Three-component denoising of earthquake signals with CATS-3C

Serafim Grubas, Mirko van der Baan
Department of Physics, University of Alberta.

Summary

Denoising is essential to improve the signal-to-noise ratio (SNR) in seismic data, which is important for accurate picking of P and S waves arrivals, localization and source mechanism inversion of the detected earthquakes. Joint denoising of three-component data (3C) can noticeably improve the accuracy of waveform reconstruction, which is crucial for more quality source mechanism inversion. We propose a modification to the denoising method based on Cluster Analysis of Trimmed Spectrograms (CATS) for joint 3C denoising (CATS-3C), which implements a shared binary mask between three components. Our experiments indicated that CATS-3C outperformed the original CATS and bandpass denoising methods in reconstructing weak signals through the mask from the strong components.

Theory and Method

Noise is an inevitable part of seismic data. Small magnitude earthquakes can be completely buried in noise, yet they are crucial for complete seismicity catalogs. In turn, denoising can significantly improve the signal-to-noise ratio (SNR) and waveform quality, which is paramount for accurate picking of arrival times of P and S waves (Akram & Eaton, 2016), subsequent localization, magnitude estimation, and source mechanism inversion of the detected earthquakes.

Three-component (3C) seismic sensors record the motion of particles in three directions (such as East, North, Depth). Data recorded by 3C sensors carry much more information about the earthquake signal polarization than 1C counterparts and is essential for phase identification (P or S wave) as well as source mechanism inversion. However, most denoising methods ignore the nature of 3C data and process each component independently. It was shown that joint denoising of 3C data could noticeably improve the denoising quality (Vera Rodriguez et al., 2012), using the fact that the earthquake arrives at all three components at the same time.

Recently, Grubas and Van der Baan (2024) proposed Cluster Analysis of Trimmed Spectrograms (CATS) to denoise earthquake signals and showed that it can significantly outperform traditional and deep learning methods. The CATS is a signal-processing technique which estimates a sparse representation of the input data by searching high-energy clusters in the time-frequency domain. The denoising with CATS has 4 main steps: 1) Time-frequency transform of the input data to get the spectrogram; 2) Automatic noise estimation using B-E-DATE (Mai et al., 2015) and trimming of the spectrogram by the estimated noise level; 3) Clustering and filtering the trimmed spectrogram to get the sparse representation; 4) Inverse transform to obtain the denoised signal.

In this work, we propose a modification of CATS for joint denoising of 3C data with earthquake signals (CATS-3C). We utilize the fact that earthquake arrives at three components at the same time. In the described above workflow of CATS denoising, we modify only the 3rd step (clustering and filtering). We combine the trimming binary masks from the three components obtained independently in the 2nd step. The united mask is then clustered and filtered. The final sparse mask is shared between the three components for further inverse transform (4th step). Such a trick allows a signal which is prominent on one component to better restore a weaker signal on another component, which can be beneficial for more accurate polarization analysis. The final workflow can be seen in Fig. 1 with a real earthquake signal contaminated with random low-frequency noise. In this work, for the first step to calculate the spectrogram, we use Continuous Wavelet Transform as it provides more accurate localization of the signal in time and frequency than conventional Short-Time Fourier Transform (Tary et al., 2014).

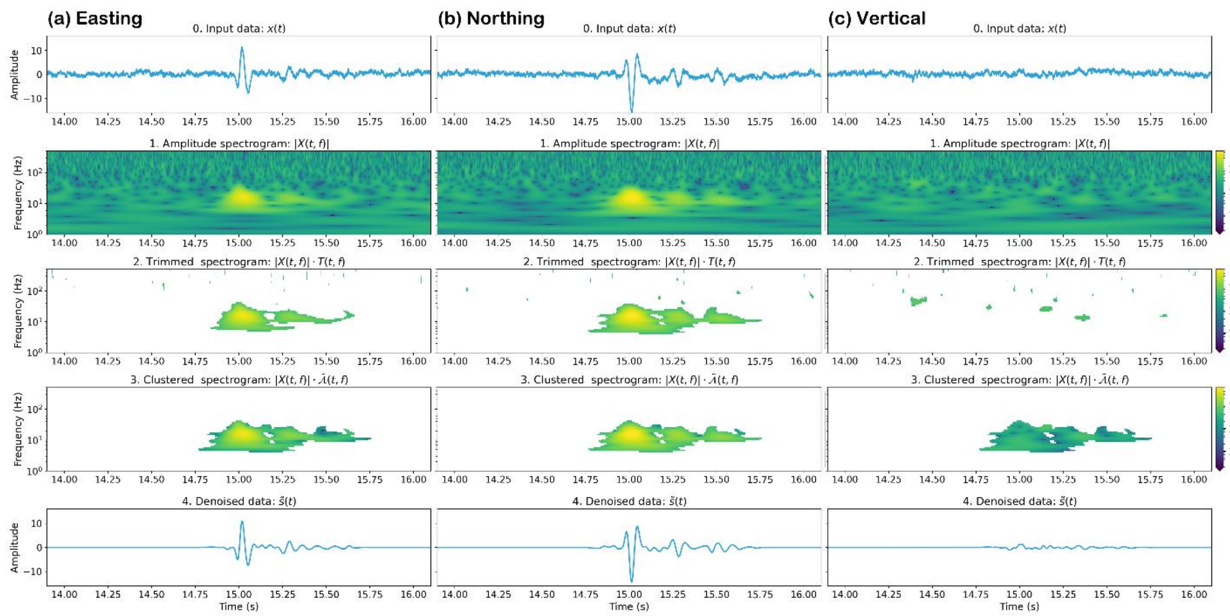

Figure 1. The workflow of CATS-3C denoising applied to the earthquake signal from Tower Lake area in Northeast British Columbia (Kao and Venables, 2021) with added low-frequency random noise. The time shown is relative to the timestamp 16 hours 57 minutes 30 seconds (Apr 9, 2021) on station 002.

Results and Conclusions

We applied CATS-3C on the same signal from Fig. 1 with the same low-frequency noise and compared it with bandpass and original CATS denoising methods. To reach the best performance for each denoiser, we tuned their parameters on the same 3C signal using the autotuning technique based on NSGA-III (Deb & Jain, 2014) via Optuna framework (Akiba et al., 2019).

We evaluated accuracy using relative L_2 norm with respect to the clean reference signal and by visual analysis of the hodograms showing the trajectories of particle motion for time window of S-wave (see Fig. 2). Fig. 2 illustrates the denoised signals and the hodograms of bandpass, CATS, and CATS-3C denoisers. From Fig. 2, we can see that CATS-3C has the smallest relative error (see numbers next to the column titles). The most challenging part of the data for denoising was on Z (Vertical) component (see Fig. 1(c) and green lines of the top row in Fig. 2). The energy of the signal was considerably smaller than the noise, which we can also see in the spectrograms of Fig. 1(c).1-3 where it is not distinguishable from noise at all. Nonetheless, much stronger signal on components E and N (Easting and Northing) provided the mask to approximate the weak signal on Z component (see spectrogram in Fig. 1(c).3). The reconstructed signal on Z components resulted in more accurate hodograms in Fig. 2 for CATS-3C than CATS and bandpass (compare trajectories on E-Z and N-Z planes, the last two rows).

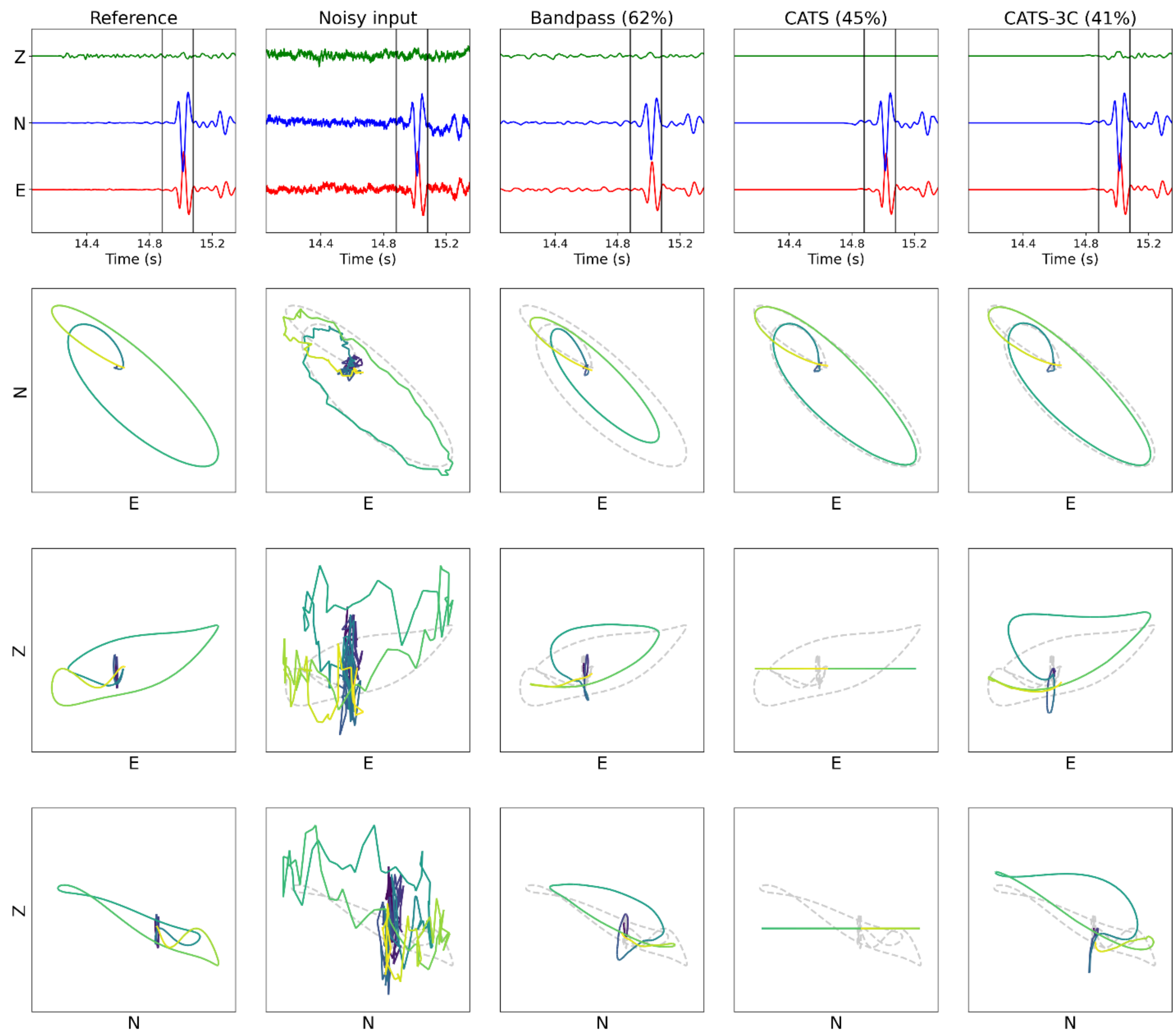

Figure 2. Comparison of the hodograms (2D projections of the particle motion) before and after denoising for the signal from Fig. 1. From the left to the right column respectively: the clean reference signal, the noisy input signal, the signal filtered by bandpass, the signal filtered by CATS, and the signal filtered by CATS-3C. The value in percentage next to the last three column titles shows the relative L_2 error of denoising. From the top to the bottom row: the three-component signal (E is for Easting component, N is Northing, Z is Vertical), and the hodograms in the E-N, E-Z, and N-Z planes respectively. The vertical lines on the top row subplots delimit the hodogram time window (S-wave) for the displayed particle motion trajectories, where the colors of the trajectories indicate time (from dark purple to bright yellow) and the gray dashed trajectories represent the ground truth reference (copy of the first column).

Contrary to CATS-3C, bandpass did not properly localize the signal in time (noise oscillations before the earthquake, compare the first and third columns in the top row in Fig. 2) and noticeably changed the original amplitudes (smaller magnitude of oscillations than the reference). CATS better localized the signal in time and restored the amplitudes, but it completely killed the weak signal on Z component (Vertical) unlike CATS-3C.

To summarize, the proposed CATS-3C modification can denoise signals on 3C data more accurately than traditional bandpass and original CATS methods, when some components have strong signal and others are weak.

Novel Information

We presented a novel modification to the denoising method CATS which enables more accurate denoising of earthquake signals in 3C data.

Acknowledgements

The authors would like to thank the sponsors of the Consortium for Distributed and Passive Sensing for supporting this research and Natural Resources Canada for providing the data (Honn Kao & Stuart Venables, 2021).

References

Akiba, T., S. Sano, T. Yanase, T. Ohta, and M. Koyama (2019). Optuna: A next-generation hyperparameter optimization framework. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*.

Akram, J. & Eaton, D. W., 2016. A review and appraisal of arrival-time picking methods for downhole microseismic data, Geophysics, 81(2), KS71–KS91.

Deb, K. and H. Jain (2014). An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part i: Solving problems with box constraints. *IEEE Transactions on Evolutionary Computation* **18**(4), 577–601.

Grubas, S., & van der Baan, M. Denoising of earthquake signals with CATS (2024). GeoConvention 2024, Calgary, June 2024.

Honn Kao & Stuart Venables, 2021. Tower Lake area, in western Canada., International Federation of Digital Seismograph Networks. DOI: 10.7914/1yev-vt66

Mai, V.-K., Pastor, D., A ̈issa-El-Bey, A., & Le-Bidan, R. (2015). Robust estimation of non-stationary noise power spectrum for speech enhancement. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, *23*(4), 670–682.

Tary, J. B., Herrera, R. H., Han, J., & van der Baan, M. (2014). Spectral estimation—What is new? What is next?. *Reviews of Geophysics*, *52*(4), 723-749.

Vera Rodriguez, I., Bonar, D., & Sacchi, M. (2012). Microseismic data denoising using a 3C group sparsity constrained time-frequency transform. *Geophysics*, *77*(2), V21-V29.