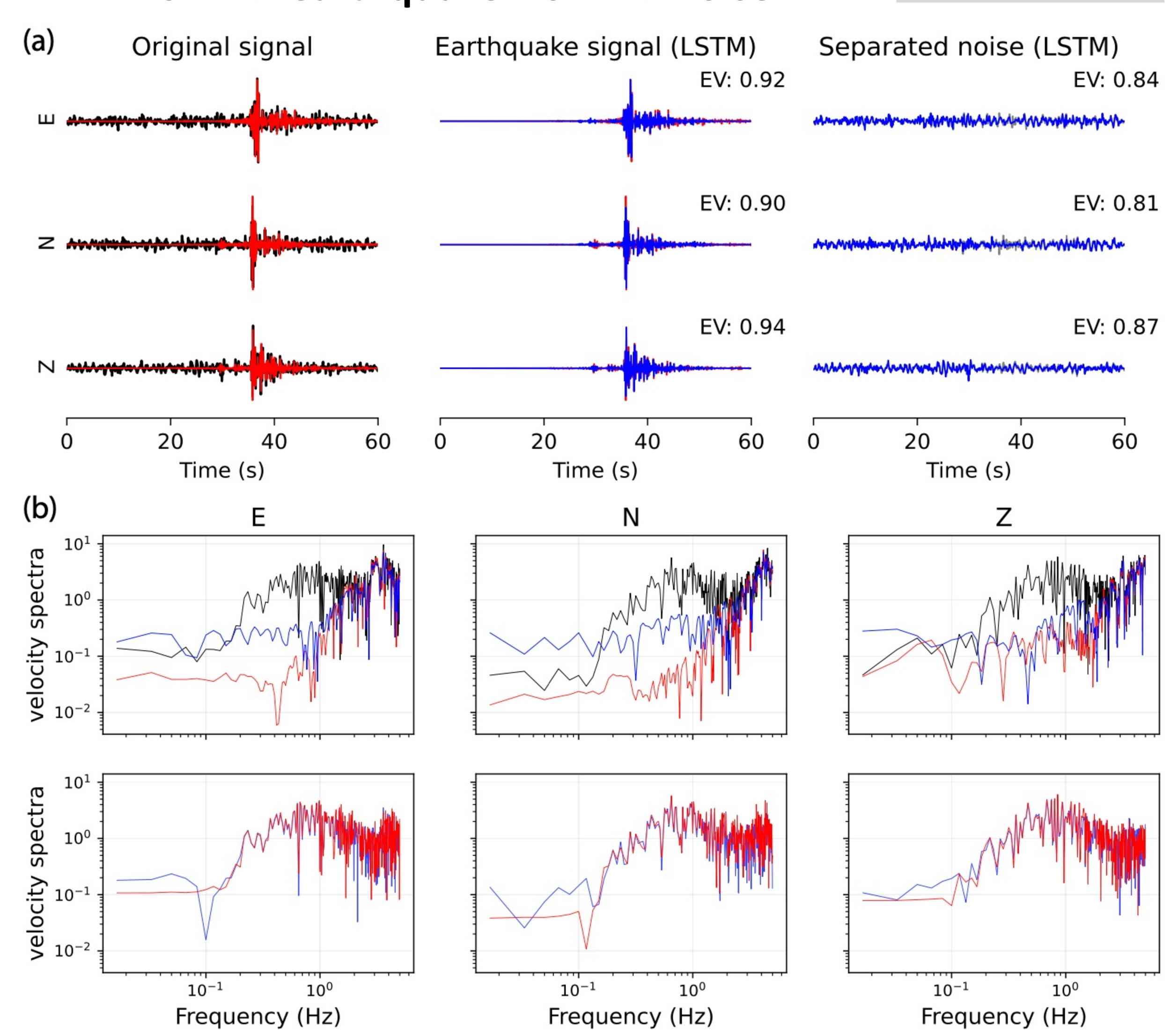
- We apply the encoder-decoder architecture (shown above) for this sequence-to-sequence regression problem.

- The bottleneck block is a key component for the encoder-decoder architecture. In this study, different choices of the bottleneck block for the feature-extraction of time-series are tested, including:
  - **None** (no specified block for the bottleneck)
  - **Linear** (fully-connected linear layer)
  - **LSTM** (Long-Short Term Memory block)
  - **attention** (dot-product self-attention mechanism)
  - **Transformer** (1-layer transformer encoder layer)

Datasets

- Our dataset consists of two parts:
  1. **Earthquake signal**: 144,000 earthquake waveforms (SNR > 10^4) from STEAD dataset (https://github.com/smousavi05/STEAD)
  2. **Ambient noise signal**: 100,000 noise waveforms from STEAD + 44,000 regional noise waveforms from IU.POHA (https://www.fdsn.org/station_book/IU/POHA/poha.html)
- Earthquake and noise waveforms are randomly combined to form the datasets with SNR (power ratio of signal and noise) varying from 10^{-2} to 10^4 (Randomly scaling + shifting).

Examples of signal separation

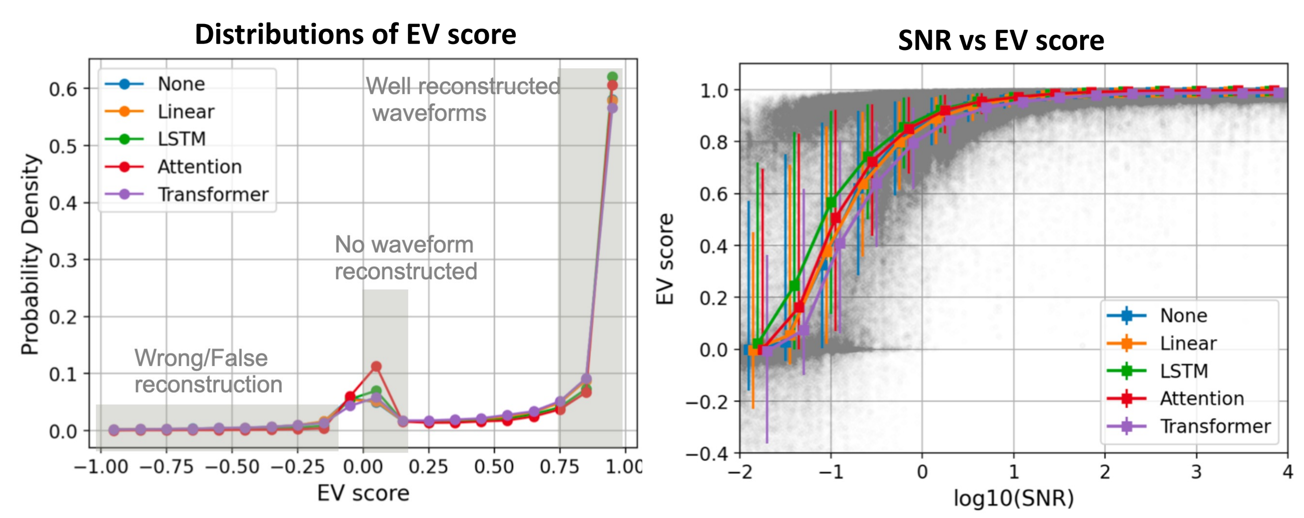


- Earthquake and ambient noise signals can be well separated, even when overlapped in the frequency domain.

Comparison between models

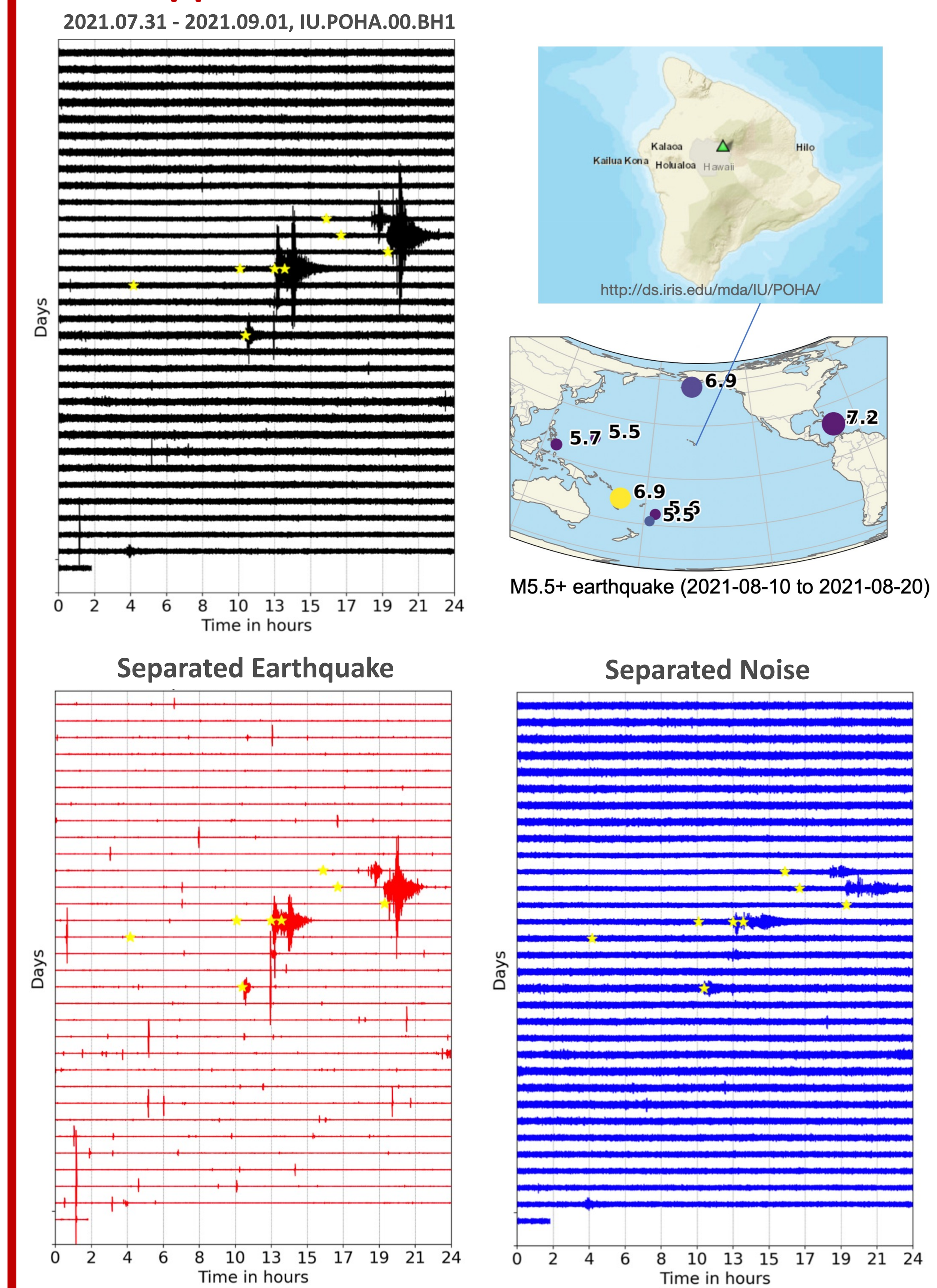
- We use the Explained Variance (EV) score to quantify the performance of trained models

$$explained\_variance(y, \hat{y}) = 1 - \frac{Var\{y - \hat{y}\}}{Var\{y\}}$$

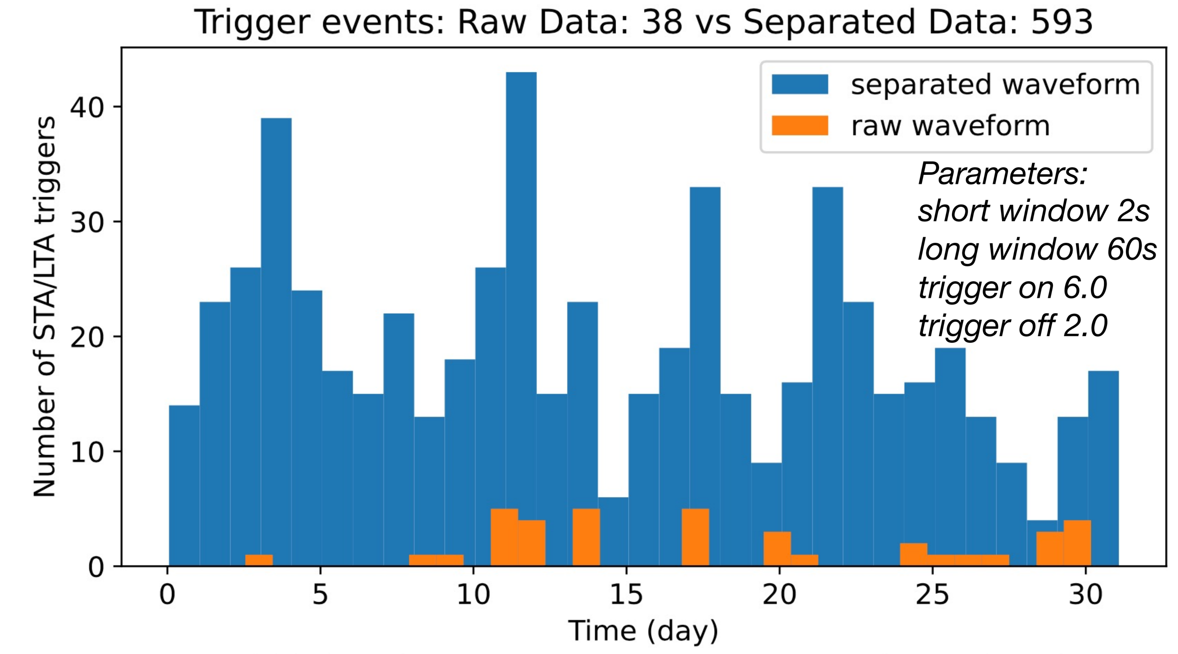


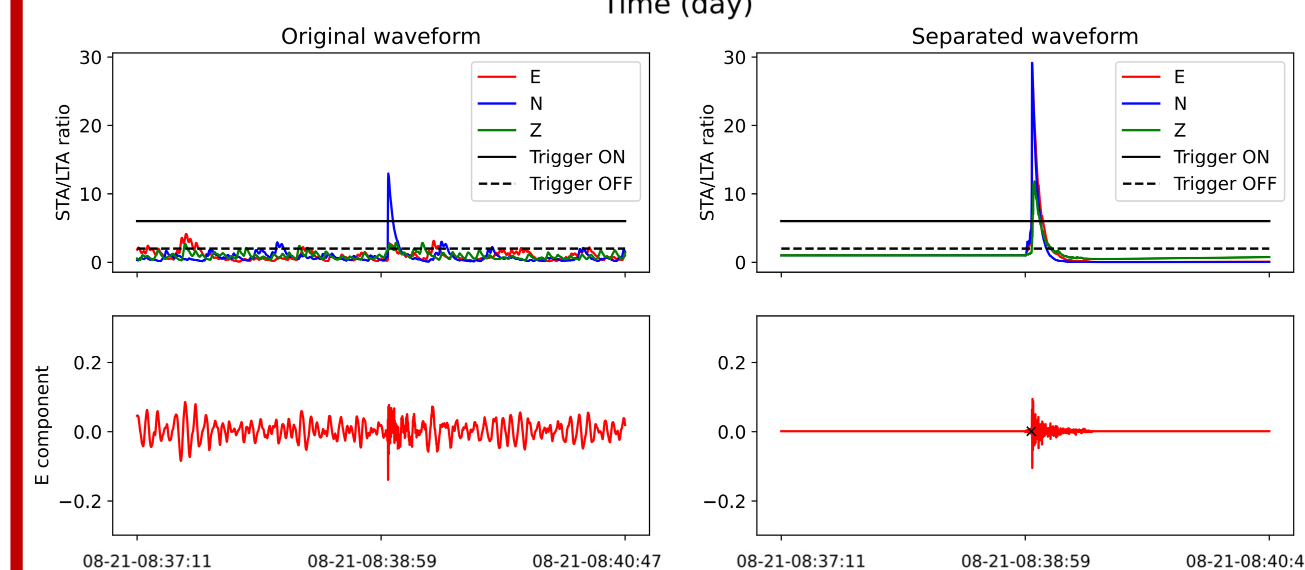
- In general, all models preform well to reconstruct both earthquake and ambient noise waveforms (> 50% well reconstructed)
- LSTM has best performance in reconstructing waveforms

Application to continous seismic data



1. STA/LTA detection





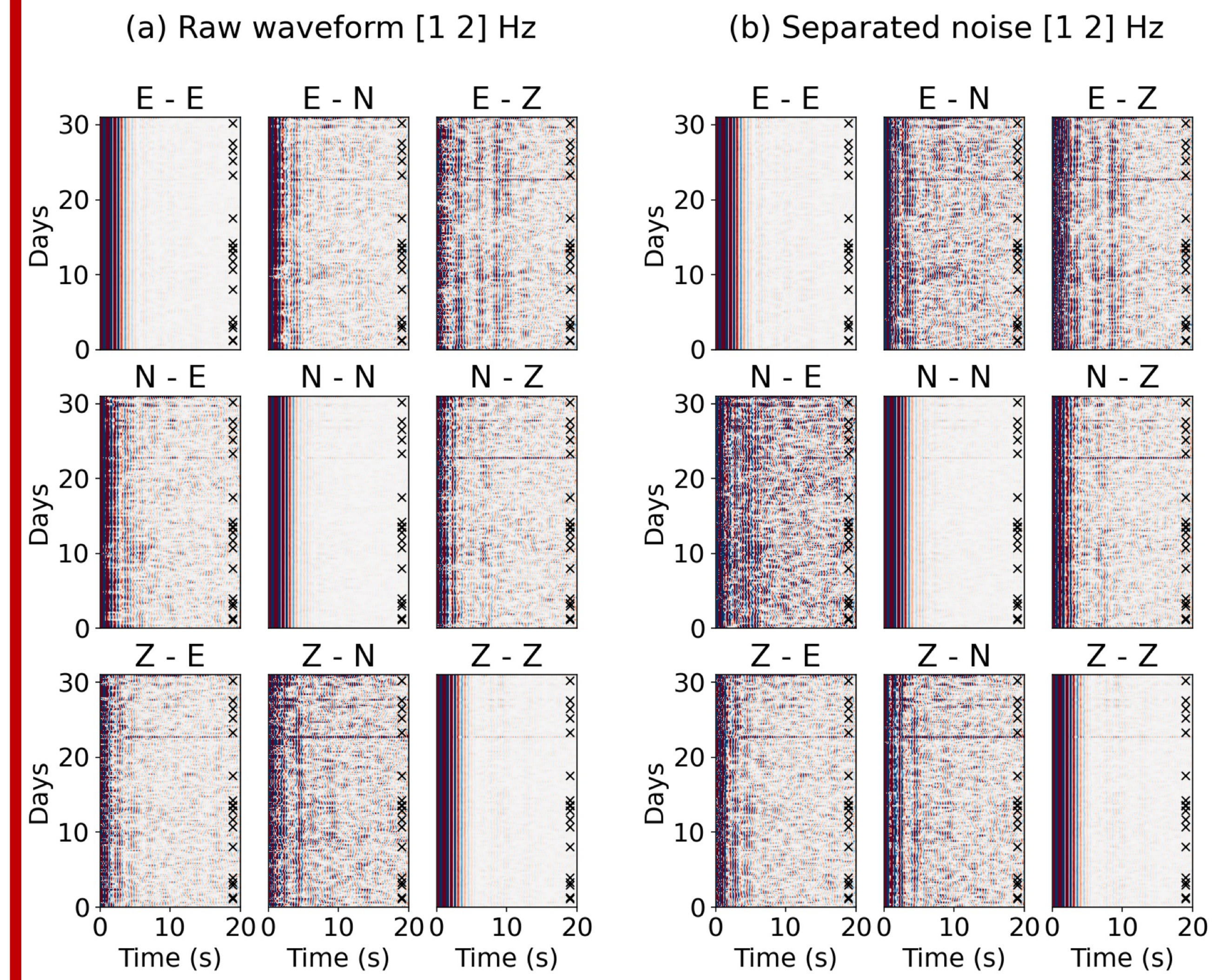
- Separated earthquake waveforms help to detect more events and allow better picking of arrival time

2. Ambient noise cross-correlation

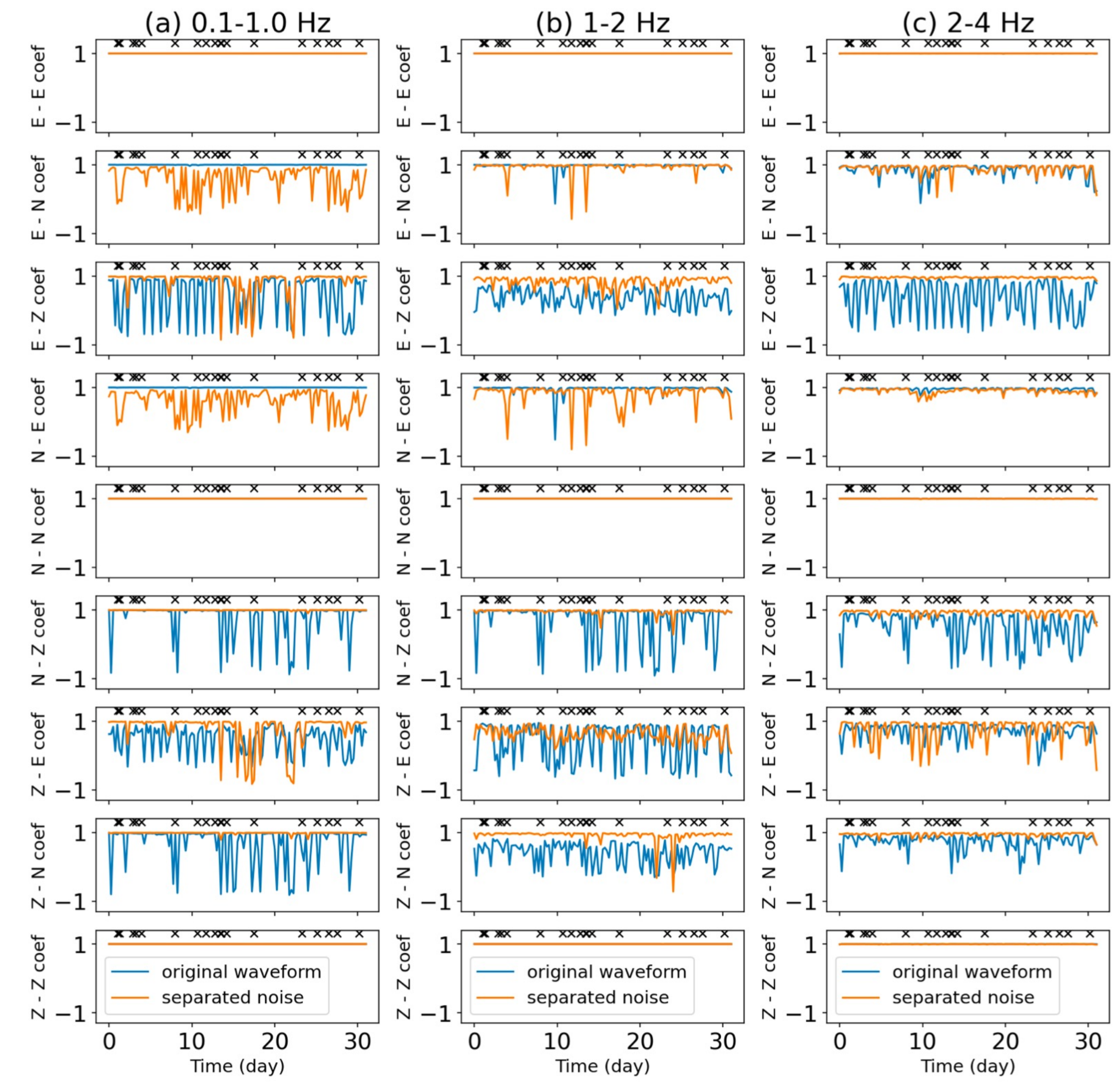
Cross-correlation functions of ambient noise between channels:

$$CCF_{ij}(t) = F^{-1}\left(\frac{\hat{a}_i \hat{a}_j^*}{|\hat{a}_i||\hat{a}_j|}\right)$$

(cross-correlation; spectral whitening)



CCF coherence (correlation with averaged CCF)



- Separated ambient noise waveforms show improvement in the coherence of CCFs.

Conclusion

- **The Encoder-Decoder network is shown to successfully separate the earthquake signal and noise signal directly in the time domain.**
- **LSTM block outperforms others in accurate separation of the signals from data with low SNR.**
- **Our network can greatly improve the quality of seismic data, and futher help in both earthquake and ambient noise seismology.**